Agent-based modelling of grassland grazing

A case study from Zeku, China

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The candidate confirms that the work submitted is his/her own, except where work which has formed part of jointly authored manuscript has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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Abstract

The livestock grazing system is one of the most important human natural coupling systems on the earth. More than one-quarter of the global land surface is managed grazing grasslands, and the intensification of animal production and grazing systems is likely to continue worldwide. Managing the grassland grazing system towards a sustainable future is, therefore, an important issue for herders, grassland managers and policymakers. This requires dynamic monitoring and assessment of the grazing system, which consists of the complexities plant growth, livestock dynamics, plant-herbivore interactions and grazing management. Leaf Area Index (LAI) is commonly used as a proxy for grassland condition. However, current studies all focus on the year-round aggregated LAI change or seasonal variation rather than the specific grazing-led LAI defoliation for each pixel, which is the important indicator for quantifying grassland grazing activities.

The contribution of this research to grassland grazing management can be summarised through three main components: a new growth function under grazing considering both the growth and senescence of grass with an estimation algorithm; the employment of a LUE-VMP model to estimate Net Primary Productivity (NPP) for improved LAI validation; and a first attempt in building an agent-based model (ABMGG) integrated with patch-specific grazing information for the assessment of various grazing management strategies. It was found that although different grazing management scenarios could not significantly improve or decrease grassland productivity, rotational group grazing performed best in terms of producing a smaller number of degraded grassland patches. Although there are some drawbacks, the agent-based modelling is highly suited to the grassland grazing system that is characterized by individual interactions and contains hierarchical grazing strategies and institutional arrangements. It is also suggested that by improvement of the data quality and extension of the model, ABMGG would be able to predict and analyze the performance of different grazing management scenarios further, and would be an important tool for aiding the sustainable development of the grazing system for both herders and policymakers.

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Chapter 1 Introduction

1.1 Background and research motivation

Grasslands are a valuable natural resource that covers about one-third of the Earth's land area (Heady, 1975; Gilmanov et al., 2010). Grasslands are referred to as savannas in Africa (O'connor and Pickett, 1992); in the regions of Eurasia, they are commonly named steppes (Bai et al., 2007); in the U.S. Midwest, grasslands are called prairies (Collins et al., 1998; Fuhlendorf and Engle, 2001b); while in South America, they are known as pampas (Altesor et al., 2006). What they all have in common is that grass is the naturally dominant vegetation. Numerous studies have reported that grasslands are of great importance for local ecosystems, including soil and water conservation (Davis, 1979), carbon sequestration (Schuman et al., 2002) and biodiversity (West, 1993). However, for centuries, in both developed and developing countries, livestock grazing has played a dominant role in removing grass biomass (Peet et al., 1999). Almost all livestock farmers, herders or pastoralists depend on grasslands and conserved products such as hay and silage and on a wide range of fodder species for their livelihoods (Suttie et al., 2005). Rapid increases in human and livestock populations have been marked that natural grasslands in many areas of the world have been extensively modified or even destroyed, particularly in arid and semi-arid environments (Milchunas et al., 1998; Watkinson and Ormerod, 2001). Humans have already profoundly affected grassland regions by grazing, mainly for short-term profit, and have ignored the long-term stability of the grassland ecosystem (Hadjigeorgiou et al., 2005). In addition, most of the grasslands are distributed in eco-sensitive areas – areas with relatively low vegetation diversity compared with forestlands, and they are, therefore, susceptible to climate change – facilitating the uneven distribution of grass forage at https://mini.eastday.com/a/n190217000041389.html?qid=03123 both spatial and temporal scales (Coupland, 1979; Dixon et al., 2014a). The spatial and temporal differences of forage availability and the complexity of interactions of grassland grazing make the management of grassland utilization challenging to secure in terms of both animal production and the renewal of natural feed resources (Jouven et al., 2010). Now more than ever, grassland grazing information is needed to monitor and precisely assess the grassland system.

It is almost impossible to have a real-time and continuous time series of *in situ* observation data on the current status of grass and grazing activities (Ali et al., 2016). Precise information on grass status and grazing activities can be obtained precisely at farm or local scale by *in situ* methods, including simple visual analysis (Rouse Jr, 1972), advanced rising plate measurement (Nakagami, 2016) and more complicated laboratory analysis (Cougnon et al., 2016; Hoffmann et al., 2016). The drawbacks of *in situ* monitoring techniques are obvious: they are time-consuming; labour-intensive; and almost impossible to apply to large scale grassland monitoring (Ling et al., 2014). On the other hand, remote sensing and modelling approaches allow for large scale monitoring and further assessment of grassland status (Rose et al., 2015). By measuring the reflectance at visible and infrared wavelengths, remote sensing can be used for identifying different grassland species and status (Todd et al., 1998; Green et al., 2016), which can be implemented on static platforms (Aubinet et al., 2012), unmanned aerial vehicles (Rango et al., 2006), and aircraft or satellite platforms (Loris and Damiano, 2006) for local scale mapping and monitoring at varying spatial and temporal resolutions. From grassland species monitoring (Geerken et al., 2005; Xie et al., 2008) and grassland biophysical characteristic quantification (Goetz, 1997; Huete et al., 2002) to grassland change detection (Cohen and Goward, 2004; Shalaby and Tateishi, 2007), the integration of multispectral and multi-temporal (Gómez et al., 2017a) remote sensing data used in combination with simulation models has been successfully demonstrated as an economically cost-effective, statistically reliable and consistent, and operationally robust tool for monitoring (Prince, 1991b) and assessing (Nagendra et al., 2013) of the status of grassland grazing systems (Svoray et al., 2013). But remote sensing techniques often have the problem of cloud cover, which will be discussed in the literature review chapter.

However, the grassland grazing system is often a non-linear (Banegas et al., 2015), multi-state, dynamic (Woodward et al., 1995b) system evolving under the interactions between nature and humans and the interactions between those two systems within time and space (Herrero et al., 2000a; Hutchings and Gordon, 2001; Seabloom and Reichman, 2001; Donnelly et al., 2002b). To monitor and assess such a complex system, knowing aggregate information about grassland is not enough to have a synthetic, objective understanding of it, that understanding of management strategies is also necessary. In fact, different grazing strategies (Woodward et al., 1995b; Wang et al., 2016) and institutional arrangements (Dong et al., 2009; Wang et al., 2013) have been proposed by herders, grassland managers and policymakers, with the purpose of a better use of grasslands. In addition, recent advances have been devoted to identifying the paradigms of grassland management (Lovett and Ockwell, 2010), which have provided basic principles and guidance, but there are still considerable challenges imposed by historical-cultural impediments and regional natural environmental differences (Johnson et al., 1983; Seabloom and Reichman, 2001). In order to model the interactions of such a co-evolving system and assess the policy implementations of grassland protection, it is of great importance to be able to account for the interactions involving stakeholders and the interactions with the environment at an individual level, which has major implications for both improving policies and developing sustainable grassland management (Bellamy and Lowes, 1999; Boyd and Svejcar, 2009).

To understand the complexity of grassland grazing systems, concepts that take the human sub-system and ecological sub-system as a whole are widely used in the natural grassland management literature (Janssen et al., 2004; Folke et al., 2005; Ostrom, 2009). For many years, grassland management has been dominated by a philosophy that simplifies this complexity with top-down control, but that inevitably results in mismatches between model outcome and the reality: scaling mismatches, synthesis of heterogeneous information, multi-scaled system interactions, complex management systems, uncertainty in causal relationships, assessment of trade-offs (Holling and Meffe, 1996) and issues with model validation. In such a human-natural coupling system, macro-level properties of grassland often emerge from individual behaviours or decisions (Levin et al., 2013). Emergence from such individuals could also produce feedbacks that affect individual decisions by managers and subsequent higher-level policy interventions (Milchunas et al., 1988; Seabloom and Reichman, 2001). Ignoring these characteristics might obscure crucial features that we observe in reality, as the risk of abrupt or irreversible grassland ecosystem changes (Levin et al., 2013). Therefore, a clear understanding of the different stakeholders and related institutions and their interactions with the system is needed to avoid such modelling problems.

1.2 Problem identification

This thesis will specifically look at the grassland of Zeku, China, which is located in the source area of the Yangtze, Yellow and Lancang rivers (the three largest rivers in China). This area has long been known as the "Water Tower of China" and Zeku is typical grassland grazing county for the area (Quanqin et al., 2013). For thousands of years, those three rivers have been of key importance to the river basin ecological environment of China and even south-eastern Asia. The Three Rivers Head source Region (TRHR) National Nature Reserve was legally established in May 2000 (Shao et al., 2016). The establishment of the nature reserve aimed to protect the Tibetan Plateau ecosystem, with an emphasis on alpine swamp meadow and the natural habitat of the unique wildlife in the region, and to promote sustainable economic development in the region (Wang et al., 2010a). Therefore, the protection of grasslands in this area is extremely important in terms of China's long term environmental, social and economic development. In addition, the status of the ecosystem in TRHR also has an inevitable international focus in regard to ecological stability and diversity of the river basin region (Fan et al., 2010a).

There are two key problems for understanding and modelling grassland grazing systems in Zeku. The first one is how to obtain precise information about grassland status and herders' grazing activities. Remote sensing data can only capture the status of vegetation at discrete time points, which obscures the wider process of vegetation development. Ignorance of the complete picture can lead to underestimates or otherwise incorrect assessments of rangeland productivity, especially in carrying capability estimations in grazing intensive regions (Lebert et al., 2006; Nyima, 2015). The information we have from current remote sensing derived datasets (for example, the MODIS LAI dataset) is very limited with regards to extracting the amount of grass that is eaten by livestock, which is the crucial indicator that would be used in guiding sustainable grazing pasture management. Therefore, we need to explore further within those datasets to estimate consumed forage between each satellite observation interval.

The second problem is how to build a model that considers not only the physical growth of grass, but also herders' decision-making and wider institutional arrangements. These must be considered in an integrated way because they all contribute to the overall dynamics of the grazing system (Browning et al., 2014). Only in this way can an objective assessment of the grassland system status be made. A new approach to model these complex systems and to overcome the above limitations is agent-based modelling (ABM). ABM has a good capability for representing the spatial and temporal heterogeneity of grassland forage productivity through the use of environmental agents. A herder can be described as a decision-making agent that can join in different institutional groups which can be used to analyse the impact of different institutional arrangements (Jun et al., 2013). The employment of ABM resource management and environmental science is a better a way than the traditional empirical or process-based models (which will be discussed in Chapter 2) in capturing the complex system characteristics of grassland grazing as it describes the interactions individually at various levels. It enables the modeller to represent the behaviour of humans more realistically, "*accounting for bounded rationality, heterogeneity, interactions, evolutionary learning and out-of-*

equilibrium dynamics, and to combine this representation with a dynamic heterogeneous representation of the spatial environment" (Filatova et al., 2013). ABM is an ideal tool to integrate with remote sensing data to further assess different grassland management scenarios.

1.3 Aims and objectives

The overall aim of this thesis is to establish an agent-based model based on the grazing information derived from remote sensing data in Zeku with the purpose of assessing various grassland management scenarios. Herders' grazing activities have a profound influence on the grassland ecosystem. The impact can be positive (e.g. promote productivity) or negative (e.g. grassland degradation or desertification) or both, depending on grazing intensities, various grazing strategies and institutional stakeholders. This thesis will study grass growth dynamics under grazing based on remote sensing data, and most importantly, by analysing the impact of different grazing strategies and institutional arrangements on grassland status using an agent-based model. The results of this thesis will be useful to guide the livestock husbandry in Zeku.

To achieve these aims, the objectives of this thesis are to:

1, review, discuss and critique the grassland grazing literature and analyse the current theories and system complexities in the grazing system in order to identify those that should be employed in the model;

2, review, discuss and critique the modelling techniques and data availability for the grassland grazing system to highlight the necessity of the techniques used for this research and to guide the model development process;

3, develop a new method to derive information about grass growth and the effect of grazing from remote sensing data;

4, design and build an agent-based model that is able to account for the different grazing strategies and institutional arrangements and use remote sensing data as an input;

5, assess different management scenarios after making sure the model has the ability to simulate the grassland status under grazing based on current grazing strategies and institutional arrangements.

1.4 Organisation of the thesis

The thesis organisation is outlined as follows:

In Chapter 2, starting with the definitions of grasslands and grassland grazing, the complexities of the grassland grazing system will be discussed; followed by the overall paradigms for modelling such complex systems, which forms the basic theory for later modelling. Then some traditional grassland grazing models and the state-of-the-art modelling technique—the agent-based models are discussed. In addition, the role of remote sensing in modelling such a complex system is elaborated as it is the most important tool for the data collection of grassland grazing.

Chapter 3 describes the study area and the data collection undertaken. After profiling the case study area, the reasons why the study area is an ideal place for agent-based modelling of grassland grazing are explained. This is followed by a detailed description of current grazing strategies and institutional arrangements in the case study area. Then, a list of the datasets used in this thesis along with descriptive statistics summarises the main features of the study area.

Chapter 4 presents a prototype agent-based model of a grassland grazing system. There are two themes highlighted in this chapter. The first section provides a rationale of the basic theory concluded in Chapter 2; the second describes the suitability of using agent-based modelling to simulate the effect of different grazing strategies and institutional arrangements, using a simplified process of the grass growth and interactions among agents.

To quantify the difference between normal vegetation growth in an area and the reduced growth that could be caused by grazing (as measured using the Leaf Area Index – LAI), Chapter 5 outlines the creation of a novel growth-grazing function for the grassland in the case study area. Two important measures are produced: improved LAI (a more accurate estimate of LAI from remotely sensed data) and expected LAI (the LAI that would be expected if where no grazing had taken place). In order to validate those results, the carbon mass of grazed LAI estimated from remote sensing is calculated, with the purpose of comparing it with statistical livestock consumption, which is also converted to carbon mass. In addition, the uncertainty of such estimation is discussed.

Chapter 6 further validates the result of Chapter 5 using a Light Use Efficiency (LUE) model. This is essentially a comparison of the results of new growth-grazing function and estimation algorithm with some *in situ* data. The chapter begins with a brief review of current Net Primary Production (NPP) models; followed by the detailed parameterization of Vegetation Phenology Model of LUE (LUE-VPM) to simulate the NPP based on improved LAI.

Chapter 7 describes the creation of the agent-based model and its use in the assessment of different grassland management scenarios. It begins by describing the model before outlining the processes of verification, sensitivity testing, calibration, and validation. The chapter concludes with the analysis of different grazing strategies and institutional arrangements, followed by recommendations for the future grassland management in Zeku. In addition, the error propagation and uncertainty analysis of the model is discussed in this chapter.

Finally, in Chapter 8, the aims and objectives are reviewed and conclusions are drawn. The chapter also documents some limitations of the research and provides suggestions for further development of the grassland grazing model and potential applications.

A table of chapters and what they mainly achieve (Table 1.1) summarises the aforementioned structure of this thesis, including detail about how the research objectives map to relevant chapters.

Table 1.1: A table of chapters and what they mainly achieve.

Chapter 1	**An introduction to the whole Thesis**
Chapter 2	➢ Review the grassland management theories and the progress of current models dealing with grass grazing system. ➢ Review the models and remote sensing methods in grassland monitoring and the gaps of current research. ➢ Identify the complexities of grassland grazing system and

	specify which should be included in the model.
Chapter 3	➢ Describe the case study area and justification for the selection of the study site. ➢ Introduce the land tenure system, grazing strategies and institutional arrangements in the case study area. ➢ Introduce the data collection undertaken.
Chapter 4	➢ Develop a prototype agent-based model describing the complexities of grassland grazing system. ➢ Preliminary analysis of the impact of different institutions on the performances of grassland grazing (the response of grassland quality, quantity and net benefit of herder agents to different institutional arrangements).
Chapter 5	➢ Develop a new growth function considering both grass growth and the effect of grazing using remotely sensed data. ➢ Results of improved, expected and grazed LAI based on this new growth function and the impact of search radius on the estimation results. ➢ Validation of the grazed LAI by comparing with statistical data with aggregated grazed grass mass. ➢ Explore the uncertainty of the estimation.
Chapter 6	➢ A brief review of NPP models and specify the reason why the LUE-VPM is used for further validation. ➢ Parameterization of LUE-VPM for the grassland productivity calculation. ➢ Validation of improved remote sensing products to further assess the accuracy of the new growth function. ➢ Uncertainty analysis of the LUE-VPM.
Chapter 7	➢ Build and evaluate the agent-based model through verification, sensitivity analysis, calibration and validation. ➢ Assess differing grazing management scenarios. ➢ Quantify the uncertainty of the agent-based model. ➢ Suggestions for the future grazing management of Zeku.
Chapter 8	➢ A synthesis of the findings of this thesis. ➢ Limitations of this work. ➢ Recommendations for future research.

1.5 Summary

The work presented in this chapter has clarified the aims and objectives of this research. By discussing the background of grassland grazing modelling, the importance of using remote sensing data and agent-based modelling for grassland monitoring and assessing was addressed. The overall aim is to provide an agent-based approach to explore the management of grassland grazing systems based on the remote sensing data, to reach the goal of analysing the performance of the grassland grazing system under different grazing strategies and institutional arrangements.

Chapter 2 Literature Review of Modelling the Complexity of Grassland Grazing

A detailed understanding of any complex system is required in order to develop a useful, representative and synoptic agent-based model of it. This chapter provides a literature review focusing on the complex nature of grassland grazing systems. It begins with a discussion of different *grassland* definitions and describes a variety of *grassland grazing systems*. It then focuses on what a complex system is and how this is different from a complicated system. The complex nature of the specific type of grassland grazing system which is the focus of this study is defined. The parts of these systems to be represented, and the general nature of the complex interactions between these parts are described. For modelling such systems, the limitations of a wide number of other approaches and the potential benefits of *agent-based modelling* are considered. The chapter provides: a brief overview and critique of different approaches to modelling grassland grazing systems; a typology of grassland grazing system models; and, a brief review of some models of each type focussing on both those designed to model the specific type of grassland grazing system that is the focus of this study, and/or those that are agent-based models. The important role of remote sensing in modelling the grassland grazing system being studied is highlighted. The chapter does not consider the difficulties of developing agent-based models of grassland grazing systems in general or the specific type that is the focus of this study. These difficulties are considered in a prototype model described in Chapter 4 and an agent-based model of grassland grazing discussed in Chapter 7.

2.1 Grasslands, grazing systems and common pool resource

Grassland can be thought of as land where the majority of land cover is grass. *Grasslands* can be thought of as regions where grassland dominates. Using this subtle pluralistic difference is one way to be clear that in grasslands, land cover and land use may vary, but that the region, on the whole, is characterised by the grassland.

Grasslands, sometimes also referred to as *rangelands*, cover about one-third of the world’s terrestrial area (Coupland, 1979; Chen et al., 2015). There are various types of grasslands, the main typology can be based on the level of human influence, how continuous, and extensive grassland is in these regions, and whether in agricultural settings the grasses are grown to feed cattle or produce cereal. Those less influenced by and that would exist without the influence of people and are sometimes called *natural grasslands* or *wild grasslands*. Those used more by people can be referred to as *agricultural grasslands* – some are farmed more extensively by more nomadic herders that may or may not deliberately manage the lands using fire; other agricultural grasslands might be more intensively farmed by more settled farmers where the movements of animals might be partly controlled using fences and walls and where the vegetation may be cut and stored as well as foraged more exclusively by domesticated breeds of *livestock* animals. There are those vast regions where there is little land-cover other than grassland, and those regions where grassland is more patchy and where there is perhaps a greater competition perhaps more naturally between grass, shrubs and trees, but also with different land use where land managers might decide to change grassland to other land cover types and vice versa.

One of the most authoritative institutions in the area of grassland science, the Society for Range Management (SRM) defines grassland as *"land on which the indigenous vegetation (climax or natural potential) is predominantly grasses, grass-like plants, forbs, or shrubs and is managed as a natural ecosystem. If plants are introduced, they are managed similarly"* (Bedell, 1998). This definition stands on an ecological perspective and is suitable for a range of situations, in either less intensively grazed regions such as Southern Europe (Zarovali et al., 2007), or intensively grazed regions such as Northern Africa (Aronson et al., 1993; Le Houerou, 2014).

There can be a huge economic value in grassland which can be realised both by harvesting forage and allowing animals to graze. A lot of grassland definitions also incorporate economic or social concepts. In the context of grassland utilization in the Mediterranean, grassland has been defined as the natural forage resource of grass communities characterized by high heterogeneity in its spatial and temporal distribution patterns (Perevolotsky and Seligman, 1998; Röder et al., 2007; Jouven et al., 2010). In social studies, grasslands have option values, that reflect the benefits from potential future use, as well as existence and bequest values, that results from the knowledge of continued existence (Lehmann and Hediger, 2004).

There are many other local legal connotations throughout different regions and disciplines (Suttie et al., 2005). Buck et al. (2015) have categorised grasslands into four types according to their biomass, mowing season, soil and slope - within the context of biodiversity conservation. In biodiversity studies, grasslands are dominated by native herbs, with a low cover of exotic species (Lunt et al., 2007; Bryant et al., 2017). Dixon et al. (2014b) defined grasslands as those where non-human ecological processes primarily determine species and site characteristics; while in land management research, grasslands are defined as primarily planted and maintained for agricultural reasons (pasture; hay; intensive livestock production). To be clear, the grasslands which are the focus of this thesis are regions where:

- the dominant land use/cover type is grassland;
- land cover is strongly affected by livestock grazing;
- livestock grazing is managed by herders and/or grassland managers that may implement different grazing strategies;
- herders and/or grassland managers may be grouped institutionally and react to the policy which may be implemented to help manage resources.

In many cases, grazing and how it is managed is one of the most influential activities on grasslands, and everything to do with the grassland can be thought of as being part of a *grassland grazing system* (Adler et al., 2001). There is much scientific evidence about the impact of different grazing patterns on: the movement and persistence of other organisms (Gonzalez et al., 1990; Hahn and Höfle, 2001; Qu et al., 2016); plant functional traits (Cingolani et al., 2005b); and, the redistribution of species composition (Frank et al., 2016) and nutrients (Ford et al., 2016). Especially in semi-arid terrestrial grasslands, grazing plays a critical role in the continuous and directional changes of grasslands at different time-scales and compositional gradients (Moreno García et al., 2014; Porensky et al., 2016). Those effects can be found across typical grazing grassland around the world, including Northern China (Yong-Zhong et al., 2005); Europe (Ellenberg, 1988; Rochon et al., 2004); Tibet-Qinghai Plateau (Cao et al., 2004); the adjacent mountains of the Himalaya

(Sundriyal and Joshi, 1990); the cold land of Patagonia (Cingolani et al., 2005b); and the Altiplano (Preston et al., 2003); Australia (Fensham et al., 1999); the Mediterranean region (Noy-Meir et al., 1989); Asia (Bösing et al., 2014); Sahara grassland (Nwaogu et al., 2016); the vast Sudano-Zambesian zones (Ahoudji et al., 2014); North America (Eby et al., 2014) and South Africa (Koerner and Collins, 2014).

For grasslands where grazing is overseen by herders or managers, *grazing strategies* and *institutional arrangements* are important and can be thought of as tools for managing resources. The choice of grazing strategy, e.g. *rotational grazing* or *continuous grazing*, may have variable effects on the frequency, severity, variation of grazing-led grass defoliation (Hart et al., 1993) and on the botanical composition of grassland (Taylor, 1989) depending on stocking densities, movement rate and other factors. Grasslands with intensive rotational grazing that have a higher number of subdivisions with longer resting periods have been shown to produce higher yields by preserving biomass and maximising plant growth (Savory and Parsons, 1980; Barnes et al., 2008; Teague et al., 2011; Jakoby et al., 2014). Although rotational grazing strategies have been shown to increase income and improve rangeland conditions, they also tend to have higher management costs (Beukes et al., 2002) and there are associated risks of forage shortage in winter period if livestock stocking rates are too high (Hart et al., 1993).

Macro-level policies can affect grassland grazing systems both positively and negatively. Research on the institutional arrangements aimed at reducing grassland grazing to mitigate *land degradation* in Sanjiangyuan, China (Wang et al., 2010b; Lu et al., 2015), suggests that the policy actually runs the risk of exacerbating poverty and instead contributing to land degradation – the reduction in the capability and capacity of the land to support ecosystems and agriculture (Yeh, 2009). It is also worth noting here that land market institutional arrangements can aggregate grazing land into larger units, which can lead to a more efficient allocation of grassland resources and economies of scale in livestock production (Gongbuzeren et al., 2016). The impact of different grazing strategies and institutional arrangements on the ecological, socio-economic and climatic conditions of grassland systems is complex which makes it hard to prescribe what management strategies and institutional arrangements might be best (Hart et al., 1993; Campbell et al., 2006; Thornton et al., 2009; Briske et al., 2015).

Grassland is generally considered as a Common Pool Resource (CPR) for its physical attributes of the resources. The CPR has two common characteristics: first, the resource is large in its scale that it is costly to exclude the potential resource users; second, the resource is not unlimited, and the use of the resource by one user reduces its availability to others (Ostrom et al., 1994).

In common grasslands, one possible situation is when the number of animals exceeds the capacity of the pasture, each herder is still motivated to add more animals since the herder receives all of the proceeds from the sale of animals and only a small cost of overgrazing. This is called *the tragedy of the commons*, a term and notion put forth by (Hardin, 1968), whereby the limited natural resources become exhausted by utility-maximizing individuals – an almost universally tragic situation where group benefit has been undermined by the dominance of individual rationality (Crépin et al., 2009; Baerlein et al., 2015). In addition, extensive free-riding resource users often problematically proliferate and deplete common-pool resources by not contributing to the upkeep of the resource (Ostrom, 2008).

Solutions to the tragedy of the commons have relied upon the centralized control of all common-pool resources. National legislation has been passed in many countries, and administrative responsibilities for managing natural resources have been turned over to centralized agencies (Wade, 1987). Unfortunately, the actions of these agencies in some cases has deteriorated the situation further (Walker and Janssen, 2002). One possible reason for this failure is that effective communication can be poor in systems of centralized control which led to the advocacy of more distributed more local (self-)organization (Hardin, 1968; Thwaites et al., 1998).

The tragedy of the commons assumes that the resources users are "*short-term, profit-maximizing actors who have complete information and are homogeneous in terms of their assets, skills, discount rates and cultural views and anyone can enter a resource and take resource units*" (Ostrom, 2008). The fact that resource users can self-organize and devise institutions to extract themselves from tragic overuse was for some time largely not recognised. Some studies have identified well-managed examples demonstrated that tragedy is not inevitable and that sustainable resource use is possible with robust, long-lasting, institutional arrangements for the governance of common-pool resources (Brady, 1993; Weinstein, 1999). Weinstein (1999) reported that large groups have more difficulty in governing common-pool resources than smaller groups, due to the communication cost among individuals, difficulty in reaching a binding and enforceable agreement or the difficulty in monitoring others conformity with rules. Non-cooperative game theory and cooperative game theory are commonly used to design strategies for managing CPRs (Ostrom et al., 1994; Huang and Smith, 2014). It can be quite efficient for relatively homogeneous groups to limit the use of their resource if there exist mechanisms for reaching binding agreements (Ostrom, 2008).

In addition, multiple-use of the grassland resource can be an important way to manage the commons. The commons can support multiple land uses going beyond the primary productive industries like agriculture and mining to support things like recreation and tourism. The extent and the type of use of land may change with demographic, technological and economic development (Edwards and Steins, 1998). To balance multiple interests, "*collective action among the user groups is required to agree to rights about access to, allocation of, and control over the resource, since resource uses by the separate user groups are interdependent*" (Steins and Edwards, 1999). The comparative analysis framework for multiple-use commons is helpful to direct attention to important factors which affect decisions of the institutions governing the resource and whether changes are necessary or desirable (Ostrom, 2002).

In especially the last few decades, policies and institutions have changed dramatically, and there has been extensive privatisation of CPRs in much of the world (Humphrey and Sneath, 1999; Wisner, 2012; Archambault, 2014; Ojanen et al., 2014). It has been suggested that the motivation for privatization is to create a better incentive for herders to improve the productivity of grasslands (Conte and Tilt, 2014; Fernandez-Gimenez et al., 2015; Moritz et al., 2015). Whether intentional or not, the effects of privatization is an interesting and complicated study not least because of the varying success this has been seen to have in both social, economic terms and with respect to the resources. With the privatization of grassland, the behaviours of herders and their decision-making can change as the relationship between herders and institutions change, and these changes can be dramatic (Jun et al., 2013).

The decision-making of herders can be affected by high-level institutional arrangements. Those institutional arrangements, in some place, are essential to promote group management. For example, in China’s grasslands, the government encourage herders to join the grazing groups by investing their lands or livestock (Xiaoyi, 2007). How those new institutional arrangements and grassland policies affect the performance of the grassland grazing system is an important topic in grassland sustainable development, and that is the crux of this study. Agent-based modelling has proved to be an effective tool to evaluate the effect of different institutional arrangement on grassland grazing systems (Jun et al., 2013), before attention to these types of model in Section 2.4.4, the following section describes the complex nature of grassland grazing systems (as introduced), and following this there is a review of different modelling approaches.

2.2 The complex nature of grassland grazing systems

Grassland grazing systems are often being modelled as complex systems. This section will discuss the common characteristics of a complex system (Section 2.2.1 and Section 2.2.2), and what are the complexities in a grassland grazing system (Section 2.2.4). In addition, the difference between a complicated system and complex system is detailed in Section 2.2.3.

2.2.1 Complex geographical systems

A system consists of entities and relations between them (Bertalanffy, 1980). A complex system is synergistic in that the properties of the whole system cannot be explained simply by somehow summing up all the properties of the constituent entities (Mitchell, 2011). Complex geographical systems are those where the entities in the system are distributed in regions on or near the surface of Earth and interact with other entities of the same type and also entities of other types, these interactions occur within regions and across regions over time, and such interactions can give rise to higher-level emergent behaviours of the system. In a geographical context, each region is connected to other regions, and the regions themselves are entities in their own right, and these may grow or shrink and move through space over time by interacting with neighbouring regions. In a physical sense, all geographical regions effectively interact through movements in air and water and with things moving across the land. Additionally, the boundaries between regions are often gradual in nature though they might also be naturally abrupt. In more managed contexts people make boundaries to abruptly change land uses and land covers from one type to another.

The entities of any complex system may self-organise and may collectively organise with entities of the same type, and this organisation may be based on the distribution and characteristics of entities of other types in the system. Complex systems tend to have no centralized overarching controlling entities that completely determine the characteristics of all other entities in the system, though often some entities have a more significant influence than others. Typically organization evolves in complex systems - emerging as a consequence of localized interactions between entities that typically further evolve and result in further organisational change (Diana, 2012). The emergence of new types of entity and new forms of organisation which begin interacting with other entities or sub-systems is in some ways the defining nature of a complex system. Though it may seem that this might lead to ever more complex systems, this is not necessarily the case, as some organisational entities might not perpetuate, they may just exist for a short time as part of a phase transition of the system, or they may be ephemeral, appearing every now and again when the conditions are right, and those conditions may even be somewhat regular and in a geographical sense, this is often part of a normal annual cycle of seasons or another cycle of climatic conditions (Miller and Page, 2007).

There are other definitions or expressions of complex systems that are worth considering, for example, Cotta and Schaefer (2017) defined complex systems as *"...composed of many components, whose structure and interaction leads to emergent properties of the system as a whole, that is, the system exhibits properties and behaviours that are not explicit in its isolated components"; while* Whitesides and Ismagilov (1999)*, in chemistry, defined a complex system as "one whose evolution is very sensitive to initial conditions or to small perturbations, one in which the number of independent interacting components is large, or one in which there are multiple pathways by which the system can evolve. Analytical descriptions of such systems typically require nonlinear differential equations. A second characterization is more informal; that is, the system is complicated by some subjective judgment and is not amenable to exact description, analytical or otherwise".*

The next section reviews complex system definitions as summarised by (Ladyman et al., 2013).

2.2.2 The properties of a complex system

Ladyman et al. (2013) summarised the common properties associated with a complex system: non-linearity, feedback or interactions, spontaneous order, robustness and lack of central control, emergence, hierarchical organisation, numerosity. However, having those properties do not necessarily mean that a system is complex, they are the key features that differentiate complex systems from other simple systems (Zeng et al., 2017).

The components of a complex system are highly interdependent, and this interdependence creates non-linearity between the parameters of the model and the outputs. Non-linearity arises from the fact that the overall system properties are not a simple linear addition of each component' properties in isolation (Bradbury and Vehrencamp, 2014). By comparison, in a linear system the next state of the system is the linear sum of the next state of each component in the system; however, the emergent behaviour can still be observed in a linear system. For example, two metallic balls attached to springs with distinct frequencies can generate an emergence of beats, which occur when the two normal mode frequencies get close. The frequency of oscillations can be calculated by the linear average of the two normal mode frequencies modulated by half the difference in the two frequencies. The trajectories of a linear system can progress to an equilibrium when the further changes stop, spiral off into infinity or exhibit oscillation at some fixed frequency, but each trajectory is entirely predictable given the relations among entities and their initial conditions (Bradbury and Vehrencamp, 2014); notice that it is perfectly possible to think in a linear way about systems that exhibit non-linear dynamics (Ladyman et al., 2013). However, it worth noticing that exponential changes can exist in a non-linear system. For example, the rate of change of the number of individuals in a population can be predicted as a function of age with a fixed distribution and an exponential growth of time (Iannelli and Martcheva, 2003), thus, complex systems are known to be shift or flip into all new regimes within a period of time, and the nonlinear behaviour of the system results from disproportionate response to proportional increases/decreases of an input on an output variable (Sturmberg et al., 2017).

Changing the values of the parameters in the non-linear systems can cause the system to be non-deterministic or stochastically chaotic. The system behaviours can be at “the edge of chaos” (Langton, 1990), in the sense that they lie in the middle ground between ordered systems and chaotic ones. This is often the result of the presence of non-linear interactions and feedback loops which often lead to self-organizing patterns (Steven, 2012). In fact, complexity is often linked with chaos which is characteristically “sensitive to the initial conditions” (Langton, 1990), and it is the central idea within chaos theory (Flake, 2001). In chaotic systems, small changes in the initial conditions may lead to dramatic differences in what is predicted yet often in the short-term (Hayles, 1991).

Feedback is an essential condition of a complex system. The entities in the system can receive feedback from the other entities, and the way the other entities interact with them at a later time depends on how they interact with the other entities at an earlier time (Ladyman et al., 2013). Yet due to the feedback loops among entities, some small change in the input value to the system can trigger a large systemic effect. However, the existence of feedbacks among entities does not necessarily mean a system is complex; it is complex if the feedback involves multiple entities and when this can give rise to higher level order/emergence (Ladyman et al., 2013).

Complex systems are not completely random but also not completely ordered, and they also tend to be somewhat hierarchical in that entities are nested inside of subsystems and are also part of larger systems or other related interdependent systems (Ladyman et al., 2013). It is sometimes reasoned that all complex systems have this multi-dimensional property and that they are composed of many entities at different levels with lots of interaction between these levels making it difficult to isolate any component or reduce the whole system to one level.

Complex systems have no top-down, centralized mechanism coordinating all the operations in the system. The entities in a complex system have a degree of autonomy, which is often formed through their capacity to adapt to the local environment based on a set of rules (Watson and Scheidt, 2005). Without centralized coordination and with a degree of autonomy, entities can synchronize their states locally, or they can cooperate with each other, which can result in the higher-level emergent patterns of the system. With autonomy and adaption, the complex system can exhibit a variety of different responses for the given changes in the system. It means that complex systems are often heterogeneous with diverse high-level emergent behaviour. Ecosystems, for example, are diverse complex systems because the entities in the systems are subject to evolutionary forces of natural selection and competition between species and their dependencies on each other for food and habitat. In grasslands, the grass itself depends on grazing (or cutting or burning) to reduce competition from larger plants, especially trees which in themselves cannot be grazed and once established can supersede grasses for so long that their seeds are no longer around to take advantage when gaps appear in a canopy.

A complex system can also involve dense interconnectivity among entities. How the entities are connected and at what scales becomes key to understanding the system (Hannigan, 2013). Spatially, for example, a system may divide into subregions where each subregion interacts with other subregions, and subregions with different characteristics or traits may interact with each other differently depending on how they are connected. For example, different subregions can be thought of connecting spatially with adjoining regions and with each other across other regions. With such degree of connectivity, the system stops being separate parts and becomes a network of connections. The key to understanding the system is then how entities flow in this network. Space may be redefined in terms of topology created by connectivity. Understanding of the system can be gained by studying the positions of entities in a network structure and by examining the degree of connectivity in the system (Jha and Sivakumar, 2017).

Emergence arises only in systems that can be described as operating across multiple levels (De Wolf and Holvoet, 2005); in other words - the system has some kind of hierarchical structure. The emergent behaviour in modelling the natural world is that the systems are organized hierarchically across spatial scales from subatomic particles, atoms and molecules that are nutrients and raw materials for life (energy, hydrogen, water, oxygen, carbon etc.), to organisms that exist at the bottom of the food chain/web (bacteria, fungi, algae, grass), to ecological regions with complex food webs (herbivores, ants, predators etc.), to the ecosystem and biosphere and solar system (Mazzocchi, 2008). At each of these levels, there are certain emergent principles that do not appear in the lower level of the system (Kesić, 2016).

Complex systems have the property of numerosity, which means there are many entities rather than one or two entities in the system. Often too there is plurality or many different types of entity. Again, we should notice that numerosity (and indeed plurality) in the system does not mean a system is complex. The overall system properties can be simply the summation of the properties of the entities in the system and not lead to emergence at other levels (Ladyman et al., 2013).

To summarise, a complex system (for the purpose of this thesis) is a system that has many entities interacting with each other or with their environment in a somewhat disorderly but definable way, where the emergent behaviour of the system arises from local or individual interactions.

Because there can still be some confusion with regard to the difference between *complex* systems and *complicated* systems, the next section attempts to distinguish these before discussing the components of the complexity in the grassland grazing systems studied.

2.2.3 The difference between complicated systems and complex systems

The terms “complicated” and “complex” are often used interchangeably; however, they are fundamentally different in dealing with the entities’ behaviours and the system structure. As highlighted in Section 2.2.1 and Section 2.2.2, complex systems refer to the emergence of unordered but robust behaviours presented by many locally and often non-linearly interacting components (Sun et al., 2016). Model complexity, however, can arise from complexity either in the model structure (Aldebert et al., 2016) or in the behaviours of the model (Duckworth et al., 2018).

In order to distinguish “complicated” and “complex” in modelling work, Sun et al. (2016) proposed the usage of “complicated model” instead of “complex model” when referring to model structure. Both models have a structure with many entities and relations between them, and the entities can be diverse and interact with each other. However, in a complicated model, the outcomes of the system are usually knowable or predictable. To understand a complicated system, the primary way is to decompose the whole system into the main structural parts, and their relations and via further decomposition subdivide these into smaller parts and relations (Poli, 2013).

The complex model, however, refers to the model behaviours/functions at the system level, which arises from lower-level interactions (as discussed in Section 2.2.2). The entities can also be diverse and interact with each other, but they cannot be individually decomposed or isolated in order to understand the system, and thus the system behaviour emerges through the network of the individual interactions (Poli, 2013). The same structure of the complex model can produce an infinite variety of outcomes (or system functions/emergence) (Poli, 2013). This leads to outcomes of the complex model that cannot be precisely predicted, and emergent behaviours caused by the complexity of the system abound (Sturmberg et al., 2017).

It is important to realise that although precise predictions of a complex system state are not possible (because a system may have multiple outcomes), predictions can still be useful and bounded with certainty estimates. This is especially important with regard to analysing the stability and uncertainty in predictions derived from a given state of the system modelled. One way to explore the sensitivities of the model or variations in predictions of a complex system is to analyse an ensemble of simulations where parameters are varied along with stochastic aspects provide for example by pseudo-random inputs. This will be illustrated in Chapter 7.

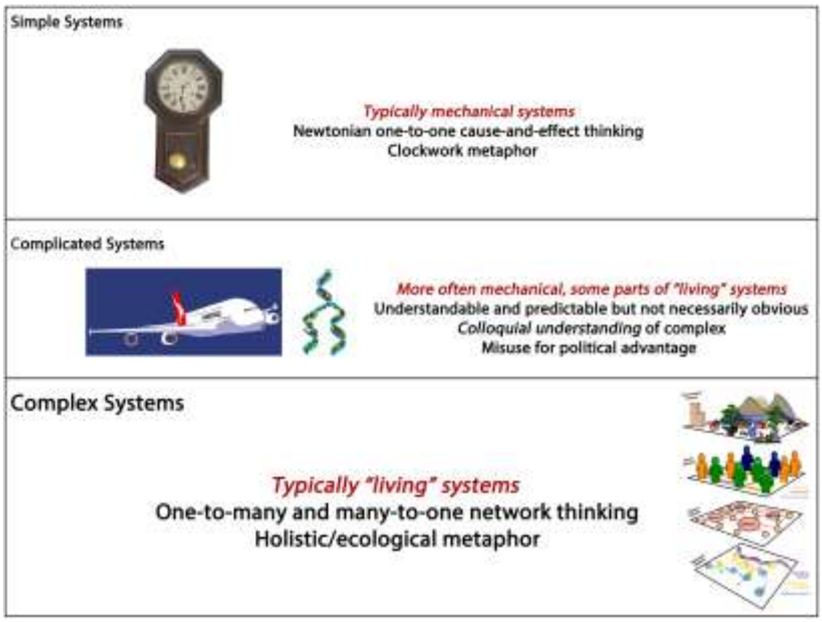


Figure 2.1: Colloquial and scientific meaning of complex from Sturmberg et al. (2017), page 427

Having summarised the properties of complex systems, distinguished complex systems from other complicated systems, and defined the grassland grazing system under study. Section 2.2.4 now focuses on the complex system nature of the grassland grazing system under study.

2.2.4 The complex nature of grassland grazing systems

Understanding the complexities of a system is the key to understanding its outcomes (Liu et al., 2007). A grassland grazing system is complex because it contains both the interactions within the ecosystem (Milchunas et al., 1988) and interactions within its social-economic system through different stakeholders (Dobó et al., 2006). The degree of complexity depends not only on the number of types of interactions but also on how this social-economic-ecological system is organized and the degree of interrelationships within each subsystem. It is a complex system that varies both in time and in space (Boyd and Svejcar, 2009). However, biological diversity is often equated with grassland complexity (Martinez et al., 2006). Descriptions and measurements of ecosystem diversity usually have a strong species and population basis (Pavlik, 1995). Those descriptions do not adequately account for the interaction among grassland components and the local environmental characteristics of grassland. They largely underestimated or ignore the fundamental effects on grassland dynamics of the behaviour of herders and/or land managers and their institutional arrangements (Dong et al., 2009).

Complexity in the grassland grazing ecosystem arises through interactions of livestock and plants in an inherently heterogeneous land resource (Tainton et al., 1996). Complex systematic behaviour can emerge from even relatively simple rules with few interactions or entities, and additionally, "*the transition from a simple to complex problem can be triggered by an increase in the scale of the problem (either spatial and/or temporal by our desire to understand simple problem at a more mechanistic level)*" (Boyd and Svejcar, 2009). The interactions within the grassland grazing system may be one directional or bidirectional and either strong or weak (Power et al., 1985).

A typical example of this complexity is the 'wolf-sheep' model as implemented using the NetLogo by Wilensky (1997). The model contains three elements: grass which grows at a certain fixed rate, sheep who travel around (often randomly) grazing and breeding, and wolves who also move around hunting the sheep and breeding. The individual behaviour of the wolves and sheep is very simple, but the model leads to complex dynamics in the population of wolves and sheep. If there are too many wolves on the grassland, they could not survive due to the limited number of sheep that can be raised on the grassland and over-predation; Similarly, if the number of sheep reach a certain degree, the sheep also could not survive due to the limited grass forage that grassland can provide (Wilensky, 1997). In addition, the grazing activities of sheep on the grassland also have an effect on the available forage produced by grassland. The interconnected relationship and individual interactions among wolves, sheep and the grass lead to the emergence of the overall stable systematic behaviours: a dynamic population of wolves, sheep and grassland productivity. However, the system could also "collapse" (sheep or wolf may die out) when one of the relations or interactions among wolf, sheep and grass is extremely weak or extreme strong (for example, the regrowth time of grass is too long or too short, the reproducing rate of wolves or sheep is extremely high or low). This means that the system behaviour depends on the initial conditions of the entities in the system. However, such dependency is quite gentle, such that tiny changes in the initial conditions will not result in the huge difference in the behaviours of the system, which is different from deterministic chaos where the system behaviour is sensitive to the initial conditions and thus they are unpredictable in the long term (Šarloši et al., 2014).

The complexities of the grassland grazing system are manifested at a number of levels or scales. The scientist, manager, government and the herder, all those who are observers of the grassland grazing system, will define the scope of interaction behaviours themselves that are relevant to particular purposes (An et al., 2005; Liu et al., 2007; Briske et al., 2011). Generally, those complexities can be categorized into four types: complexity of the forage distribution (Seagle and McNaughton, 1992); complexity of the livestock population (Fynn et al., 2016); complexity of the plant-livestock interaction (Cronin et al., 2015); and the complexity associated with management strategies (Lemaire et al., 2014). When modelling such a complex system, it is important to choose an appropriate scale and perspective to analyse (Belsky, 1987). As an integral part of the grassland grazing system, herders and institutions' actions contribute to the complexity of grassland grazing (Christina Prell, 2009).

2.2.4.1 The complexity of forage distribution

Different plant species have different digestibility for livestock, and abiotic factors (e.g. precipitation, temperature) have a dominant effect on the distribution and availability of forage (Walker, 2012). The floristic composition of vegetation (Pucheta et al., 1998), especially edible and productive species, determine the forage available for grazing due to its digestibility (Jouven et al., 2006); nutrient content (Whitehead, 2000); and accessibility (Bakker et al., 2003). Abiotic factors have an intense pressure and lead to large-scale changes to vegetation composition "*from increased nitrogen deposition to altered disturbance regimes and new suites of plant species (many weedy) in regional floras*" (Huenneke and Ward, 2003). In addition, researchers have found socio-economic changes can influence resource use patterns (Crecente et al., 2002), which in turn directly impact on the vegetation (Gordon et al., 2004). Factors such as changes in institutional control, levels of unemployment and local perceptions of rights have resulted in a dramatic increase in harvesting of natural resources in the world's grasslands (Twine, 2005a; Rohde et al., 2006). Increased grazing intensities have a significant impact on the vegetation, which in turn reduces local resource supply (Kantrud, 1981; Qu et al., 2016). This results in increasing reliance on resources purchased from commercial harvesters or on substitute resources (Warford, 1987). In addition, the social-economic factors such as changes in institutional control, levels of unemployment and local perceptions of rights and responsibilities since democratic elections have resulted in a dramatic increase in harvesting of vegetation and the resultant impacts on the vegetation thus form a feedback loop between society and the natural environment (Twine, 2005b).

2.2.4.2 **The** complexity of plant-livestock interactions

The livestock population is complex because it is controlled by the condition of the grassland, the growth of livestock, herders' willingness and power to gain from grassland, as well as the social-economic demands of livestock production (Seré et al., 1995; Turner and Williams, 2002). There are a number of direct effects of grazing on plants, which may subsequently affect their population dynamics (Hutchings and Gordon, 2001). In addition, other herbivores that live in the grassland are an important part of the grassland ecosystem (Farnsworth et al., 2002); in the grassland of Zeku, more than 200 species coexist (Zhou et al., 2007b), although it is common for most of the biomass in the herbivore population to be derived from three or four species (Suttle et al., 2007). However, there is a considerable degree of dietary overlap between those herbivores, with plant species preferred by one type of animal generally thought to be favoured by other species as well (Milton, 1999).

In the past, it was generally believed that positive feedback between grazed grass and grazing herbivores was the norm (Srivastava and Jefferies, 1996). However, livestock grazing can also have negative effects on plant growth as a consequence of defoliation, and reduced biodiversity and stability of the grass ecosystem – leading to reduced productivity (McNaughton, 1993). In addition, the trample effect on grassland of livestock can lead to soil compaction to the extent that inhibits grass growth (Turner, 1987; Cluzeau et al., 1992). On the other hand, the effect of grazing on resource distribution affects animal grouping patterns, social behaviour and the mating system (Bradbury and Vehrencamp, 2014). Removal of biomass and photosynthetic tissue tends to reduce plant growth rates (McNaughton et al., 1983), can increase mortality (Dyer, 2003) and decrease fecundity (Hanley et al., 1995). So, livestock has direct effects on vegetation as a result of the selection of bite site, bite depth and the amount of trample. Those behaviours play a key role in creating spatial heterogeneity in the grassland grazing (Hutchings and Gordon, 2001), and can form hotspot grazing sites (Person et al., 2003), where the productivity of plants is relatively high with abundances of nutrients and minerals (Augustine et al., 2003). "*Heterogeneity is created as a consequence of particular parts or components of the sward*" (Hutchings and Gordon, 2001).

2.2.4.3 The complexity of grassland management

Grassland grazing strategies and institutional arrangements, which involve the individual complexities discussed above, are key in a complicated grazing system. This means management approaches need to protect and conserve natural resources and enable the herders to maintain their livelihoods (Quinn and Ockwell, 2010). However, most grassland management policies were developed based on the concept of increasing and sustaining livestock production by reducing rangeland heterogeneity and favouring the most productive, most palatable forage species for livestock grazing (Fuhlendorf and Engle, 2001a). Obviously, this rangeland management approach is incapable of providing an ecological framework for maintaining heterogeneity of grassland systems (Fuhlendorf and Engle, 2001a). In fact, maintaining heterogeneity is important to maintaining productivity as well as biodiversity of grasslands (Fuhlendorf et al., 2006);

The complexities mentioned above have contributed to the formation of different paradigms when modelling such a complex system—equilibrium and non-equilibrium conditions. The next section focuses on these different paradigms.

2.3 Ecological paradigms for modelling grassland grazing systems

Due to the complex nature of the grassland grazing systems and the various types of the grassland grazing systems, equilibrium and non-equilibrium paradigms are employed to understand grassland dynamics. This section, therefore, discusses these two paradigms before reviewing the specific models for grassland grazing systems. The equilibrium paradigm is discussed in Section 2.3.1.1, followed by a review of the non-equilibrium paradigm in Section 2.3.1.2. Critiques of those two paradigms are discussed in Section 2.3.2, where state and transition models are briefly introduced.

2.3.1 Equilibrium and non-equilibrium paradigms

Paradigms play a critical role in science and help to establish models of nature that can be used to identify problems and interpret results (Kuhn and Hawkins, 1963; Andersen et al., 2006). The paradigms for rangeland management and modelling are, therefore, the important ways to understand the grazing system for both grassland managers and modellers (Illius and O'connor, 1999; Fuhlendorf and Engle, 2001b). Grassland grazing systems often have esoteric problems and experience unpredictable events and issues that can have major effects. This makes it a challenge to build a model of any grassland grazing system (Haijing Gong et al., 2006). For many years, scientists have been looking for general and simple models to solve specific problems. This has proven a difficult aim to realise when modelling a complex natural world that is coupled with complex human activities (Liu et al., 2007).

There are numerous optimization methodologies and technologies for managing the grassland grazing systems (Liu et al., 2007a; Alberti et al., 2011; An, 2012a; Boumans et al., 2015), but losing insight of interactions among factors and lack of the knowledge of the specified systems are critical defects which lead to results that do not match actual data (Power et al., 1985). Simulations of such systems need to consider not only vegetation processes, but also biochemical processes, as well as climate factors (Liu et al., 2007). In addition, different management practices and the interaction between grassland and livestock are also important aspects that cannot be ignored. Furthermore, even for a very simple system, we also need to consider time, space, extreme events and discontinuity, which make the problem much more complicated. In order to understand the grassland grazing system under study, some parts of the system may be adequately expressed using simple linear models, whereas others may require methods to handle nonlinear dynamics. It should also be noted that as more factors need to be considered, the data requirements also increase, which can be problematic as data are often sparse, incomplete and may contain significant amounts of noise and error.

The complex nature of grassland grazing systems has imposed the equilibrium and non-equilibrium debate on the theory of grassland modelling, which has important ramifications for identifying problems and interpreting modelling results (Agassi, 1966). Ecologists have been debating the validity of two current paradigms for the assessment of the vegetation dynamic on grasslands. The equilibrium paradigm assumes that the dynamic system will always return to its pre-disturbance state or pre-disturbance trajectory when disturbance has stopped (O'Neill, 2001), that is, the system has the ability to regulate itself or balance itself against the internal drivers (for example, overgrazing) or external disturbance (for example, climate change). It postulates that, once disturbance occurred in a system, the system either returns to tie former equilibrium or equilibrates within a new “domain of attraction”, which is a new level of equilibrium (Hodgson and Illius, 1996).

The non-equilibrium theory supposes that the system has a limited capacity for such regulation (Wu and Loucks, 1995). This section will discuss in detail. In terms of modelling grassland grazing, *“the equilibrium model stresses the importance of biotic feedbacks such as density-dependent regulation of livestock populations and the feedback of livestock density on vegetation composition, cover and productivity. Range management under this model centres on carrying capacity, stocking rates and range condition assessment. In contrast, non-equilibrium grassland systems are thought to be driven primarily by stochastic abiotic factors, notably variable rainfall, which results in highly variable and unpredictable primary production. Livestock populations are thought to have negligible feedback on the vegetation as their numbers rarely reach equilibrium with their fluctuating resource base”* (Vetter, 2005). Researchers have devoted much time to finding a suitable paradigm for the sustainable development of grassland grazing according to a different characteristic of the grassland, and equilibrium and non-equilibrium theory play to that theme (Derry and Boone, 2010). This thesis will then discuss the detail of the equilibrium and non-equilibrium theories and their critiques.

2.3.1.1 Equilibrium paradigm

Equilibrium paradigm suggests a tight coupling of the plant-herbivore system. A system in equilibrium does not change dramatically, but it may still change seasonally, so temporal scale and resolution is important; that is, the vegetation composition might change a lot over a year, but is pretty similar at the same time of year (year to year) on a broad scale - and that this is a form of equilibrium even though things are continually changing. In fact, in the evaluation of grassland grazing systems, the equilibrium theory emphasizes the continuous and reversible vegetation dynamics (Briske et al., 2003).

The equilibrium theory has developed from the European and US perspective of the rangelands in temperate climates, where "*the developmental study of vegetation necessarily rests upon the assumption that the unit or climax formation is an organic entity*" (Clements, 1916), which is known as "range model". It assumes that the grazing intensity proportionally counteracts secondary succession, in a continuous, directional manner, to modify species composition variously (Westoby et al., 1989). The range condition is determined by the relative position of the community composition along a successional gradient. It assumes that the composition of a presumed pre-settlement climax community is the expected excellent range condition (Dyksterhuis, 1949).

Equilibrium theory assumes that the vegetation composition will progress towards a climax community under the climate and soil conditions, through the process of succession (Begon et al., 1986). The climax community is therefore considered to be the most stable plant community that could occur. The disturbance, either internal drivers like grazing intensity, or external disturbance such as drought, will result in the vegetation being "pushed back" to an earlier successional stage, and once internal or external disturbance ceases or removed, the natural processes will lead back to the climax condition (Briske et al., 2003). In equilibrium theory, overstocking and overpopulation are recognized as the primary cause of degradation of grasslands. The management regimes aim to control the stocking rate and change the land tenure to maintain the grassland in an optimal condition.

The stable state of such equilibrium grazing system can be evaluated by the carrying capacity of grassland, which is a widely applied method to management the grassland grazing system in many places around the world and especially to pastoral systems in some areas of Africa where livestock are primarily dependent on grassland grazing (Unruh, 1993; Lebert et al., 2006). Under the equilibrium theory, the secondary production (mainly livestock production) of the grassland is linearly related to the successional status of vegetation; then it is possible to calculate the number of herbivores that can be supported on the range—carrying capacity (Quinn and Ockwell, 2007). This density dependence assumption in the carrying capacity means the quantity of herbivores on the grassland is controlled by the primary production of the vegetation on the land. The management of the grassland grazing system is then to maintain the vegetation at some optimal sub-climax composition with the purpose to maximize the livestock production.

The carrying capacity provides a powerful planning and management tool which has formed the basis of many proposed development interventions designed to ensure the continued sustainable exploitation of these grassland ecosystems (Sandford and Overseas Development, 1983; Mulindwa, 2009). Setting the carrying capacity of grassland implies that there is an equilibrium between a certain level of sustained livestock production and the grassland forage provision of grassland (Zubrow, 1971). The carrying capacity assumes a climax vegetation production, which is dependent on the soil and climate, potentially occurs at a particular site (Heady, 1975). In livestock grazing systems, population density affects vegetation production and condition which leads to less vegetation being produced – plants need enough maturity to grow at their fastest rates, and if they are grazed to a lesser extent, then they grow more slowly (Evans et al., 2006).

So based on this concept, the mainstream of equilibrium scientists' efforts is to identify the climax capacity of grassland or the optimal carrying capacity of grassland (Shuan et al., 2007). Applications such as the prediction of grassland degradation or the modelling of grassland livestock system collapse from livestock overgrazing are widely discussed both in academic areas and by policymakers (Derry and Boone, 2010). It is also argued that climatic variability is the single largest cause of poverty in pastoral societies due to the spatial heterogeneity of resource distribution (Ojima et al., 1993; Parton et al., 1995). However, it seems that in regions where intensive dairy or beef production is highly dependent on the availability of grassland resources, the notion of a carrying capacity is not helpful, as potential livestock production is not restricted by the amount of available land, but it's primary productivity which varies based on climatic and other factors as discussed (Svenning, 2002; Smit et al., 2008).

Under the equilibrium theory, grazing intensity has a profound impact on species, see Figure 2.2, where H stands for the stocking rate of herbivores, and S represents the change in proportional species composition. These figures demonstrate a theoretical relationship between plant species and herbivores based on long-term grazing trials. "ΔS=0 is the line where all points are stable with respect to grazing intensity" (Hodgson and Illius, 1996). However, what cannot be ignored is that although grazing is a key factor affecting plant composition, other abiotic factors including human activities (Bowles and Gintis, 2011), are usually more important than grazing (Arévalo et al., 2011).

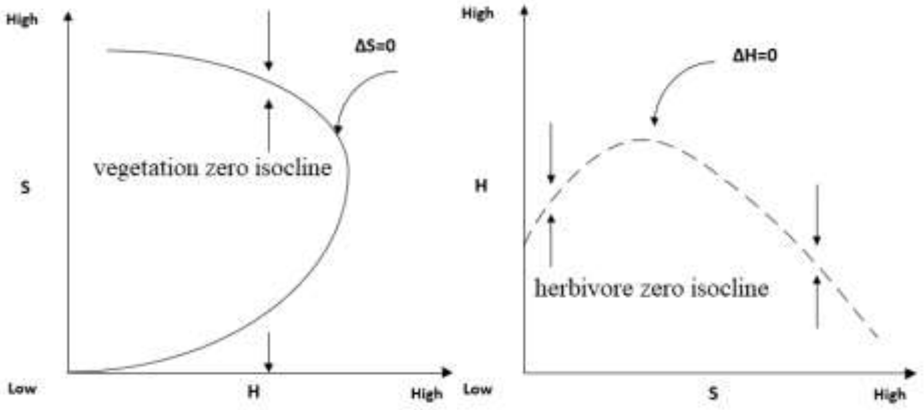


Figure 2.2: Plant-herbivore relationship from Hodgson and Illius (1996), page 286. The vegetation compositional zero isocline (ΔS=0, left figure) and the herbivore zero isocline (ΔH=0, right figure) in the plane of plant species composition (S) and stocking rate (H). Arrows indicate the direction of change.

As for the impact of grassland grazing on biomass productivity, Zhao et al. (2011b) have a detailed explanation of experiments showing that different grazing intensities have a different impact on the above-ground net primary productivity (ANPP), the "increase-maximum-decrease" productivity pattern emerges during the period of the experiment. With the increase of grazing intensity, ANPP tends to decrease, and it is more obvious in the heavy grazing area. The plants on the grassland provide the forage for livestock grazing, and most importantly, livestock affects the growth of plants via selective foraging (Stebbins, 1981a) and in how they trample the ground (Phelan et al., 2013).

However, researchers have found that grazing activities have an over-compensatory effect on plant growth (Vickery, 1972; López-Mársico et al., 2015), but the overall effect depends on the net effect of compensation and inhibition, and it is highly affected by the specific environmental conditions and the management measures. That is, overgrazing reduces grassland productivity, but moderate, rational grazing can promote grassland productivity (McNaughton, 1979b; Luo et al., 2012).

As can be seen from the right of Figure 2.2, with the increase of the change in proportional species composition, the stocking rate presented a "rapid increase—max—slow decrease" trend. This indicates that plant composition has a strong effect on the grassland carrying capability. The "*zero isocline for herbivore* $\Delta H=0$ *means all joining points in the S-H space at which the herbivore population is constant for the given value of S*" (Hodgson and Illius, 1996), page 285, where the constant is the maximum stocking rate that can be maintained on the grassland. The management approach to equilibrium systems is generally to reduce the heterogeneity and to maintain stability. "*In such systems, the perception is that the more diverse the system, the more complex the management required to optimize production and maintain system stability. Management actions aimed at dampening fluctuations in the system are effective because the manager has relatively strong control over the dynamics of the system via manipulation of management inputs, such as fertilizer levels, stocking rates and burning schedules*" (Hodgson and Illius, 1996).

2.3.1.2 Non-equilibrium paradigm

The equilibrium paradigm addresses the importance of vegetation competition and plant-herbivore interactions on ecosystem behaviour, which are the important negative feedback mechanism that regulates the ecosystem (Briske et al., 2003). This is a high degree of internal system organization and regulation (Chesson and Case, 1986). However, when applying the equilibrium paradigm to the sub-Saharan African, where annual plants are the important component of the plant community, it cannot depict the reality of the grassland (Vetter, 2005), and it received criticism for its ineffective over-simplification of vegetation dynamics (Westoby et al., 1989). It is argued that grassland grazing systems are non-equilibrium because the environmental variability seldom allows the system to equilibrate (Behnke et al., 1993). The vegetation composition depends on a variety of factors rather than the plant competition or the plant-herbivore interactions at the succession stages (Sullivan and Rohde, 2002).

The non-equilibrium paradigm has been proposed by grassland scientists, sociologists and socio-economists to describe the dynamics of grazing systems susceptible to climatic variability and for which animal populations periodically collapse (Behnke et al., 1993). The density-dependent plant-herbivore interactions are weak or even do not exist in the non-equilibrium, and the abiotic factor, especially rainfall, are the dominant factors driving the productivity, distribution and composition of the vegetation (Quinn and Ockwell, 2007).

Under the non-equilibrium paradigm, the patterns of highly variable climatic factors are more important in determining the productivity and the composition of grasslands compared with livestock grazing, and they are also the important drivers of the system that vegetation and herbivores do not reach equilibrium (Quinn and Ockwell, 2007). The animal populations need most of the time recovering from the natural disasters (for example, drought or prolonged snow) and rarely reach densities at which density-dependent mechanism acts to moderate the animal populations (Fernandez-Gimenez and Allen-Diaz, 1999). This has the effect of decoupling the plant-herbivore relations that historically underpin 'equilibrium' theory in grazing systems; with non-equilibrium theory it is proposed that because of decoupled plant-herbivore interactions livestock have little impact on forage resources (Sullivan and Rohde, 2002) and so are not to blame for the degradation of grassland that, in extreme circumstances, has been claimed to lead to desertification (Dean et al., 1995).

According to the non-equilibrium theory, the grassland grazing system has no equilibrium points in plant-herbivore space (Sullivan and Rohde, 2002). Plant-herbivore dynamics track external (abiotic) variability rather than plant and herbivore density-dependent interactions (Vetter, 2005). As such, the policy advice is to support the development of pastoralist coping strategies to deal with climate variability, and that the land tenure and accessibility of the land are more important than stocking rates (Briske et al., 2003). It has proved that the fluctuations in primary productivity driven by low and erratic precipitation, which in turn breaks the density dependence between herbivore populations and the available forage on the grassland (Ellis and Swift, 1988).

The differences between the equilibrium and non-equilibrium paradigms are shown in Table 2.1. The equilibrium paradigm existed at the very beginning of the scientific inquiry, while the non-equilibrium paradigm emerged more recently when assessing the effect of external disturbance on the system (Wu and Loucks, 1995). But in essence, both paradigms were used to interpret the system behaviour in response to internal or external disturbance (Briske et al., 2003). They are in a way saying the same thing, but are using different ways to say it (Derry and Boone, 2010). In fact, neither paradigm is sufficient to interpret and evaluate the system dynamics for all grasslands (Lockwood and Lockwood, 1993; Briske et al., 2003). In areas with intensive plant competition and plant-herbivore interactions, the equilibrium paradigm has been proved more effective in interpreting the dynamics of vegetation (Walker and Wilson, 2002; Stringham et al., 2003). But models based on the equilibrium paradigm are limited by a stable equilibrium status with reversible continuous change. The non-equilibrium paradigm is more effective than the equilibrium paradigm in the places dominated by the events, which could cause non-reversible and discontinuous changes in vegetation dynamics (Walker, 1993).

Table 2.1: The characteristics of equilibrium and non- equilibrium grassland grazing, modified from Hodgson and Illius (1996), page 283

	Characteristics	Equilibrium theory	Non- equilibrium theory
Philosophical viewpoints	Stability	Stable and non-resilient	Unstable, resilient
	The balance between plants and animals	Stable – negative feedback determines equilibrium position	Plant and animal populations fluctuate widely – 'non-equilibrium.'

	Appropriate models	Succession (range condition), stable isoclines, relatively simple dynamics	State and transition, complex dynamics
Real world ecological differences	Environment	Uniform—rainfall high and consistent	Variable – rainfall low and erratic
	Floristic	Comprised of perennial plants	Comprised largely of annual plants
	Forage flow	Relatively constant and predictable	Variable and unpredictable
	Driving forces	Grazing and fire, ‘management – driving’ – the level of management input determines response, e.g. stocking rate, fire frequency, etc.	Moisture availability, ‘event-driven’ – chance and contingency of non-biological (e.g. rainfall) and biological (e.g. grazing) events determine dynamics
Management policies	Management control	Strong	Weak
	Management of complexity	Manipulative to reduce heterogeneity 1. sedentary – camping, rotation and regulation of animal nos 2. manipulative – aim to maximize stability and uniformity 3. control selection	Exploitation of heterogeneity 1. migratory-transhumance to exploit resource heterogeneity 2. opportunistic and flexible – aim to maximize production while reducing risk 3. allow selection

2.3.2 Critiques of equilibrium and non-equilibrium paradigms

Both the equilibrium paradigm and non-equilibrium paradigm have been widely employed in interpreting the vegetation and livestock dynamics, and they have been discussed in the last two sections. The core challenge is to identify under what circumstances the paradigms apply to better understand the grassland grazing system (Vetter, 2005).

The dichotomy between density-dependent assumptions in equilibrium paradigm and abiotically driven population dynamics assumptions in the non-equilibrium paradigm has been criticised for being a temporal and spatial overcomplication of the dynamics of grassland grazing systems. In southern Zimbabwe (Scoones, 1990) and southern Ethiopia (Desta and Coppock, 2002), during the non-drought years, density-dependent dynamics can be observed. When the quantity of the livestock reaches the carrying capacity of the grassland, the competition among livestock will increase, and therefore the reproductive rate has been decreased, and mortality rate has been increased, and this lead to an overall reduced secondary productivity (Jones and Sandland, 1974). However, during the drought years, the density-independent occurs. The rainfall has limited the forage availability, on which the population of livestock actually highly depends, while the competition for grass forage is less important in regulating the population of the livestock (Ellis and Swift, 1988). Therefore, neither equilibrium nor non-equilibrium is able to describe the dynamics of the livestock population along with the timelines in such systems.

In addition, the equilibrium paradigm is exclusively applied at the coarse scales (Pickett et al., 1992), while the non-equilibrium paradigm is often at multiple scales (Fuhlendorf and Smeins, 1996); "*the quality, quantity and seasonal availability of forage differs between parts of the landscape, and that people and livestock do not utilize all areas at the same frequency and intensity. Herded animals use the landscape differently to animals kept in paddocks, resulting in different impacts on different parts of the landscape. Some areas are more resilient to transformation than others, either because livestock cannot access them for prolonged periods (e.g. annual grasslands, grazing areas far from permanent water) or because the dominant plant species are tolerant of heavy defoliation (e.g. stoloniferous grasses). Patterns and processes in such heterogeneous landscapes are scale dependent, such that inferences about large-scale behaviour cannot reliably be made on the basis of smaller-scale observations*" (Vetter, 2005). The scale-dependence is an important prerequisite for the assumptions for the implications of equilibrium and non-equilibrium paradigms, but it has not been clearly defined upon those two paradigms (Walker and Wilson, 2002). "*Many range ecologists are struggling to overcome the mismatch between the scales of ecological investigation and those at which ecological processes in rangelands take place. While there is now a plethora of experimental results at the plot scale, larger-scale data from heterogeneous landscapes are still scarce*" (Vetter, 2005).

A critique of the current paradigms demonstrates that the criteria based on which distinguished the two is not enough to represent the dynamics of the grassland grazing system. Numerous researchers suggest that species composition may vary substantially in response to disturbances, while ecosystem variables including species richness, productivity and energy use, may remain relatively constant (Chesson and Case, 1986; Tilman and Downing, 1994; Wardle et al., 1999; Brown et al., 2001). It has even been hypothesized that species fluctuations may represent a compensatory mechanism that contributes to ecosystem stability (i.e. homeostasis from Ernest and Brown (2001)) in numerous ecosystems (Seabloom, 2007), which indicate that the emphasis on vegetation compositional dynamics alone may be an insufficient criteria to evaluate these two paradigms.

Evidence summarised by Friedel (1991) has shown that the vegetation responses to grazing, drought and fire are often not linear and reversible. That equilibrium and non-equilibrium are extremes along a continuum and that many systems encompass elements of both, are widely supported (Ellis and Swift, 1988; Sullivan and Rohde, 2002; Oba et al., 2003). There are multiple thresholds of the rangeland states, which leads the employment of State-and-Transition models (ST models) as an alternative to the rangeland succession model (Westoby et al., 1989).

The ST model incorporates multiple successional pathways, multiple steady states, thresholds of change (Stringham et al., 2003), and it enables the modelling of both continuous and discontinuous dynamics of the vegetation (Briske et al., 2003). Although the ST models can be considered to as a non-equilibrium paradigm (Westoby et al., 1989; Briske et al., 2003), they also have been used to understand the grassland grazing system with succession-based equilibrium models(Phelps and Bosch, 2002).

The main principle of the ST model is to construct a realistic model of the dynamic system, which can be either reversible or irreversible, equilibrium or non-equilibrium (Cingolani et al., 2005a). This flexibility of the modelling framework in the ST model makes it continuously developed and clarified, and it becomes a "management language" rather than an ecological theory (Westoby et al., 1989). The vegetation dynamics can fall into either transient dynamics (*"driven by disturbance or weather events, produce significant but temporary changes in vegetation composition or production that can be reversed in a few years to several decades"*) or state transitions (*"involve persistent changes in vegetation such that recovery of the former state is dependent on unacceptably long recovery times, active restoration, extreme events, or a reversal of climatic change that occurs over several decades or never occurs"*) (Bestelmeyer et al., 2003). However, many ST models are developed based on a narrow set of ecological and management practices, and a limited emphasizing on livestock production (Knapp et al., 2011). In addition, it may be difficult to identify a reference state as "healthy" (Stoddard et al., 2006), and the mechanism behind the change is not clearly represented in the model (Wintle et al., 2011).

As for the grassland grazing system in this thesis, vegetation dynamics are the primary focus. A better way to understand the dynamics of grassland grazing is to put the debate between equilibrium and non-equilibrium theory aside, and take the ecological, socio-economic and institutional effect of grassland grazing into consideration, analysing it at a broader scale (different grazing strategies and larger spatial/temporal scale) (Oba et al., 2003; Richardson et al., 2005), even if it does not encompass all the processes or states argued in the equilibrium or non-equilibrium paradigms (Ellis and Swift, 1988; Briske et al., 2003).

2.4 Grassland grazing system models

In this section, specific models of grassland grazing systems will be reviewed. This includes empirical models (Section 2.4.2), process-based models (Section 2.4.3) and agent-based approaches (Section 2.4.4). The common characteristics and the pros and cons of those models will be discussed at the end of each section.

2.4.1 Introducing the different types of model

A variety of models have been developed to help understand the dynamics of the grassland grazing systems. Each specific model tends to be used to provide a summary and understanding of the observed data or some phenomenon of the system being studied. Models are useful for the interpolation, extrapolation and prediction of the real world system (Thornley, 2001). Models for grassland grazing systems can be deterministic or stochastic, dynamic or static, mechanistic or empirical, mathematical or computational, and vary based on the purpose of the models. This section contains subsections which describe the main types of model which are introduced briefly in this first part. The characteristics and limitations of current models are summarised at the end of each subsection. Agent-based modelling approaches are summarised in Section 2.4.4.

Deterministic models tend to produce definite quantities or exact predictions for a system based on clearly defined relationships. Clements (1916)'s succession pathway is an example of such a deterministic model used to predict succession in a grassland grazing system, where "*succession towards this climax is a steady process. Grazing pressure produces changes which are also progressive and are in the opposite direction to the successional tendency. Therefore, the grazing pressure can be made equal and opposite to the successional tendency, producing an equilibrium in the vegetation at a set stocking rate*" (Westoby et al., 1989). Deterministic models can be used to better understand uncertainty by varying their initial conditions. Weather models, for example, are typically deterministic, but their initial conditions (temperature, pressure, etc.) can never be known precisely. Therefore, the initial conditions are varied slightly across numerous model runs, and the distribution of the results provides information about the uncertainty associated with the weather forecasts. Where all models produce quite different results from only small variations on the initial conditions, the deterministic model suggests that there is a large degree of uncertainty in the system. In addition, the parameters in the deterministic models can also cause the uncertainty of the model outputs. For example, in the Light Use Efficiency (LUE) model (details can be found in Section 6.3), the values of the parameters (for example, the maximum radiation conversion efficiency or the projected leaf area per unit mass of leaf carbon) are not the same when it is employed in a new place with different vegetation compositions. By varying the value of the parameters, we can estimate the distributions of the grassland productivity, and the uncertainty of the LUE model can be inferred. The parameter values of the LUE model are usually kept fixed (typically we use the average values of multiple measuring sites for a giving vegetation species) while the model is running. This is the common way to use the deterministic models.

On the other hand, stochastic models consist of at least one random element as part of the model to represent the relevant processes behind it. One critical problem with the stochastic models though is that they can be difficult to validate or explain the mechanism behind the model outcomes (Thornley, 2001). In a stochastic model, some of the parameters or processes can be described by a probability distribution, for example, the direction of the next movement of the livestock on a land can be simply modelled through picking up a random direction, and it can change throughout the period of the model running.

When describing a model as dynamic, what is meant is that it is designed to represent the change in the status or quantities of the system over time. There are two main types of dynamic model. One which ticks at regular intervals, where some things are modelled for example from day to day or from year to year. Whereas others can be event-based and one set of events tends to be scheduled to occur in more continuous handling of time, for example, baby animals can be scheduled to appear at around about a set time in a model. In addition, there can be a hybrid that mixes these two treatments of change over time. In such models, the time t is often being expressed as an independent variable in the ordinary differential or difference equations (in a discrete manner) mathematically, for example, the rates of changes in the shoot and root mass described in Johnson (2013a)'s grassland productivity model. *Static models* (as opposed to dynamic models), however, do not model changes over time and therefore cannot produce time-dependent status or quantities.

An *empirical model* is usually used to explore the quantitative relationships with two or more things (which can be described as either mathematical or statistical equations), without the consideration of any scientific content but still following a particular principle (Standiford and Howitt, 1992). A *mechanistic model*, however, can additionally provide a certain degree of understanding or explanation of the phenomena being modelled (Thornley, 2001). "*A mechanistic model is a structure of empirical components. Any empirical component can be modelled mechanistically at still lower levels. However, any model or scientific explanation has to stop somewhere, and a mechanistic model is therefore always incomplete*" (Thornley, 2001). However, it also clear that a well-constructed mechanistic model should be flexible and transparent to modification and extension without practical limit. Section 2.4.2 will discuss more on such models.

A *mathematical model* is a description or explanation of a system state, phenomenon or processed by mathematical language and concepts; it may present with a combination of either deterministic or stochastic, dynamic or static, mechanistic or empirical, mathematical or computational models. With the increasing availability and capability of computational resource, more computing power has enabled the modelling of lower levels in systems where previously this was not possible because of the associated difficulty (Levin et al., 1997). Such low-level components and mechanism usually are difficult to be described in a mathematical manner as a whole, for example, the foraging behaviours of the herbivores (Dumont and Hill, 2004a). Those *computational models* provide a new way to explore the higher-level system behaviour that arises from entities in the lower level.

This thesis will review the models of grassland grazing systems in three categories: empirical models (Section 2.4.2), process-based models (Section 2.4.3), and individual-based or agent-based models (Section 2.4.4).

2.4.2 Empirical models

Empirical models of the grassland grazing systems are often static models which aim to explore the relationship between the driving factors and the response indicators (Van Oijen et al., 2018). Usually, data are collected that captures the state or quantity of the entities in the grassland grazing system, but the data alone cannot provide more than a description or summary of the entities. the empirical model is the most intuitive and direct way to understand such data. In many process-based models, some processes are also presented by the empirical relationships (Thornley, 2001), and they are, therefore, the important models for the grassland grazing systems.

The empirical models can be used in a linear regression fashion. For example, Bai et al. (2007) used a linear regression model (species richness = a × productivity + b) under different grazing intensities in Xilingol Grassland in China to explore the effect of grazing on grassland productivity and species diversity. It has found that grazing decreased both primary productivity and species richness. Couvreur et al. (2006) identified a linear relationship between the proportion of fresh grass in the cow diet and milk fatty acid composition and also butter properties. However, these two examples only involve one driving factor to the response variable, There are empirical models that the number of driving factors are more than one, which leads to the employment of multivariate regression models. For example, Verbyla and Venables (1988) used a multivariate regression model with constraints which can be written as two seemingly unrelated regressions, to examine the effect of the sex and grazing regimes on the growth of the lambs on the grassland. Further vegetation-environment relationships were revealed through a multivariate regression, which aimed to explore the effect of seasonal fire, bison grazing and climatic on the residual aboveground productivity after grazing and abundance of plant functional groups (Coppedge et al., 1998).

More generalised linear and additive mixed models were developed by Woodcock et al. (2005), where the effect of grazing on the vegetation structure was quantified; the impact of different management treatments (grazing, mowing, mulching twice per year, mulching once per year, succession) on functional and floristic development was investigated using generalised linear models (GLM) (Römermann et al., 2009). The generalized linear mixed model (GLMM), which was an extension of GLM models, was employed by Jamil et al. (2013) to identify which species traits and environmental variables associated with the species distribution; and also, van Klink et al. (2015) found an overall significant positive effect of increasing grazing intensity on plant diversity by using GLMM.

A generalized additive mixed model (GAMM) allows the researcher to break the total variation into fixed effect, random effect and the residual variation (Dumont and Hill, 2004a). For example, by adding gradient direction and year as random effects, Sasaki et al. (2018) suggested a nonlinear relationship between the distance from the livestock camp and the cover of each vegetation functional group except forbs.

In addition, non-linear regression models are outlined by Brown et al. (1976), where the effect of age on the lifetime growth of beef cattle was quantified. Frank and Hofmann (1989) found a nonlinear relationship between air temperature or growing degree-days (GDD) and growth stage scale (HGS) under different grazing intensities for western wheatgrass. Nonlinear species-interaction models have been used to explore the effect of the pairwise interactions among the species in the vegetation communities on the grassland diversity (Connolly et al., 2013). Carmel and Kadmon (1999) used a slope-aspect interaction model under different grazing intensities to explore the effects of grazing and topography on long-term vegetation changes (Carmel and Kadmon, 1999) for a mountainous area in the Mediterranean region of Israel. More structuralized equation model can be found in the evaluation of abiotic factors controlling species densities in both grazed and un-grazed coastal meadows, and it is actually an extended multivariate regression model (Grace and Jutila, 1999).

With the increasing availability of spatial data, more spatially explicit empirical models were developed. An example is Amiri et al. (2014)'s work which aimed to identify suitable land for livestock grazing considering the spatial heterogeneity and vulnerability of the vegetation to drought and erosion. More recently, Tsutsumida et al. (2017)'s work on spatial and temporal trends of livestock population change used geographically weighted principal component analysis (GWPCA). Such models have to date tended to be implemented at the landscape scale considering the spatial heterogeneity of the grassland ecosystem in different landscapes (Roy and Tomar, 2000).

Generally, empirical modelling is rooted on the key principle of William James's “radical empiricism”, which postulates that all knowledge is rooted in connections that are given-in-experience (James, 1976). Empirical modelling aspires to craft the correspondence between the model and its referent in a way that its derivation can be traced to connections given-in-experience. The underlying philosophy of empirical models has been described by James (1976), that "*the knowing can easily be explained as a particular sort of relation towards one another into which portions of pure experience may enter. The relation itself is a part of the pure experience*"; such models give an intuitive and flexible representation of the relations among things. However, as the data collected in the grassland grazing systems are usually under certain local climatic, vegetation and soil conditions, when extrapolating of empirical models to the new conditions, they may be speculative or even false interpretation of the system (Van Oijen et al., 2018); in addition, the empirical models are usually built under certain spatial and temporal scale, from laboratory via field scale to global scale, the results from different scales are sometimes contradictory (Reichstein and Beer, 2008).

2.4.3 Processed-based models

Process-based models are based on theoretical understanding of relevant ecological, biophysical or physicochemical processes, and they provide a useful framework to incorporate specific responses to novel conditions (Cuddington et al., 2013). A definitive system for classifying process-based grassland grazing models may not exist. Scholarly literature about grass models is vast and diverse. This section focusses on process-based models involving interactions or feedback between vegetation and grazing animals, or at least the effect of grazing is considered in the model (either embedded in the input data or the processes of the model).

Three types of process-based models can be distinguished according to their modelling purpose: grassland process models; grassland livestock production models; and, decision support systems. A similar classification can be found in Feenstra (1998). This review does not intend to list all the models but rather, to provide an overview of current models with some pros and cons.

2.4.3.1 Grassland process models

Grassland process models focus on the process of vegetation development and interactive feedbacks between this, the environment and livestock. The dynamics of vegetation can be represented from the scale of individual plants to large scale regions. A variety of environmental conditions and geographical places have been investigated using such models. As vegetation dynamic depends on climatic conditions, models are also developed to explore the effect of climate change, grazing and management regimes on grassland ecosystems through biophysical or ecological processes of the system (Anderies et al.).

An example is the Discrete-Time Model of Woodward et al. (1995b) , which is a relatively simple model of pasture growth and removal. The model assumes the rate of grazing by each animal is proportional to the herbage mass of the field. The results showed that compared with grazing stocking rate and the initial conditions of the grassland, grazing management has no or little effect on grassland productivity. The main issue with this model is that it relies heavily on detailed data about the physical condition of grasslands and thus is thought likely to be unsuitable for modelling area where the physical conditions are very variable and how they vary is not well understood (Woodward et al., 1995b).

A more complicated model is the Tropical Pasture Simulator developed to simulate the grass growth in Kikuyu (Herrero et al., 2000b). The model considers vegetation physiological processes: light interception and photosynthesis; leaf area expansion; growth; ageing; and, senescence of plant tissues. The grassland productivity dynamics were simulated under rotational or continuous grazing with responses to nitrogen fertiliser, temperature and irradiance.

The Carbon Cycle of Grassland (CCGRASS) was developed for long-term studies of the effect of grazing on vegetation productivity - to evaluate the carbon sequestration in the soil (Dasselaar et al., 1995). In the model, the contribution of grazing to the soil carbon sequestration depends on the site-specific stocking rate, herbage intake per animal and the herbage digestibility. In addition, the CENTURY model, which is a widely used vegetation productivity model, was developed to simulate the dynamics of carbon (C), nitrogen (N), phosphorus (P), and sulphur (S) for different plant-soil systems for either grassland systems, agricultural crop systems, forest systems, or savanna systems (Parton, 1996). For the CENTURY model, the grazing effect on the vegetation was simply assumed proportional to the vegetation mass.

At the leaf scale, Coughenour (1984) constructed the GRASS model to examine the effect of grazing on the grass growth, water use and light interception, but the effect of leaf angle on the productivity was not considered. By including and excluding livestock grazing in the simulation, the Hurley Pasture Model (Thornley and Cannell, 1997) was used to reveal the impact of grazing on grassland. Thornley and Cannell (1997) suggested that grazing can drastically alter the magnitude and sign (positive or negative) of the response of grasslands to climate change, especially accounting for rising temperatures.

A comparison of some of grassland process models is shown in Table 2.2. The common drawbacks in these are summarised at the end of Section 2.4.3.2.

Table 2.2: Comparison of grassland process models, modified from Feenstra (1998) and (Ehrhardt et al., 2018)

Model	Spatial resolution	temporal resolution	Pros/cons	Key reference
Tropical Pasture Simulator	1 m^2	daily	A mechanistic model representing the growth of vegetative tropical pastures under rotational or continuous grazing with responses to nitrogen fertilizer, temperature and irradiance that can be used as a tool to study management options for the development of sustainable grazing systems; Too many parameter values need quantified when applying to novel conditions, and plant population dynamics are not explicitly presented in the model.	(Herrero et al., 2000a).
Discrete Time Model	1 ha	daily	A simple process-based modelling that can simulate the effect of different grazing management	(Woodward et al., 1995b)

			strategies (rotational or continuous grazing) on grassland productivity; Needs sufficient and precise information about the system, which makes it difficult to be applied to the other areas, and it only focuses on the productivity of the system.	
CCGRASS	site	yearly	Well suited for management and climate interaction on soil and plant dynamics; Effects of grazing and mowing incorporated from site-specific experimental data, and it does not include the effects of the other herbivores in the model.	(Dasselaar et al., 1995)
CENTURY	1 m^2	monthly	Well suited for studying the biogeochemical cycling: C, N, P, and S dynamics for the plant soil, and seasonal effects of burning and grazing simulated; Only simplified herbivore Routing.	(Parton, 1996)
GRASS	1 m^2	monthly	Well-designed for the assessment of the impact of grazing on African grassland systems: shoot number, C, and N budget, energy balance, and water budget; Physiologically based grazing-plant feedbacks at leaf level makes it difficult to be applied for large-scale studies.	(Coughenour, 1984)
Hurley Pasture Model	site	yearly	Simulate the fluxes of C, N, and water and allows for the study of soil-grass-animal interactions with mature, nonlactating sheep; Grazing effect is associated with stocking rate, and like all the other models, many parameters are needed.	(Thornley and Cannell, 1997)
APSIM	site	daily	It is flexible for the users to assess the management actions, and grazing in rotations (based on SGS model, which is also listed in this table) and is a major strength of the model; It does not handle phosphorus properly and, unless configured with GRAZPLAN, only a simple representation of the grazing animal is possible.	(Holzworth et al., 2014)

CenW	1 ha	daily	The generic structure and comprehensive inclusion of many key processes and system feedbacks. It thus responds both directly and indirectly to a wide variety of changes in external environmental and management conditions. It is also embedded in a user-friendly interface that allows a wide range of changes to management or environmental condition to be readily implemented; CenW relies on the assumption of a horizontally uniform plant canopy and includes no sophisticated phenological routines. It is thus suitable for grass swards or forests with uniform tree cover, but not suitable for modelling isolated plants.	(Kirschbaum et al., 2015)
SGS	1 m^2	daily	DairyMod contains a detailed simulation of photosynthesis, growth, C partitioning in response to water and N stress, designed for grassland systems and includes a sub-model of the animal and its effects on the pasture through grazing and the spatial modelling of the deposition of excreta, as well as capturing sward dynamics, such as the competition between grasses and legumes, grazing offtake rates and cutting residuals; The model does not simulate herd dynamics, tactical buying or selling of animals. The model does not account for plant death *per se*.	(Johnson, 2013b)
DayCent	1 m^2	daily	It examines soil C and N dynamics for a wide range of C (CH4 and CO2) and N (N2O, NOx, NH3, and N2) gas fluxes, and it is adjusted based on the site-specific information; DayCent does not explicitly simulate animals and therefore cannot simulate enteric methane nor can the model simulate multi-species cropping or grassland systems.	(Parton et al., 1998)

SPACSYS	site	daily	It links plant, water and nutrient cycling together, and the model can simulate root architecture; The model has a large number of parameters and is only applicable to plot and field scale.	(Wu et al., 2007)

Note: the site means the model was implemented in a relatively small place where the experiment or observation data was collected.

2.4.3.2 Grassland livestock production models

Grassland livestock production models consist of various components for the simulation of livestock productivity. These include how the grass is converted into meat or milk or how grazing effects grass growth. Some researchers have found that there was a linear relationship between animal production and vegetation utilisation rate (Bellamy and Lowes, 1999); but, in fact, it is quite complicated to identify the relationship between grass and livestock due to their dynamic and bidirectional features. The dynamics of livestock production depends on such herbivore-plant interaction (Hutchings and Gordon, 2001). However, more experiments or grassland monitoring work needs to be done to get the right value of parameters in specific areas (for example, grazing time and frequency) (Vries and Daleboudt, 1994; Johansen et al., 2004; Augustine and Derner, 2013).

An example is the vegetation dynamics in the rangeland production and utilization model (SPUR) (Hanson et al., 1988). SPUR enables the quantification of the effect of grazing management, environmental variation, and fertilizer application on livestock production through carbon (C) and nitrogen (N) flow in the soil-plant-animal continuum (Hanson et al., 1988). A more detailed model on dairy cow grazing with mathematical description of the daily energy requirement for growth, fatting and milk yield was shown in Topp and Doyle (1996)'s model, which includes both abiotic factors (temperature, water, light, nutrients) and biotic processes (growth and senescence), as well as the energy partitioning in the cow (conversion of nutriment to milk or fat). In addition, the PaSim (Calanca et al., 2007) and the DairyMod (Johnson, 2013b) models are both process-based models, which involves C and N cycling through the shoot and root compartments, and in particular, compared with the other models, the livestock rotations between paddocks in the DairyMod enables it to simulate the effect of managemental practices.

Table 2.3 provides a summary comparison of grassland livestock production models. One of the major limitations to all of the models listed in Table 2.3 is that they are highly site-dependent models. The values of parameters and the relationships in the models are derived from local or regional observations. However, the properties of livestock and the types of livestock varies spatially, which make them sometimes difficult to be implemented in the new conditions.

Table 2.3: Comparison of the grassland livestock production models, modified from Feenstra (1998), page 9-17

Model	Spatial	Time	Pros/cons	Key reference
SPUR	1 m^2	daily	Simulate C and N dynamics for the plant-soil system, and simulates plant-herbivore interactions at multi-site or	(Hanson et al., 1988)

			pastures, and it can simulate the effects that changes in temperature and precipitation regimes and CO2 may have on milk production and silage conservation; However, the vegetation composition in the model is complicated. Not suited for tropical or phosphorous limited soils.	
Topp and Doyle Model	site	daily	Simulate changes in above and below ground plant production, simulate the growth, milk production, and grazing; Unsure of model performance in tropical conditions.	(Topp and Doyle, 1996)
DairyMod	1 m^2	daily	The same as SGS in Table 2.2, they are integrated into one system. DairyMod is a sub-model which can simulate herd size, calving dates, animal weight, lactation status etc., and livestock rotations between paddocks; But the livestock dynamics have not being represented, tactical buying or selling of animals.	(Johnson, 2013b)
PaSim	1 ha	daily	An animal module (sheep or cattle) in the model simulate the ingested biomass, milk production, gain of live weight, animal excreta and CH4 emissions; PaSim does not yet consider nutrients other than N. Carbon pools are distributed over the whole soil profile rather than described in the soil layer, and it does not take into account plant competition.	(Calanca et al., 2007)

Note: the site means the model was implemented in a relatively small place where the experiment or observation data was collected.

Although this chapter has not reviewed the literature on all process-based models of the grassland grazing systems, the common characteristics and drawbacks of these diverse set of models can be summarised as follows:

- The models represent the dynamics of vegetation and herbivore via either biophysical process, chemical cycling, eco-functioning or energy flows, which make them capable and available to simulate lots of diversified grassland grazing systems.
- The values of the parameters are usually site-dependent (under certainty spatial or temporal scale), which means the models may be difficult to apply in new conditions, though they may work fine in the case study areas where they have been applied.
- Climate data are commonly used as a driving force behind the growth of the vegetation, but the errors propagated from the uncertainty of such data are rarely reported.
- The evolution and co-evolution of the interactions between plants and herbivores are not well-represented.
- Plant-herbivore feedback is simulated in a “static” way (herbivores cannot move), and the stochastic nature of foraging behaviour of livestock is usually disregarded.

2.4.3.3 Decision support systems

What cannot be ignored is that grazing activities are under the guidance and involvement of humans that often try to maximise the utility of natural resources, and optimise biological utilization efficiency via grassland management (Heitschmidt and Stuth, 1991; Vallentine, 2000; Conant et al., 2001). It is possible to achieve high and stable productivity of grasslands by balancing grazing activities and grassland ecosystem protection (Pompilica and Romulus, 2014). This kind of management could especially benefit degraded grasslands, whilst helping to maintain the living standards and livelihoods of herders (Kim et al., 2006). Any reasonable grassland management strategy is constrained by various factors including meat price (Bernués et al., 2011), national policies (Li and Huntsinger, 2011), and local culture (Maurer et al., 2006).

Decision support system (DSS) models allow the user to examine the potential effects of management decisions in a given system based on a set of decision rules that have been formulated in the model (Feenstra, 1998). In the mid-1990s web-based decision support systems were developed to enable users to monitor, investigate, analyse and predict likely outcomes of the decision on grasslands. One such recently developed model is the FORAGE model, which aims at facilitating the best management practice for grazing land (Zhang and Carter, 2018). The structure of the FORAGE is shown in Figure 2.3.

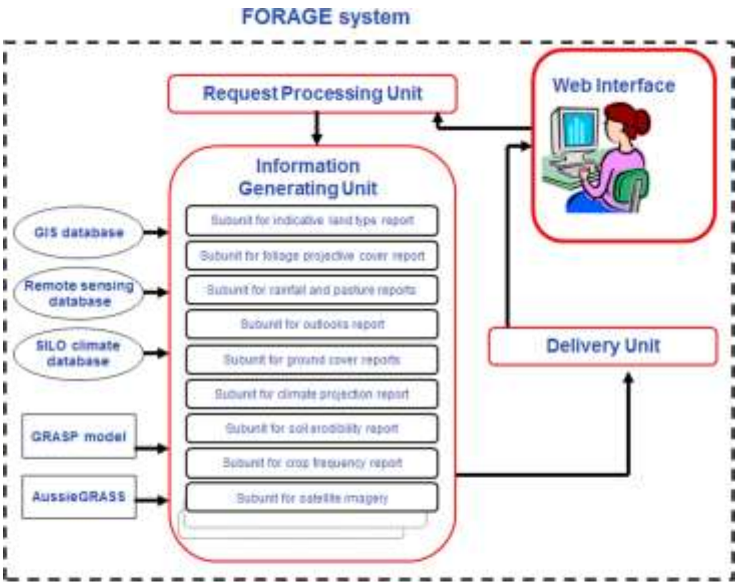


Figure 2.3: Structure of the FORAGE system (the arrows indicate information flow) from Zhang and Carter (2018), page 304

The underlying theory of the FORAGE system is the GRASP model, which is a deterministic, point-based, native pasture model developed for semi-arid and tropical grasslands (Chilcott et al.). GRASP is an empirical model designed to simulate aspects of grass production and to predict soil water, pasture growth and animal intake by separating the processes of soil evaporation, pasture transpiration (McKeon et al., 1982). Thus, the defects of FORGE are similar to all the other empirical models, which have been discussed in Section 2.4.2.

Another typical DSS model is GrazPlan, which was designed to simulate the biophysical processes of grassland grazing (Donnelly et al., 2002b). GRAZPLAN is a suite of the biophysical process-based simulation tools for Australian grazing system management (Donnelly et al., 2002b). It has been developed by CSIRO Plant Industry to test the sustainability of different management strategies (for example, stocking rate and selection of pasture species) with an economic purpose (Freer et al., 1997). The DDS tools were designed to generate cost and price indices to enable estimation of production risk in financial as well as in biological terms (Moore et al., 1997a). Daily weather information is needed as input for the model (Donnelly et al., 2002a). The pasture growth part involves a process-based model considering the daily root and shoot growth of the grass, based on the light use efficiency model (LUE, which will be further reviewed in Chapter 6) (Moore et al., 1997b). It highly depends on the observed climatic, vegetational and the empirical values from the other models, which makes it impossible being implemented in the areas where for example the daily climatic data are not available. The basic relationships in the GRAZPLAN family are shown in Figure 2.4, and the more detailed description can be found in (Donnelly et al., 1997; Freer et al., 1997; Moore et al., 1997b).

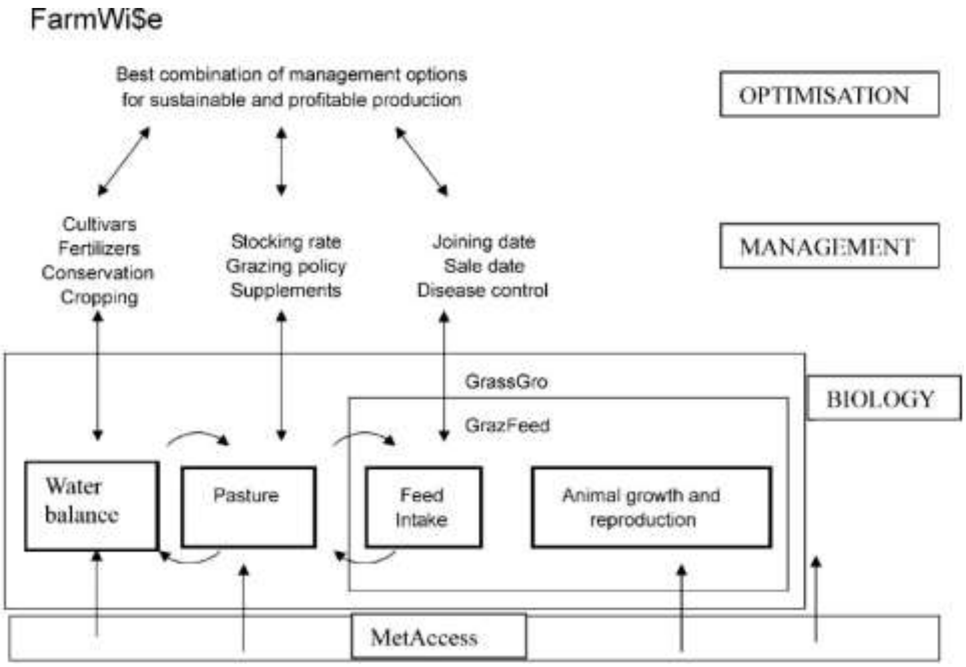


Figure 2.4: The relationship between the GRAZPLAN family of decision support (DS) tools and the GRAZPLAN pasture and animal models, Donnelly et al. (2002b), page 117

An example of a state-and-transition model implemented in a DSS is the Landassess spatial decision support system, which was developed in collaboration with government agencies responsible for pastoral land management in the Northern Territory, Australia. Landassess is based on a state and transition model assessing sustainable grazing management within spatially variable paddocks, and it examines the approach used to handle some of these modelling issues (Briske et al., 2005; Bashari et al., 2008). It is based on a number of alternative stable system states derived from vegetation change, soil erosion risk, animal forage preference and a suite of possible transitions associated with the change from one state to another. A transition from one state to another state is defined in terms of alternate causes that would lead to a change of vegetation state. Landassess provides a representation of the driving interactions between ecological systems and human management interventions. The deficiencies of the DSS are in part a consequence based on the State-and-Transition models, a critique of which was outlined in Section 2.3.2.

There are too many DSS relating to grassland grazing system to pay them individual attention in this review. Yet, in general, the DSS of grassland grazing systems are either based on empirical, process-based or integrated models (including agent-based models, which are outlined in Section 2.4.4). A more detailed discussion on DSS for the management of grassland grazing systems can be found in Stuth and Lyons (1993).

In summary, process-based models of the grassland grazing systems are often the mathematical (and usually computer-based) representation of one or several processes characterizing vegetation dynamics, livestock dynamics, energy and/or chemical cycling. The processes can be affected by either biotic factors or abiotic factors. Each of the processes is, in essence, the description of the functioning which contributes to a higher level (bottom-up model) or lower level (top-down model) functioning, and the output of one process can be the input of the other process. The processes in the model enable us to capture the important biological or physiochemical mechanism mechanisms driving the behaviour of the grazing system. However, as the earth itself has a variety of vegetation and herbivore types, and the heterogeneity in climatic and natural condition across different spatial and temporal scales makes the description of the processes sometimes only meaningful in unique grassland ecosystems (Vandvik and Birks, 2002). In addition, the process-based models reviewed thus far have weaknesses with regard to describing or integrating the evolution or coevolution of vegetation and herbivores on grassland (McNaughton, 1983). Although there is research on the compensatory growth of the vegetation caused by grazing (McNaughton, 1983) or coevolution of the plants and herbivores (Stebbins, 1981b), the accuracy of long-term predictions and the behaviours of the grassland grazing systems need more scientific attention especially with regard the evolution or coevolution of the plants and herbivores.

2.4.4 Agent-based models

As discussed in previous sections, numerous models have been built for the grassland grazing systems. However, “any model with a natural resource management application should ideally incorporate the human systems associated with that resource” (Deadman, 1999). For grassland grazing modelling, it has been argued that a grassland forage productivity sub-model (natural system) and a grassland livestock grazing sub-model (human system) should be combined to discover the relationships and regularities under the interactions of those components (An, 2012b; Wang et al., 2013). Efforts within the human systems of grasslands have been taken up in the fields of grassland economics (Burt, 1971; Röder et al., 2007; Ritten et al., 2010), institutional arrangement assessment, game theory analysis of grassland management and perception studies of humans (Quinn et al., 2003; Bunting et al., 2013).

In addition, as the grassland grazing system is part of the regional or global ecosystem (Thornton and Herrero, 2001), it is highly dependent on environmental factors, such as climate change (Stokes et al., 2008; Fan et al., 2010a; Graux et al., 2011; Jun et al., 2013; Ye et al., 2013; Jakoby et al., 2014), ecology (Douglas et al., 1998; Cingolani et al., 2005a; Soder et al., 2007; Arévalo et al., 2011) and the physical properties of the land (Aronson et al., 1993; Dean et al., 1995; Phelan et al., 2013). Grassland grazing systems have socio-economic or ecosystem service values (Lamarque et al., 2011). Therefore, the models of grassland grazing systems are often presented as integration with climate models, socio-economic models or management models (Ellis et al., 1987; Smith and Foran, 1990; Parsons et al., 2001). These are important research area, but they are beyond the focus of this thesis, and instead, this thesis concerns one particular type of the integrated models of the grassland grazing system—Agent-based Models (ABM), which is an effective tool for exploring grassland grazing complexities (Bell, 2011).

Similar to the complex system, there is also no precise definition of ABM and definitions vary across disciplines, but it commonly an ABM consists of three key components (Macal, 2010):

- a set of agents with attributes and behaviours;
- relationships or connections among agents and rules or ways they interact;
- agents can additionally interact with their environment;

By explicitly considering the components of a system consisting of individual agents, ABM can be used to understand how system properties emerge from interactions among lower-level entities (Grimm, 1999). In this particular way, an ABM of a grassland grazing system is fundamentally different from an empirical or process-based model of the same system. ABMs have the potential to more realistically model by considering the decision-making or interactions among individuals, which may be difficult or impossible to do with other models.

It is a bottom-up tool that has been employed both in theoretical (Lilibeth et al., 2014) and empirical studies (Juliette et al., 2011; Wang et al., 2013) in grassland grazing. The quantitative computational features of ABM make it easier to describe the heterogeneity, learning and adaptation, evolution and interactions of various agents (Gimblett, 2002). *"A community of agents acts independently of any controlling intelligence, they are goal-driven and try to fulfil specific objectives, they are aware of and can respond to changes in their environment, they can move within that environment, and they can be designed to learn and adapt their state and behaviour in response to stimuli from other agents and their environment"* (McLane et al., 2011).

The decision-making process of agents can be described in a flexible and context-dependent way with the specification of interdependencies and feedbacks/interactions between the agents and their environment (Groeneveld et al., 2017a). Currently, the decision-making in the ABM is based on either *ad hoc* assumptions or established theories. The later has been credited as more transparent and comprehensible for communication or reuse of the model when compared with the former (Groeneveld et al., 2017a). The agent's decision-making can be made based on the economic theories such as expected utility theory, rational decision-making theory, bounded rationally theory and stochastic medications of expected utility theory, or on psychological human decision-making theories such as planned behaviour theory (Groeneveld et al., 2017a). A further detailed investigation of the agent's decision-making theories can be found in Groeneveld et al. (2017a) and Balke and Gilbert (2014), and the employment of the decision-making theories when building the ABM is still insufficient across disciplines (Gimblett, 2002), therefore, it is suggested that a structured, guided framework (such as *MoHuB* framework, see Schlüter et al. (2017)) should be developed on the choose of theories and factors in the ABM, and the participatory evaluation or the empirical research could deep our understating of human decision-making (Groeneveld et al., 2017a).

2.4.4.1 Previous modelling of complexity: limitations and future research directions

The use of ABM in grassland grazing modelling is still in its very early stage, although ABM has been widely used in the field of land use/cover change modelling. Examples include the Land Use Dynamic Simulator (LUDAS) (Le et al., 2010), FEARLUS-ELMM (Polhill et al., 2007), and AgriPoliS (Happe et al., 2006). They were not strongly related to grassland grazing, but they used ABM for simulating grassland changes (spatial distribution pattern of the grassland), and for exploring how environmental and socioeconomic factors affect the decision-making of grassland owners, for example, whether the pastoralists should change the grassland to cropland for agriculture use (Le et al., 2010). A more recent review of the ABM in land use/cover models can be found in (Parker et al., 2003; Groeneveld et al., 2017b) and (Groeneveld et al., 2017b). But none have considered plant-herbivore interactions and the process of the vegetation development, which limited their use in understanding the vegetation dynamics of the grassland grazing system. In a similar research area—wildlife ecology and management—specific models were developed to simulate the behaviours of animals. The animal, landscape and man simulation system (ALMaSS) was used to assess the effect of changing landscape structure or management on key animal species (Topping et al., 2003). ABM has even been employed in wildlife ecology and management by exploring the selectivity of their habitat, and how they respond to environmental changes (McLane et al., 2011). A summary of these studies can be found in McLane et al. (2011). Such models have not included the effect of social system and human's decision-making, as well as the policy effect on the behaviours of animal, which make them difficult to be used directly in evaluating the management practices of the grassland grazing systems.

Agent-based models consider the grassland, the pastoralists and a policy maker as a complex adaptive system (Abel, 1998). In order to better understand such Coupled Human and Natural Systems (CHANS), agent-based modelling for the CHANS should make use of both empirical knowledge and decision-making theories (An, 2012b), which indicates that the social theories that can explain agent actions and interactions can be used for modelling CHANS (Jun et al., 2013). Actually, the agent-based models of grassland grazing can be linked with ecological and socio-economic submodels. While the ecological sub-system is commonly a simplified version of the more comprehensive model and the relations in the model are usually empirically based (Gross et al., 2006a). As such, an example would be a socio-economic sub-system which typically affects the decision-making of the 'regulator' or the behaviour of pastoralists. The regulator comprises the policy and institutional environment within which pastoralists make management decisions. The decision-making of the regulator or the pastoralists should be ideally based on theory (although *ad hoc* assumptions are widely used in the ABMs) (Abel, 1998), with consideration of cultural anthropology, economics, organisational and management practice, and political-economic background. Potential decision rules for pastoralists should ideally be developed in discussion with experts on grassland management and simplified for the model (Levin et al., 2013).

There are agent-based models focused on the population dynamics of herders, pastoralists and nomads in the grassland grazing system. An example work can be seen from Kuznar and Sedlmeyer (2005); (Rogers, 2013), whose work aimed at exploring the interactions among pastoral nomads and peasants by trading or raiding for goods according to different wealth condition. Grazing is just a simple overall decrease in productivity in the model. The fixed grassland productivity assumption and the lack of plant-herbivore interaction make it unable to simulate the vegetation and livestock dynamics under different management practices. The Common Resources Management Agent-based System CORMAS was employed by Saqalli et al. (2010) to explore the evolution of the village population under different family originations. The CORMAS model consists of a biophysical environment linked with the social and economic status of the human agents, and it considers the relationships and dependencies between villagers (who are the livestock and landowner) and their differentiated accesses to economic activities (agriculture, livestock keeping, seasonal migration, dry-season gardening). It has found that the larger group proportion and specializations led to an increase in the village populations' robustness. In the model of Hailegiorgis et al. (2010), the effect of climate change on the population dynamics of the herders was analysed, and the authors found that cooperation and conflict were at the minimum due to the significant reduction of the population of herders when drought happened; but after the population recovered to some extent, cooperation and conflict increased dramatically. Kennedy et al. (2010) have developed an agent-based model for exploring the competition of the grass and water pole utilization, which caused the emergence of the conflicts. It was found that greater environmental scarcity leads to faster domination by a single ethnic group. However, the oversimplified ways of handling the conflicts when using resources, and the *ad hoc* assumptions about herders' knowledge of resource availability make the simulation results vary dramatically. Therefore, the uncertainty of the model should be quantified (Kennedy et al., 2010).

For the simulation of the mobility of the pastoralists, an example is the HouseholdsWorld model (Rogers, 2013), which used lineage and clan as the basis for the household. It aimed to simulate the herder's population and mobility under clan leadership, collective or local social network. It has found that the regions with dense populations and by expanding the scope of landscape knowledge could improve micro-mobility to mitigate social restrictions effectively, and therefore the herder' population expanded but became poorer. In the less densely inhabited regions, more knowledge of the landscape expanded the mid-range of the wealth distribution without expanding the number of poor herders. Milner-Gulland et al. (2006) have used an agent-based model to explore the impact of agents' decision-making on flock dynamics under climatic and economic change, which included both household decision-making and vegetation-herbivore interactions. Agents optimise their investments in an uncertain environment by allocating their wealth between livestock and capital. It found that winter forage availability is the key determinant of overall livestock number, and if there was enough winter forage, larger herds were predicted to settle away from the village. Okayasu et al. (2010) further used this model to explore the spatial distribution of the wealthy herders and poor herders. The authors found that agents they can co-exist in the area because even in the dry year when the home pasture could not provide enough forage for the whole animal population, the wealth herders (who own more livestock) could move to the remote pasture to reduce the grazing pressure on the home pasture because they can afford the moving costs. Although the poor herders may not move to the remote pasture due to the high moving costs, they could better access the home pasture as the grazing pressure had been reduced. However, this model cannot be used in the region where the movement of herders is determined by the other non-economic factors, for example, privatised lands where other herders do not have access to; secondly, the effect of the water availability and other social factors, for example, market, education and medical services, on the decision-making of herders also have not been considered in the model (Okayasu et al., 2010). In addition, the plant-herbivore interactions and the policy and institutional arrangements are not considered in the model.

There are also agent-based models focusing on livestock dynamics in the grassland grazing system. An example is Milner-Gulland et al. (2006)'s work, which was discussed in the previous paragraph. Dressler et al. (2018) examined the effect of household' behaviours on the resilience of the pastoral system considering the feedback between pastures, livestock and household livelihood. The results showed that short-term profit-oriented behaviours of the herders led to long-term pasture degradation and livestock loss. A satisficing behaviour constrained the herd size, but it diversified income source of herders, and therefore, led to improved pasture conditions and higher total livestock numbers. An example of the other works can be found in Aktipis et al. (2011), who even used ABM to explain how the gift-giving relationship under exchange scenario improves the herd longevity.

With regards to the employment of ABM to the study of grassland grazing systems, ABMs have improved the popularity of plant-herbivore interactions and the behaviours that determine herbivore foraging (Dumont and Hill, 2004b). The Simulation of Ecological Compatibility of Regional Development model (SERD) was an example of a household involved and spatially explicit model that integrated with socio-ecological stock-flow (Gaube et al., 2009). But the temporal resolution was 1 year, which means the short-term effect of plant-herbivore interactions was ignored in the model. A more detailed ABM of plant-herbivore interactions has been constructed to simulate movements of cattle grazing corn residues (Liu et al., 2016). That model involved the employment of a GPS tracking system, with which the real-time behaviour of herbivores was identified, but grassland management strategies and institutional arrangements were not considered.

There are models that concern both the decision-making of the pastoralists and regulators, based on the biological process of vegetation and herbivore, as well as the policy and institutional regimes with real-world observation data. Janssen et al. (2000) built an adaptive agent model, which includes competition between grass and shrub, and heterogeneity in the vegetation growth rate. The decision-making of the pastoralist was based on the economic status of the pastoralists and the ecological status of the grassland. The different policies changed the opportunity cost according to the threshold of percentage of properties (an indicator for grassland status). However, the real-time learning of pastoralists and novel management strategies and combinations were not considered in the model. In addition, using a fixed climatic (a 5-year moving average of the historical rain data) driving data means the model was only suitable in a stable climatic environment. In addition, the thresholds of the percentage of properties are *ad hoc* assumptions, which limit the use of this model to the other regions. Similar research was carried out by Gross et al. (2006b), where a conceptual framework of an adaptive ABM has been built that tried to link the climatic condition, biophysical processes, and institutional arrangements. The decision-making and learning of the individual are considered by updating the usage of fixed rules when there was sufficient environmental or economic perturbation to the system. However, the fixed stocking rate assumption and assumed values of the parameters in both the biophysical and pastoral sub-models make the results susceptible to the uncertainty caused by such setting. Jun et al. (2013) analysed the social-ecological performance of different institutional arrangement experiments with the employment of agent-based modelling, and revealed cooperation mechanisms under climate change adaptation (Jun et al., 2013), but the absence of real productivity and livestock grazing data in the model make the results less convincing.

A model of particular relevance is that of Sakamoto (2016) who developed an agent-based model based on remote sensing data. In this model, the moving behaviours of the pastoralists were driven by the availability of the local resource represented by the vegetation index and the movement cost. The spatiotemporal patterns of the land use intensity caused by the movement of the pastoralists were reproduced. However, there are numerous *ad hoc* assumptions about the behaviours of the pastoralists (for example, grazing range, frequency and carrying capacity), which make it less credible when applied to a place where the conditions violate such assumptions. Also, the results of the model have not been validated, and the effect of different grazing strategies and institutional arrangements have not been considered. Troost and Berger (2014) analysed the uncertainty of the ABM at the farm-level; the importance of interactions among agents was highlighted in this fully connected agent-based model. Their work addressed the uncertainty in model structure, as well as gaps and fuzziness caused by data uncertainty and *ad hoc* model assumptions, but such uncertainties can be reduced by cautious calibration and comprehensive uncertainty analysis. This is an important research area in modelling the grassland grazing system and will be further illustrated and discussed in Chapter 7.

To conclude, it appears from the literature that common character of the agent-based approach and their defects in modelling of grassland grazing are:

- the biophysical parts (vegetation dynamics) in the ABM of grassland grazing systems are commonly empirical-based, which makes the development of the vegetation highly dependent on the historically observed data, and they have all the defects that the empirical model shares;
- ABMs of grassland grazing systems usually involve large numbers of input datasets, parameter values and the *ad hoc* or theory-based assumptions, and they are sometimes derived from the data with uncertainty, but there are few examples of research that addresses such uncertainty. This is partly due to the difficulty with collecting data or carrying out the experiment; it is also important to balance modelling complexity with uncertainty (Holling, 2001);
- the plant-herbivore interactions in the models are simply assumed to be a negative effect on the plant productivity—direct loss of the equivalent consumed by the herbivore. Neither the evolution or coevolution of the plant and the livestock are considered, nor the compensation/suppression effect of the livestock on the plant growth is considered;
- the models mainly focus on the vegetation productivity or the quantity of the livestock, the broader scale of the vegetation dynamics (for example, composition, diversity or resilience) as well as the livestock (for example, meat and milk quality);
- institutional arrangements and grazing strategies are recognized as the important policies in managing grassland resources, more in-depth, multi-scale, multi-level analysis of different managemental consequences should be carried out;
- the aggregated overall regional/farm/site scale dynamic of the vegetation or the livestock can be well-presented in the model output, but the spatial distribution patterns are rarely to be seen from the existing researches, especially the model with real-world data;

2.4.4.2 Modelling the grassland grazing system in Zeku

For the Agent-Based Modelling of Grassland Grazing (ABMGG) presented in this thesis, the interactions between herders and different institutions have the nature of individual-based features, which can be affected by the different decision-making practices of individual resource users. Classical models of natural resource use centre more on the economic inputs and outputs at the system level (Burt, 1971), but it has long been realised that human activities are the most powerful factor affecting those interactions and decision-making, and it can be a disaster for the ecosystem when the plundering of natural resources occurs (Vitousek et al., 1997; Wackernagel and Rees, 1998). So, the dynamic patterns of grazing which are controlled by individual decision-making activities need to be modelled to find the optimal strategy to maximise the output of natural resources and maintain a sustainable ecosystem.

Modelling the behaviour of an individual is complicated work because of their various characteristics and decision-making processes. For example, households may expand their livestock scale, increase capital or invest in other businesses after selling their livestock. Individual behaviour could also be affected by the degree of information one has, the availability of forage can lead to distinctive moving behaviour, while individual responses to external cues can lead to aggregative behaviour at the larger scale (Juliette et al., 2011). The interventions of administrations aimed at improving sustainability, efficiency or equity of use of resources affect individuals differently, depending on factors such as their assets, aspirations or location (Milner-Gulland et al., 2006). In addition, the ownership of land in China is in the hands of the state (government). The government plays an important role in allocating the grassland resources to herders. In addition, the government is also the policymaker who has the final decision-making right over how to use the land, through subsidies or penalties. It is an indispensable part of the grassland grazing model. So the framework of agent-based modelling of a grassland grazing system should consider the strategy of the government, which should balance between the socio-economic demand, ecological demand and the interest of all stockholders. Hence in order to understand the impact of policy interventions on both individuals and the overall system it is useful to take an individual-based approach albeit with the government acting on the individuals.

Herders in the Three-River Headwaters Region of China depend heavily on the annual production of natural forage, or herbage, from grasslands (Foggin, 2008). But to best utilize this forage they must understand the seasonal productivity of the annual grassland ecosystem (Menke, 1985). Four factors: precipitation; temperature; soil characteristics; and residue largely control forage productivity and seasonal species composition. These factors also change the timing and characteristics of the four distinct growth phases: winter hibernation, break of the quiescent season, rapid spring growth, and peak forage production. Many of these patterns can be used to guide management decisions. As the seasons progress, the patterns become set and the outcome more predictable in reality (Menke, 1985).

However, existing grazing ABM models have a key assumption which is that long-term land degradation does not occur in the model system. This means that grazing in a particular season does not affect the next season’s forage availability (Milner-Gulland et al., 2006). But, in fact, this is an inaccurate assumption for the Three-River Headwaters Region of China, where overgrazing contributed a lot to grassland degradation (Liu et al., 2008a). This has a great impact on the sustainable development of the regional ecological environment and grassland husbandry, and seriously threatens the ecological protection of associated areas. Some research has also indicated that overgrazing is the most prominent factor in the region’s grassland degradation (Zhang et al., 2014a).

We can control the livestock quantity to some degree to reduce the pressure on grassland, but it is difficult to estimate the potential livestock-carrying capacity of grassland in different regions and different seasons in such a sensitive and fragile area, because of the complicated co-evolutionary relationship between grass and livestock, which can be seen through the lens of plant-herbivore interactions (Knapp et al., 2012). Traditionally, herbivory was considered detrimental to grassland, and much research has the assumption that herbivory has a purely negative impact on plant growth because it suppresses the growth of plants (Crawley, 1983; Baldwin, 1990). However, both theoretical and empirical studies in grasslands suggest that individual plants, as well as net primary productivity (NPP) at the ecosystem scale, may respond in a neutral or even a positive manner to grazing (Douglas et al., 1998). This is an interesting and important topic in grazing agent-based systems, and methods to estimate the grass yield accurately would be of great value to the scientific management of grassland and the decision-making associated with animal husbandry.

2.5 The role of remote sensing

To overcome limitations in the spatial-temporally explicit data on grassland status, researchers urgently need a tool with the capability of real-time observation of grassland status. Remote sensing is an important tool for monitoring and assessing such a complex system consisting of grass, livestock and human management. Remote sensing is the science of obtaining and interpreting information from a distance, using sensors that are not in physical contact with the object being observed (Lillesand et al., 2014). It is widely used in the field of earth surface observation by visible and non-visible radiation, where radiation interacts with surface materials and the atmosphere (Liaghat and Balasundram, 2010) to enable sensing. However, due to its perceived inability to quantify rangeland vegetation regardless of season or condition, it was not applied for the management of grassland at an early stage in the science (Hunt Jr et al., 2003).

Remote sensing has been useful in detecting green vegetation, but senescent or cured vegetation was missed (Marsett et al., 2006), which was one of the most important sources for winter feeding (Hudson and Watkins, 1986) and an important component in intercepting rainfall to reduce soil erosion (Li et al., 2008) and as well as a source of fine fuels for grassfires (Kidnie et al., 2015). With the availability of a wide variety of sensors and platforms, remote sensing has gradually become an important tool for grassland management (Asner et al., 1998; Hunt Jr et al., 2003; Numata et al., 2007). The combination of *in situ* experiments and remote sensing observations especially enable near real-time monitoring of grassland status under grazing and detecting human pressure on the grassland system (Pickup et al., 1994; Kawamura et al., 2005).

Remote sensing provides temporal and spatial patterns of grassland change and has been used to estimate the biophysical characteristics of grasslands (Numata et al., 2007). Canopy biophysical parameters can be inferred from vegetation structural and biochemical properties and the quantity and quality of incoming radiation observed by remote sensing (Adam et al., 2010), which are the key parameters for predicting both the radiative and chemical balance of grassland systems (Asner et al., 1998). The applications of remote sensing based on this vary from grassland classification (Langley et al., 2001), and productivity change (Prince, 1991b) to biophysical variables such as such as LAI (Asner et al., 2003), biomass (Tucker et al., 1985b), photosynthetically active biomass (Tucker, 1979), green herbage ratio (Loris and Damiano, 2006), soil moisture (Vinnikov et al., 1999) and energy flux components (Kustas and Norman, 1996).

Another important use of remote sensing on grasslands is grazing activity monitoring. Kawamura et al. (2005) has proved that the normalized difference vegetation index (NDVI) obtained by the moderate resolution imaging spectroradiometer (MODIS) to estimate grazing spatial distribution and grazing intensities was an effective tool (Kawamura et al., 2005); Feng and Zhao (2011) further confirmed that livestock grazing could be monitored at broad scales by remote sensing (Feng and Zhao, 2011).

However, the grassland status and grazing information are all accompanied by errors and/or uncertainties. Remote sensing usually uses discrete snapshots representing the status of the earth surface; but in some cases, the standard discrete information could provide an unrealistic representation (Foody, 1999). Another uncertainty is the mismatch between the group samplings of training data (Illyés et al., 2007), which are used to derive the relation between remote sensing observation and grassland properties (Darvishzadeh et al., 2008). In addition, remote sensing derived datasets are frequently contaminated by clouds or sensor error (Congalton, 1991). Therefore, the reprocessing of remote sensing data is needed before using it, and this will further be discussed in Chapter 5.

2.6 Summary

In this chapter, the features of grassland grazing systems have been reviewed. The review revealed four aspects of the complexities of grassland grazing systems which caused the debate within the scientific modelling communities about the differences between equilibrium and non-equilibrium theories. Current models dealing with the complexities were reviewed in three categories: empirical, process-based and integrated models. The characteristics and drawbacks were discussed. Consideration of the complexity of grass and livestock dynamics, plant-herbivore interactions, different grazing strategies and institutional arrangements were introduced. Agent-based modelling is introduced in Section 2.4.4, and its attempted use in modelling the grassland grazing system under study is justified. In addition, the role of remote sensing in monitoring and assessing the grassland grazing system for such an agent-based model is highlighted.

Chapter 3 The Study Site

This chapter provides an overview of the study area and explains why the study site has been selected. The natural condition and livestock grazing system in Zeku will be elucidated to give a clear understanding of the system. It also describes the new trend of grazing management and the new grassland tenure system in Zeku, based on which the land market and group grazing play an important role in the grazing system of Zeku; in addition, three basic grazing strategies will be explained.

3.1 Selection of the study site

In this thesis, Zeku County was selected as the case study area for the Agent-based Modelling of Grassland Grazing (ABMGG) system; it is an ideal place to do research about the impact of livestock grazing on grasslands under different grazing strategies and institutional arrangements. Zeku is relatively far away from the Hoh Xil Natural Reserve region, where other large herbivores may have the dominant influence on grassland forage dynamics rather than livestock (Zheng et al., 2000). Although there exist other large herbivores and small mammalian herbivores in Zeku, and some even heavily threaten the soil quality and local ecosystem (Shengde and Haining, 1993), this thesis does not consider the effect of other herbivores due to the fact that the livestock grazing has a dominant role in the grassland forage consumption (Suonancairang, 2006; Zhou et al., 2007a).

The second main reason for selecting Zeku is the relatively exclusive land use in Zeku, that almost all the land in Zeku is covered by grass (Suonancairang, 2006). Zeku County is located in the southeast of Qinghai Province. The total land area is about 6600 km^2, of which grassland area accounts for 95%, including 6200 km^2 exploitative grassland (95% of the total grassland area) (Zhou et al., 2007a). Most importantly, there is no agricultural cropland in Zeku, making the abstract modelling simpler by ignoring the effect of agricultural activities (Zhou, 2015).

In addition, in early 2003, all the grasslands in Zeke were privatised via household contracts (Ma et al., 2003). That means individual users of grassland have the “final say” right in terms of grassland use, they can make decisions about which grazing strategies should be undertaken for livestock grazing, and whether they join the grazing group in the village; agent-based modelling fits extremely well with the individual and institutional decision-making of grassland grazing in Zeku.

3.2 Geographical overview of Zeku

The geographical location of Zeku is shown in Figure 3.1; it is one of the seventeen counties in the Qinghai Three River Head Source Conservation area (TRHR). The three rivers: Yellow River, Changjiang River and Lan-Changjiang River, are of great ecological significance to the Qinghai-Tibet Plateau with elevation varying from 3450 m to 6621 m; the area is known as “China's water tower” (Liu et al., 2008b). The main vegetation types are alpine meadow, alpine steppe, and marsh, with some temperate steppe and alpine desert (Dong et al., 2002). The TRHR is located in the world's highest altitude region with the most diversified biodiversity; it has China's largest wetlands at a high elevation area (Wang et al., 2010b). The

TRHR region suffers from global climate change as well as increasing human activities: overgrazing; poaching of plants and wildlife; gold mining, etc. (Huakun, 2005), which have endangered the ecosystem stability of the region (Jin et al., 2008; Zhou et al., 2009). The growing concern of national ecosystem security and sustainable economic growth prompted China to launch the Ecological Protection and Restoration Program (EPRP) in the TRHR region in 2005 (Wang et al., 2010b). The overall aim of EPRP is to conserve and rehabilitate the ecological functions of the region through ecological migration, grazing bans, wetland protection, and degraded grassland restoration (Yin and Yin, 2010). A total of 7,500 million yuan (at present, 1 pound = 8.7 yuan) was budgeted for the EPRP in “12th Five-year Plan” and this amount doubled in the “13th Five-Year Plan” (Wang et al., 2010b), which shows the great importance and determination associated with protecting this area.

The elevation of Zeku is above 3500 meters for the vast majority of the land, of which the highest elevation is 4971 meters, and the lowest is 2800 meters. The average annual temperature is -3 ℃ to 2.8 ℃, with no absolute frost-free period. The herbage growth period usually lasts about 150 days (Zhou et al., 2007a). Annual average rainfall ranges from 437.2 mm to 511.9 mm, and is mainly concentrated from May to September; usually, the amount of rainfall in the southeast is more than that of the northwest (Suonancairang, 2006). Annual solar radiation is about 580-650 KJ/cm^2, and annual sunshine hours is about 2500-2600h, with 4.1 m/s annual average wind speed, and there are 44 days windy days on average, of which the maximal windy days can reach 98 in extreme years (Du et al., 2010). Due to the special natural geographical environment, extreme weather such as serious prolonged snow, hail, drought, and sandstorms happens frequently, traditionally, "*a minor catastrophe happens within three years, a moderate catastrophe happens within five years, and a great catastrophe happens within 10 years*" (Zhou, 2015), prolonged snow and drought happens almost every year in some areas, which seriously affects the stability of grassland livestock husbandry in Zeku. This is an important factor that could affect the decision-making of herders. This thesis will show this effect by a prototype model in Chapter 4.

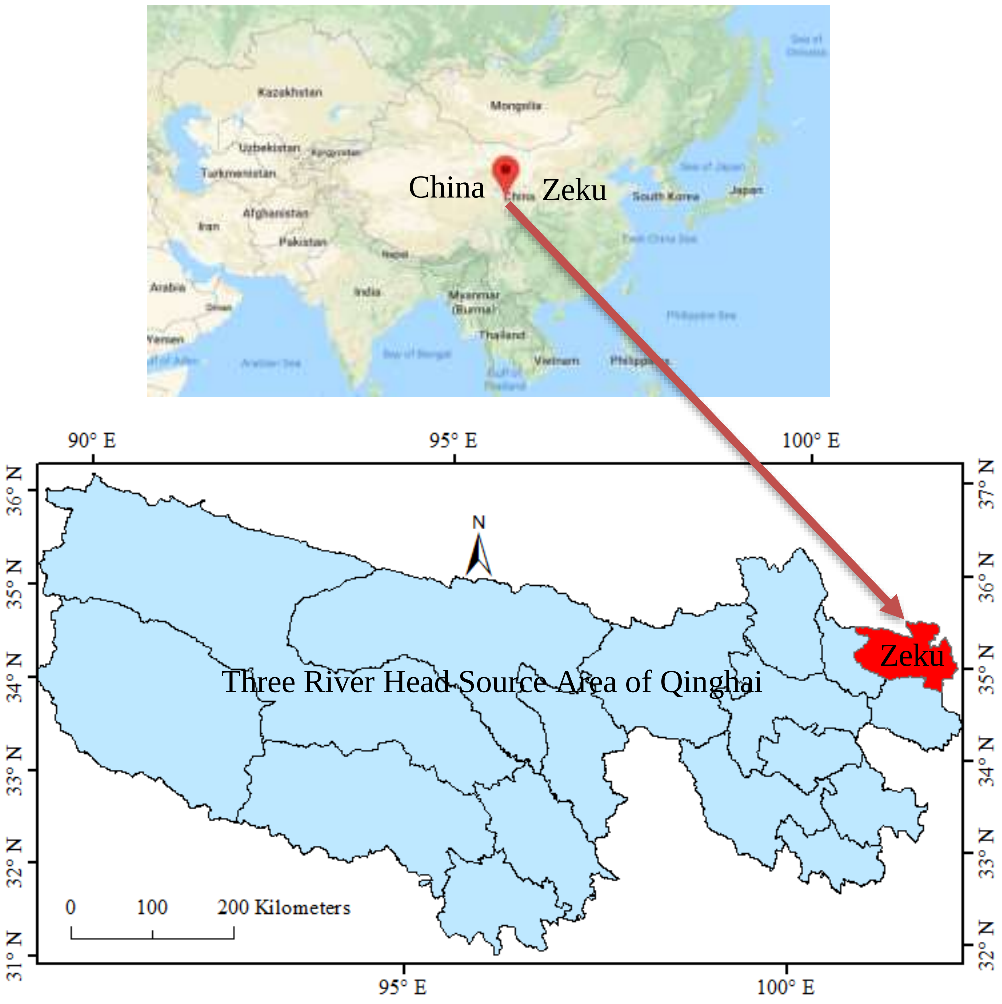


Figure 3.1: Geographic location of Zeku, China

3.3 Grassland resource overview

The data used for describing the land use/cover status is the Global Land 30 meters product (GlobalLand30), which is mainly derived from 30-meter multispectral images, including Landsat TM and ETM+ multispectral images and multispectral images from the Chinese Environmental Disaster Alleviation Satellite (HJ-1). Landsat TM and ETM+ images are free to the public and can be downloaded from USGS (http://landsat.usgs.gov/) at Level 1T; while the HJ-1 images are from the China Centre for Resource Satellite Data and Application (http://www.cresda.com). The overall accuracy is 83.51% (Jun et al., 2014; Wulder and Coops, 2014; Yu et al., 2014). The definition of different land use/cover type is shown in Table 3.1:

Table 3.1: Definition of land use/cover type in GlobalLand30, from GlobeLand30 product guide (http://www.globallandcover.com)

Code	Type	Content
10	Cultivated land	Lands used for agriculture, horticulture and gardens, including paddy fields, irrigated and dry farmland, vegetation and fruit gardens, etc.

20	Forest	Lands covered with trees, with vegetation cover over 30%, including deciduous and coniferous forest, and sparse woodland with cover 10-30%, etc.
30	Grassland	Lands covered by natural grass with cover over 10%, etc.
40	Shrubland	Lands covered with shrubs with cover over 30%, including deciduous and evergreen shrubs, and desert steppe with cover over 10%, etc.
50	Wetland	Lands covered with wetland plants and water bodies, including inland marsh, lake marsh, river floodplain wetland, forest/shrub wetland, peat bogs, mangrove and salt marsh, etc.
60	Water bodies	Water bodies in the land area, including river, lake, reservoir, fish pond, etc.
70	Tundra	Lands covered by lichen, moss, hardy perennial herb and shrubs in the polar regions, including shrub tundra, herbaceous tundra, wet tundra and barren tundra, etc.
80	Artificial Surfaces	Lands modified by human activities, including all kinds of habitation, industrial and mining area, transportation facilities, and interior urban green zones and water bodies, etc.
90	Bareland	Lands with vegetation cover lower than 10%, including desert, sandy fields, Gobi, bare rocks, saline and alkaline lands, etc.
100	Permanent snow and ice	Lands covered by permanent snow, glacier and icecap.

Grassland is the dominant land use/cover type in Zeku (Figure 3.2), and covers about 95% of the total land area; the second land use/cover type is wetland, which accounts for about 3% of the total land area; cultivated land only occupies about 1.5% of the total land area; forest, shrubland, water bound, artificial land, bare land and permanent snow and ice land are all less than 1% of the total land area. By comparing of the land use/cover change between 2000 and 2010, it has found that the land use/cover is quite stable in the area, with just some tiny changes during those 10 years. Grassland area in 2010 has decreased by about 0.6% compared with that of the year 2000. Wetland has increased by about 0.7% during this period while the region of permanent snow and ice has increased by about 0.1%; the other land use/cover changes are all less than 0.1%. Due to such tiny conversion of grassland from and to the other land use/cover types, the effect of structural change of grasslands in Zeku can be ignored in the ABMGG.

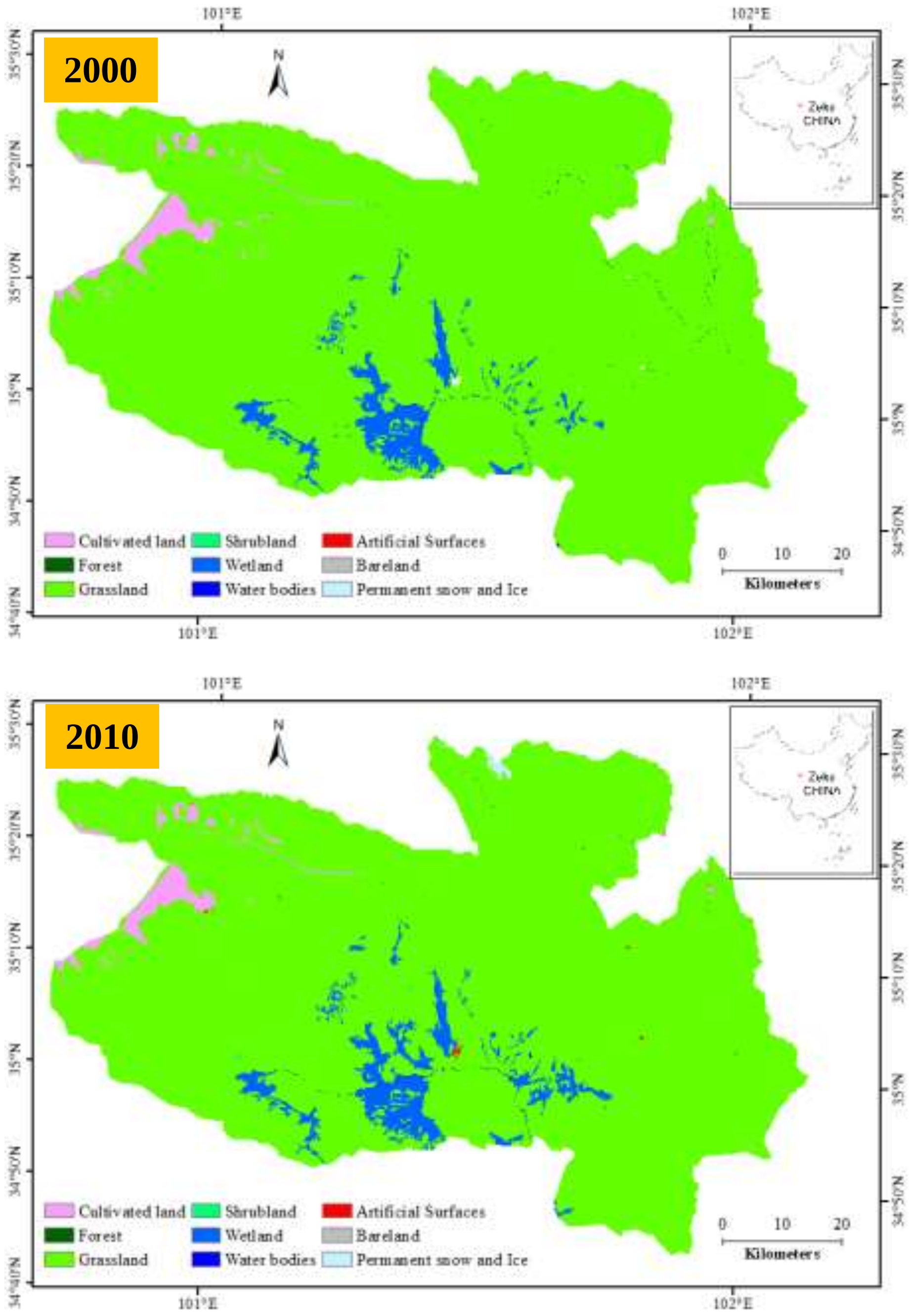


Figure 3.2: Land use/cover of Zeku, 2000 & 2010

The vegetation type of Zeku belongs to alpine meadow family, which dominated by *Kobresia* species (Zhou et al., 2006). Some palatable grass species can be found in this alpine meadow family such as *Kobresia pygmaea*, *Kobresia capillifolia*, *Kobresia schoenoides* (Figure 3.3). *Kobresia* is the local dominant species at Zeku, with a high degree of coverage ranging from 80% to 95%; in addition, it has a great resistance to grazing activities and is one of the most palatable grass species for livestock grazing in Tibet area (Zhao et al., 2011b). They are the most common and the most efficient species at photosynthesis in a cool and wet climate, and they have high protein content, high crude fat content, high nitrogen-free-extract and high calorific value, but relative low content of coarse fibre (Xue et al., 2005; Zhan-hong et al., 2007). Alpine meadow lands are therefore excellent grazing destinations within the Tibet area (Wen et al., 2004).

Kobresia pygmaea: photo from *http://cyperus.onlineflora.cn/taxonomy/term/5383?language=zh-hans*

Kobresia capillifolia: photo from *http://cyperus.onlineflora.cn/taxonomy/term/5345*

Kobresia tibetica: photo from *http://cyperus.onlineflora.cn/taxonomy/term/5373*

Stipa purpurea: photo from *http://www.plantphoto.cn/tu/28678*

Figure 3.3: Photos of typical grass species in Zeku, China

The spatial distribution of the grass species is diverse across 17 main species (Figure 3.4). Given the dry and cold weather, the vegetation species on the grassland in Zeku have evolved to the natural conditions, and different grasslands have developed their own structures and compositions to adapt to the local environment (Wang et al., 2008). By calculating the area of each main species in Zeku, results show the grassland is dominated by three main species, of which *Kobresia pygmaea* is the largest species covering 53.8% of the total area in Zeku; while the second widely distributed grass species is *Kobresia capillifolia*, accounts for 19.57% of the total land area; however, the percentage of another grass family, *Carex*, is just 10%; the rest of the species are all less than 5% of the total land area. These plants enrich the soil via their living (dominant portion) and dead root biomass (Kaiser et al., 2008) and have been used by pastoralists for about 8800 years (Miehe et al., 2009). Alpine meadows in Zeku have the highest levels of edible grass forage in the Qinghai-Tibet area, which supports a reasonable density of grazing livestock (Zhou, 2001). These different grass species dominated patches have different physical properties in terms of solar radiation attenuation, root-shoot ratio and digestibility, which will affect the accuracy of the grassland productivity estimation in Chapter 6 and increase the uncertainty in the validation process of grazing-led LAI defoliation in Chapter 5. Unfortunately, there is no species-specific biophysical properties dataset in Zeku, and constructing such a dataset would require a considerable scientific and financial investment.

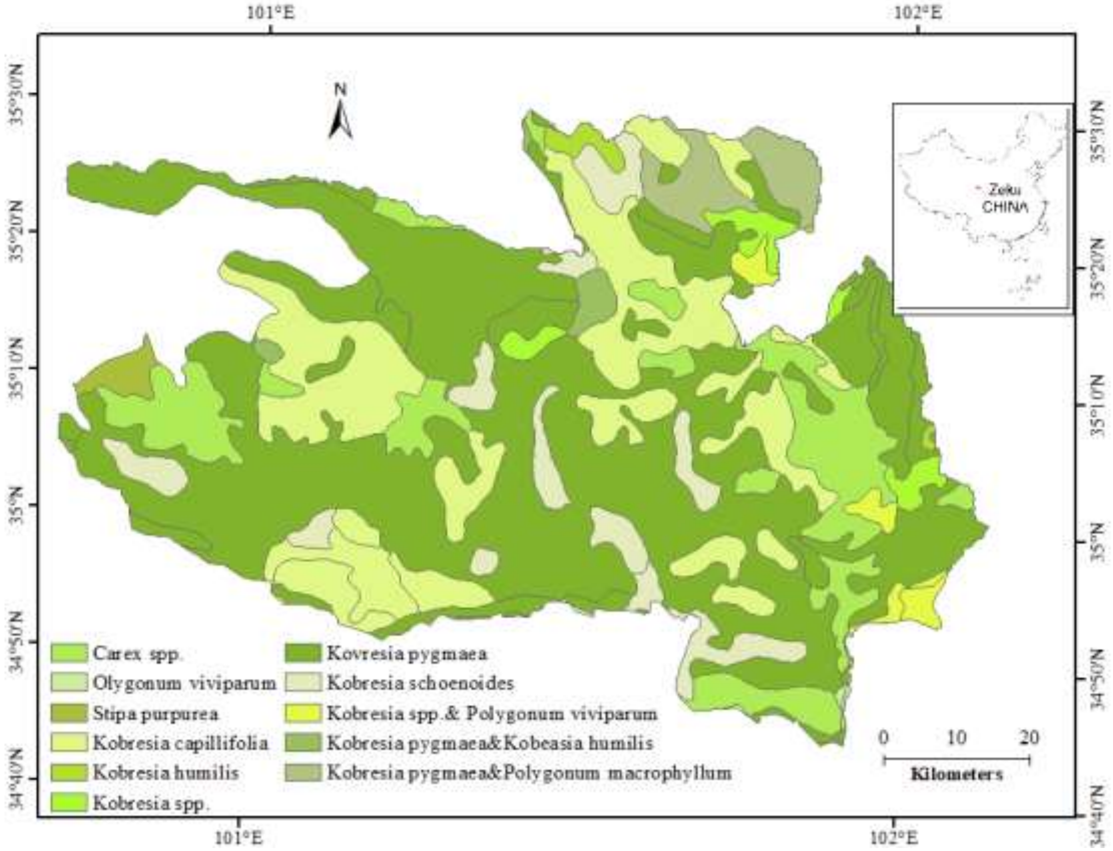


Figure 3.4: Grassland type of Zeku, data from Yang et al. (2007)

Precipitation and temperature are the two main causes of seasonal difference across grassland resources (Del Grosso et al., 2008; Shen et al., 2011). From the climate monitoring data from 1960 to 2012 (Figure 3.5), it can be seen that precipitation has a strong fluctuation in yearly variance from May to September, with the monthly average precipitation variance reaching as high as 100 mm, varying from 50 mm to 125 mm; those months have the highest monthly average precipitation during the year as well, with the lowest precipitation of 25 mm and highest precipitation of about 200 mm. The other months see a smaller mean and variance of monthly average precipitation.

In contrast, the monthly average of maximum temperatures or monthly average of minimum temperatures, do not have an increased variance within the months from May to September, but they do have the highest average temperature with regard to both maximum and minimum temperature. The maximum temperature reaches as high as 15 ℃ with a tiny fluctuation in July and August; and only in July and August, the average minimum temperature is above 0 ℃. Both the temperature and precipitation data from the observations for 52 years (1960~2012) shows an increase gradually from January to July when they reach their yearly maximum, and then decrease to their yearly minimum in December (Figure 3.5). In alpine meadow ecosystems on the Qinghai-Tibetan Plateau, the vegetation growing season is shortened mainly by low temperature, although abundant solar radiation and precipitation during the growing season are likely to favour plant growth during the short growing season (Kato et al., 2004).

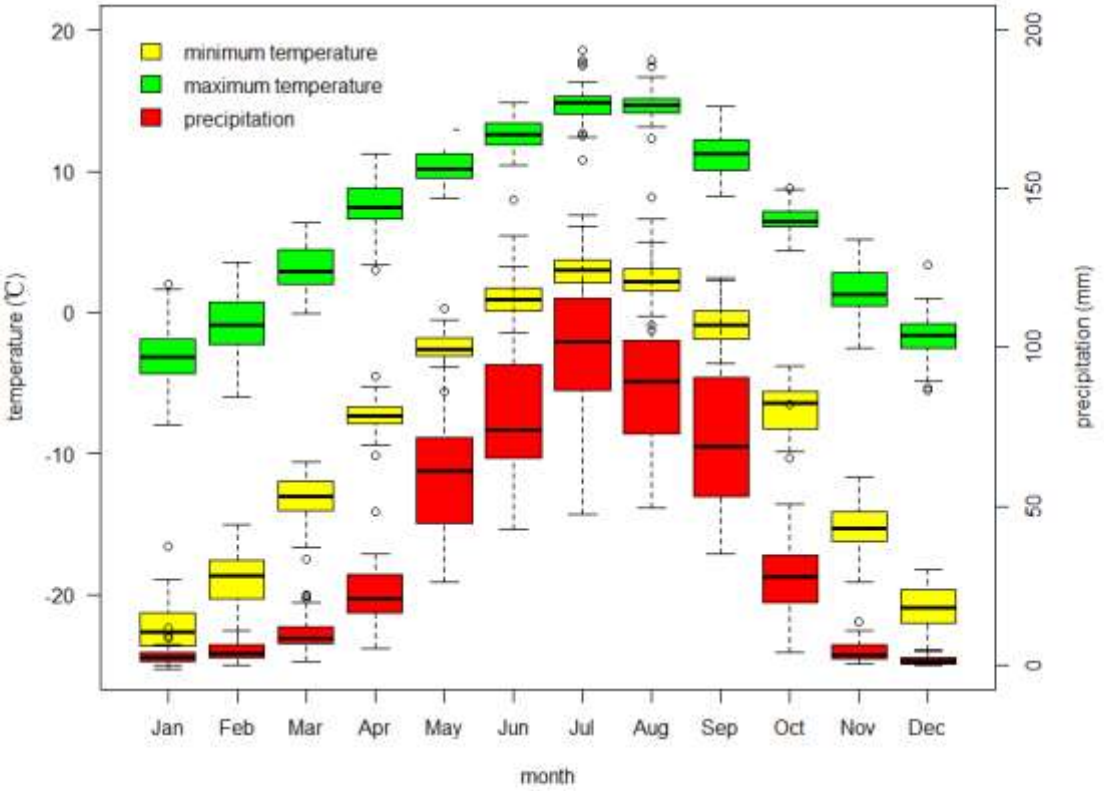


Figure 3.5: Average monthly rain and temperature of Zeku, 1960-2012 (data from the National Meteorological Information Center: http://data.cma.cn/data)

3.4 Livestock grazing profile

Zeku governs two towns (called “zhen” in China) and five rural townships (called “xiang” in China), along with one state-owned farm. These include in their zones some 64 administrative villages. At the end of the year 2011, the total population was 70664, and the livestock husbandry population was 59611. Livestock stock number was about 0.856 million (0.112 million yaks, 0.665 million sheep and 0.017 million horses). The net income per capita was about £300 (Zhou et al., 2007a).

The livestock husbandry of Zeku is basically the same as in the past situation, heavily relying on natural grass forage feeding (Zhou et al., 2007a). The economic development is not stable due to the seasonal difference of grass forage (see Chapter 5 and Chapter 6 for detail), livestock and precipitation. According to statistics in 2006, each sheep unit occupies 0.009 km^2 of available pasture area theoretically, and artificially improved grassland areas account for only 0.45% of available pasture area (Ma et al., 2003; Zhou, 2015). The livestock capacity is 1.13 million sheep units, but in actuality, the land has been carrying 1.56 million sheep units, of which 0.43 million sheep units are overloaded (Shao and Fan, 2012). At the same time, due to the large percentage of grassland in this area and the uneven distribution of water resources (Figure 3.5), serious water shortages have occurred in some areas, especially in the central and western regions where these are a big issue for stable development; water is often at more than 1 km's distance for both people and livestock.

Household livestock structure

Household data in this study is mainly from the field survey in 2012 provided by the Centre for Chinese Agricultural Policy (Huang et al., 2016). This field survey was supported by the National Key Programme for Developing Basic Science (2012CB95570001) project "Impact of Climate Change on Key Parameters of Socio-economic System in Typical Regions", which was led by the Centre for Chinese Agricultural Policy, Chinese Academy of Science. The current author was part of the survey team. The investigation method we used was stratified random sampling. Three counties were chosen in the Golog Tibetan Autonomous Prefecture, Huangnan Tibetan Autonomous Prefecture and Hainan Tibetan Autonomous Prefecture respectively, according to three criteria:

Criteria 1, average grassland area: Zeku; Tongde; and Maqin are the smallest, medium and largest average grassland size per capita areas in all the 10 counties under those three autonomous prefecture administrations;

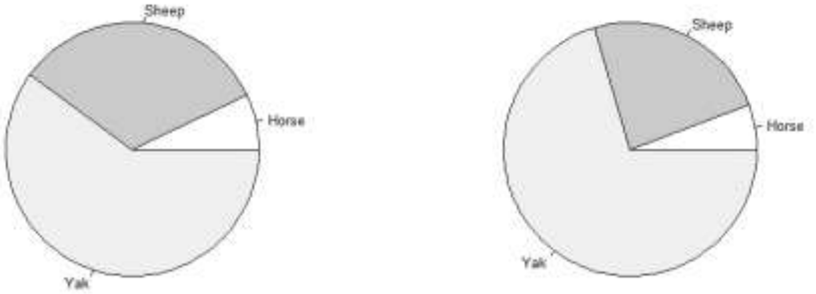
Criteria 2, population: the total population of Tongde and Maqin are the biggest in their own autonomous prefecture regions. Zeku and the Xingmei have almost the same population. Hence, either one of them could be representative;

Criteria 3, total GDP: Zeku and Maqin have the biggest GDP in their own autonomous prefecture regions. Although the population of Tongde is a little smaller than that of Zeku, the difference is not significant;

According to the three criteria above, the weighted average score of each county was calculated and, considering the climate, altitude and the accessibility for vehicles, Tongde, Zeku and Maqin were chosen as the field survey counties.

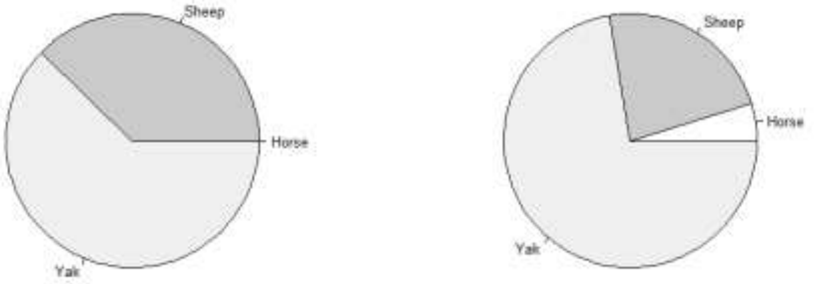
Sample size: the sampling size of each county was determined by its total population size, the ratio of the total population of the three countries is 1.6:1.2:1, hence the sampling size was 2:1:1. Then, we randomly chose the towns and villages within each county. Finally, the sampling size of Zeku was 52, Tongde was 54, and Maqin was 101.

From all 52 field survey records, the main big livestock were yak, sheep and horse (Figure 3.6, panel 1), and the horse was used only for transportation purposes; it is an important vehicle for herdsman riding for grazing. This is why there are basically no horses sold during the year (Figure 3.6, panel 3). Although other wild large herbivores exist in Zeku, due to the small population of them, this thesis only considers yak, horse, goat and sheep as grassland foragers.



1 livestock structure

2 livestock on hand at the beginning of year



3 livestock on sale within the year

4 livestock inventories at the end of year

Figure 3.6: Livestock structure of Zeku, China, 2011.

A sample size of 52 households suggests average access to 100-300 mu (0.067 km^2-0.200 km^2) of winter pasture, while that of summer pasture is 100-500 mu (0.067 km^2-0.333 km^2). This means that in the modelling process, where our cell size is 0.21 km^2 (the size of remote sensing data used in this thesis), a large proportion of herdsmen will share the same land patch. There are two ways of handling this problem: one is dividing the land parcel to the herdsman agents according to their proportion, and another is merging the sharing herdsman agents to one. The second way is adopted later in this thesis.

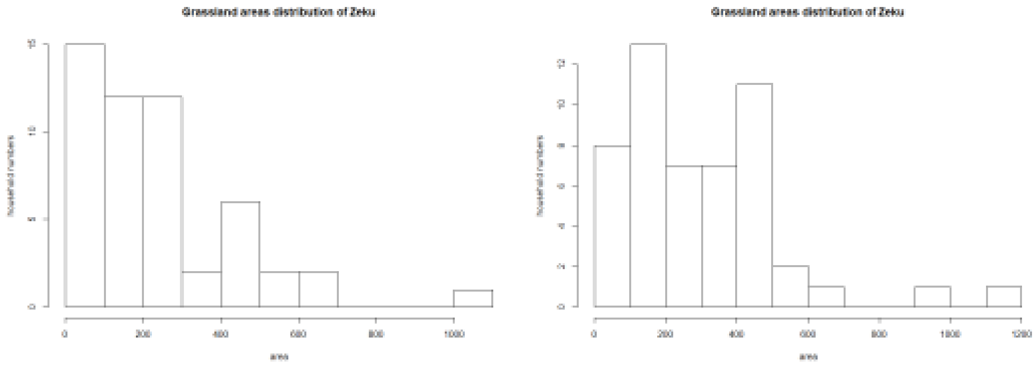


Figure 3.7: Household winter natural grassland area (left) and household summer natural grassland area and summer artificial grassland (right) distribution in Zeku, 2011

3.5 Grassland tenure system in Zeku

In order to explore a sustainable way of grassland grazing and to avoid falling into the dilemmas of the “Tragedy of the Commons” (Hardin, 1968), scientists and policy-makers have rolled across the privatisation of the grassland in some regions, and this has become the policy arrangement interfacing with grassland degradation in Zeku. However, grassland degradation is a controversial question in academic communities. The perspective that climate change and overgrazing are the key drivers of grassland degradation is contentious (Liu and Diamond, 2005; Harris, 2010). The land tenure system adopted in Zeku has not fundamentally change the “common” use property of the grassland, where under the “Tragedy of the Commons” situation the resource users cannot be excluded and the one uses of the limited resource means reduced availability of the resource to the others, everyone’s maximum use of the resource will lead to the exhausted resource, and thus “Tragedy of the Commons” may be an important factor contributed to grassland degradation (Wu, 2011; Aryal et al., 2013; Cao et al., 2013; Li et al., 2013). For the Agent-based Modelling of Grassland Grazing (ABMGG) in this thesis, this new land tenure system implies that herder agents have the right to make decisions about how to use their grassland (except change the land use type, e.g. change the patch from grassland to cultivated land which is not allowed by the government). They can lease the land from the other herders or invest their lands to local cooperative institutions.

Grassland conservation projects: a new trend emerges

To counteract ecosystem deterioration in the TRHR, the Chinese government implemented the “Ecological Protection and Restoration” project in 2005, allocating 7.5 billion Chinese yuan (about £0.7 billion) to carry out ecological restoration and degradation control in the TRHR (Wang et al., 2010a), and the second round funding is 16 billion Chinese yuan (about £1.7 billion) (Commission, 2014; Shao et al., 2016). This is the largest project for nature reserve protection and reconstruction in China, and includes ecological emigration, ecological compensation and returning grazing to grassland etc. It aims to benefit the local environment, but how it affects the interest of stakeholders such as herders and local institutions, whose decision-making behaviour can directly change the status of the grass (Huang et al., 2016), is a complicated question. For example, herders would give up grazing if subsidies are reasonable, and tend to reduce the grazing livestock amounts if penalties are high. Nevertheless, in general, their aims are to maximise herd sizes, and more livestock means more foraging on the grassland, and if the grassland cannot supply that number of livestock, the resilience of the grassland ecosystem can be endangered (Shao et al., 2016).

A new trend in the TRHR is for the local government to encourage the herders to take part in ecological animal husbandry economic cooperatives (grazing groups), which are based on the current condition of the local environment at a village level (Zheng, 2012). They focus on improving husbandry productivity for more economic gain and protecting the local ecological environment at the same time (Cao et al., 2011). What is more, the development of the local grazing groups can effectively liberate the labour force and curb overgrazing by more advanced management (Li, 2011; Conte and Tilt, 2014). Models of grassland forage dynamics under their various grazing strategies and institutional arrangements are fundamental to understanding the grassland ecosystem status, that is, whether grassland is overgrazed or overcompensated. What is more, identification of grazing “hot spots”, where heavy grazing happens, is crucial to protecting the grassland with precautionary measures.

From state control to privatization

For a long time, there has been no clear and comprehensive grassland use right system in the TRHR. Up to the early 1950s, the people's communes were some sort of institutional structure having land use rights. However, communes were dismantled by the government and the land resources became collectively owned (Hongbo, 2005). The grassland was disregarded by the reformist policy-makers and became seriously degraded consequently. In 1985, the proclamation of the Grassland Law had expressed an official attempt to devolve grassland use rights and liability from the state and collectives to the individual, through grassland was still owned by either the state or the collective. Households just have the land use right but do not own the land. They are allowed to lease the grassland use right for 30 years at a time by contract (Yundannima, 2012). The boundaries between collectives would be assessed or reassessed every 30 years, and the pastures appraised in terms of stocking rates. Finally, a system of incentives and penalties was implemented to ensure that the producers abided by the carrying capacities of the grassland assigned to them. Thus, the efforts of government departments and research institutes were to assess the grassland carrying capacities quickly and accurately and to enforce them (Yan et al., 2005).

The grassland tenure system embedded in the Grassland Law was based on the assumption of the tragedy of the commons (Hardin, 2011), and held that subsidies and penalties could provide an adequate incentive for households to manage their livestock with concern for the grassland ecosystem and towards sustainable grassland development (Harris, 2010). After the Grassland Law, there were reiterated Land Administration Laws in 1986, 1998, and 2004, the amended Grassland Law of 2002, the Rural Land Contract Law of 2002, and the Property Law of 2007 that reinforced this concept (Yundannima, 2012). "*Traditionally, what was termed 'grazing along with water and grass' typified local animal husbandry production systems. Pastures for each of the four seasons were distinct, with frequent movement among them. However, with the implementation of grazing tenure laws, the scope and space of available grassland were reduced. In addition, with barrier fences separating each household's allotment, herders lost the ability to transit seasonally*" (Cao et al., 2011). The characteristics of the current grassland tenure system are:

- households have the "final say" of how to use their contracted land, but the rights to land are still collectively held (Manderscheid, 2001);
- a rotational grazing strategy is widely suggested and adopted;
- cooperative grazing groups have been strongly supported by the local government both institutionally and financially in recent years.

However, the ambiguity of state-owned and collective-owned definitions in those laws and the inconsistency of basic unit grassland use rights allocation in terms of whether pasture should be used individually or collectively creates unsolved problems for grassland management, and is one of the main reasons for many grassland inequalities and even conflicts (Ho, 2005; Cao et al., 2013; Ma et al., 2015). Some researchers even doubt this new grassland tenure system and have proved that traditional Tibetan nomadic grazing systems were often well managed and had elaborate regulations of seasonal transhumance (Goldstein et al., 2003; Bauer, 2005; Bauer and Nyima, 2011). In addition, they recommend that while institutional arrangements should not stop, if possible they should aim to restore the traditional nomadic style grazing (Banks et al., 2003; Swift, 2012).

3.6 Grazing strategies in Zeku

There are three basic grazing strategies in Zeku: rotational; continuous; and un-grazed (reserved land for winter fodder or other purposes). Due to the fact that all the land patches are contracted to individual households, and there is no precise data about individual strategies that have been taken, precise analysis of the impact of different grazing strategies and institutional arrangements on the grassland status directly is currently impossible and needs prioritization. However, those grazing strategies and institutional arrangements exist in Zeku and play an important role in the grassland grazing system. A thorough understanding of management is necessary to reveal the hierarchal structure of plant-herbivore interactions.

The rotational grazing strategy is adopted for all the group grazing land (from both our survey in 2016 and literature later cited). "*Under rotational grazing, only one portion of pasture is grazed at a time while the remainder of the pasture "rests". Pastures are subdivided into smaller areas (referred to as paddocks) and livestock are moved from one paddock to another. Resting grazed paddocks allows forage plants to renew energy reserves, rebuild vigour, deepen their root system, and give long-term maximum production*" (Undersander et al., 2002). For example, the land patches in one grazing group may be divided into three, the livestock, therefore, can forage on the first sub-group in May and then move to the second sub-group in June and finally the third sub-group in July. The number of sub-groups and grazing duration in each sub-group are decided by individual herder's or groups' management skills experience. The rotational grazing strategy on large heterogeneous grassland has proved to provide adequate lengths of time between successive defoliations, and deterioration of heavily grazed grassland thus could be reduced; it is important to the sustainable management of grassland and grassland restoration (Teague and Dowhower, 2003). In addition, rotational grazing could increase the soil organic carbon and nitrogen, ground-litter accumulation and reduce potential soil contamination, while reducing the Nitrate and extractable P concentrations due to the increased grass growth compared with continuous grazing (Pavlů et al., 2003; Sanjari et al., 2008). A relatively bigger number of subdivisions could lead to a longer rest period for grassland, and this is a recommended grazing management strategy for the recovery of the soil after each grazing in both physical and chemical dimensions (Sanjari et al., 2008).

With continuous grazing, on the contrary, livestock grazes on the land continuously throughout the season (Brummer and Moore, 2000), and there is no "rest" time for grass growth. Continuous grazing would contribute to the loss of ground cover, soil organic carbon and nitrogen and other soil biological properties (Hiernaux et al., 1999). Both above-ground productivity and below-ground productivity are higher for short duration pastures than for continuous grazing pasture (Michael et al., 1991). Although the consumption of individual livestock is relatively similar under both extensive and intensive management, the livestock production per area unit is significantly decreased under extensive continuous grazing (Pavlů et al., 2006). It could change the composition and structure of grassland vegetation (Pavlů et al., 2003). Lower quality of grass forage has been confirmed on continuous grazing lands (Sharrow, 1983). It has been proved that by excluding livestock grazing from continuous grazing lands, the status of the grassland can improve recovery with litter accumulation, and the development of annual and perennial grasses (Yong-Zhong et al., 2005). This concept has also been widely used in Zeku's grasslands with fencing assisting degraded grassland restoration (Qing-shan, 2009).

3.7 Institutional arrangements in Zeku

There are two institutional arrangements in Zeku: group grazing and the land market. Group grazing is a higher level policy that affects the herders' grazing strategies. Group grazing is an important institutional arrangement in Zeku. It has been proved to be beneficial to the optimisation of resource utilization and improvement of herders' livelihoods (Tian et al., 2009) due to economies of scale : grazing leads to more professional management, grazing techniques, and stronger response to natural hazards; and it has been successful in implemented optimization of livestock structure, production and the livelihood of herders (Han-qing, 2011). In addition, a well-managed group grazing strategy in this area is a potential mechanism for developing sustainable livestock husbandry and social stability (Sheng, 2012): the rotational grazing strategy was implemented by all the grazing groups, and the group rotational grazing works by groups pooling land which is then subdivided to provide rotational pastures. Then main characteristics can be summarised as (Huang and Li, 2017):

- herders can become a shareholder of the grazing group by investing their grasslands and/or livestock;
- livestock are fed by group according to their species, sex, raising purpose and etc.;
- grasslands are divided into sub-groups which have a clear grazing order, grazing frequency and grazing duration;
- herders work in a specialized way according to their experience, professional knowledge and qualification;
- the profit of herders is allocated according to the amount of their investment (grasslands and/or livestock).

The grassland market is based on the rationale that market-based land redistribution can increase the forage availability for grazing and thus achieve better grassland resources use efficiency, and support more livestock production and improve herders' income by making use of capital-led redistribution and re-aggregation of land and economies of scale in the grazing system (Zhang et al., 2007). The grassland market means individual households have the legal right to transfer the use-rights of their grasslands to a third party for animal husbandry by renting or sub-contracting (Ma, 2003). One herder rents or leases land from another herder at the beginning of the year, and then they can manage some of their livestock on that rented land. This, in essence, is a kind of smaller scale group grazing, but in line with market demand. The land market makes up for the loss of livestock mobility and the spatial connectivity needed to deal with the heterogeneity of grassland resources (Yeh, 2011). The relationship of these two institutional arrangements and three grazing strategies is shown in Figure 3.8. Almost no herders will lease land for the purpose of just leaving it there for conservation purposes. Therefore the land market arrangement has no effect on the un-grazed strategy. The sedentary grazing is a fixed site grazing strategy, and the herders would not move to the other places.

But in this thesis, sedentary grazing means the livestock will continue to graze on one pixel or land patch. So the sedentary here indicates continuous grazing.

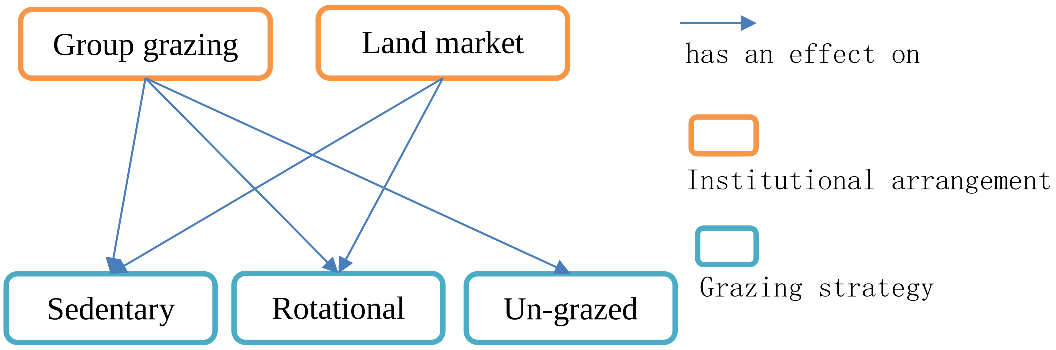


Figure 3.8: Relationship of institutional arrangements and grazing strategies

Chapter 4 Developing a conceptual model of ABMGG

The Agent-based Modelling of Grassland Grazing (ABMGG) aims to provide a dynamic grassland simulator under different grazing strategies or institutional arrangements. Chapter 2 outlined the theories (equilibrium and non-equilibrium) and paradigms for modelling the grassland grazing system. Chapter 3 has a detailed profile of the grazing system in Zeku. In this chapter, a conceptual model will be discussed by incorporating current grassland grazing modelling theories with the local grassland management in Zeku. The conceptual model is critical to verify the key processes of the model and to test the modelling theories. This chapter will discuss the conceptual models of grassland grazing using Netlogo5.1 (Wilensky and Rand, 2015) focusing on forage-livestock dynamics, individual-level interactions and grassland management of the grazing system in Zeku. This chapter will compare the different grazing strategies and institutional arrangements, under which the socio-economic and ecological performance of grassland grazing system will be different.

4.1 A conceptual and empirical explanation of ABMGG

A conceptual model is a simplified abstraction of a real system (Heath et al., 2009). It relies upon the knowledge of known theories of the real system and is based on the assumptions of the parameters describing the abstracted system (Simon, 2012). "*The conceptual model forms the foundation of an ABM; an invalid conceptual model indicates the model may not be an appropriate representation of reality. For a model to be completely valid, it must be validated both conceptually and operationally*" (Heath et al., 2009). A high-quality conceptual design for an agent-based model is critical to the early detection and correction of system development errors (Wand and Weber, 2002; Onggo and Karpat, 2011), and, where there is participatory development, to represent the actions of stakeholders with an adequate detail in the system (Pastor and Molina, 2007; Parker and Filatova, 2008). This conceptual design can then be transferred to a software product which is functionally equivalent to the conceptual specification, and has the ability to model changes of the entity behaviours and the dynamic and the temporal relationships among them (Chen et al., 1999; Pastor and Molina, 2007). The conceptual model of ABMGG is thus important and essential for the successful modelling of the grassland grazing system at an early stage.

The key for the conceptual ABMGG model is how to describe the behaviours of herders and the impact of different institutional arrangements on the grassland dynamics (e.g. livestock population and grassland forage availability), and the performance of grassland grazing (e.g. net income of herders and number of patches degraded). The conceptual model of ABMGG must be able to integrate with equilibrium and/or non-equilibrium theory; and most importantly, the natural growth of grass and the effect of different grazing strategies and institutional arrangements on the grassland system must be appropriately considered. In addition, the complexity of the interactions between grass and livestock should be included in the model. The conceptual model should also consider the availability of the data needed for the parameters, which is the main limitation on the later transition from the conceptual to the real model development. The outputs should include the grassland status and forage production after grazing as well as the economic status of herders. This chapter will explain the conceptual framework of ABMGG and the socio-ecological theory behind them. As said before, ABMs should have an *acceptable* representation of herders, livestock, grass growth, grazing strategies and institutional arrangements. Importantly, defining what makes a model ‘acceptable’ is extremely difficult, so this chapter will also discuss the means by which acceptability is determined.

Prolonged snow is an event that is considered to happen randomly in Zeku, affecting the grass growth in the early spring (Zhang, 2010). Un-predictable extreme climatic events like prolonged snow will break the equilibrium status of the forage and livestock population, and result in a new equilibrium status for the system. The next step for the conceptual model in this thesis is to convert these theories into an executable computer program.

An abstract landscape with equally divided pasture patches is designed in the conceptual model (because the data on grassland patches is all derived from remote sensing datasets with a spatial resolution of $463 \times 463m^2$, it is easier to have equally divided pasture patches in the conceptual model). In the conceptual model, each land patch has a randomly assigned initial amount of available forage and a random growth rate for each month, representing the heterogeneity of the natural grassland productivity. Pastures and livestock are owned privately by herder agents, all of the livestock are measured by sheep units, currently, and a matured yak can be transferred in to 4.5 sheep units (Su et al., 2003). For each time step of the model, the available grass forage is a summation of newly increased grass forage and the remaining forage in the end of the last step. The livestock on the patches will eat a certain amount of grass forage, thus the forage after grazing is the available forage minus the grazed material.

In assessing the results, it is assumed that if the aboveground grassland productivity left after the first year grazing is less than 50% of its initial assigned above-ground grassland productivity, the patch will be counted as a degraded grassland patch. The model will check the overgrazing status for each step during the simulation runs. This measure is chosen as a temporary estimate; the definition of three different biomass reduction metric related to grassland degradation from the Chinese National Criteria are shown in Table 4.1 (Su et al., 2003). A degraded grassland patch has lower grass productivity after grazing, and this decreased grass productivity is used to represent the damage to plants by overgrazing. This simplified metric (Table 4.1) of grassland degradation provides an alternative perspective on the grassland status to productivity.

Table 4.1: National criteria of parameters for degradation in terms of aboveground grassland productivity

items		Degree of degradation			
		Ungraded	Light Degraded	Medium Degraded	Severely Degraded
Aboveground grassland productivity	Total decrease ratio (%)	0-10	11-20	21-50	>50
	Edible decrease ratio (%)	0-10	11-20	21-50	>50
	Inedible and toxic increase ratio (%)	0-10	11-20	21-50	>50

The grass growth rate for each patch in the model is a random value between 0 and 5 from October to May, and a random value between 0 and 60 from June to September. This is used to represent the seasonal variation of grassland forage. These simply randomized growth rates are used to represent the complexity of grass growth under grazing. The consecutive comparison experiment of grass growth under different grazing intensities in the Three River Head Source area (TRHR) is a typical example that shows this complexity. The Absolute Growth Rate (AGR) and Relative Growth Rate (RGR) are used in the experiments to describe the net biomass accumulation per unit time (Zhao et al., 2011a):

$$\mathbf{AGR} = \frac{W_1 - W_1}{t_2 - t_1} \text{ And } \mathbf{RGR} = \frac{\ln W_2 - \ln W_1}{t_2 - t_1} \qquad \textbf{Eq. 4-1}$$

, where W_1 and W_2 are the biomass at time t_1 and t_2 respectively.

Table 4.2 (Zhao et al., 2011a) shows the AGR of total above-ground biomass under different grazing intensities during the growing season (June, July, August & September), from which we can see the diverse impact of different grazing intensities on the first year and the second year's growth of grass. For summer pastures, the above-ground biomass reached a maximum value in July under slight grazing and with a control group (grazing free) for both the first year and the second year; while under medium and heavy grazing, the maximum above-ground biomass appeared at August for the first year. However, for winter pastures, no matter under what kinds of grazing intensities, the maximum above-ground biomass were all in August for the first year and in July for the second year. Although there are some changes in AGR under different grazing intensities in the grassland grazing system in Zeku, the results here provide an example of the complexity of different grazing intensity patches within the grazing system and have demonstrated the importance of incorporating grazing in the grass growth model (this will be further discussed in Chapter 5).

Table 4.2: AGR of total aboveground biomass under different grazing intensities, from Zhao et al. (2011a), page 205 (unit: gm^{-2}d^{-1})

Pasture type	month	Control group		Slight grazing		Medium grazing		Heavy grazing	
		1st year	2ed year	1st year	2ed year	1st year	2ed year	1st year	2ed year
Summer	June	0.98	1.11	0.83	0.94	0.69	0.71	0.48	0.62
	July	3.58	6.90	3.01	4.31	1.97	3.58	1.48	3.58
	August	1.88	4.08	2.05	2.53	2.23	3.36	2.73	1.39
	September	-0.79	-0.52	-0.75	-0.31	-0.52	-0.35	-0.97	-0.71
Winter	June	0.82	1.85	0.73	1.60	0.67	1.47	0.70	1.02
	July	0.89	3.97	0.76	4.51	0.71	4.96	0.68	2.61
	August	2.2	1.8	2.75	1.57	2.32	1.80	2.31	1.21
	September	-0.11	-0.93	-0.12	-4.08	-0.23	-0.44	-0.17	-0.68

Table 4.3 shows the percentage of different grass species under different grazing intensities. With an increase in grazing intensities, the percentage of edible species (*Cyperaceae* and *Poaceae*) were decreased substantially in both summer and winter pastures, while the percentage of poisonous species were increased (Zhao et al., 2011a). Assuming the productivity doesn't change overall, the interannual percentage of palatable grass species have decreased on heavy and medium grazed lands, and they have increased in the control group and slightly grazed lands. This can be explained by the increased percentage of palatable grass species, which has a negative effect on poisonous species. In summer pasture lands of medium and heavy grazed areas, although the stimulation of grass regrowth caused by grazing-led defoliation can compensate for the loss of grass biomass, the suppression effect of those palatable species on unpalatable or poisonous species will be weaker, which in return will improve the productivity of unpalatable or poisonous species (1998). In addition, livestock grazing would increase the amount of sunlight transmission to the lower layers of the grass (Yonghong and Shiping, 1999). This is why Table 4.3 shows increased productivity of *Cyperaceae* species compared with that of the control group. The example here illustrates the complexity of livestock-herbivore interactions, which will be included in the ABMGG. But, in order to make the conceptual model as simple as possible at this stage, the model set the growth rate of available forage for grazing at a random value for different seasons to account for all the considerable variance associated with all the above effect.

Table 4.3: Percentage of different grass species under different grazing intensities (from Zhao Zhao et al. (2011a), page 204 (unit: %)

	Grass type	Heavy grazing		Medium grazing		Slight grazing		Control group	
		1st year	2ed year	1st year	2ed year	1st year	2ed year	1st year	2ed year
summer	Cyperaceae	28.14	25.45	35.28	35.20	40.55	37.47	27.33	25.96
	Poaceae	14.07	9.16	25.81	25.82	29.44	33.44	40.14	47.69
	Edible species	37.07	41.38	24.32	24.73	21.69	20.07	16.67	11.97
	poisonous species	20.79	24.01	14.59	15.45	11.33	9.02	9.86	5.38
	% palatable species	42.21	34.60	61.09	62.02	66.98	70.91	67.48	73.66
	interannual change of % palatable grass	-7.61		-0.07		3.93		5.88	
winter	Cyperaceae	31.03	25.91	35.98	28.38	38.32	29.88	41.09	32.80
	Poaceae	29.49	29.78	25.64	33.37	27.22	37.90	27.50	1.25
	Edible species	25.66	28.46	24.96	25.47	22.40	20.94	20.42	16.87
	poisonous species	13.81	15.86	13.42	13.78	12.06	11.28	11.0	9.08
	% palatable species	60.52	55.68	61.62	61.75	65.55	67.78	68.59	74.05

	interannual change of % palatable grass	-4.84	0.13	2.23	5.46

Prolonged snow is an external driver that causes a rapid decrease in grassland productivity and the loss of livestock. For the moment, prolonged snow hits pastures in the agent world randomly, and each parcel has the same probability to be hit. The grass productivity of the parcel hit by prolonged snow and its neighbourhood parcels (i.e., within a radius) are influenced by the snow. The impact of snow on grass productivity was simplified by setting a certain degree of loss of assets and a sharp decrease in grassland productivity. When prolonged snow happens, the herder agents tend to overuse their pastures if they cannot find available parcels for migrations and/or do not have enough money to buy fodder. In the real world, the restoration of livestock populations after climate hazards is from both natural reproduction and purchasing livestock from markets. In the real world, the price of buying lambs fluctuates when hazards happen (Wang et al., 2013), but this model will assume constant costs.

Herder agents are assigned a random number of sheep and assets initially. Each herder occupies one land patch, and all land patches have their own herder agent. Herder agents raise livestock on their pastures; the model does not consider the breeding process of livestock and nor does it consider herd deaths, save under snow-based disasters. At the end of each year, herder agents have the possibility of selling their sheep to gain benefits (assets), and at the beginning of each year, herder agents will buy a certain number of lambs with a certain probability. We assume that the number of sheep owned by each agent is stable during the other times of the year. The influence of market incentives on the livestock management behaviours of herders is not included in the model to keep the model simple.

The framework of AMBGG is shown in Figure 4.1. There are two main sub-models. The human system is designed to simulate the decision making of herders including selling, buying of livestock and joining groups. The natural system accounts for the natural growth of grass. The interactions of the model include livestock grazing and grass response to grazing, which will be further affected by macro-level grazing strategies and institutional arrangements. There are also two types of outputs: socio-economic results and the ecological results of the grazing system. At the base, the land tenure system is the core for forming the grazing strategies and institutional arrangements in Zeku.

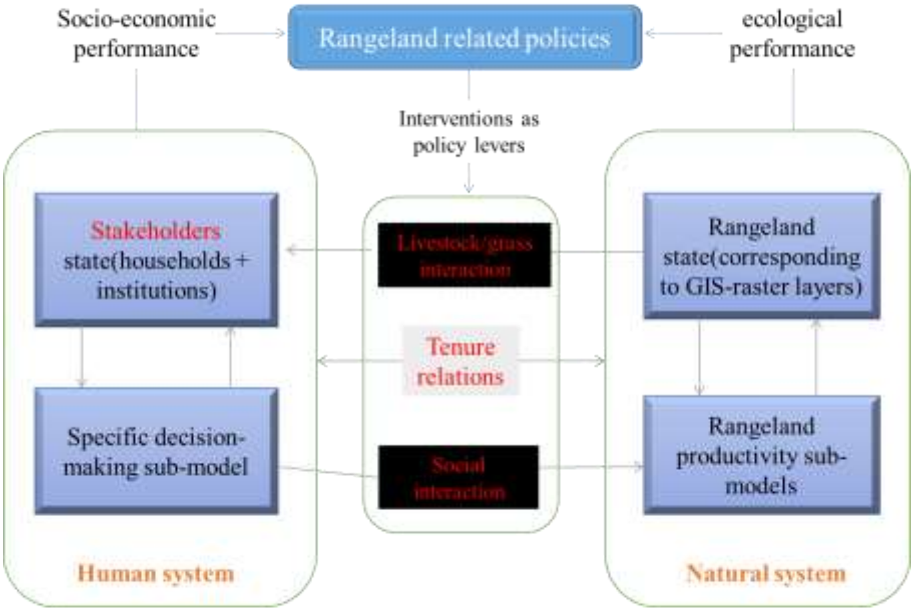


Figure 4.1 : The framework of ABMGG

4.2 Agent-based modelling of grassland grazing

As has been mentioned in Chapter 3, rotational grazing is a common grazing strategy for the herders in Zeku due to the unique climate conditions with long-lasting winters and short summers. Zeku is located in the subnival belt in China; summer is the most productive season of the whole year, and the short summer grazing period contributes a lot to winter grassland grazing pressure (Sanzhi, 2001). According to our field survey, the winter grazing period is from October to May (the following year), this is mainly on stored fodder; while the summer grazing period just lasts from June to September. In addition, different behaviours of the herders will lead to different ecological and economic performance for the grassland grazing (e.g. net income of herder and grassland quality). The prototype model in this chapter will be used to explore three different management: sedentary grazing (un-grazed), land market and group grazing (see Chapter 3 for details). Institutional management strategies have their own socio-economic mechanism that affects the performance of grassland grazing.

Grassland productivity

Grazing-led loss of grass productivity could affect the overall grassland productivity (McCarthy et al., 2016b). It has been proved that grazing could affect the grass biomass accumulation, nutritive value and utilization (Stobbs, 1975; Pontes et al., 2007; Ganche et al., 2013; Tuñon, 2013). Researchers have further confirmed it is the main reason for the grassland productivity change of grazing systems (Mott, 1960; Baudracco et al., 2010; McGregor et al., 2014; Pulido et al., 2016) except climate change. Although a moderate grazing severity could lead to the improvement of grassland utilization (Baudracco et al., 2010), the impact of grazing severity on grassland productivity has been extensively studied but inconsistently reported (Rawnsley et al., 2014), which were similar to the results in Table 4.2 and Table 4.3, and the evaluation of such effects are often complicated due to the various grazing decisions and natural conditions (Clark et al., 2016). One of the most simple and effective indicators of grassland change under grazing is the quantity of grass forage, and this has been widely used in grassland grazing studies (McNaughton, 1979a; Lezama et al., 2014; Chang et al., 2015; Sabatier et al., 2015; Zhang et al., 2015; McCarthy et al., 2016a). In this prototype model, the total available forage under grazing throughout the year can be calculated by the subtraction of grazed forage eaten by livestock from the total newly grown available forage, which can be express as:

$$\mathbf{TNGAF} = \sum_{1}^{n}\sum_{1}^{12}(\boldsymbol{GGR_{mi}}.\boldsymbol{LPA_i} - \boldsymbol{LG_{mi}})$$

Eq. 4-2

TNGAF is the total newly grown available forage of all the patches during the year, $\boldsymbol{GGR_{mi}}$ is the grass growth rate in month m of land patch i, $\boldsymbol{LPA_i}$ is the total area of land patch i. LG_i is the grazed amount of forage by livestock at land patch i during month m; n is the total number of patches.

Grassland degradation

Another important indicator for quantifying the effect of grazing is the degradation status. In fact, over the last few decades, the degraded grasslands caused by overgrazing account for the largest proportion of land degradation among all major biomes (Salvati and Carlucci, 2015; Kwon et al., 2016a). Grazing-led degradation poses a big threat to sustaining and/or increasing global livestock productivity, which serves multiple purposes including economic, social and ecological functions (Salvati and Carlucci, 2015; Kwon et al., 2016b). On the other hand, livestock also plays a critical role in maintaining soil nutrients in grassland, as livestock manure accounts for more than half of the total nitrogen phosphorus for grass growth (Sheldrick et al., 2003; Bouwman et al., 2013). Given the importance of livestock and grazing severity on grassland degradation, it is necessary to report the grassland degradation status to identify cost-effective strategies of sustainable grazing. In Zeku, although the judgement of grassland degradation has many factors to consider, this prototype model just keeps it simple with the one definition of grassland degradation according to the productivity change (Su et al., 2003), which can be expressed as:

$$\text{TND} = \begin{cases} C_{i>50} & \textit{serverely degraded} \\ C_{21\le i\le 50} & \textit{medium degraded} \\ C_{11\le i\le 20} & \textit{light degraded} \end{cases}$$

Eq. 4-3

, where i is the percentage of decreased available forage productivity to the forage productivity of the base year and C is the number of degraded land patches at this level.

In Section 3.6 of Chapter 3, different grazing strategies and institutional arrangements have been discussed. How do those management scenarios affect the herders' economic status and grassland status? There are three different management scenarios designed in the prototype model: sedentary grazing (un-grazed, it is called continuous grazing as well in the literature), pasture rental market and Ecological Animal Husbandry and Economic Co-operative Grazing (EAHECG, which is a group grazing management scenario in essence but has a different name). The model will report both the economic status of the herders and the degradation status of the land patches under these three management scenarios:

Sedentary grazing

The monthly (month “m”) net benefit of each agent (agent “i”) under the sedentary grazing can be calculated by:

$$NBAS_{im} = AI_{im} + PPU_m . WGoL_{im} - LFC_{im} - TMC_{im}$$

Eq. 4-4

and the monthly (month “m”) total benefit of the agent (agent “i”) can be calculated by:

$$\mathrm{NBAS}_m = \sum_1^n NBAS_{im} = \sum_1^n \mathrm{AI}_{im} + PPU_m . \sum_1^n \mathrm{WGoL}_{im} - \sum_1^n LFC_{im} - \sum_1^n TMC_{im}$$

Eq. 4-5

, where $\boldsymbol{NBAS_{im}}$ is the net benefit of agent i at month m, and $\sum_1^n NBAS_{im}$ is the net benefit of all the agents, and the total number of agent is n. $\boldsymbol{AI_{im}}$ is the asset investment benefit of agent i at month m, $\boldsymbol{PPU_m}$ is the price per sheep unit at month m, $\boldsymbol{WGoL_{im}}$ is the weight gain of livestock of agent i at month m, $\boldsymbol{LFC_{im}}$ is the cost of buying lambs or calves and fodder of agent i in month m. $\boldsymbol{TMC_{im}}$ is the transhumance cost of agent i at month m.

Where the monthly available forage for each land patch can be calculated by:

$$AFS_{mi} = AFS_{(m-1)i} \cdot (1 + GR_{im}) - \mathrm{NoL}_{im} \cdot CoL_{im} - L\mathrm{oSD}_{im}$$

Eq. 4-6

and the monthly total available forage can be calculated by:

$$AFS_m = \sum_1^n AFS_{(m-1)i} \cdot (1 + GR_{im}) - CoL_{im} \cdot \sum_1^n \mathrm{NoL}_{im} - \sum_1^n \mathrm{LoSD}_{im}$$

Eq. 4-7

, where $\boldsymbol{AFS_{mi}}$ stands for the available forage of land patch i at month m, $\boldsymbol{AFS_{(m-1)i}}$ is the available forage of land patch i at month m-1(last month), $\boldsymbol{GR_{im}}$ is the increase rate of forage of land patch i at month m; $\sum_1^n AFS_{(m-1)i} \cdot (1 + GR_{im})$ is the total available forage at month m before livestock grazing. $\boldsymbol{CoL_{im}}$ is the consumption of forage by livestock (per sheep unit) within land patch i at month m, $\mathrm{N}\mathbf{oL}_{\boldsymbol{im}}$ is the number of livestock of agent i at month m, and $\sum_1^n \mathrm{NoL}_{im}$ is the total amount of livestock on the grassland land for month m; $\boldsymbol{L}\mathbf{oSD}_{\boldsymbol{m}}$ is the amount of forage loss if prolonged snow hits the land patch i at month m, and $\sum_1^n L\mathrm{oSD}_{im}$ is the total forage loss due to the prolonged snow in month m. In the conceptual model, the growth rate of the grass is represented by a random amount forage increase (absolute value with unit kg) rather than a growth rate for simplification.

Pasture rental market

The monthly (for example, month “m”) net income of the agent (agent “i”) is:

$$NBAR_{im} = \mathrm{NBAS}_{im} + LPTO_{im} - LPFO_{im} - TC_{im}$$

Eq. 4-8

and the monthly total net income of agents can be calculated by:

$$\mathrm{NBAR}_m = \sum_1^n NBAR_{im} = \sum_1^n \mathrm{NBAS}_{im} + \sum_1^n LPTO_{im} - \sum_1^n LPFO_{im} - \sum_1^n TC_{im}$$

Eq. 4-9

, where $\boldsymbol{NBAR_{im}}$ is the net income of agent i at month m, and $\sum_1^n NBAR_{im}$ is the total net income for all the agent at month n, and the number of the agents is n; $\boldsymbol{LPTO_{im}}$ is the net income of leasing pasture to others of agent i at month m, and $\sum_1^n LPTO_{im}$ is the total net income of leasing pasture to others for all the agents; $\boldsymbol{LPFO_{im}}$ is the cost of leasing pasture from others of agent i at month m, $\boldsymbol{TC_{im}}$ is the cost of transportation for migration of agent i at month m, and $\sum_1^n TC_{im}$ is the total cost of leasing pasture from others for all the agents;

The monthly available forage of land patches is:

$$AFR_{mi} = AFR_{(m-1)i} \cdot (1 + GR_{im}) - \mathrm{NoL}_{im}(1 \pm \varphi) \cdot CoL_{im} - L\mathrm{oSD}_{im}$$

Eq. 4-10

and the monthly total available forage can be calculated by:

$$AFR_m = \sum_1^n AFR_{(m-1)i} \cdot (1 + GR_{im}) - CoL_{im} \cdot \sum_1^n (1 \pm \varphi)\mathrm{NoL}_{im} - \sum_1^n L\mathrm{oSD}_{im}$$

Eq. 4-11

, where $\boldsymbol{AFR_{mi}}$ stands for the available forage of land patch i at month m, $\boldsymbol{AFR_{(m-1)i}}$ is the available forage of land patch i at month m-1 (last month), and $\sum_1^n AFR_{(m-1)i} \cdot (1 + GR_{im})$ is the total available forage of all the lands before grazing;, $\boldsymbol{\varphi}$ is the percentage of livestock migrated to the newly leased land patch (for leaseholders it would be a "-", while for landlords it would be "+"; $\sum_1^n (1 \pm \varphi)\mathrm{NoL}_{im}$ is the total livestock moved in/out the original lands in the whole region.

EAHECG (or group grazing)

The EAHECG organisation is an economic group that aims at improving the development of livestock husbandry. It is an effective organization dealing with employment and overgrazing in Zeku and was strongly encouraged by the local government. In ABMGG, we set 3 EAHECG groups initially, each of them has 7 herders.

The monthly (month "m") net income of agent (agent "i") can be calculated by:

$$NBAC_{im} = AI_{im} + PPU_m.WGoL_{im} \cdot \alpha_i + PPU_m.WGoL_{im} \cdot (1 - \alpha_i) \cdot (1 + \pi) - LFC_{im} - TC_{im}(1 - \mu) - SPC_i$$

Eq. 4-12

The total monthly income of agents:

$$\mathrm{NBAC}_m = \sum_1^n NBAC_{im} = \sum_1^n A\mathrm{I}_{im} + PPU_m.\sum_1^n \alpha_i \cdot \mathrm{WGoL}_{im} + (1 + \pi)\sum_1^n WGoL_{im} \cdot (1 - \alpha_i) - \sum_1^n LFC_{im} - (1 - \mu)\sum_1^n TC_{im} - \sum_1^n SPC_i$$

, where $NBAC_{im}$ is the net income of agent i at month m, $NBAC_m$ is the total net income of all agents at month m, and $\sum_1^n NBAC_{im}$ is the total the net income of all the agents; $(1 - \alpha_i)$ is the proportion of livestock invested in the ecological animal husbandry economic co-operative, π is the increased proportion of cooperation benefit. μ is the decreased cost proportion of the transhumance cost with the increase in the number of co-operators, SPC_i is the cost of sharing the pasture of agent i, and $\sum_1^n SPC_i$ is the total cost of sharing the pasture of all the agents.

The monthly available forage for each land patch is:

$$AFE_{mi} = AFE_{(m-1)i} \cdot (1 + GR_{im}) - \left(\alpha_i \cdot \mathrm{NoL}_{im} + \frac{(1-\alpha_i)}{LSPG_i} \cdot \mathrm{NoL}_{im} \cdot \mathrm{LPPG}_i\right) \cdot CoL_{im} - Lo\mathrm{SD}_{im}$$

and $\sum_1^N \mathrm{LPPG}_i = 1$, $\sum_1^N LSPG_i = 1$

Eq. 4-13

The total monthly available forage is:

$$AFE_m = \sum_1^n AFE_{mi} = \sum_1^n AFR_{(m-1)i} \cdot (1 + GR_{im}) - CoL_{im} \cdot \left(\sum_1^n \mathrm{NoL}_{im} \cdot (\alpha_i + \frac{\mathrm{LPPG}_i}{LSPG_i} \cdot (1-\alpha_i))\right) - \sum_1^n Lo\mathrm{SD}_{im}$$

Eq. 4-14

, where $\sum_1^n AFE_{mi}$ is the total monthly available forage for all the agents at month m; α_i is the percentage of livestock of agent i invested in the co-operative, $LSPG_i$ is the livestock proportion of agent i invested in the co-operative, LPPG_i is the percentage of land area of agent i invested in the group, and $\left(\sum_1^n \mathrm{NoL}_{im} \cdot (\alpha_i + \frac{\mathrm{LPPG}_i}{LSPG_i} \cdot (1-\alpha_i))\right)$ means the total livestock consumption of the forage of all the group grazing herders; the rest are the same as they have been explained earlier.

4.3 Model specification

All the values of parameters are assumed in the conceptual model of ABMGG (Figure 4.8). There are three types of parameters: land patch related parameters, livestock and herder agent related parameters and grazing strategy parameters. Land patch related parameters describe the initial productivity of grass forage and the grass growth of different seasons. Livestock and herder agent related parameters account for the grazing activities on grassland: the quantity of livestock owned by the herders and the quantity of grass forage consumed by livestock. Other parameters are related to the grazing strategies and institutional arrangements: market cost for leasing/renting, the cost for joining/leaving the grazing groups and the number of grazing groups. At present, little information is known about patch specific grassland productivity and livestock grazing (Chapter 5 develops a method to extract this information from remote sensing data). Here, all the values are assumed, and they are shown in Table 4.4.

Table 4.4: Variables in the conceptual models and their assumed values

Type	Parameters	Value	source
Land patch	Pasture size per land patch	1 km^2	Assumed
	Percentage of edible grass	100%	Assumed
	Grassland productivity	Random (next rows)	Assumed
	Summer growth rate	Random 60 (kg)	Assumed

	Winter growth rate	Random 5 (kg)	Assumed
livestock	Consumption rate of grass per sheep unit	0.5kg per sheep weight	Assumed
	Weight gain from grazing per sheep unit	0.1kg per sheep weight	Assumed
herder	Number of Land patches owned	1	Assumed
	Asset	random	Assumed
	Number of sheep bought at the beginning of the year	19	Assumed
	percentage of sheep sold at the end of the year	90%	Assumed
	Probability of buying lambs or calves	50%	Assumed
	Probability of selling sheep or yaks	50%	Assumed
	Transhumance cost	200	Assumed
market	Price of leasing land patch	0	Assumed
	Transportation cost per patch-unit	0	Assumed
Snow disaster	Percentage of productivity loss from snow disaster	90%	Assumed
	Probability prolonged snow occurs	0.1%	Assumed
Co-operative Group	Registeration cost for co-operative	0	Assumed
	Numbers of co-operatives	7	Assumed
	Exit cost of leaving a cooperation group	0	Assumed
	The proportion of livestock invested in co-operative within the group	100%	Assumed
	The proportion of land invested in co-operative within the group	100%	Assumed

Three models are developed representing the sedentary, land market and group grazing practice respectively. The values of the parameters for all three models are the same as those listed in Table 4.4. When degradation happens (less than 50% of the initial randomly assigned forage, and see Eq. 4-3), the herders are assumed to sell half of their livestock in the sedentary grazing model. Herders can rent land in good condition for livestock grazing from other herders when degradation happens in the land market model. In the group grazing model, some of the herders are formed the grazing groups at the beginning of the year, and the herders in the same grazing group share the land resource. Only when the available forage in the group is less than 50% of the initially assigned available forage, then the herders in the group will sell half of their livestock. At the start of the year, herders are assumed to buy a fixed number of livestock (for example lamb or calf) for next year’s grazing, and sell 90% of their livestock at the end of the year. Since the transhumance cost is assumed to be a fixed number, and it only affects the net benefit of the herders in June and November, it was excluded in calculating the monthly net benefit for all three models. In addition, the income from the investment is not considered in these three conceptual models.

4.4 Computational simulation

The overall purpose of the computational simulations is to understand the economic (net income of herders) and ecological (numbers of degraded land patches) performance of the grassland grazing system under the three institutional arrangements. For each patch, different grazing strategies or institutional arrangements could have a diverse effect on the growth of grass and the dynamics of livestock, but when considering all the grassland patches as a whole, do these managements have the same effect? The results of a computational simulation would be helpful in understanding whether those management strategies are the cost-effective ones, or how can they be more effective in the future with the aim of realizing sustainable grassland management.

Through 500 repeated simulations with the same parameter values, the stable outputs of the models can be obtained. However, the results presented in this section would, of course, vary when the values of the parameters are different from the assumed values. However, there is limited data on the uncertainty of the assumed parameter values in the conceptual models; therefore, this section aims to provide an example of assessing the grazing strategy and institutional arrangement by using ABM. A further sensitivity analysis in Section 4.5 will explore the effects of parameter value changes on the model outputs. The reason for choosing 500 repetitions is that it is large enough to produce a stable mean value of the properties of the model outputs. We can see that, with the increase of the number of repeated simulations, the mean values and the standard errors are close to a certain fixed range; especially when the number of the repeated simulations exceeds about 400 for all the conceptual models (see Figure 4.2, Figure 4.3 and Figure 4.4).

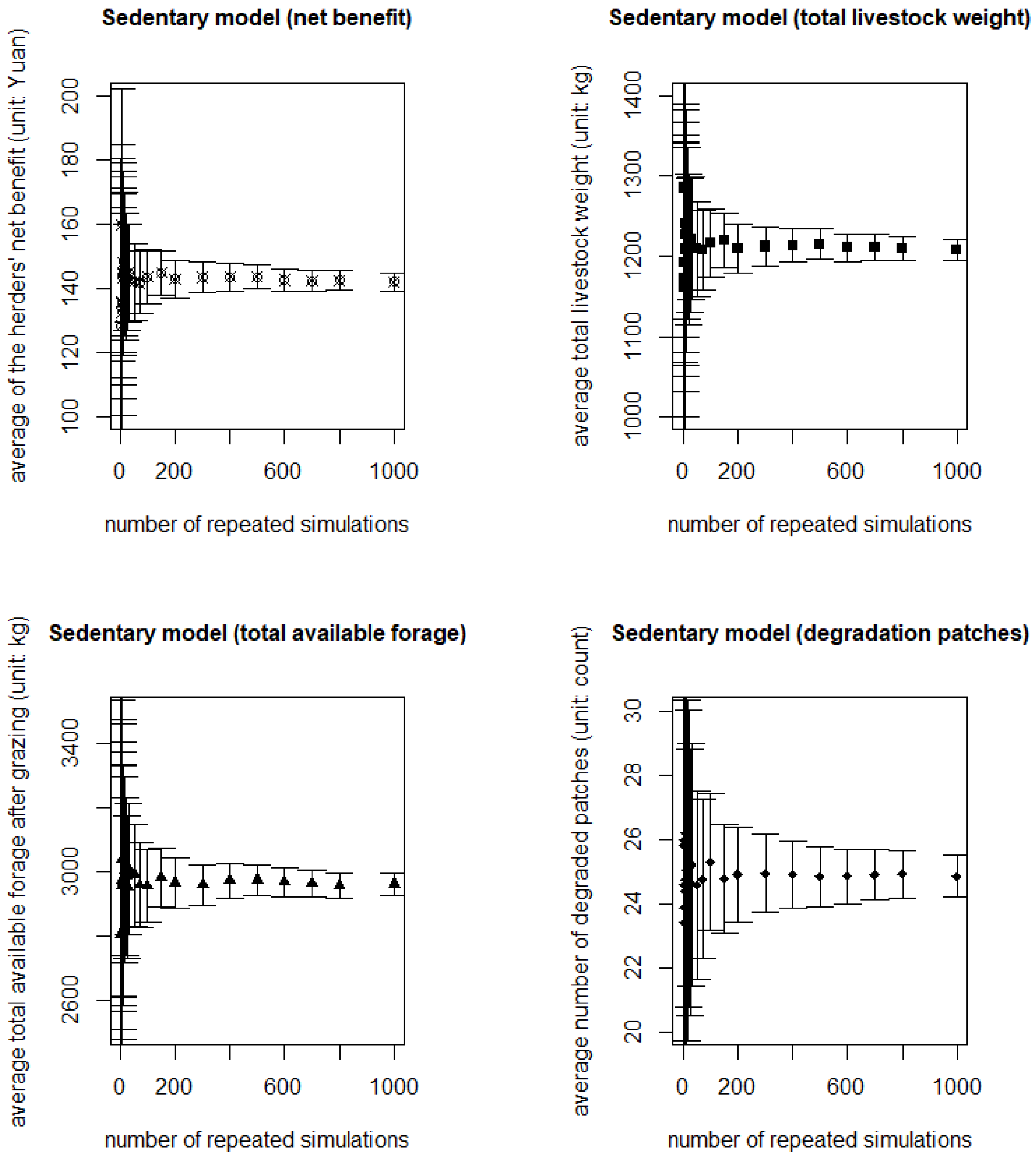


Figure 4.2: The means and standard errors of the model outputs with different numbers of repeated simulations in the sedentary model

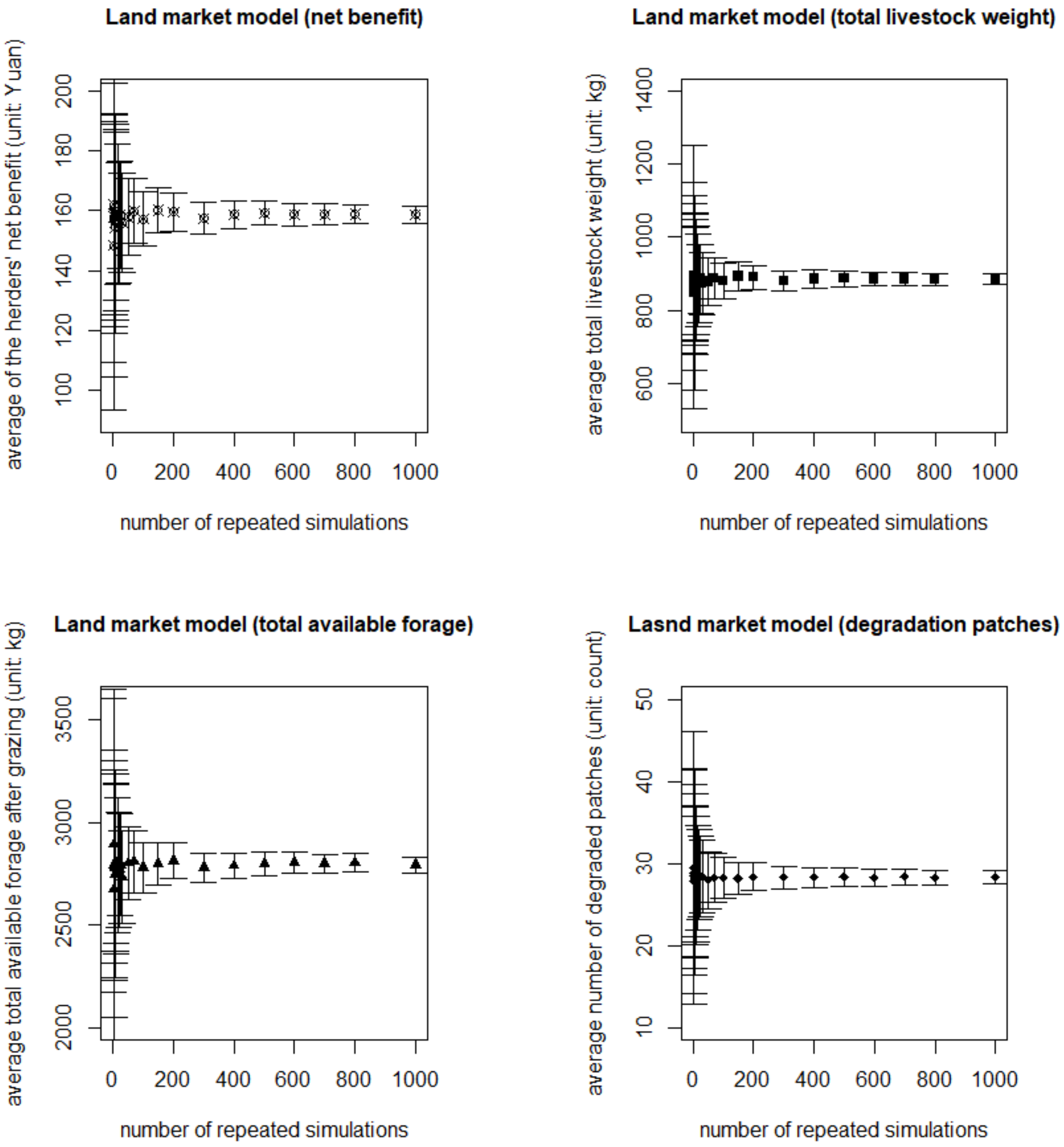


Figure 4.3: The means and standard errors of the model outputs with different numbers of repeated simulations in the land market model

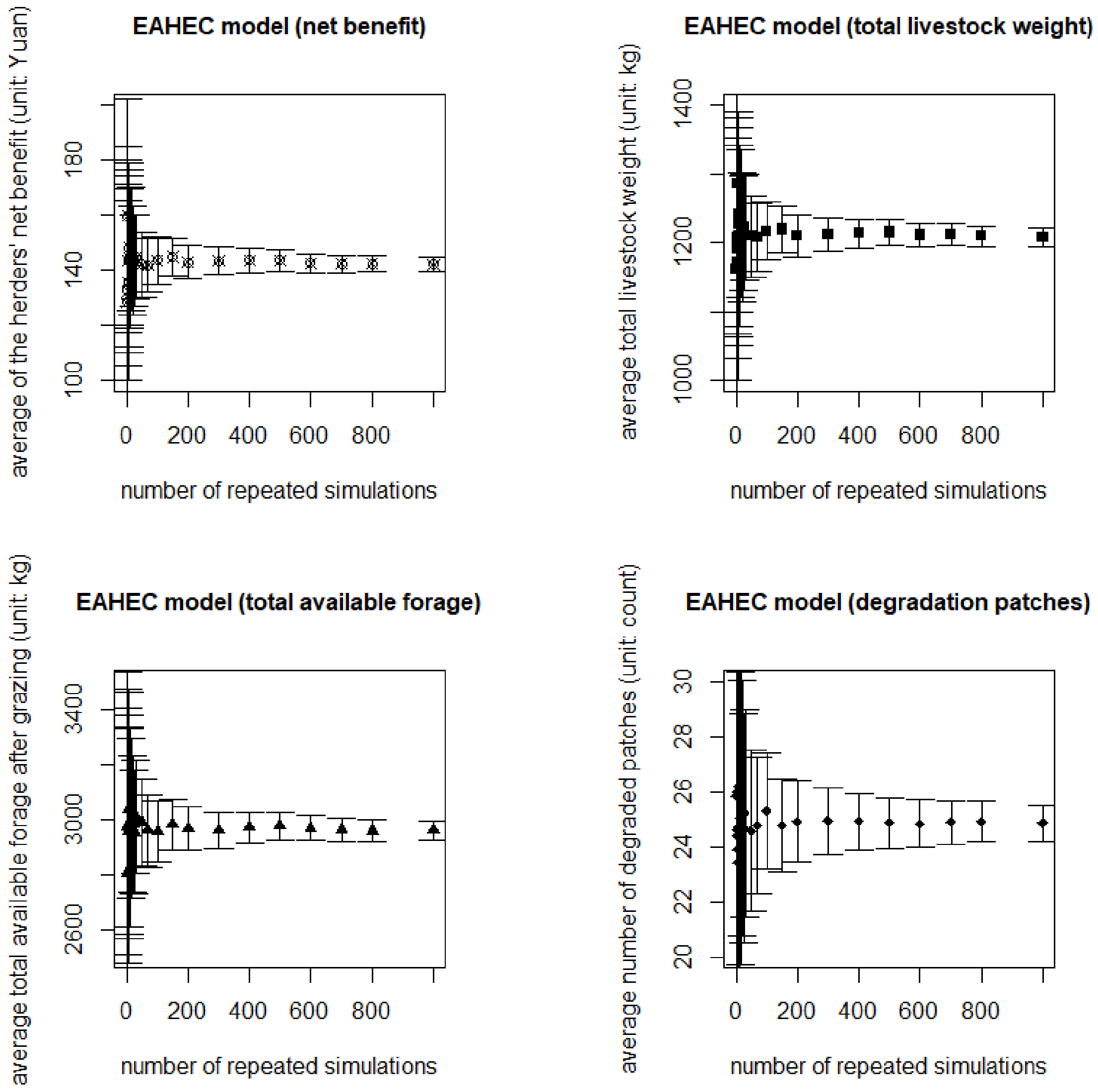
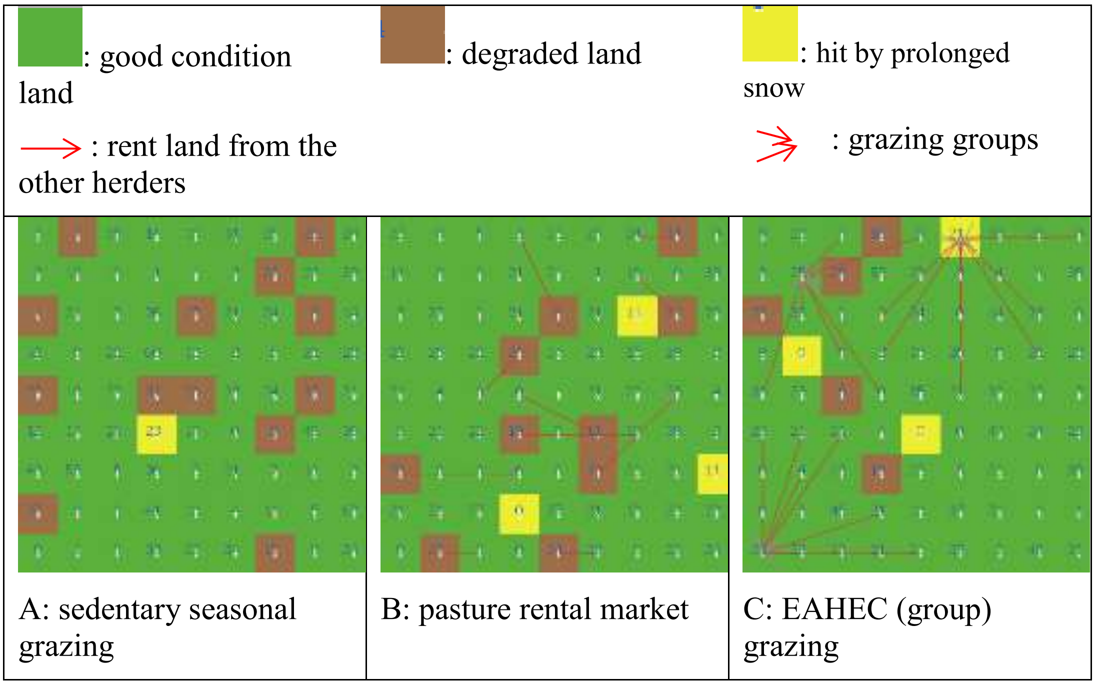


Figure 4.4: The means and standard errors of the model outputs with different numbers of repeated simulations in the EAHEC (group grazing) model

The models were run for 20 simulated years from January 2000 to 2020. Figure 4.5 shows the screenshots of ABMGG in 2020. The green land patches in all snapshots mean good conditions of the grassland, i.e. degradation do not happen; brown ones stand for the land patches that are degraded, and the yellow ones represent the patches that are hit by prolonged snow. The arrows in the screenshot of pasture rental market model show that the herders' lease land from their neighbours, and they change dynamically according to the status of the land patches. When one land patch is degraded, ABMGG will change its background colour to brown, and the herder agent will lease land from its neighbour. However, when the condition of a land patch is good (green colour), the herder agent will end up the leasing relationship and take the livestock back to his/her own land to save money. The lines in the screenshot of the EAHEC model show the initially established co-operatives, which will be kept the same until the end of the simulations; that is, there are no other herders joining/leaving the group during model runs. The models check land patch status at every time step to identify the degraded land patches. A severely degraded patch is defined as that the available forage is less than 50% of its initially assigned value. All the parameters values are the same in those three grazing management scenarios. The mean values of the model outputs with their standard variance as shown in Figure 4.6, Figure 4.7, Figure 4.8 and Figure 4.9.



A: sedentary seasonal grazing

B: pasture rental market

C: EAHEC (group) grazing

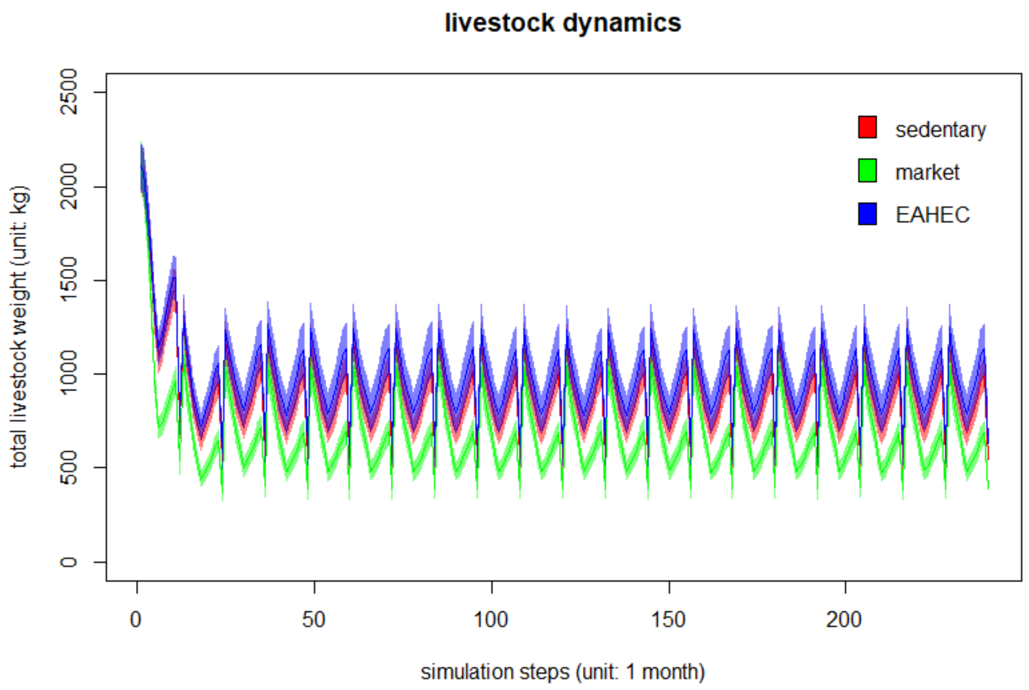
Figure 4.5: Screenshots of three institutional arrangements in ABMGG

Population and forage dynamic

In order to keep the conceptual model simple, livestock here actually stands for the livestock *weight*livestock* number for each land patch. As we can see from Figure 4.6, the overall dynamics of livestock and forage is the same under these three managements. Notice there are some extremely large numbers of the livestock in the first few years; this is because the initial model setting is not “appropriate”. This does not matter much for evaluating the modelling results. Due to the natural growth of forage and the decision making of herder agents, overgrazing (the patches with a lot of livestock but limited available forage) will trigger the selling behaviour of herders. These large values, therefore, represent large numbers of livestock that exist only for a very short period in the first year.

In the three prototype models, herders will buy some yaks and sheep in January (step 1, 13, 25…). After reaching a stable forage-livestock pattern, we can see the maximum overall weight of livestock appear in February (step 14, 26, 38…) due to the buying behaviour of herders. The selling behaviour is assumed to occur at the end of the year, hence the minimum overall weight of livestock present in the next month (January). From Figure 4.6, there is a local maximum livestock weight in July and local minimum weight of livestock in November for each year. This is because the summer growing season has a greater forage growth rate, and there is plenty of available forage for livestock grazing. During the non-summer growth seasons, the growth rate is smaller, and the prototype model will check the degradation status of land patches; therefore the herder agents have to either sell some of their livestock or rent land from others.

The seasonal dynamics of available forage are well represented. We can see a greater available forage from June to September (step 6, 7, 8, 9, 17, 18, 19, 20…) compared with the other months. The maximum total available forage appears in September (step 9, 21, 33…), and minimum total available forage occurs in June (step 6, 18, 30…). From Figure 4.6, an obvious difference in available forage of the three models can be seen: the EAHEC has the largest available forage, followed by the sedentary grazing, while the pasture rental market has the smallest available forage. This is mainly because on EAHEC grazing land patches, the average number of livestock is much larger than that of the other two. The pasture rental market and EAHEC grazing management can actually 'reduce' the heterogeneity of the grass forage distribution; thus a higher productivity land can raise more livestock. The pasture rental market and EAHEC grazing can optimize the livestock number on the land by increasing accessibility of the grass forage (compared with sedentary grazing). This prototype results match well with the field based analysis (Hart et al., 1993; Pavlů et al., 2003), which means the conceptual design of the prototype model is reliable and consistent with current studies.



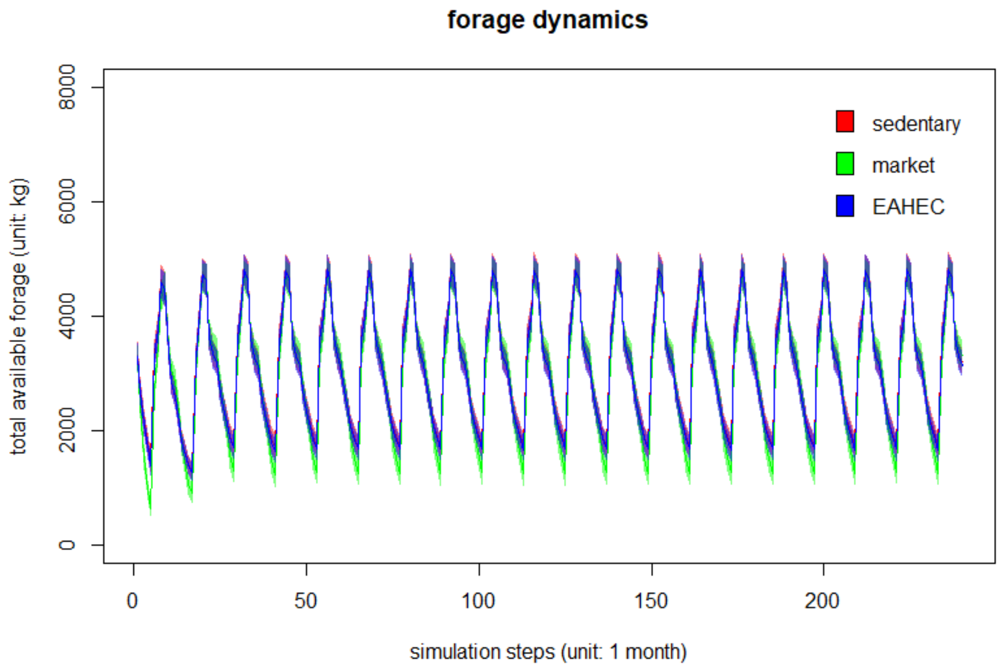


Figure 4.6: Dynamics of livestock and available grass forage during 2000-2020

The emergent pattern of the grassland grazing system is that the livestock population and the available forage “twist” together (Figure 4.7). When there is an increased overall weight of the livestock, the available forage will decrease due to the increase in livestock consumption. The forage increases fast from June to September, but it decreases gradually after September. This is expected to represent the seasonal dynamics of grass growth. Therefore, different grazing management strategies lead to similar emergent patterns with regards to the dynamics of the livestock and forage.

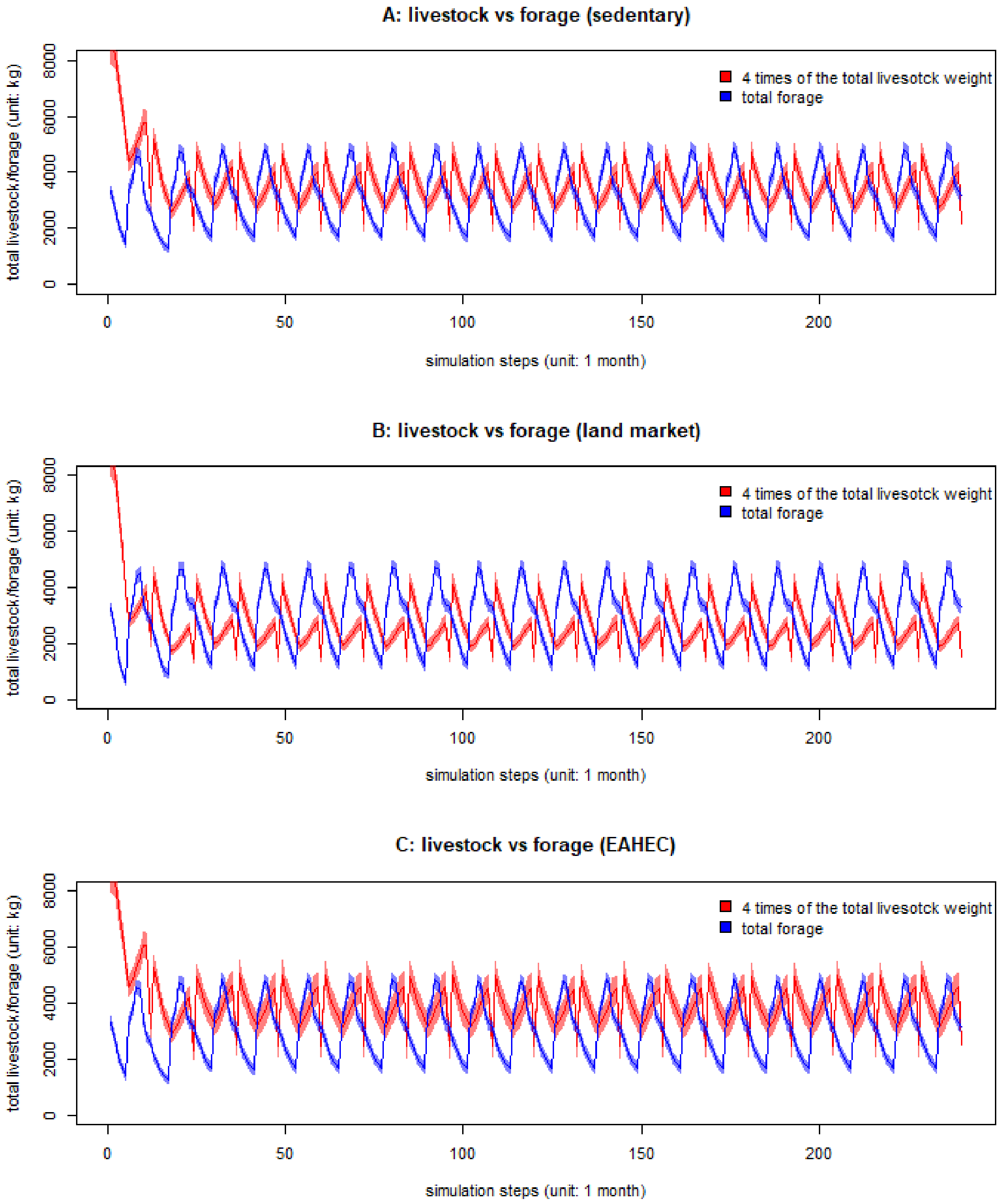


Figure 4.7: Average livestock and forage trend from 2000.01 to 2020.01 under sedentary seasonal grazing, pasture rental market and EAHEC arrangements

Another important aspect of evaluating the grazing system is economic performance. Although Zeku is located in the national reservation area, the herders have lived in the same natural-grazing lifestyle for thousands of years, and it is impossible to exclude grazing for both cultural and economic reasons, and thus grazing still exists in this national reservation area. Livestock grazing is almost the only way of gaining income for the majority of herders in Zeku (Zhou et al., 2007a). The evaluation of the natural contribution to herders' income is important for both academic research and policy-making (Campos et al., 2016). The value of the private amenities associated with grassland grazing, such as the enjoyment of the grazing lifestyle (Kemp and Michalk, 2007; Oviedo et al., 2012), are not considered in this thesis. In fact, the herders in Zeku are low-income groups compared with the people in the northeast of China; livestock provides food and almost the only source of income supporting herders' livelihoods for the vast majority (Zhou et al., 2007a).

Different grazing strategies and institutional arrangements will affect the herders' economic benefits from grassland grazing (Li et al., 2015b). Research has found that a continuous grazing strategy leads to a decrease of the herders' net income and this, in turn, could affect grassland grazing management practices (Rittenhouse and Roath, 2002; Michalk et al., 2003). It is difficult to identify the impact of different grazing intensities on livestock production and herders' economic benefits through laboratory experiments (McCollum III et al., 1999), but it is possible to evaluate the herders' income when using agent-based modelling by exploring with different grazing management strategies (Jun et al., 2013). When the stocking rate is high in continuous grazing grassland, the weight gains of grazing livestock decrease (Ackerman et al., 2001; Miguel et al., 2003), and this could further affect the economic benefit (Whitson et al., 1982). Empirical analyses have shown that the net income per cow was higher for dairy farms that employed moderate very intense grazing than for dairy farms that employed extensive grazing in Pennsylvania and New York (Hanson et al., 1998). For the effective and sustainable development of the grazing grasslands, the economic measures need to be considered under those different grazing strategies and institutional arrangements to improve grassland condition while increasing herders' incomes (Pannell et al., 2006).

Net income

The results of net income of the three models are shown in Figure 4.9. They are calculated by the average of individual herder agents' net income for each step. The maximum net income appears in December, and the minimum net income stands in January for each year. This is because herder agents will sell their livestock at the end of the year, and buy baby lambs and yak at the beginning of the year. In addition, the models assume that transhumance happens in June when livestock travels to the summer pasture lands and November when livestock get back to the winter pasture lands. The transhumance happens at the cost of losing net income. From Figure 4.8, the average net income increases slower from June to September compared with the other months. Due to the higher grass forage growth rate from June to September, the livestock have enough feeding forage, and there is less weight of livestock being sold during those months; the available forage is less (see Figure 4.7) in the other months, and therefore the livestock is more likely to be sold, as the land patches will be more likely to be degraded. The sedentary grazing performs better compared with the EAHEC and pasture rental market with regard to the average net income of herder agents. The EAHEC produces the least income, indicating that EAHEC is not economically effective compared with sedentary grazing and the pasture rental market.

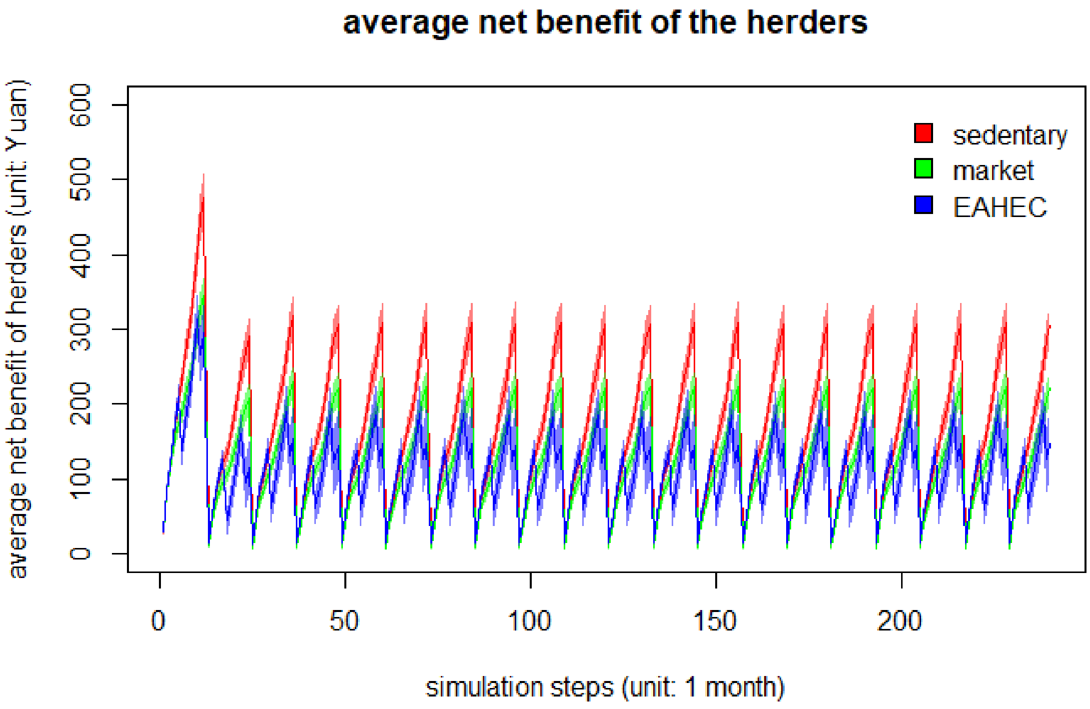


Figure 4.8: Economic performance under three institutional arrangement

Sedentary continuous grazing is widely recognized as a key factor in grassland degradation caused by overgrazing (Teague and Dowhower, 2003). The main reason is that, on continuous grazing lands, the selective behaviour of livestock would contribute to the higher stocking rate on patches with palatable species (Teague and Dowhower, 2003; von Müller et al., 2017); while rotational grazing, to some extent, would force the livestock to move to the other patches strategically. Various forms of rotational grazing have been proposed as alternative grazing strategies that are likely to avoid degradation (Norton and Bartle, 2014). The theory behind this is that rotational grazing lands can provide some rest time between grazing events (Teague and Dowhower, 2003), which allows palatable species to recover from the defoliation and compete effectively with less palatable species. However, researchers have found that continuous moderate grazing management promoted biomass production as well (Oñatibia and Aguiar, 2016). Therefore, the grazing intensity also plays an important role in grazing-led grassland degradation as "*intensive grazing has been proved unsustainable because maximization of livestock revenue incurs high supplemental feed costs, marginalizes net household income, and promotes larger flock sizes to create a positive feedback loop driving grassland degradation*" (Briske et al., 2015). It is, therefore, of great significance to report the degradation status under different grazing strategies and institutional arrangements.

Degraded patches

Figure 4.9 shows the numbers of degraded patches, which are simply defined as the patches where available forage decreased by 50% to their initially assigned values. A sharp decrease in the number of degraded patches can be seen from June to September each year due to the fast growth of the grass. Another local sharp decrease in the number of degraded patches is at December when the livestock are sold. On the whole, we can see that the EAHEC performs best in terms of the number of degraded patches, of which the mean and variance is much smaller than the other two. Under the EAHEC management, herder agents can choose an alternative land patch to graze rather than continuously graze on their own land patch when prolonged snow happens. Herder agents in the land rental market model can rent land from other herders when there are not enough forage on their own lands, this may lead to the degradation on both lands. Thus the highest number of degraded patches can be seen in the sedentary model from Figure 4.9. Therefore, the most stable strategy is group grazing (EAHEC), which produces a smaller number of degraded patches and smaller standard deviation of them (blue area).

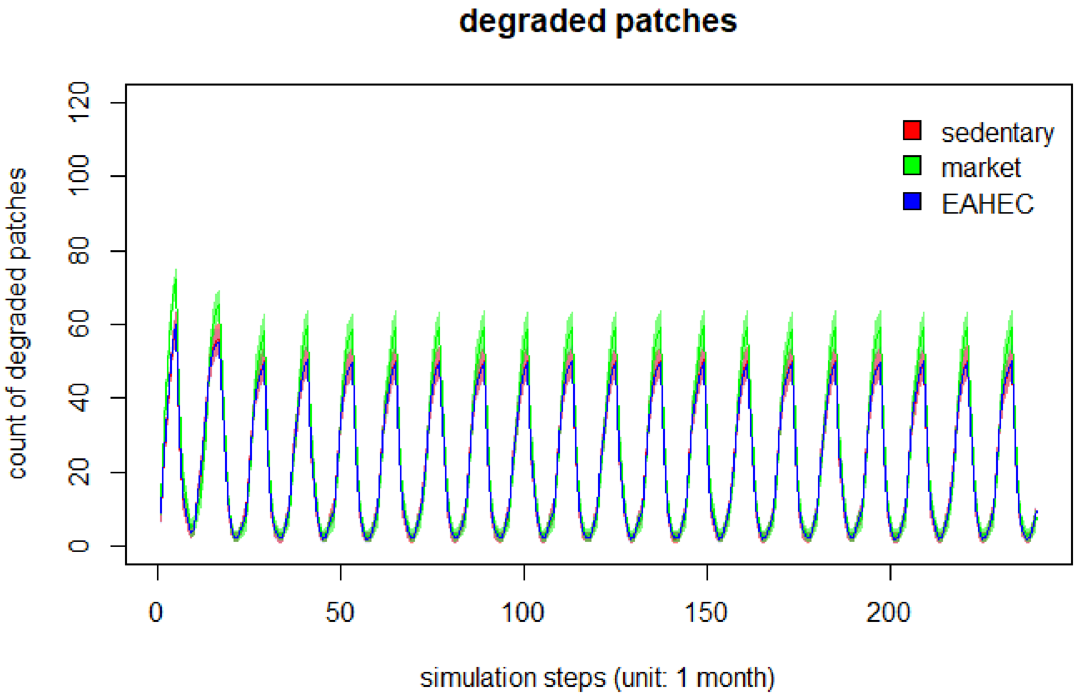


Figure 4.9: Ecological performance under three grazing management

4.5 The sensitivity analysis of the models

The results presented in Section 4.4 are all based on the assumed values of the parameters, and changes in these values may lead to different model outcomes. Therefore, a sensitivity analysis is necessary to understand the conceptual models further. The aim of the sensitivity analysis is to explore the response of the model to the parameter value changes. One direct way is numerical simulation with different parameter value sets, and if there are too many parameters (for example, hundreds of parameters), the common way is to identify the most influential parameters and only explore the sensitivity of these parameters.

In this section, six parameters in the sedentary and land market mode, and eight parameters in the group grazing model (EAHEC) are analysed by using partial (rank) correlation coefficient (PCC/PRCC), which is used to measure the relationship and the strength of the relationship between parameters and outcomes of the model (Saltelli et al., 1993; Manache and Melching, 2008). PCC can be used for measuring linear relationships, and PRCC is used for the measurement of non-linear but monotonic associations.

For each model, four aspects of the model outputs are evaluated: net benefit of the herders, livestock dynamic, forage dynamics and the number of degraded patches, which are all measured by their average value during 2000~2020. There are multiple years (2000~2020), multiple steps (46 steps for each year) and multiple dimensions (four aspects) of model outputs with single parameter value set for each model. This thesis uses the mean value of each dimension of the model outputs during the 20 years, with 2000 parameter value sets created by Latin Hypercube Sampling (LHS) method (Stein, 1987). LHS is a stratified sampling method without replacement, which partitions each parameter distribution (see Table 4.5 for the value ranges of the parameters, which are also assumed values to cover the majority of all possible situations) into certain intervals of equal probability, and selects one parameter value from each interval. The interval sizes are determined by the probability density distribution of the parameters. For each parameter value set, the models are repeated 5 times to extract the mean value of the model outputs (four aspects).

Table 4.5: parameters value ranges used for sensitivity analysis

parameters	Lower limit	Upper limit	Unit
numLambToBuy	0	1000	kg
snowProbility	1	10	%
lambPrice	1	1000	Yuan
sellPrice	1	1000	Yuan
forage_consumption_per_weight	0.01	1	kg
weight_gain_factor	0.01	1	-
numberCooperative	1	6	-
numberParticipant	3	10	-

The results of the PCC/PRCC analysis for the sedentary, land market and the group grazing (EAHEC) models are shown in Figure 4.10, Figure 4.11 and Figure 4.12 respectively. Each figure shows the relationship between parameters and the four dimensions of the model outputs. There are strong negative relationships between the amount of livestock (parameter “a”, see Figure 4.10) bought at the beginning of the year, price (parameter “c”), the forage consumption per livestock weight (parameter “e”) and the average net benefit (model output) of the herders for all the models. This is reasonable as the cost would be higher with the increase in the price or the quantity of the livestock (lamb or calf). The forage consumption per livestock weight (parameter “c”) plays as a consumption coefficient role in the models. With a higher value of the forage consumption per livestock weight, the less livestock can be raised on the land, which in turn leads to the lower net benefit to the herders. The weight gain of livestock from grazing (parameter “f”) is contrary to the forage consumption per livestock weight (parameter “c”) as a higher livestock weight gain from grazing means that more livestock (measured by weight) can be raised on the land, and this further leads to greater average net benefit for the herders.

For the livestock dynamics, there is a monotonically negative effect of the forage consumption per weight (parameter “e”) on the overall livestock dynamic (measured by weight), while a positive effect of forage consumption per weight (parameter “f”) on the livestock weight. The other parameters, however, show no obvious influence on the overall livestock weight, as they are more of economic value for the herders.

The amount of livestock bought at the beginning of the year (parameter “a”) has a weak positive effect on the overall available forage on the lands in sedentary and group grazing (EAHEC) model, but it has a strong negative effect on the overall available forage in land market model. One reason would be that more livestock means more consumption of forage and therefore less available forage can be observed in the land market model. Such evidence can be seen from the effect of weight gain from grazing (parameter “f”), which has a strong negative effect on the overall available forage for all the models. However, when overgrazing happens, the herders must sell half of their livestock, and the reduced livestock could result in an increase in the availability of the grass forage. In addition, the overall livestock weight on the sedentary and group grazing model is smaller than that of the land market model, so the effect of selling behaviours is more obvious on the sedentary and group grazing model.

It is interesting to see that the weight gain from grazing (parameter “f”) has a positive effect on the number of degraded patches for the three models; and the forage consumption per livestock weight (parameter “e”) has a weak or no effect on the number of degraded patches for the three models. This is because the overall livestock quantity depends on the increase rate of the livestock, which is determined by the weight gain from grazing (parameter “f”); the higher increase rate of the quantity of the livestock means the greater the demand for grass forage and, therefore, the higher the chance of the patches being degraded. The forage consumption per livestock weight (parameter “e”) affects the quantity of livestock on the grassland due to the limited forage, but it cannot improve or decrease the overall rate of forage consumption. When the consumption of the forage is the same, the lower value of the forage consumption per livestock weight means the land can support more livestock, but the overall weight does not change.

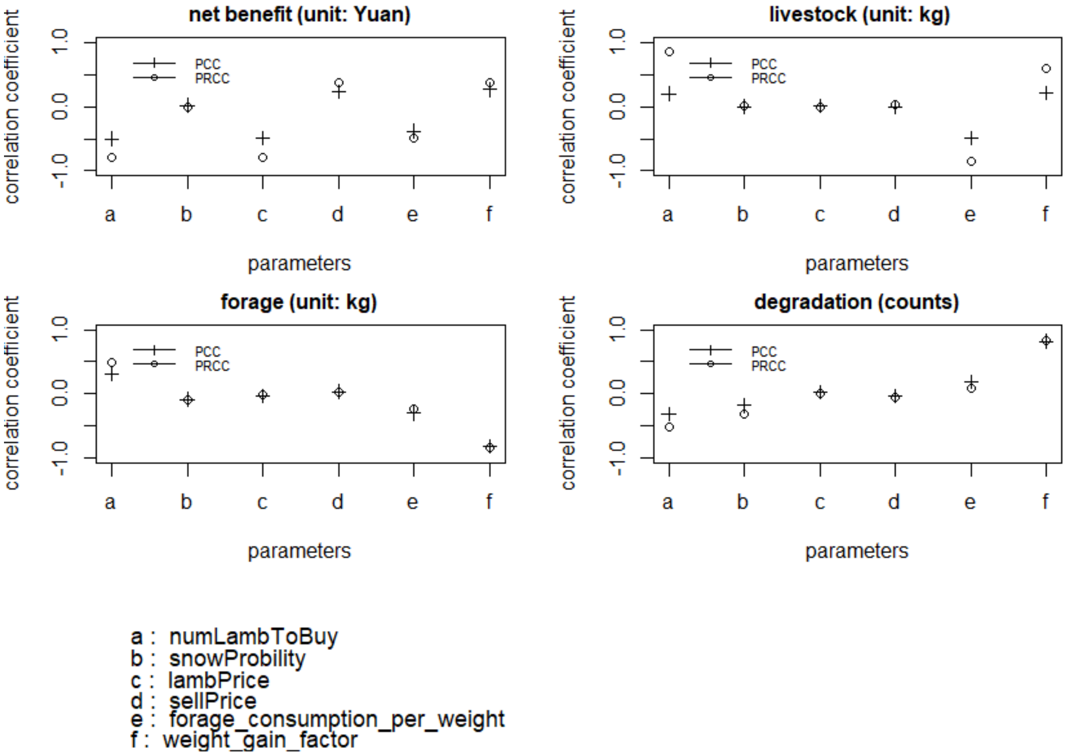


Figure 4.10: Results of the PCC/PRCC analysis of the sedentary model

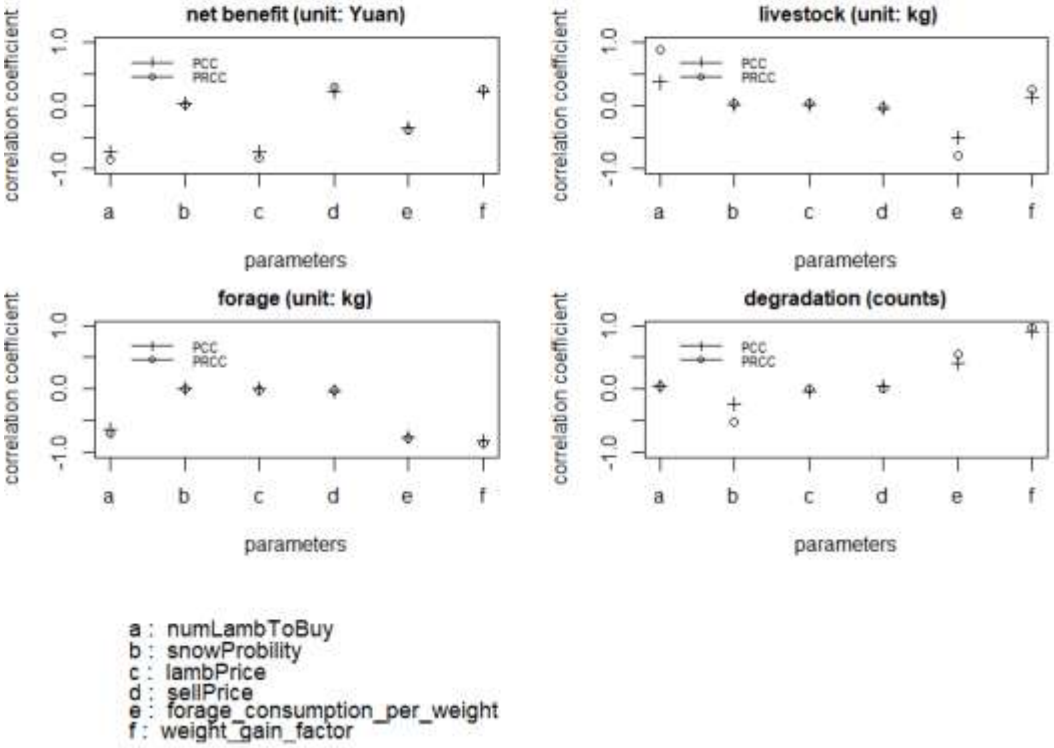


Figure 4.11: Results of the PCC/PRCC analysis of the land market model

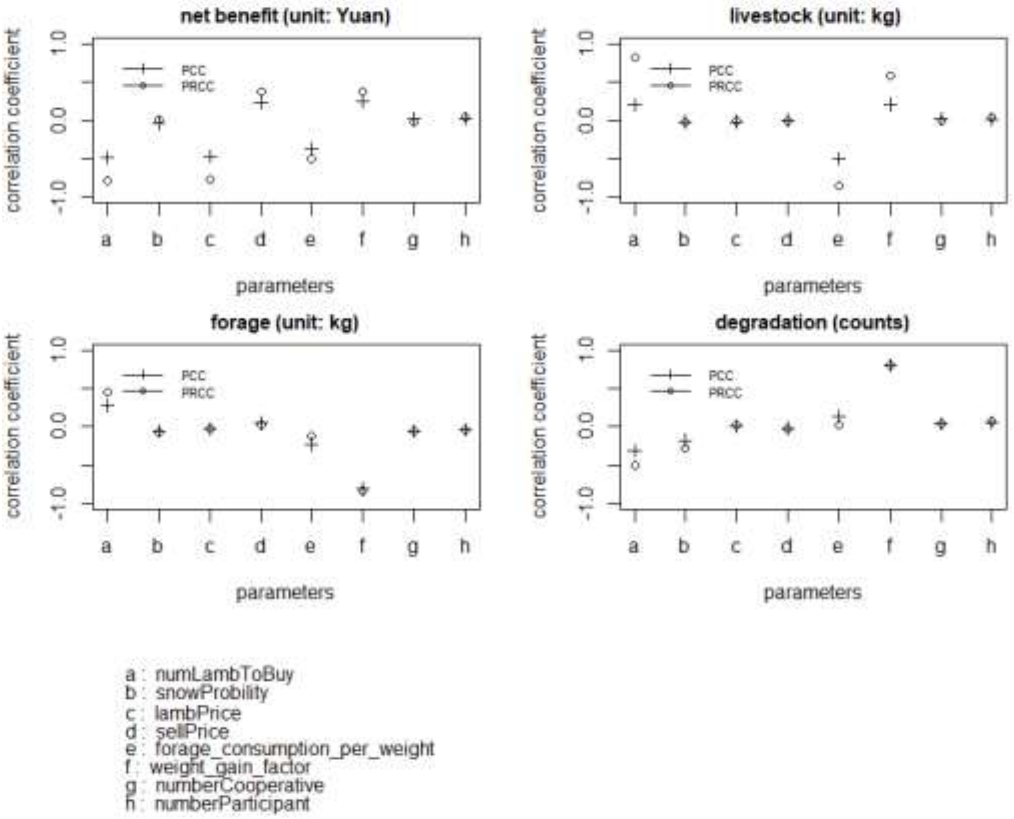


Figure 4.12: Results of the PCC/PRCC analysis of the group grazing model (EAHEC)

4.6 Summary

This chapter introduced the conceptual design associated with building prototype models under different grazing strategies and institutional arrangements. Three main grazing management scenarios were modelled to understand their impact on the economic and ecological performance of the grassland grazing system. Results showed that EAHEC has the largest available forage, followed by sedentary grazing, while the pasture rental market has the smallest available forage. Essentially, the livestock population and the available forage presented a dynamic pattern: when one was rising, the other was falling. This prototype model is helpful to understand the dynamics of the grassland grazing system, which is essential in realizing the aim of dynamic grassland management under different grazing strategies and institutional arrangements. However, notice again that all the parameter values are assumed in those conceptual models, the work of the next chapter in this thesis is then to extract spatio-temporal explicit information on grass status and grazing activities.

Chapter 5 Identifying Grazing-led LAI changes from Remote Sensing Derived Datasets

In Chapter 4, a prototype has been developed to model the dynamics of the grassland grazing system in Zeku. However, all the parameter values are assumed or abstract values. The results of the prototype model can only be used as a reference test of the basic modelling theories or as a way of assessing the feasibility of agent-based modelling of grassland gazing. The values of the grazing system in Zeku would surely be different from the prototype models, meaning the next challenge is how to collect the patch-specific data needed for the successful modelling of the grassland system in Zeku. As discussed in Chapter 2, remote sensing derived datasets provide high spatiotemporal information for the land, which can be further explored to extract grazing information for the grassland specifically. This chapter will discuss in detail how to extract grazing information based on Moderate Resolution Imaging Spectroradiometer (MODIS) datasets. The results of this chapter will be further used in Chapter 6 for validation and in Chapter 7 for the parameterization of Agent-Based Model of Grassland Grazing (ABMGG).

5.1 Problem identification

Remote sensing derived datasets are extensively employed in the field of grassland monitoring (Potter et al., 1993; Field et al., 1995; Piñeiro et al., 2006; Gao et al., 2013). In this research area, Leaf Area Index (LAI) is the commonly used measure to quantify the vegetation status of grassland (Fang et al., 2012). LAI is generally defined as the total one-sided green leaf area per unit ground area for flat broadleaf plants (Monteith and Reifsnyder, 1974) or one-half the total green leaf area per unit ground area for needles of conifers (Chen and Black, 1992) in describing radiation interception of plants. It gives an estimation of the green leaf area of the vegetation. The LAI is a key parameter for assessing the carbon and energy in the biosphere (Verger et al., 2015; Swain et al., 2016; Zhang et al., 2016), photosynthesis (Verrelst et al., 2016; Wei et al., 2016) and biomass production (Prieto-Blanco et al., 2009). It plays an important role in measurement and monitoring of land surface characteristics to assist policymakers in making decisions concerning the management of our environment (Cohen and Justice, 1999; Tian et al., 2002).

The *in-situ* measured LAI of plant canopies be obtained either directly by green leaf collection or indirectly from the physical properties of green leaves; a detailed discussion on these measurements was presented in Jonckheere et al. (2004). Large-scale *in-situ* measurement of LAI is almost impossible due to the disadvantage of being extremely time-consuming and/or labour-intensive (Jonckheere et al., 2004). Remote sensing of vegetation spectral information acquired from moderate resolution optical sensors provides an alternative way of observing canopy LAI, and extended the LAI observation process from the regional to global scale (Buermann et al., 2001; Tian et al., 2004). Datasets such as CYCLOPES (Baret et al., 2007) and GLOBCARBON (Deng et al., 2006) from Satellites Pour l'Observation de la Terre or Earth-observing Satellites (SPOT/VEGETATION) since 1998; Moderate

Resolution Imaging Spectroradiometer LAI (MODIS LAI) from TERRA-AQUA sensors since 2000 (Yang et al., 2006) report the global vegetation LAI.

Among all the global LAI products derived from remote sensing, the MODIS LAI dataset is one of the most widely used (Hill et al., 2006; Fang et al., 2008). Compared with the value of other vegetation indices which vary with soil conditions (Fang et al., 2015), local viewing and illumination conditions (Los et al., 2005; Galvão et al., 2013; Croft et al., 2014) and canopy structure (Croft et al., 2014), MODIS LAI reduces these effects by taking the canopy and scene geometry specifications into account when estimating (Jensen et al., 2011). Therefore, MODIS LAI changes, especially time-series MODIS LAI changes, are suitable and consistent for the detection of vegetation status changes. It is widely used and extensively validated around the world (De Kauwe et al., 2011). It expands our capability to estimate and monitor the biophysical characteristics of vegetation across a relatively large area with high geolocation accuracy (Gitelson et al., 2007). By comparing the LAI of two different catchments in South Africa, Palmer and Bennett (2013) use MODIS LAI to identify the grassland degradation of communal grasslands; Bobée et al. (2012a) reported the seasonal dynamics of grasslands by the employment of time series MODIS LAI observations. Mayr and Samimi (2015) further validated the consistency of MODIS LAI by comparing the spatial patterns of field-measured LAI, LAI derived from High-Resolution RapidEye Imagery and MODIS LAI.

MODIS LAI retrieval techniques are mainly based on the spectral and angular sampling of the radiation field reflected by vegetation canopies. The LAI values of MODIS data depend on biome-specific properties; it was derived based on a global-scale 3D radiative transfer model (Knyazikhin et al., 1998a). It provides the best fit LAI to measured data by considering background effects (soil reflection), and biome-specific spectral and angular information for vegetation (Knyazikhin et al., 1998b). This approach minimises the number of unknowns when solving the inverse problem of retrieving LAI from the atmospherically corrected and bidirectional reflectance distribution function (BRDF) corrected MODIS spectrum 1–7 (Myneni et al., 2015). The main Look-Up-Table (LUT) uses the spectral information of the red (648 nm) and near-infrared (NIR, 858 nm) bands, and a backup algorithm uses the empirical relationship between Normalized Difference Vegetation Index (NDVI) and canopy LAI (Myneni et al., 2015). Together they generate the LAI averaged over all acceptable solutions. If no solution exists, a backup routine using biome-specific conversion algorithms for the vegetation index is applied for LAI. A detailed description of MODIS LAI modelling can be seen in Fensholt et al. (2004); Knyazikhin et al. (1998a); and Myneni et al. (2015).

However, the remote sensing derived datasets are affected by noise caused by aerosols and bidirectional reflectance distribution factors (Sakamoto et al., 2005). The MODIS estimation algorithm may fail, and an empirical LAI would generally be used to fill pixels where this is the case. For example; radiation is strongly affected by clouds, meaning the MODIS LAI needs to be reprocessed before use. Thus, noise reduction is necessary before phenophase can be detected correctly.

Yet due to the presence of cloudiness and seasonal snow, instrument problems and other issues, there are lots of gaps and noise in the data which make the “good quality” data discontinuous and inconsistent in space and time-series, and limits the potential for identifying the amount of LAI grazed by livestock. Numerous researchers have looked at noise reduction methodologies, such as polynomial transformation and median filters (van Dijk et al., 1987; Popescu et al., 2003), locally adapted moving windows (Jönsson and Eklundh, 2004), Temporal Window Operations (PARK et al., 1999), logistic curve fitting (Zhang et al., 2003a; Bradley et al., 2007) and The Best Index Slope Extraction (Viovy et al., 1992). These improved LAI are widely used for a broad view of pixel-specific vegetation dynamics at both regional level (Bobée et al., 2012b; Jin et al., 2017) and global level (Zhang et al., 2017).

However, when looking into the vegetation dynamics for each time period in grazing monitoring, the improved LAI dataset has the disadvantage that it demolishes the original grazing information through spatiotemporal averaging (Hansen et al., 2003; Fang et al., 2008; Xiao et al., 2011; Yuan et al., 2011; Zhang et al., 2012; Liu et al., 2017). In the context of grassland, especially in intense grazing areas (Gignoux et al., 2001), the grazing-led LAI changes caused by livestock grazing could have a significant effect on the quantity and quality of grass productivity (Matches, 1992). None of these noise reduction techniques can be applied in grazing information extraction related processing at Zeku, or, indeed, any other area where grazing is important in calculating carbon cycling. Remote sensing data can only capture the time period status of vegetation, rather than the whole process of vegetation development; nevertheless, improvements can be made. Ignorance of the grazing activities that may cause LAI change can lead to underestimates or otherwise incorrect assessments of grassland Net Primary Productivity (NPP), especially in NPP based carrying capability calculations in grazing intensive regions (Lebert et al., 2006; Nyima, 2015).

In addition, grazing is considered to be the most influential factor for grass biomass dynamics (Numata et al., 2007). By using tracking data recorded by GPS, remote sensing has been employed to quantify grazing intensities by Kawamura et al. (2005), and this work suggested a poor negative correlation ($R^2 = 0.217$, $P < 0.01$) between remote sensing estimated plant biomass as conducted currently and grazing intensities (Kawamura et al., 2005). This represents an important unknown in grazing information, yet it is clear from grazing studies that all year round grazing is detrimental to vegetation and has led to pasture degradation compared with a winter grazing only pasture (Kayhko and Pellikka, 1994).

Grazing may directly lead to the change from green land to bare land, and a grazing-led LAI change could be observed in the grass growth season (Miller-Goodman et al., 1999; Tsalyuk et al., 2015). The LAI value of land patches will generally be underestimated due to the LAI consumption by herbivores (in this thesis, mainly livestock), especially in grazing intense areas (Gignoux et al., 2001). The ignorance of the effect of herbivore removers of vegetation is acceptable on a global scale of vegetation carbon assimilation or fixation, especially in forest areas, where herbivores contribute little to the plant LAI fluctuation. Nevertheless, in the context of rangeland, especially in intensive grazing areas, the grazing-led LAI changes could have a significant effect on the quantity and quality of grassland productivity.

In fact, some researchers have even argued that grazing coupled with climate change are the main factors contributing to regional grassland degradation and even desertification (Dean et al., 1995; Harris, 2010). It may directly lead to the change from green land to bare land, and under those circumstances, it is expected that a rapid decrease of LAI would be observed even in the grass growing season. Considering the problem, it is of great importance to identify the spatial distribution and quantity of grazing-led LAI changes on grassland. The basic concept associated with extracting grazing information from remote sensing is similar to that of other land observations or monitoring, that is, *"identify and measure easily observed (via remote sensing) features that are related to more complex features or phenomena that a range scientist or manager wishes to identify, measure, and judge the significance of "* (Tueller, 1989).

The aim of this chapter is therefore to estimate the grazing-led LAI changes by the employment of MODIS LAI datasets. However, the information we have from MODIS LAI datasets is very limited with regards to extracting the exactly grazing-led LAI changes directly, which is the crucial indicator that would be used in guiding sustainable grazing pasture management; therefore, we need to explore further within those datasets to estimate grazing-led LAI changes at each satellite observation interval. There are two main difficulties directly or indirectly related to the MODIS LAI datasets:

- MODIS LAI datasets are inevitably affected by clouds or other modelling error (Myneni et al., 2015). When we only use "good quality" data, the other pixels (non-good quality) make the dataset discontinuous. We need to pre-emptively decide how to fill these "non-good quality" pixels reasonably and consistently in a manner that is best for estimating grazing-led LAI changes on grassland.
- How to estimate the grazing-led LAI changes during the grass growing season based on the LAI after grazing observed by MODIS. This depends on how we calculate expected LAI before grazing. For a specified pixel, both the effect of current grazing and previous grazing should be considered simultaneously.

To solve these two problems, we need to develop a new integrated growth grazing function that can describe seasonal growth cycles of the grass LAI under grazing. By fitting the new growth-grazing function to reliable data, the gaps of the MODIS LAI data will be filled in a reasonable fashion. The MODIS LAI datasets will be used for the estimation of grazing-led LAI defoliation by using the new growth function in Section 5.4.

The rest of this chapter deals with time-series MODIS LAI changes during the summer growth period of the grass, which is the green grass period as the LAI is based on the greenness of the plants (Kang et al., 2003). The GlobalLand30 (Yu et al., 2014) data is used to extract grassland information. Due to the relatively tiny changes of land use/cover in Zeku from 2000 to 2010 (see Chapter 3), we assume the land use/cover has not changed during the estimation period (2003~2012). The estimation algorithm discussed in Section 5.6.3 is used to calculate grazing-led LAI changes for every 8 days. Then this estimation will be used to fit the new growth function (Section 5.4), based on which the improved (including grazing) and expected LAI (assuming no grazing) is to be estimated. Finally, rotational grazing, continuous grazing and un-grazed pixels will be distinguished according to the grazing frequency of estimated results. Since there is no direct data to validate the estimation of grazing-led LAI changes, we use two indirect ways to validate it (one is discussed in this chapter, the other will be discussed in next chapter).

5.2 Overall framework

Estimation of grazing-led LAI changes is mainly based on the MODIS LAI datasets of grasslands for Zeku. The framework of grazed LAI estimation during the summer growing season is shown in Figure 5.1.

After extracting the grassland LAI for Zeku based on MODIS LAI and GlobalLand30 land use/cover datasets from 2003 to 2012, the “good quality” LAI data (unaffected, for example, by cloud) were retained by setting the LAI value of “non-good quality” pixels to “NA”. The retained “good quality” LAI data are not continuous over the 46 observations taken during the year (see below) due to the “NA” settings. This chapter focuses on the grass growth period for the estimation of grazing-led LAI changes. The value of LAI basically stays the same during the winter period (remote sensing can reflect little grass information in winter, due to the grassland burning in Zeku, the LAI value mainly reflects a constant soil information value) for grassland in Zeku. The first work is then to detect the phenophase of the grassland in Zeku. A change detection technique was employed to estimate the starting date and end date of the grass growing season. The initial background LAI (mainly soil information) can be calculated after phenophase detection.

A new grass growth function is developed to describe the growth of grass under grazing. In order to fit this new growth function, the initial background LAI, current LAI (MODIS “good quality” LAI) and the expected LAI (LAI before grazing with the effect of the previous grazing) need to be determined. An estimation algorithm is then developed to extract the value of expected LAI for each pixel, which considering both current grazing and the effect of the previous grazing. Finally, by curve fitting, an improved LAI and expected LAI would be produced. The grazing-led LAI changes are then the difference between expected LAI and improved LAI. The rest of this chapter will outline the fitting of the new growth function. But first, we will introduce the conventional growth function and the new growth function:

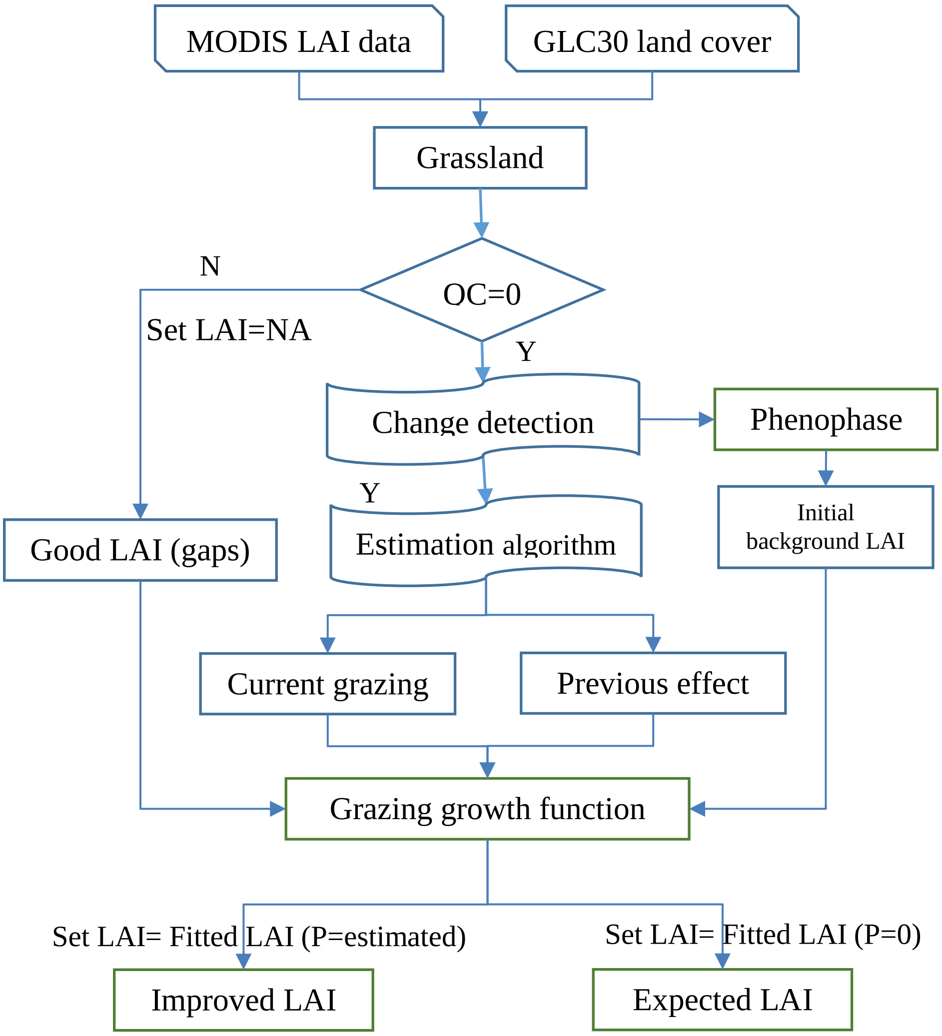


Figure 5.1: Concept framework for quantifying grazing-led changes in Zeku, China

5.3 Conventional growth function

Growth functions are widely used in biological science. Most commonly, the simple exponential growth function and the logistic growth function are the two widely used empirical models in plant growth (Thornley and Johnson, 1990). With empirical statistical fitting, they can reflect the smooth growth of plants easily; but like the other empirical models, conventional growth functions have a common drawback: they can only deal with a theoretical smooth growth of plants. When the plant growth is affected by external events (grazing or mowing), the statistical fitting of such data will lead to relatively high modelling errors. Therefore, it is difficult to deal with situations where current plant growth is affected by grazing or mowing that took place some time ago. Researchers have reported that these factors could produce a totally different growth rate (Grant et al., 1983; Thornley and Johnson, 1990). Figure 5.2 shows three growth phases of a perennial plant. The conventional growth functions work well with Phase I and Phase II, which follows a logistic or exponential growth curve. The basic forms of conventional growth functions can be summarised as the following equations:

$$\boldsymbol{dW}/_{\boldsymbol{dt}} = \boldsymbol{\mu W} \qquad\qquad \rightarrow \boldsymbol{W} = \boldsymbol{W_0 e^{ut}}$$

Eq. 5-1

$$\text{or} \quad \boldsymbol{dW}/_{\boldsymbol{dt}} = \mathbf{\mu W}\left(\mathbf{1} - \boldsymbol{W}/_{\boldsymbol{W_{max}}}\right) \rightarrow \mathbf{W} = \boldsymbol{W_0 W_{max}}/_{\boldsymbol{W_0} + (\boldsymbol{W_{max}} - \boldsymbol{W_0})\boldsymbol{e^{-ut}}}$$

Eq. 5-2

where W is the current plant LAI and t is the current time, W_0 is the initial value of W, W_{max} is the final value of W.

However, in many cases, especially when dealing with LAI data derived from remote sensing, the above functions cannot explain the growth behaviour at Phase III, where defoliation or senescence dominates the plant development process. This is because, in general, in the above growth equations, the growth rate only depends on the current vegetation status; it could never be negative to represent when senescence or defoliation is dominating the plant development. This is the key reason for the consequent difficulties when interpreting the modelling results. This is a well-known issue; for example Parsons, Schwinning and Carrère (2001) highlight that "*using a logistic growth curve that is empirically based on data from infrequent severe defoliation can ironically lead to the interpretation that greatest yields would be achieved using continuous lenient grazing*". In addition, the statistical fitting process will diminish the effect of grazing or mowing, and lead to unreasonable explanations for the growth of plants in some circumstances.

Considering the fact that grass development is highly related to defoliation in the near past, Schwinning and Parsons have therefore modified the logistic growth function (Eq. 5-2) by introducing a patch state factor after the last defoliation (Schwinning and Parsons, 1999), which is an important step forward in integrating grazing-led defoliation into the model. This modified grass growth function can be expressed by the following equation:

$$\boldsymbol{dW}/_{\boldsymbol{dt}} = \boldsymbol{\mu W}(\mathbf{1} - \boldsymbol{W'}/_{\boldsymbol{W_{max}}})\left(\mathbf{1} - \boldsymbol{W}/_{\boldsymbol{W_{max}}}\right)$$

Eq. 5-3

with W' standing for the initial condition for regrowth after the last defoliation (the regrowth factor). When $W' \rightarrow 0$, this equation is just the same as a conventional logistic function. Under other conditions, the growth rate can be affected by the regrowth factor W' as well. The difficulty that appears when using this equation is how to collect W' data, as it is assumed as a "pre-known" constant value for each time interval. There is still no perfect solution for W' determination yet; lab experiments are generally unrealistic, while remote sensing methods are unable to derive this regrowth factor after defoliation as they can only capture the final status of grass under grazing.

5.4 New growth function under grazing

One way to estimate the grazing-led LAI change is to estimate the full growth curve and compare it with the recorded one. For years, researchers have been devoted to finding a simple function that describes the basic characteristic of plants' growth. For perennial grasses, which are the dominant species in the Zeku, Qinghai-Tibet area, the LAI dynamics during the year can be described by a curve with three growth stages (Figure 5.2). This can be observed both in field measurement (Hoffmann et al., 2005) and by remote sensing (Garrigues et al., 2008; Xiao et al., 2011). In this chapter, a new empirical growth function will be discussed that models the dynamics of LAI. It considers both the growth and defoliation of a plant, as well as the effect of grazing. The estimation process starts by identifying the grazing-led LAI changes caused by livestock during the grass growing season for each 8-day period; the parameters of this new growth function for each pixel being fitted by the employment of the MODIS LAI dataset.

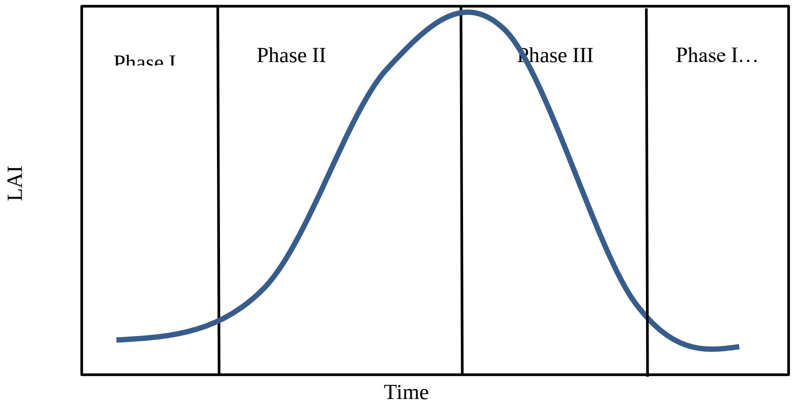


Figure 5.2: LAI during a regrowth follows a bell curve as the canopy develops from low LAI (Phase I: low LAI increase rate) to maximum LAI (Phase II: high increase rate, growth dominated) and then to low LAI again (Phase 3: high LAI decrease, senescence dominated).

The defects of a conventional growth function when describing the live grass mass accumulation can be summarised as:

- senescence factor is totally ignored;
- the lack of parameters representing the grazing effect on growth.

A feasible way to deal with those problems is to add senescence defoliation (leaf changes colour from green to yellow) and grazing-led defoliation coefficient to the exponential growth function according to the nature of plant development. In this way, the whole processes of plant development can be described appropriately in one function. The ordinary exponential growth function is detailed in Thornley and Johnson (1990). When considering livestock grazing, the new function can be expressed as:

$$\boldsymbol{\frac{d(L_t+G_t+GB_t)}{dt} = k_1(L_t+G_t+GB_t) - k_2(L_t+G_t+GB_t)t}$$

Eq. 5-4

Where L_t is the current LAI that can be observed; G_t is the grazing-led LAI loss; GB_t is the previous grazing effect on current LAI. $k_1(L_t+G_t+GB_t)$ represents the current total growth rate, which is proportional to the current LAI, this is widely examined in ecological related studies (Johnson and Thornley, 1983; Thornley and Johnson, 1990); while $k_2(L_t+G_t+GB_t)t$ represents the total senescence rate, and is proportional to the current LAI. Notice that it takes the time as a weight; $\mathrm{f}(t)=t$, and is calculated in a time-dependent manner; the total senescence rate is linear to time t, this is according to the observations from Borrás et al. (2003) and Leopold et al. (1959); although this relationship may be linear or non-linear across plant species, this chapter uses linear for simplicity. There is an improvement that can be made to the function, which is that, given the quantity of growth is the effect of growth and senescence combined, that growth is proportional to its current LAI (L_t); equally, senescence rate can be related to both current LAI (L_t) and time t; it can be written as:

$$\boldsymbol{\frac{d(L_t+G_{t+GB_t})}{(L_t+G_t+GB_t)} = (k_1 - k_2 t)dt}$$

Eq. 5-5

To integrate this equation, it is written as:

$$\boldsymbol{\int_{L_0}^{L_t} \frac{d(L_t+G_{t+}+GB_t)}{(L_t+G_t+GB_t)} = \int_0^t (k_1 - k_2 t)dt}$$

Eq. 5-6

where $\mathrm{L(t = 0)} = L_0$ is the initial LAI. This equation now can be solved to have:

$$\boldsymbol{ln \frac{(L_t+G_t+GB_t)}{(L_0+G_0+GB_0)} = k_1 t - k_2 t^2}$$

Eq. 5-7

in fact, at the start, $G_0 = GB_0 = 0$, and therefore we have:

$$\boldsymbol{\frac{L_t+G_t+GB_t}{L_0+G_0+GB_0} = \frac{L_t+G_t+GB_t}{L_0} = \frac{L_t+G_t+GB_t}{L_t} * \frac{L_t}{L_0} = \frac{1}{P} * \frac{L_t}{L_0} = \frac{L_t}{PL_0}}$$

Eq. 5-8

where P is defined as the percentage of LAI or live mass which has been observed (remaining LAI after grazing):

$$\boldsymbol{P_t = \frac{L_t}{L_t+G_t+GB_t}}$$

Eq. 5-9

Substituting Eq. 1.8 into the integrated growth equation Eq. 1.7 , we can get:

$$\boldsymbol{L_t = L_0 P e^{k_1 t - k_2 t^2}}$$

Eq. 5-10

this is the basic form of the new growth model. When using it, an initial LAI value is set in L_t– it is more convenient to have an initial background value (L_m, or background value) in the function when fitting the observed data; in fact $L_t = L_{observed} - L_m$, thus, it becomes:

$$\boldsymbol{L_{observed} = L_m + L_0 P_t e^{k_1 t - k_2 t^2}}$$

Eq. 5-11

We additionally define

$$\boldsymbol{PB_t = \frac{GB_t}{L_t + G_t + GB_t}}$$

Eq. 5-12

$$\boldsymbol{PG_t = \frac{G_t}{L_t + G_t + GB_t}}$$

Eq. 5-13

where PG_t is the percentage of current grazing-led LAI change, PB_t is the effect of previous grazing on LAI change. Then we can have the following relation between PB_t, PG_t and P_t:

$$\boldsymbol{P_t = 1 - PB_t - PG_t}$$

Eq. 5-14

Substituting this into Eq. 5-11, we have the final equation:

$$\boldsymbol{L_{observed} = L_m + L_0(1 - PB_t - PG_t)e^{k_1 t - k_2 t^2}}$$

Eq. 5-15

and usually, $L_m = L_0 = \min\{L_t\}$.

Notice that at the start point, when t=0, the value of the exponential part would be 1, and the observed LAI $L_{observed}$ would be double the initial background value, which is not true in real-world situations. Therefore, when using this function to fit against the observed data, a mitigate constant variable C, needs to be added to the exponent part of the function to adjust growth and senescence of grass:

$$\boldsymbol{L_{observed} = L_m + L_0(1 - PB_t - PG_t)e^{k_1 t - k_2 t^2 + C}}$$

Eq. 5-16

where C is an empirical parameter to be estimated, and the value of C can be estimated through the non-linear fitting of this equation against the “good quality” MODIS LAI data. In general, this new growth-grazing function can improve the accuracy of the regression coefficient if we intend to find a curve across the sample points that match as reasonably as possible. This new growth-grazing function is not enough alone; it needs to be accompanied by a grazing-led LAI change estimation algorithm (step 1~4 in Section 5.6), which will be discussed in Section 5.6.3, where PB_t and P_t will be calculated.

The next sections outline the components of a curve fitting procedure with regard to this new growth function; this procedure following the framework in Figure 5.1.

5.5 MODIS LAI and GlobalLand30 data processing

The LAI datasets here were gathered from the MODIS collection 6 LAI (MOD15A2H006). Similar to the other remote sensing derived products, LAI is affected by off-nadir viewing, sun angle, background material reflectance and atmospheric aerosols; in addition, LAI has an asymptotic or saturation response to high levels of plant densities (Tucker et al., 1985a). To solve this problem, there is a quality control (QC) value stored as 8 bits of data (Figure 5.3) for each pixel (here about 463×463 m²) in MODIS LAI data. The unit of the LAI is m^2/m^2, and the scale factor is 0.1 (meaning the real value is 10 times than that of the MODIS LAI data recorded). The MODIS LAI products use the Sinusoidal grid tiling system (Figure 5.3). Tiles are 10 degrees by 10 degrees at the equator. The origin of this tile coordinate system is (0, 0) (horizontal tile number and vertical tile number) in the upper left corner and proceeds right (horizontal) and downward (vertical). The tile of the case study area is (26, 5).

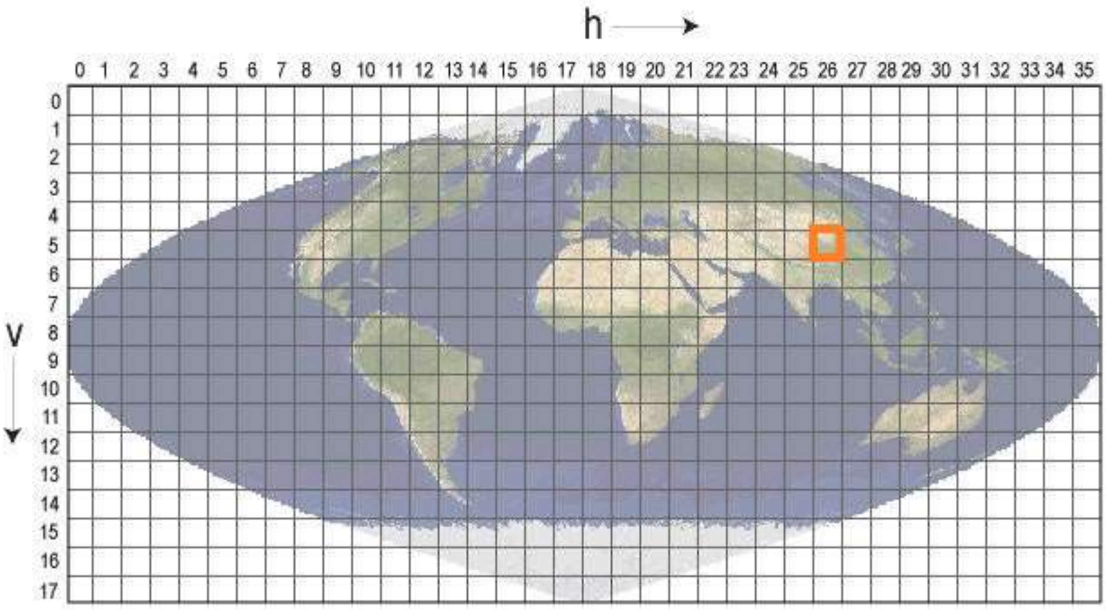


Figure 5.3: Sinusoidal Tiling System and the tile of Zeku (red box), figure modified from Myneni et al. (2015), page 5

Table 5.1: MCD15A2 quality control (QC) definition (from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd15a2)

Bit	**Parameter**	**Bit**	**FparLai_QC**
0	MODLAND_QC bits	0	Good quality (main algorithm with or without saturation)
		1	Other Quality (backup algorithm or fill values)
1	Sensor	0	Terra
		1	Aqua
2	DeadDetector	0	Detectors apparently fine for up to 50% of channels 1,2
		1	Dead detectors caused >50% adjacent detector retrieval
3–4	CloudState (inherited from Aggregate_QC bits {0,1} cloud state)	00	0 Significant clouds NOT present (clear)
		01	1 Significant clouds WERE present
		10	2 Mixed cloud present on the pixel
		11	3 Cloud state not defined, assumed clear
5–7	SCF_QC (five level confidence score)	000	0, Main (RT) method used, best result possible (no
		001	1, Main (RT) method used with saturation. Good,very usable
		010	2, Main (RT) method failed due to bad geometry, the empirical algorithm used

	011	3, Main (RT) method failed due to problems other than geometry, empirical algorithm used
	100	4, Pixel not produced at all, value couldn't be retrieved (possible reasons: bad L1B data, unusable MODAGAGG

In this chapter, only the data with QC=0 are used in order to avoid introducing any further uncertainties or errors to the model. In the MODIS LAI dataset, we have LAI observations every 8-day period which in total is 46 observations each year; these are the "best" pixel available from all the acquisitions of the Terra sensor from within the 8- day period. The average percentage of the number of “good quality” (QC=0) pixels to the total number of grassland pixels is shown in Figure 5.4; the average ratio is 81.52% for Zeku during 2003~2012. The time range of the dataset is from 2003 to 2012. Figure 5.5 shows a single pixel example of a QC=0 LAI time series at one pixel in Zeku, where we can see the obvious discontinuity when only QC=0 is used. Different colours represent different years. We can see the maximum values of LAI for these years are different, and the “gaps” caused by “non-good quality” settings occur at various dates of the year. The first problem of grazing information extraction when using MODIS LAI data is how to fill in these “gaps” reasonably and accurately. But before doing so, a basic understanding of the profile of the grassland grazing in Zeku is needed.

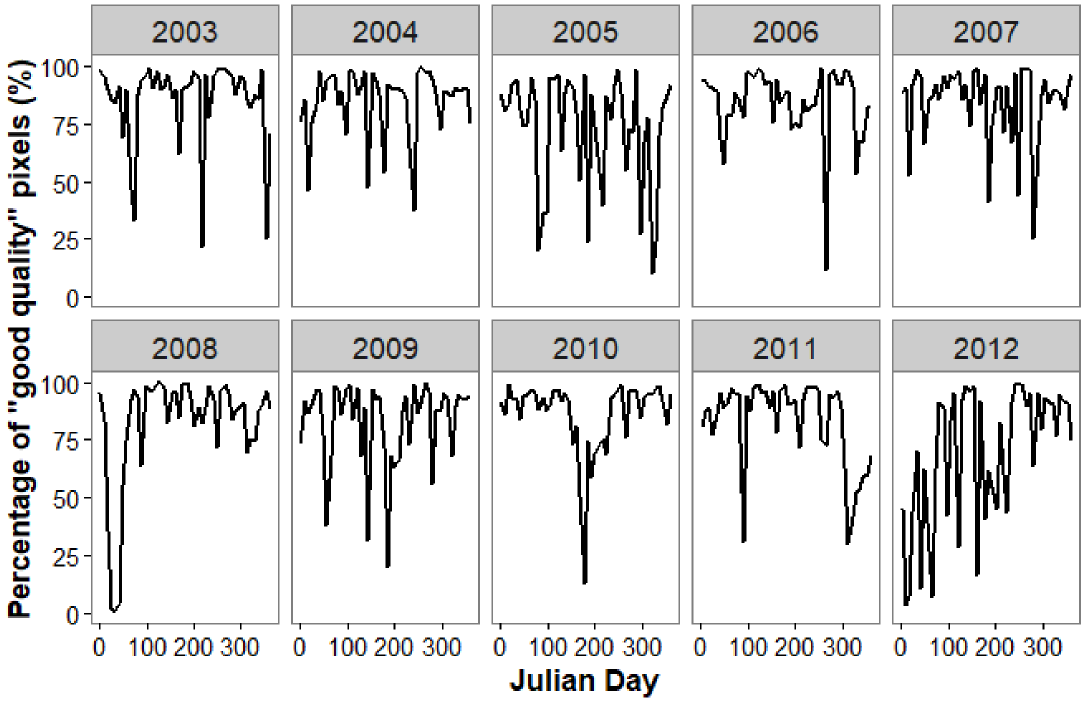


Figure 5.4: Percentage of “good quality” (QC=0) pixels for MODIS LAI in Zeku, China

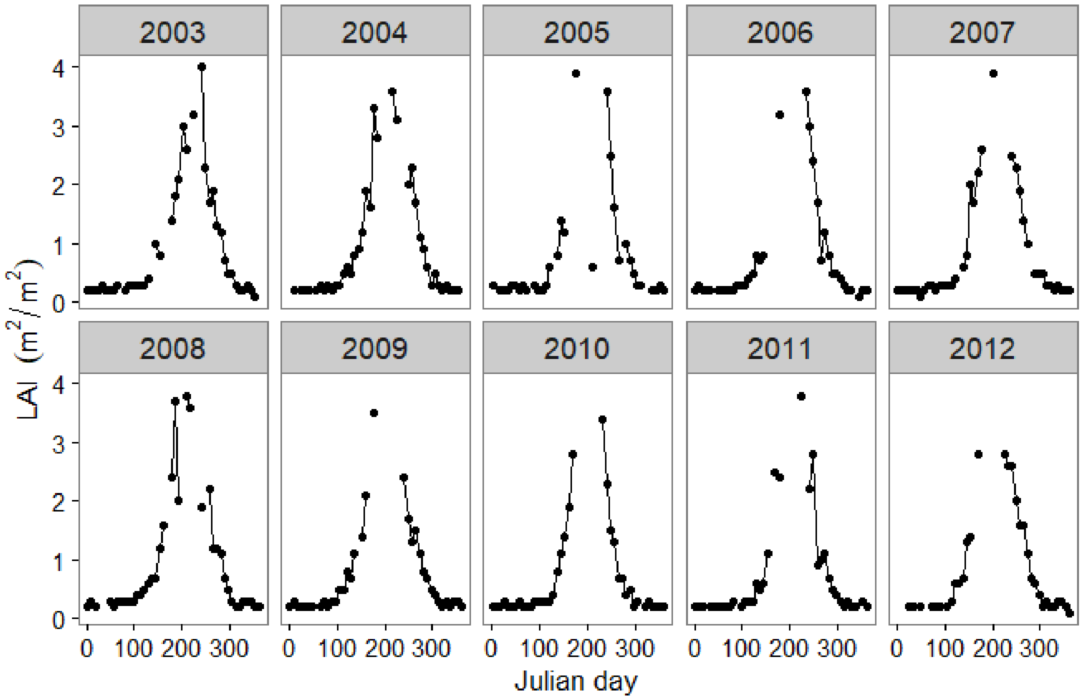


Figure 5.5: **An example of discontinuous time-series LAI**

Since there is no exact spatial boundary data of the distribution of winter and summer pasture lands, a field survey was conducted by the Centre for Chinese Agricultural Policy, Chinese Academy of Science in 2012 (Table 5.2), see Chapter 3, with the purpose of understanding the impact of climate change on herdsman' daily life and the local environment in The Three Rivers Head Source Region in China. As noted in Chapter 3 in Zeku, there were 52 field survey records, the main big livestock was yak, sheep and horse (Figure 3.6 panel 1), with the horse only used for transportation purposes. Horses are an important vehicle for herdsman riding for grazing, and thus, there are no horses sold during the year (Figure 3.6 panel 3). Although there are other large wild herbivores existing in Zeku, due to their small population size, this thesis only considers yak, sheep, horses and cows as grassland foragers.

After 2003, all the land patches were contracted to the herders (as discussed in Chapter 3), so we can assume nomadic grazing does not exist in Zeku County. The basic land patch statistics from the field survey data are shown in Table 5.2. The average summer pasture area is about 0.22 km^2, which means the average area of land patches in Zeku is a little bit greater than the MOD15A2H006 pixel cell area (0.21 km^2), but if the herders join the ecological economic cooperation grazing group (group grazing), the total area of the group is much bigger than a pixel cell area. This group grazing area then becomes rotational grazing pasture land during the grass growth seasons.

Table 5.2: Winter and summer pasture land area from field survey data, Zeku, 2012[1] (unit: km², the total pasture and group data are from Livestock Husbandry Bureau of Zeku)

	households	total area	Mean area	percentage
Winter pasture	51	9.33	0.18	44.84%
Summer pasture	53	11.48	0.22	55.16%
Total pasture	13504	5409.77	0.40	--
cooperative pasture	5147	1501.80	0.29	--

Other important information is the land use/cover status. It is important that if there are severe land use/cover changes during the estimation years in Zeku, the land use/cover status should be updated accordingly with the estimation of the year's changes. The land cover data is from the 30 meters Global Land Cover dataset (GlobalLand30). The overall classification accuracy reaches 83.51% (Kapaa= 0.78). Specifically, the accuracy for grassland is 76.88%. The coordinate system is WGS84 (UTM Projection) (Chen et al., 2015). As it is organized in tiles, four of the tiles are downloaded to cover the extent of Zeku County (tile numbers are: N47_30_2010LC030, N47_35_2010LC030, N48_30_2010LC030 and N48_35_2010LC030). After mosaicing, re-projection and extraction, the data is resampled to about 463m spatial resolution by the majority percentage principle (same as the MOD15A2H006 LAI dataset). It is assumed that the land cover type has not been severely changed during the modelling period (see the land use/cover change analysis in Chapter 3).

5.6 Processes for grazing-led LAI changes estimation

The estimation of grazing-led LAI changes consists of four steps: phenophase detection, calculation of initial background LAI, preliminary estimation of grazing-led LAI changes and the fitting with the new growth function. This section will elaborat on each step by detail.

5.6.1 Step 1: phenophase detection

The first element of the analysis is identifying the grass growth period. To do this, we utilise change point detection, applied to the 8-day MODIS LAI data time series. The change point detection is to identify the location of change (single or multiple) in the statistical properties of a sequence of observations that change in the series data. In fact, identifying the phenological stages of plants can facilitate the estimation of plant growth under various regional climates (Sakamoto et al., 2005;

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[1] In order to understand the impact of climate change on herder's daily life and the local environment, the Centre for Chinese Agricultural Policy, Chinese Academy of Science had managed the investigation in Three Rivers Head Source Region in China, supported by the National Key Programme for Developing Basic Science (2012CB95570001), "the impact of climate change on key parameters of socio-economic system in typical regions", 气候变化对典型区社会经济系统影响的关键参数研究

Motohka et al., 2010). Advanced or delayed heating will result in obvious changes in plant productivity (Sakamoto et al., 2005). Based on the time series analysis of the vegetation index data, a trend has been found of earlier greening in the northern latitudes between 45° N and 70° N since 1981 (Myneni et al., 1997a). With climate data, the results of phenological stage detection based on MODIS LAI data can be improved (Kang et al., 2003).

Notice that there are 29423 valid pixels in Zeku on the 463m MODIS LAI map. Instead of identifying the change points for each of those pixels, the change points based on the mean values of those pixels are identified using change point detection technique. The results, therefore, contain the mean start dates and end dates of grass growth for the whole region. Changepoint detection methods are widely used to identify the location of the change in the statistical properties of a sequence of observations that change in time series data. The cost-penalty function is a commonly used method (Killick and Eckley, 2014) in identifying the change points. The change point approach is to minimize the value of Eq. 5-17:

$$\sum_{i=1}^{m+1} \left(C y_{(\tau_{i-1}+1)} : \tau_i \right) + \beta f(m)$$

Eq. 5-17

where C is a cost function for a segment, the log-likelihood is a commonly used cost function (Horváth, 1993); τ_i is the ith change point and the total number of change points is m; $y_{(\tau_{i-1}+1)} : \tau_i$ represent the ith segment, the $\beta f(m)$ is a penalty to guard against over fitting. This chapter uses the PELT method, which assumes the penalty is linear to the number of change points, that is, βf (m) = βm (Jackson et al., 2005; Killick et al., 2012), as a choice of penalty function with the Modified Bayes Information Criterion (Zhang and Siegmund, 2007). For this research, we need to identify the change point where the mean value of the ith segment has a maximum likelihood statistic which minimizes the value of the cost-penalty function. The change detection software used here is the R “changepoint” package developed by Killick and Eckley (2014).

At least two change points wound be expected according to Phase I in Figure 5.2: the beginning and end date for grass growth which makes the mean value of LAI of the segments divided by them have a maximum likelihood statistics.

The following figures (Figure 5.6) show the mean LAI distribution from 2003 to 2014, from which the most conservative change points were chosen as the start and end dates of the growth season. There is a basic symmetrical trend for each year. On the left side, all the figures basically fit logistic growth in which growth processes dominate, but after they reach the peak value, there is an obvious decrease of LAI for each year, which could be explained by senescence and/or defoliation processes. They are quite similar to Figure 5.2, but due to the effect of grazing, lots of fluctuations are present on the curves.

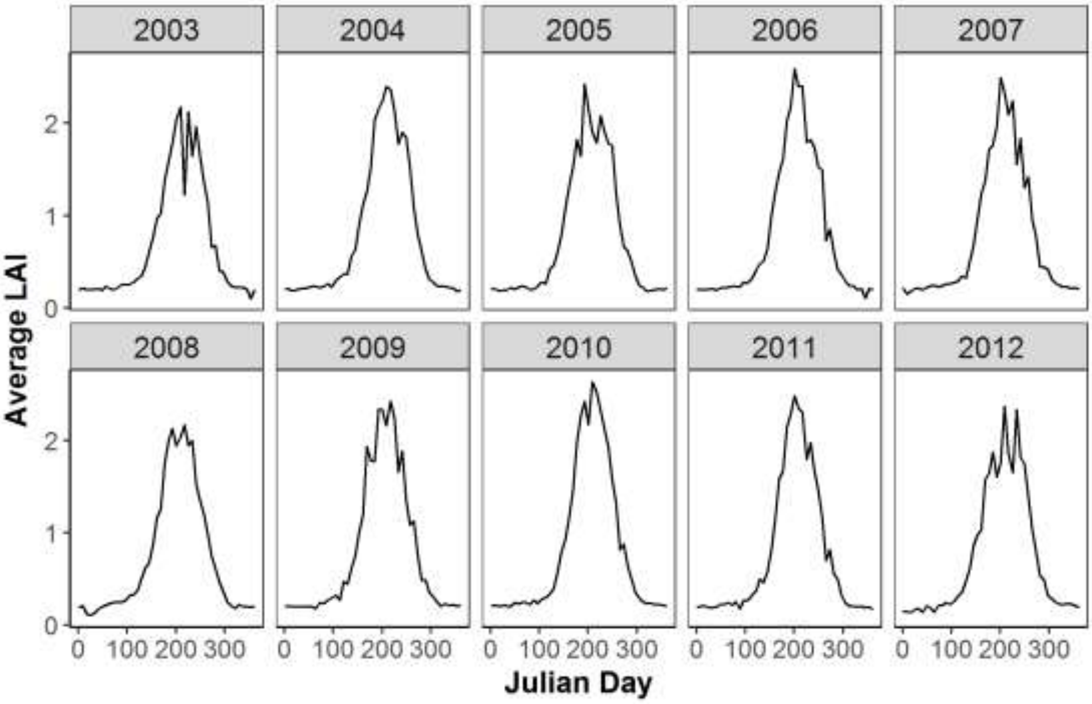


Figure 5.6: **Average MODIS LAI for each 8-days from 2003 to 2012 (QC=0)**

Figure 5.7 shows the results of change point detection, where the values of two neighbouring pixel-mean segments are significantly different from each other, and the most obvious phenomenon is that all the change points for each year are basically symmetric around the winter period. The change points are where the mean value of the two neighbours are changed such that the maximum likelihood statistics minimize the cost-penalty function. The most obvious phenomenon is that all the change points for each year start and end appear at the change from a stable to a rapid increase (for the beginning) and at the sharp deceleration to a stable level (for the end), indicating the start of the fast-growing period and the end of the rapid senescence period respectively. These points appear at a relatively fixed time and the LAI value during the year, we can see they can basically connect one line parallel to the x-axis. We can also see the peak growth point, where the maximum value of LAI is observed. There are other change points detected among the peak point and the first and last change point for each year; these are either represent the most fast growing season or the fast senescence season; but due to the effect of grazing, these points are not fixed at both time and LAI value. Considering this and based on the conservative principle, the minimum date of the first change point is chosen as the start day of the fast-growing season, and the maximum value of last change point is the start day of the senescence dominated period for the whole set of datasets.

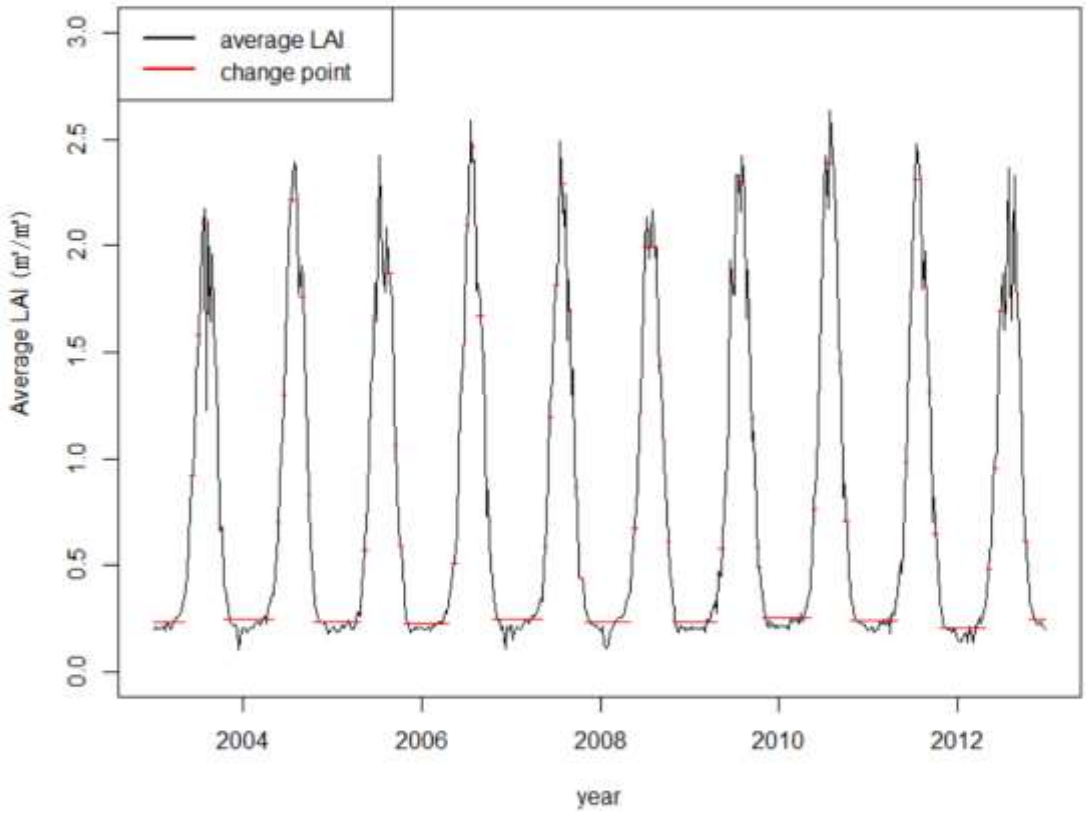


Figure 5.7: **Change points detection of the mean LAI values (QC=0) in Zeku, 2003-2014**

All the change points are also shown in Table 5.3. The start and end dates of the grass growth period are used to extract the modal value of MODIS LAI (taken from those points with QC=0) during the non-growth season (date 1-14 and date 37-46); which is taken as the initial value of LAI (or background LAI). The initial background LAI will be used to fitting our new growth function (see below).

Table 5.3: Detected change points of mean LAI (QC=0)

year	Change points (Julian Day)	Observation in the year
2003	137 169 185 209 217 241 265 281	18 22 24 27 28 31 34 36
2004	129 153 177 225 257 281	17 20 23 29 33 36
2005	129 153 185 201 249 265 289	17 20 24 26 32 34 37
2006	113 145 177 217 257 281	15 19 23 28 33 36
2007	129 145 169 193 225 257 273	17 19 22 25 29 33 35
2008	121 153 169 233 257 281	16 20 22 30 33 36
2009	113 145 161 185 225 241 273	15 19 21 24 29 31 35
2010	129 153 169 225 257 289	17 20 22 29 33 37
2011	145 161 177 217 257 289	19 21 23 28 33 37
2012	129 161 201 249 273	17 21 26 32 35
2013	137 153 169 193 225 249 281	18 20 22 25 29 32 36

2014	129 153 185 209 241 273	17 20 24 27 31 35
final choice	Start date{113}, end date{289}	Start date{15}, end date{37}

5.6.2 Step 2: Initial background LAI

After identifying the phenophase by using the change point detection technique, the first element of curve fitting, which is the initial background LAI, can be calculated using the LAI data during winter periods. The initial background values of LAI during the non-growth seasons are taken as constant in spite of the fluctuations (caused by the noise or error within the MODIS LAI data). Since the data used are the “good” quality LAI data (see Section 5.5), and all the unreliable or uncertain data are left as “gaps” in the time series LAI datasets; the initial background values of LAI should be observed during the non-growth seasons, and the majority of them should be the same (no greenness information can be detected by remote sensing during this period).

For global scale research, a series of calculation algorithms are generally integrated into the initial background LAI calculation schema (Yuan et al., 2011), which consists of a conditional multi-year average, TIMESAT SG filter, local per class mean, per class mean and multi-year per class mean. In addition, improved ecosystem curve fitting (VCF-ECF) has been proved a useful method when producing continuous field products (Hansen et al., 2003). A detailed comparison of these techniques can be found in Hird and McDermid (2009).

In fact, MODIS LAI product provides green vegetation green LAI (Myneni et al., 2002), the LAI in winter for perennial grass is more informative of the background environment (such as soil type), rather than the grass status. In the LAI studies, one assumption is to keep LAI the same during winter. For example, it may be assumed that there is not much change in LAI beyond the growing season and consequently LAI during this period can be set to be constant (Liu et al., 2002). Therefore, producing an LAI winter image for the non-growth season is a very common way to reprocess the LAI data (Simic et al., 2004). We can, therefore, take the mode of the LAI values during the non-growth season as the initial background LAI value, which is the starting LAI value (or background LAI value) for the year’s growth.

In addition, although we can use the mean value of LAI during the non-growth periods, individual plant phenology varies according to the different latitude or different land cover types **(**Zhang et al., 2003b**);** the results of grass phenophase in Section **5.5** is the average date of the start and end dates of all the pixels, which means it may be late for some pixels while too early for other pixels, the initial background value of LAI can vary spatially. If the initial background LAI is taken as the mean value of the LAI during the non-growth period detected in Section **5.5,** the results would be inaccurate for many pixels. Therefore, in this thesis, the modal value of MODIS “good” quality LAI is used as the initial background LAI**.**

5.6.3 Step 3: preliminary estimation of grazing-led LAI changes

The next step is to calculate the grazing-led LAI changes for each pixel preliminarily. The values of this calculation will be used to fit with the new growth function (PB_t and PG_t in Eq. 5-16). When comparing the LAI growth curve of rotational grazing, continuous grazing and no-grazing (where grass is preserved for winter use), the LAI curve should be exactly the same as the full growth curve in no-grazing pixels (Figure 5.2); while pixels of rotational grazing pixels should present a fluctuated profile (Figure 5.19). Despite expectations, during the fast growth period, the LAI value may be smaller than its previous value due to the grazing LAI defoliation. Utilising such features we can estimate the grazed LAI and the effect of previous grazing.

For each pixel, here we define

- full growth LAI as the theoretical LAI curve if there is no grazing (without the effect of previous grazing and current grazing);
- expected LAI as the LAI before grazing (with the effect of previous grazing but without the effect of current grazing); and
- observed LAI as the LAI after grazing (with the effect of current grazing and previous grazing, it is the LAI to be improved). The observed LAI is a time-series point data (46 points during the year).

When there is an adverse observed LAI value, we can calculate the expected LAI by the new growth function and compare it to that of observed LAI recorded. The field measurement of grazing treatment suggests that when grazing stops, grassland LAI can regrow to pre-grazing levels (Harrison et al., 2012; Jerrentrup et al., 2015). Taking this model, it is assumed that local maxima in the growth curves represent expected seasonal growth.

In addition, MODIS LAI was estimated associated with the day when the highest fraction of Photosynthetically Active Radiation (fPAR) was observed during every 8-day period, and those days have not been recorded in the MODIS LAI datasets. This thesis assumes an equal day's interval (8-days) starting on the last day. The uncertainty of the estimation of the grazing-led changes caused by such assumption will be further analysed in Section 5.10.2.

An illustration of how the grazing-led LAI change is calculated is shown in the following figure (Figure 5.8) and elucidated below:

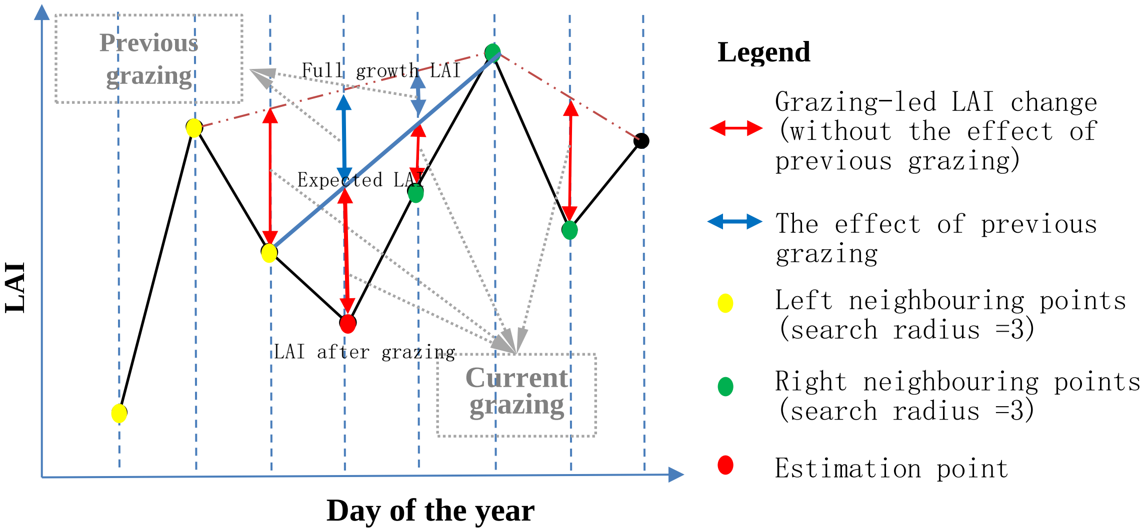


Figure 5.8: Illustration of grazed LAI estimation

For example, the red point in the figure represents the current estimation point i, yellow points are the left neighbouring points with neighbourhood radius 3 (For MODIS, the unit is an 8-day period), while the green points are the right neighbours. The grazed LAI is then the difference between expected LAI and observed LAI (arrowed red segments), the effect of the previous grazing on current growth is calculated by the difference of full growth LAI and expected LAI (arrowed blue segments). The algorithm can be summarised as:

- for each time slice point i (means ith observation recorded by MODIS LAI, i=1, 2…46), the time-series LAI points data is divided into its left neighbour points set (from point i-r to point i-1; r is the radii, ranging from 1 to 46, it is defined as the radii to search the neighbouring points for current estimation point) and right neighbour points set (from point i+1 to point i+r) by a predefined neighbourhood radius r. In this chapter, the radius is allowed to range from 1 to 21. The estimation algorithm will choose the radius which minimizes the root mean squared error (RMSE) for each pixel (see below).
- Search for the point with maximum LAI in the left neighbouring points set and right neighbouring points set separately (the left maximum LAI point $P_m = \max(P_{i-r}, \dots, P_{i-1})$ and the right maximum LAI point $P_n = \max(P_{i+1}, \dots, P_{i+r})$).
- Calculated the full LAI for point i, utilising the time difference as a weight,
  - ✓ if $P_m < P_n$, the full LAI is: $LAI_{full} = P_m + \frac{i-m}{n-m} * (P_n - P_m)$
  - ✓ if $P_m > P_n$, the full LAI is: $LAI_{full} = P_n + \frac{n-i}{n-m} * (P_m - P_n)$
  - ✓ if $P_m = P_n$, the full LAI is: $LAI_{full} = P_m = P_n$
- Calculate the difference between full LAI and observed LAI. If this difference is bigger than zero, calculate the observed percentage of LAI by: $P_i = \frac{LAI_{P_i}}{LAI_{P_i} + difference}$; if not, this percentage will be set to 100%.
- If the previously observed percentage of LAI P_{i-1} is smaller than 100% (means it has been grazed previously), change the left neighbour to point i-1, do step 3 and we can get PB_i (PB_t in Eq. 5-15); If not, set $PB_i = 0$.
- The estimation error can be evaluated by the sigma value of the nonlinear fitting of *Eq. 5-15*, which indicates the average fitting residual.

PB_i and $(P_i - PB_i)$ will be used as the input values for $\boldsymbol{PB_t}$ and $\boldsymbol{PG_t}$ in Eq 5-16 respectively, and the values of parameters (k$_1$, k$_2$ and C in Eq 5-16) can be estimated through non-linear fitting with Eq 5-16. One problem needs to be further clarified before we can use this estimation algorithm, that is, whether 8-days' time interval is a proper time to observe the effect of livestock grazing. The field measured LAI of grazing treatments in years 2007 and 2008 (Harrison et al., 2012) strongly showed that grass regrowth took 1~2 month depending on the duration and severity of livestock grazing recently (Figure 5.9). Sensitivity analysis of the regrowth duration of Guinea grass has found 55d was the best regrowth duration for the recovery of dry matter yield (Santos et al., 2014). As for the time of grazing (early or late grazing), the reserve-dependent growth function (Jing et al., 2012) was integrated into the CATIMO grass model (Bonesmo and Bélanger, 2002), which showed that regrowth happened on both early and late defoliation by cutting (cutting has the same effect as grazing, both are removers of leaves), and it took 1~3 months for the regrowth of grass to its previous state during the grass growing season (Figure 5.10). All of these field measurements and simulations showed that grazing would cause a direct and sharp LAI decrease. This is the basis for the remote sensing monitoring of livestock grazing on grassland. As long as the satellite observing time interval is frequent enough; ie. a shorter period than the regrowth time, the change of grazing-led LAI defoliation can be extracted from the time series LAI data.

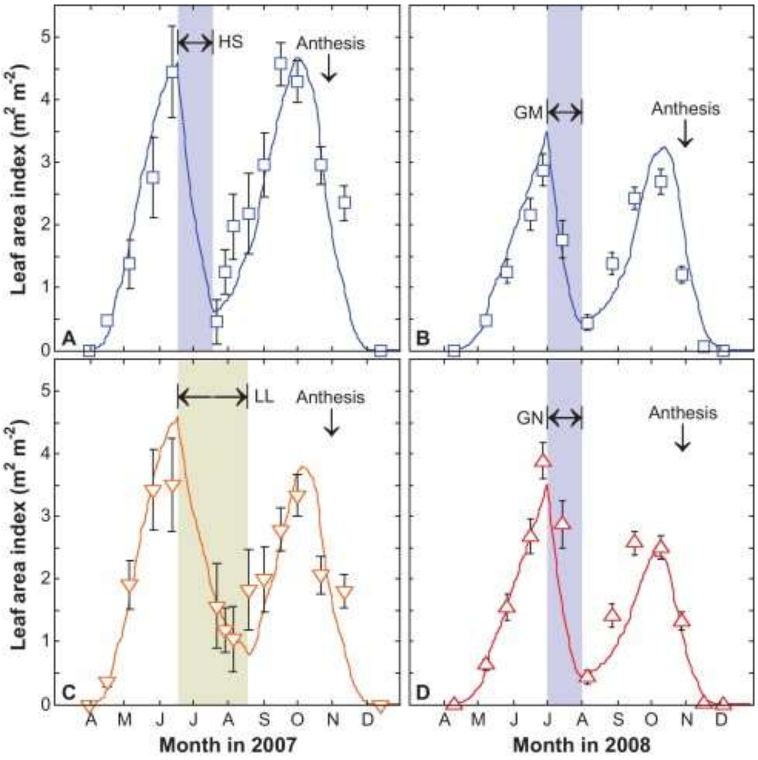
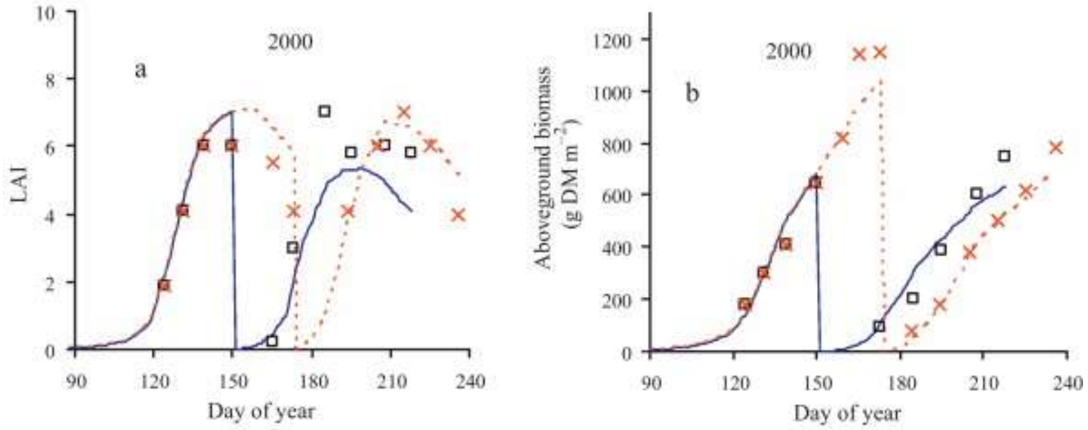


Figure 5.9: **Measured (points) and simulated (lines) leaf area indices of grazing treatments (A) HS, (B) GM, (C) LL and (D) GN during 2007 and 2008. Shaded regions represent the duration of grazing and vertical arrows show the observed dates of anthesis. Measured values are means ± one SEM (*n* = 3). Treatment abbreviations: GM, grazed Mackellar; GN, grazed Naparoo; HS, heavy short; and LL, light long. All grazing treatments were performed at 68 DSE ha^{-1} for 31 d, except LL which was performed at 34 DSE ha^{-1} for 62 d, figure from Harrison et al. (2012)**

Calibration



Validation

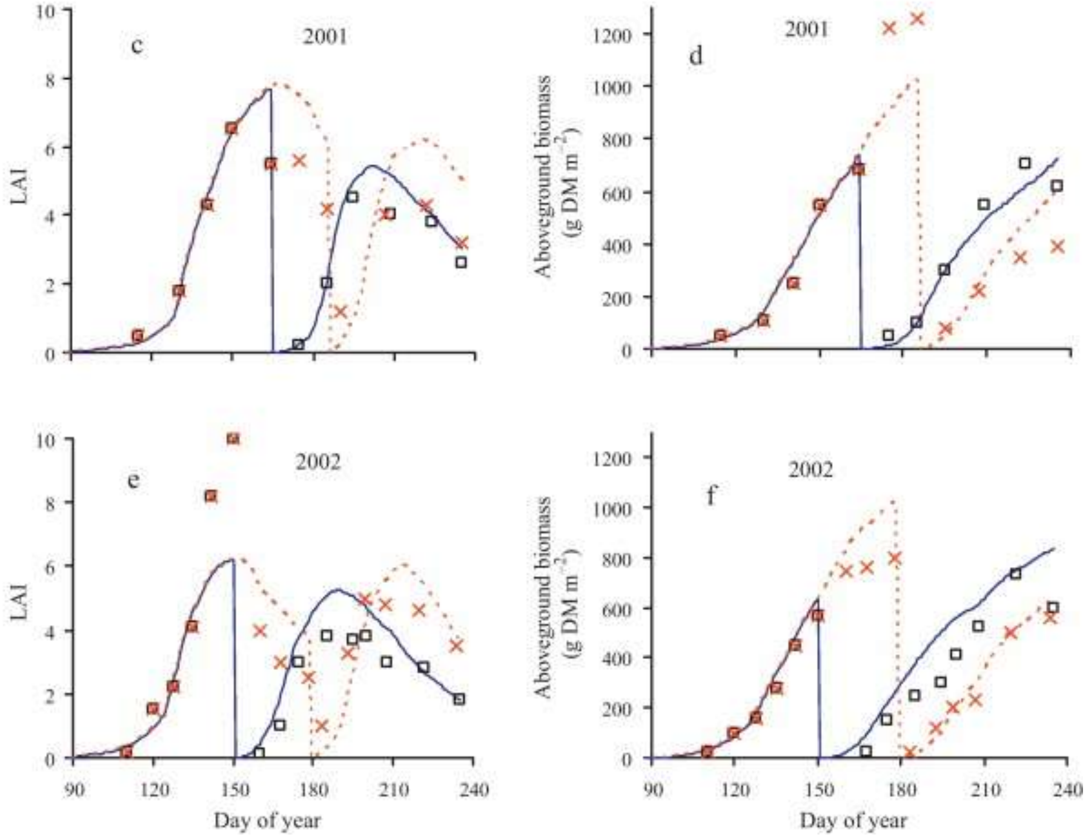


Figure 5.10: Simulated (lines) and measured (symbols) values of leaf area index (LAI, left) and aboveground biomass (right) versus day of year for the primary growth and regrowth of timothy with an early harvest (□, —) or a late harvest (×, - - -) in 2000 (calibration) and in 2001 and 2002 (validation) in Norway. This figure is from Jing et al. (2012) and data can be found in Höglind et al. (2005).

5.6.4 Step 4: Fitting with the new growth function

Having preliminarily estimated the grazing-led LAI changes and full growth for each point on the per-pixel LAI curve, and knowing the initial background LAI, the analysis can proceed to fit the growth curve to the observed growth points, filling in the "non-good quality" pixels (improved LAI). The improved LAI can be calculated by the new growth equation directly; while the expected LAI is calculated by setting PG_t=0 (percentage of current grazing). The expected LAI is calculated by making sure the percentage of winter pasture area (44.8%) is same as the percentage of the pixels estimated where no grazing happens; we use the percentage of pixels with the smallest estimated grazing-led LAI changes for the match up and set the preliminary estimation of grazing-led LAI changes to 0 ($P_t = 1$, $PB_i =$ estimated PB_i and $PG_t = 0$). Note PB_t should stay the same as has been calculated in step five, as the whole estimation algorithm depends on the previous status of vegetation, and if there is no grazing at the current time period it does not mean the previous time period has no grazing as well. The grazing-led LAI change (without the effect of the previous grazing) can then be calculated by taking the difference between expected LAI and improved LAI.

5.7 Modelling results

Having outlined the algorithm in theory in previous sections, the specific results associated with the components are now presented.

5.7.1 Result: Initial background LAI

In order to achieve fitting with the new growth function (Eq. 5-16) discussed in Section 5.4, the first thing is to determine the initial background LAI value, that is, the value of $\boldsymbol{L_m}$. This is the point from which the grass starts to grow, it is therefore the minimum LAI value for each pixel during the year as explained earlier. The published minimum value for LAI of grasslands are in a range from 0.3 to 2.0, for example, in Majella National Park, Italy, the measured minimum LAI of the grassland is 0.39 m^2/m^2 (Darvishzadeh et al., 2008), while have reported a minimum LAI between 1 m^2/m^2 and 2 m^2/m^2 for four grass species in Mead, Nebraska, United States (Mitchell et al., 1998).

The result of the initial background LAI values of Zeku is shown in **Figure 5.11.** The majority of the pixels have a value of 0.2 m^2/m^2, which accounts for 82% of the total pixels. In the South and Eastern part of Zeku, a lot of the pixels have the value of 0.3 m^2/m^2, but they occupy just 12% the total pixels. In the northeast of Zeku, there are some pixels that have the initial LAI of 0.1 m2/m2, but these are only 5% of the total pixels. The pixels beyond these three values are less than 1% of the total pixels. The results here will be further used in the statistical fitting of the new growth function **(Eq. 5-16)** for each pixel**.**

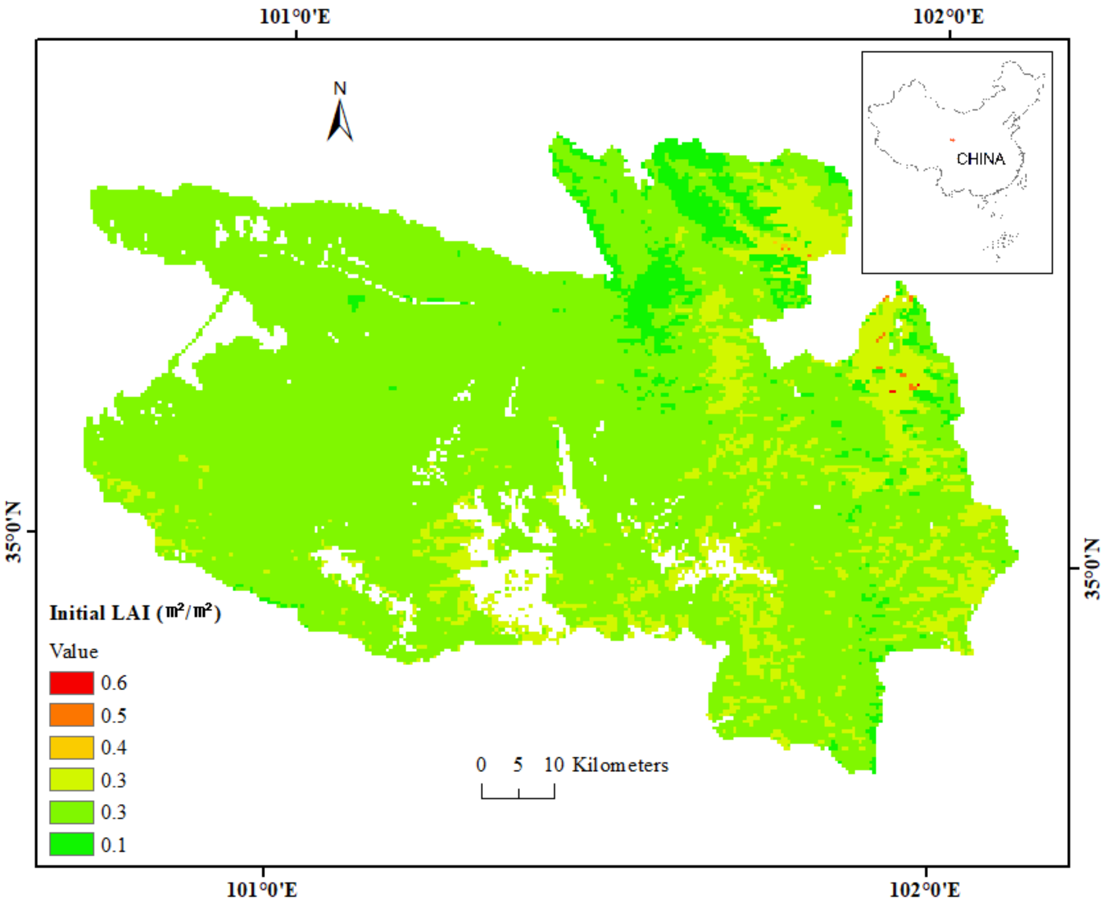


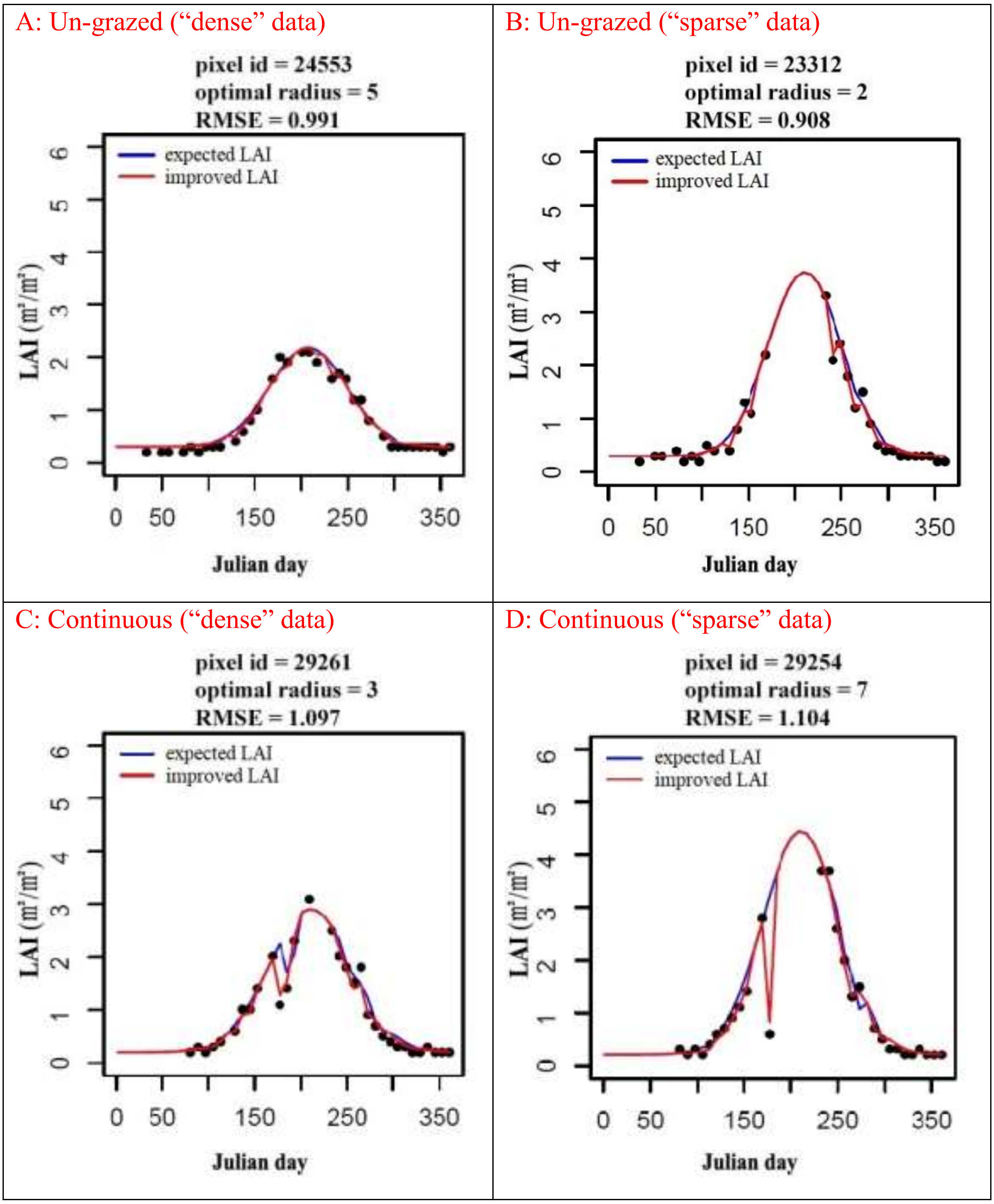
Figure 5.11: Initial LAI of the grassland in Zeku, 2003~2012

5.7.2 Results: curve fitting with the new growth function

Using the estimation algorithm discussed in Section 5.6.3 and the results of the initial value of LAI in Section 5.6.2, the new growth function can be fitted for each pixel (see Figure 5.2 for example). Missing data during key parts of the growing season strongly influence the results of curve fitting based on MODIS Vegetation Index data **(**Zhang et al., 2006**)**, but this problem can be well resolved by fitting the new growth function. From the right side of the figures (marked as "dense" data figures: A, C and E) in Figure 5.12, there are lots of "missing" points compare with their left counterparts (marked as "sparse" data figures: B, D and F). We can see that those "missing" points were reasonably filled with improved LAI (yellow curves).

The assumption is that there is no grazing in the periods of no data that is not at least in part captured by points either side of the missing data, where this is the case the algorithm will underestimate grazing**.**

The improved LAI data, where the "gaps" were filled, and the value of LAI is replaced by the new growth function based on MODIS LAI "good" quality data, can be derived directly (green curves in Figure 5.12**).** Similarly, the expected LAI data, which represents the LAI values of the pixels if no grazing happens, can be calculated (red curves in Figure 5.12**).** We can see the new growth function fits well with the "good" quality data points. In addition, Un-grazed, continuous and rotational grazing pixels can be classified according to the estimated grazing frequencies, as will be discussed later.



A: Un-grazed (“dense” data)

B: Un-grazed (“sparse” data)

C: Continuous (“dense” data)

D: Continuous (“sparse” data)

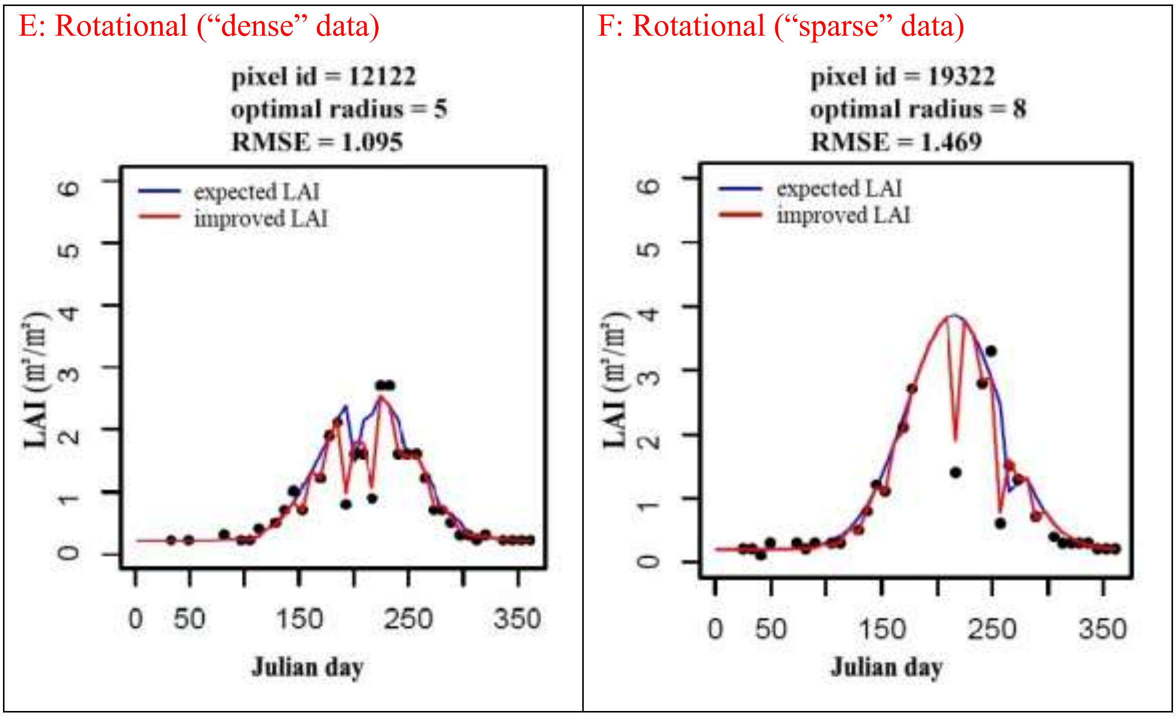


Figure 5.12: Examples of fitting the new growth function with MODIS "good" quality LAI data for un-grazed, continuous and rotational grazing pixels (left side figures: "gaps" did not appear at the key points; right side figures: "gaps" did exist at some key points)

5.7.3 Results: estimated grazing-led LAI changes

As discussed in Section 5.6.3, the grazing-led LAI changes for each pixel are the difference between the expected LAI (under no grazing but with previous effects) and the improved LAI (LAI after grazing, which can be observed by remote sensing).

Our field survey in 2012 showed that the percentage of un-grazed grassland is 44.8% in Zeku (Huang et al., 2016; Huang et al., 2017). This thesis uses this percentage to filter out small LAI fluctuations, which cause overestimates of grazed LAI due to the effect of modelling error and background noise within the MODIS LAI data (Li et al., 2014), that is, the percentage is used to truncate out the un-grazed areas even where there is low fluctuation (which might be low-level grazing or error). The uncertainty of this estimation is explored in Section 5.10.

The estimated grazed LAI are shown in Figure 5.13, ranging from 0 m^2/m^2 to 15.34 m^2/m^2, with the annual average grazing-led LAI change from 7.2 m^2/m^2 to 9.08 m^2/m^2 during 2003~2012. Note that there is a consistent spatial pattern whereby the southeast part of the region has higher grazed LAI than that of its counterparts; this is similar to the pattern found by other researchers (Fan et al., 2010b).

Given an estimate of the grazing-led LAI changes, these figures can be converted to equivalent leaf mass and aggregated to a summated total for each year. This will be shown in the validation section.

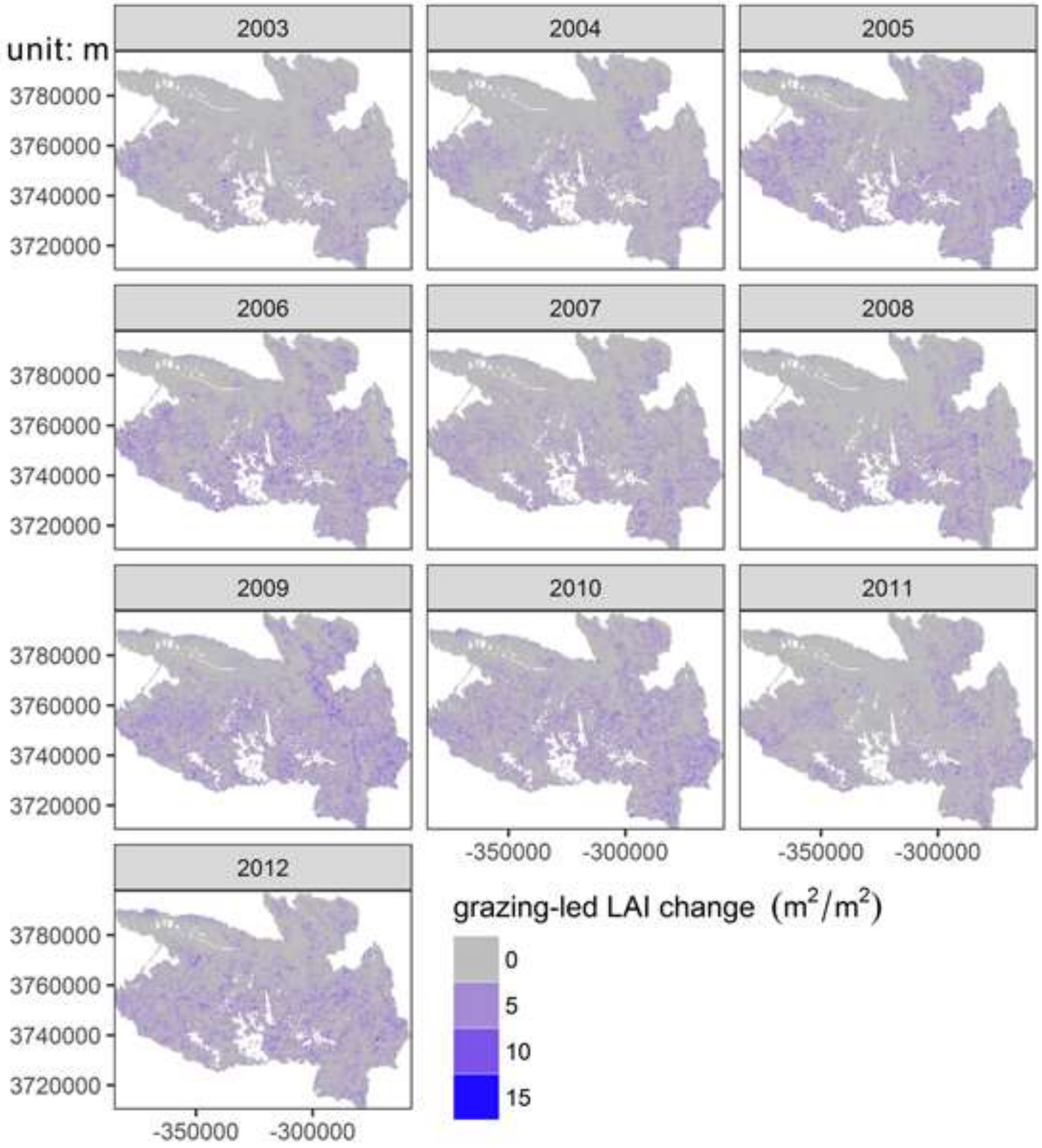


Figure 5.13: Estimated grazing-led LAI changes

5.7.4 Results: grazing frequencies

Based on the grazing-led LAI changes discussed above, the grazing frequencies (revisit times) can be easily calculated by counting the number of nonzero grazing-led LAI changes for each pixel, that is, the number of points where the calculated value of PG_t is bigger than 0 during the year (46 points of 8-day periods). Figure 5.14 shows the results of estimated grazing frequencies, after filtering with the above threshold for the whole region. Rotational grazing should have the highest grazing frequency as the livestock will move in or move out more times and thus, more frequent grazing-led LAI changes should be detected. While for un-grazed pixels, the difference between the improved LAI and expected LAI would be zero and therefore the grazing frequency is 0 (see panel A and B in Figure 5.12). The estimated grazing frequencies for continuous grazing pixels would be 1 because after livestock moved into the pixels, they will continuously graze, they will not move to the other pixels and therefore, just one sharp decrease can be observed in LAI curve.

Based on the grazing frequencies counted for each pixel, the grazing type can be further inferred: if no grazing happens (with 0 grazing frequency), the pixels will be classified into un-grazed pixels; if the grazing frequencies are 1, the pixels will be regarded as continuous grazing pixels; while the rest of the pixels are rotational grazing pixels with grazing frequencies greater than 1, which means the livestock was moved in and out at least twice during the growth period. The spatial distribution of these three grazing types is shown in Figure 5.15. These maps will be further used in Chapter 7 as the grazing type data for each year. The validation of these results will be discussed in later sections both in this chapter and the following chapter.

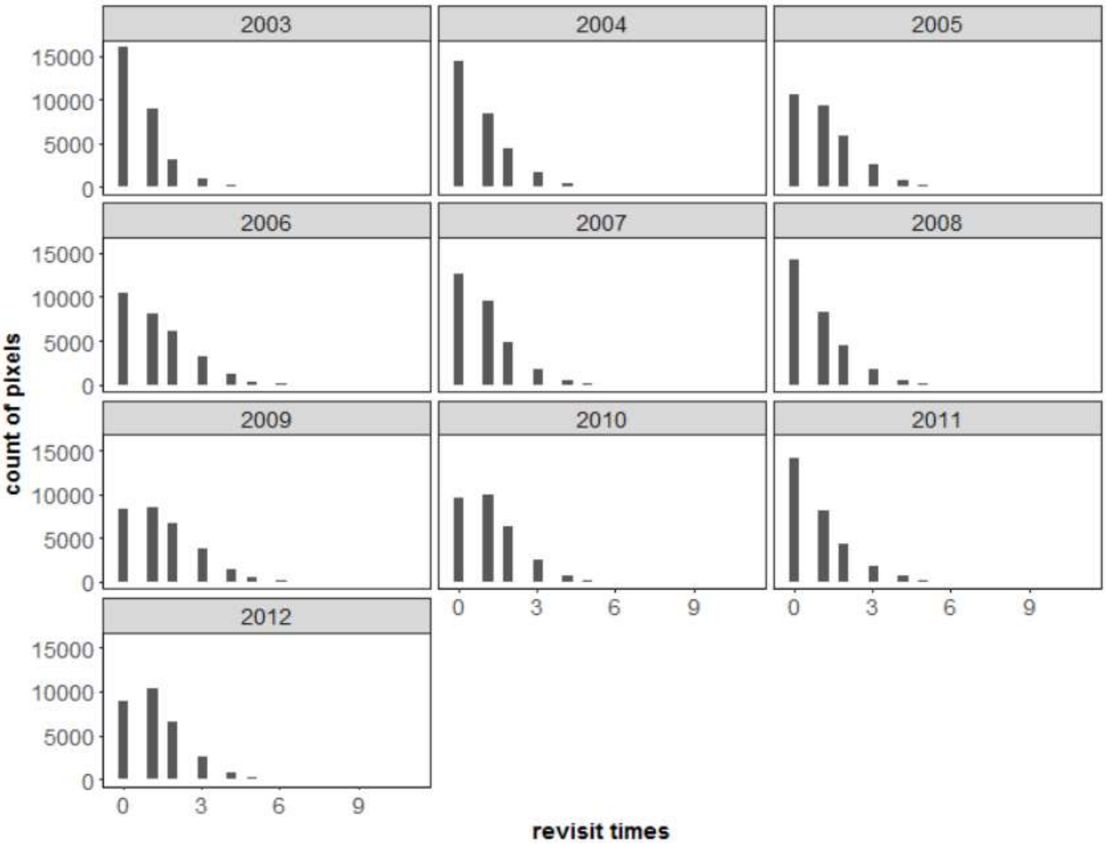


Figure 5.14: Distribution of estimated grazing frequencies

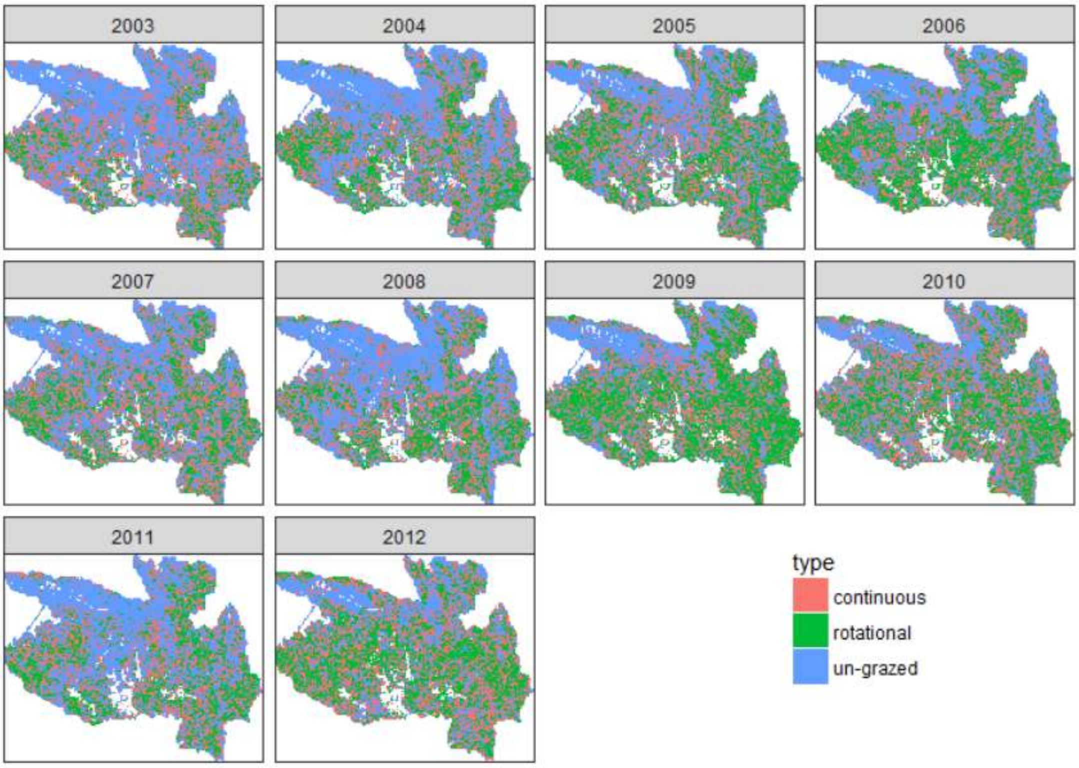


Figure 5.15: Classified grazing types of Zeku from 2003 to 2012.

5.8 Impact of neighbour radius on grazed LAI estimation

The neighbourhood radius used in estimating the grazed amounts could potentially have a significant effect on the grazed LAI estimation. There is a contradiction when choosing an appropriate neighbourhood radius. A smaller neighbourhood radius is expected to be more precise, but may equally underestimate grazed LAI. A greater neighbour radius value would also potentially increase the error of the searching algorithm, especial near inflexion points of the LAI growth curve. This section, therefore, looks at this sensitivity. In the algorithm, each pixel has its own radius calculated using its data. However, as a sensitivity test, we will here look at the effect of fixing a radius for all pixels. Setting the neighbour radius at values of 1, 2, 3 and 4 neighbouring points separately, the distributions of the aggregated grazing-led LAI changes are shown in Figure 5.16. It is clear that there are differences in the distributions between search radius 1 and search radius 2, and, likewise, 2 and 3. But values are almost the same between searching radius 3 and 4. Making a ‘natural breaks’ assumption, therefore, the best search radius value is 3 in this sensitivity analysis, indicating the actual calculated optimal search radius for all the pixels should be distributed at least around 3. More directly, by plotting out the histogram of optimal neighbourhood radius for all the pixels (Figure 5.17), which shows the optimal radius that minimizes the average fitting residual between “good quality” remote sensing data and their fitted values using Eq. 5-15; these results are consistent with the sensitivity test reported, of which the distribution is centred at radius 3.

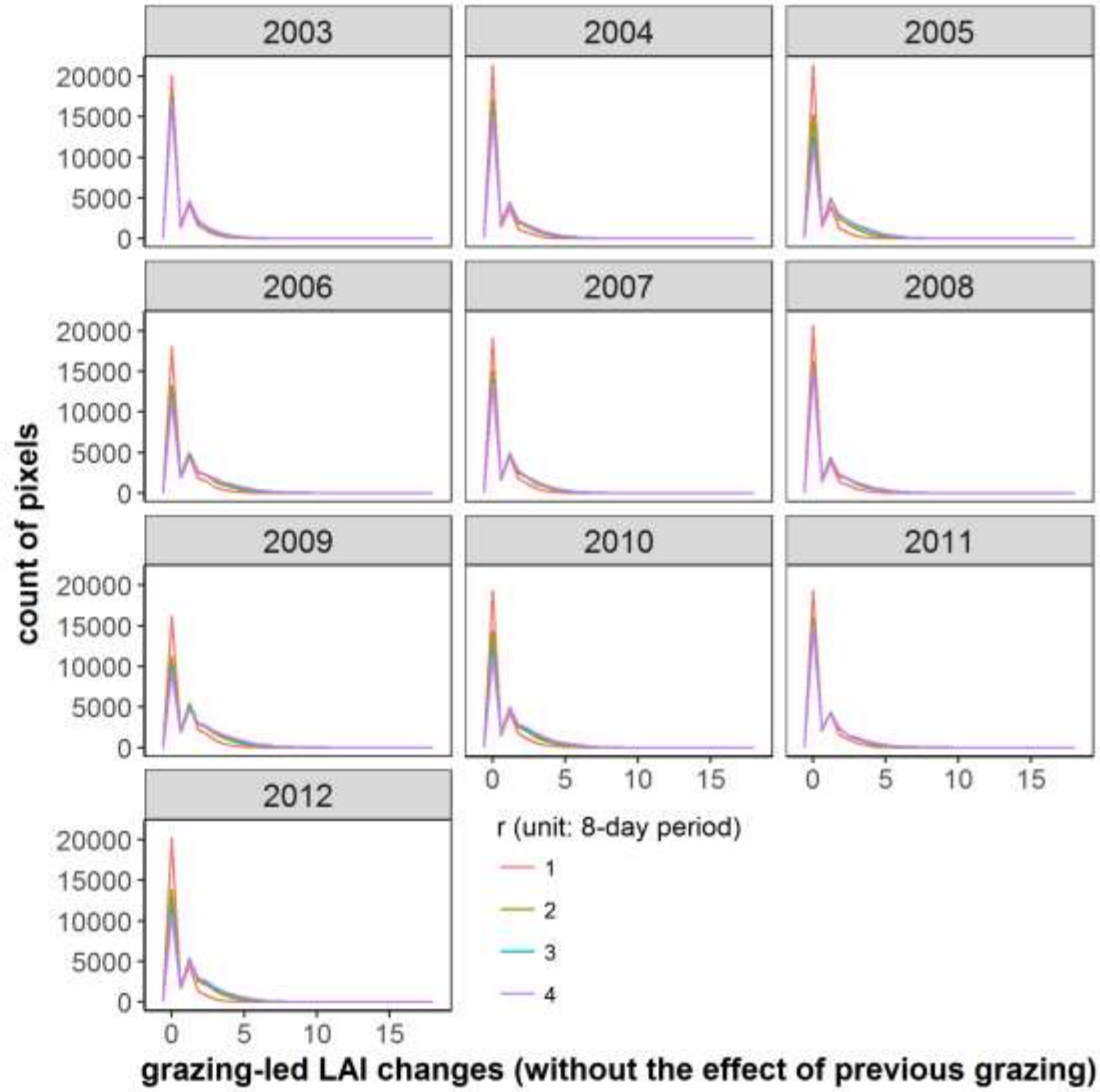


Figure 5.16: Distribution of estimated grazed-led LAI changes at neighbour radius 1, 2, 3 and 4

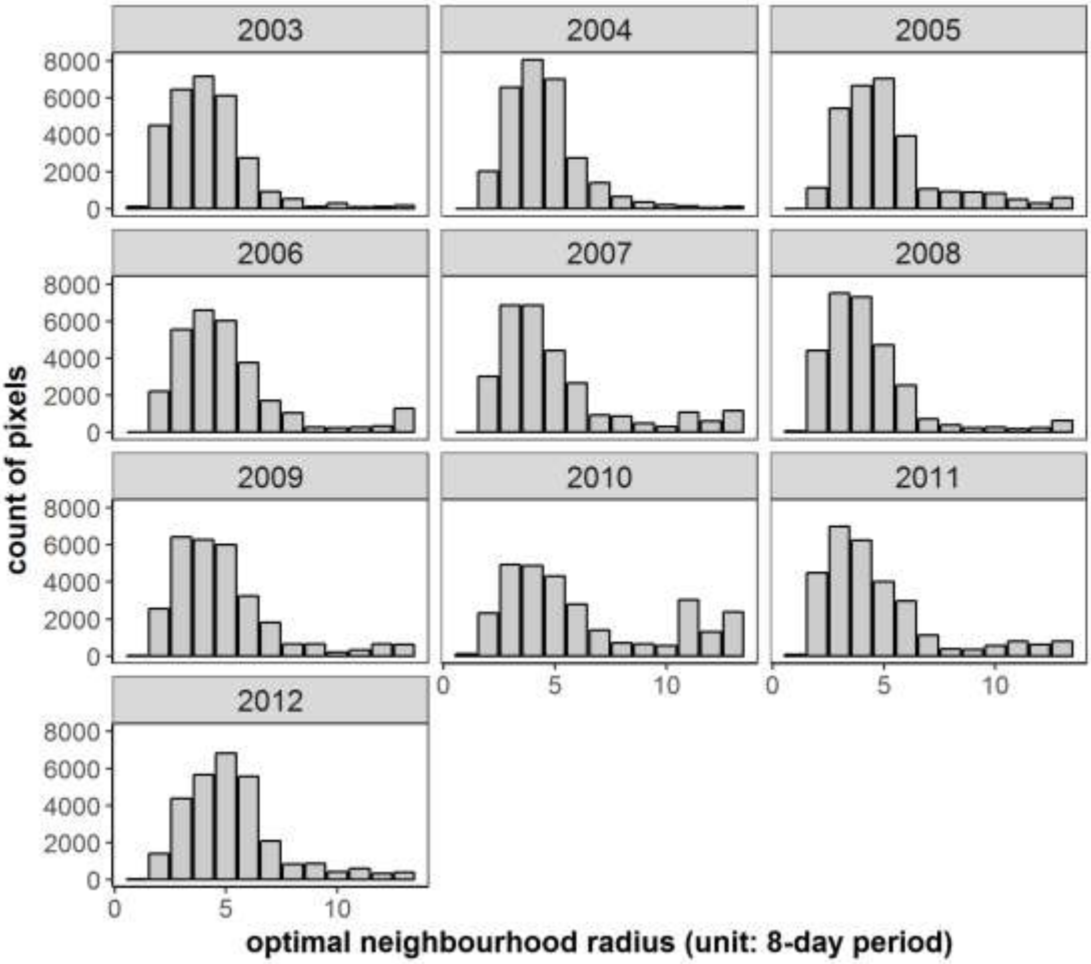


Figure 5.17: Histogram of optimal neighbourhood radius for all pixels when choosing minimum RMSE

As is introduced in Section 5.6.3, the estimation algorithm will choose the radius for each pixel which minimizes the RMSE for that pixel. In fact, one way to evaluate the strength of fit is to assess how far off the model is for the real data. The magnitude of a typical residual can give us a sense of generally how close our estimates are.

However, recall that some of the residuals are positive, while others are negative. In fact, it is guaranteed by the least squares fitting procedure that the mean of the residuals is zero. Thus, it makes more sense to compute the square root of the mean squared residual, or root mean squared error (RMSE). R (the software used here) calls this quantity the residual standard error. Notice that in linear regressions, the sums of the total squared errors has a specific manner: $SS_{\text{regression explained}} + SS_{\text{residual error}} = SS_{\text{total error}}$, indicating the relationship between variables is linear; and therefore an R-squared value is commonly reported when using linear fittings; it is used to report the ratio of the total variance can be explained by the linear regression models; however, in non-linear fittings, such an opportunity does not exist, that is $SS_{\text{regression explained}} + SS_{\text{residual error}}$ does not equal SS_{total}, and the value of R-squared is no longer between 0 and 100% (Schoolfield et al., 1981; Fox, 2002).

To make the non-linear estimates unbiased, many classical statistical models have a scale parameter, typically the standard deviation of a zero-mean normal (or

Gaussian) random variable which is denoted as σ (sigma) is used to extract the estimated parameter from a fitted model (Fox, 2002). In R, the sum of the squared residuals is divided by the degrees of freedom; RMSE then becomes,

$$\mathrm{RMSE} = \sqrt[2]{{}^{1}\!/_{(n-p)} \sum_{i} e_i^2}$$

Eq. 5-18

where (n-p) stands for the degree of freedom, n is the total number of observations, p accounts for the number of parameters to be estimated, and e_i is the i$^{\text{th}}$ weighted residual, which is calculated based on the difference between observed LAI (MODIS "good quality" LAI) and fitted LAI (improved LAI). A smaller RMSE value means a smaller overall non-linear regression error and thus the fitting result is better. The first step in the estimation algorithm (see Section 5.6.3) therefore uses RMSE to choose the optimal search radius for each pixel; in R, it is also called the square root of the estimated variance of the random error.

Figure 5.18 shows an example of how the optimal neighbourhood radius is selected in the estimation algorithm for one pixel. The RMSE values are calculated with the neighbourhood radius ranging from 1 to 9. With increasing neighbourhood radius from 1 to 7, the RMSE values are decreased significantly from 4.96 to 1.94. However, the RMSE value has increased to 1.97 when the neighbouring radius is 8, and it increased to 1.95 when setting the neighbouring radius to 9. Therefore, the optimal neighbouring radius is 7 as it has the smallest RMSE value. For each pixel, the optimal neighbourhood radius was calculated on a yearly basis (46 observations for each year). The overall distribution of the RMSE values will be analysed in the next section.

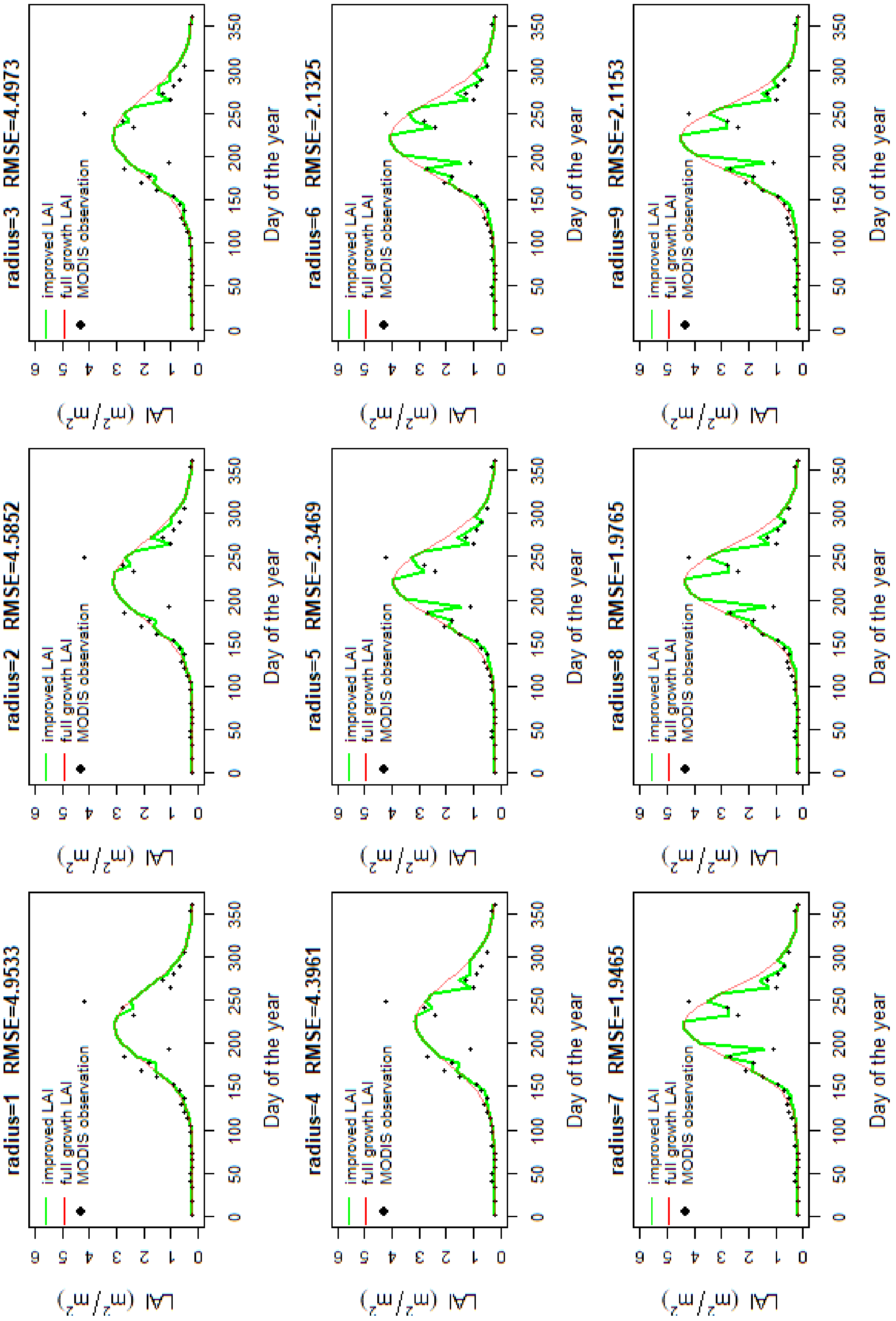


Figure 5.18: An example of optimal neighbouring radius selection

5.9 Grass growth under different defoliation severity

The indicator used in this thesis is LAI, which will be used to extract grazing information based on the equations in Section 5.4 shortly. This section is an example of a theoretical analysis of the growth function under two typical grazing strategies:

continuous grazing and rotational grazing. Note that LAI is based on the greenness of vegetation, so it mainly provides the grazing information during the grass growth season (both the growth dominated period and the senescence dominated period), beyond which remote sensing cannot reflect the change of perennial grass. Some grass is harvested for winter stocks, but the amount is very small, and the local herders tend to keep one spare grassland area un-grazed for winter, according to a field survey in 2012 (Huang et al., 2016). In addition, no matter how much grass has been consumed by livestock during winter, the grass should be able to recover next year as long as the soil condition and grassroots have not been severely affected by livestock browsing or trampling (Hoffmann et al., 2016), though grazing does have an effect on the next year's growth as discussed in Chapter 2. This is an important area that should be considered in growth functions, but it is beyond the scope of this thesis, involving, as it would, agricultural tests. In this thesis, this does not influence results greatly, given that the growth function will be estimated empirically for each year separately. It is not a multi-year growth-grazing integration function.

Globally, livestock grazing can be divided into two types with regard to the land tenure system. In some places, grasslands are a free-access natural resource for herders: everyone in the village or tribe could have their livestock grazing on the grasslands. The second is limited-access grasslands, which have either been contracted to the herders or are private, only the owner having the right to raise livestock on the grasslands. As is discussed in the "Case Study Area" chapter (Chapter 3), the grasslands in Zeku have been contracted to herders, meaning that the use of the land is spatially constrained.

Rotational grazing, continuous grazing and un-grazed land are the three grazing patterns found in limited-access grasslands. The grass on the un-grazed lands will be used as livestock's winter forage; no grazing activities occur on these lands during pasture summer growth period. Livestock would graze on rotational grazing or continuous grazing lands, the difference being that there is a "rest period" of grass for rotational grazing: livestock moves to neighbouring land patches then back to grazed land again.

For the agent-based modelling of rangeland grazing, it important to assess the effect of defoliation severity on the observed LAI or net instantaneous growth rate when making a rational decision. As such, we need to understand grazing-led defoliation. This assessment is based on the LAI development function (see Eq. 5-15). Here, the abstract results generated by Eq. 5-15 under three different grazing defoliation severities are shown in Figure 5.19.

The results show that different grazing regimes are likely to have a negative effect on observed LAI, a bigger percentage of grazed LAI means there will be a smaller observed LAI. The same is true for the instantaneous growth rate of LAI. Compared with a continuous grazing strategy, an intermitted grazing strategy will be preferred because the observed LAI would at least for this model regrow to the same amount as an un-grazed one after a recovery period. However, these results are based on the assumption that livestock will consume the same percentage for every 8-day period around the year. Another assumption is that the parameters k1 and k2 stay the same in spite of grazing, which may be not true in reality – plants may grow at different rates under grazing due to the over/under compensation of grazing both in the long term (McNaughton, 1983) and short-term (Gignoux et al., 2001) grass development. In fact, a fitted growth function can only reflect growth parameters under the current grazing method and intensity. The local maximum of LAI could be present as a result of either overcompensation of grazing or under compensation of grazing on the grass. Remote sensing can only capture the status of grass under grazing, but cannot distinguish what kind of effect is (over or under compensation) on grass growth, which is highly depended on grazing intensities (Hickman and Hartnett, 2002). The figures here are an illustration of how grazing severity would affect the observed LAI and its instantaneous growth rate if these parameters remain unchanged. This is why we cannot use this function to predict LAI under grazing. It is a year-round grass growth under grazing function rather than a predictive plant-livestock interaction function.

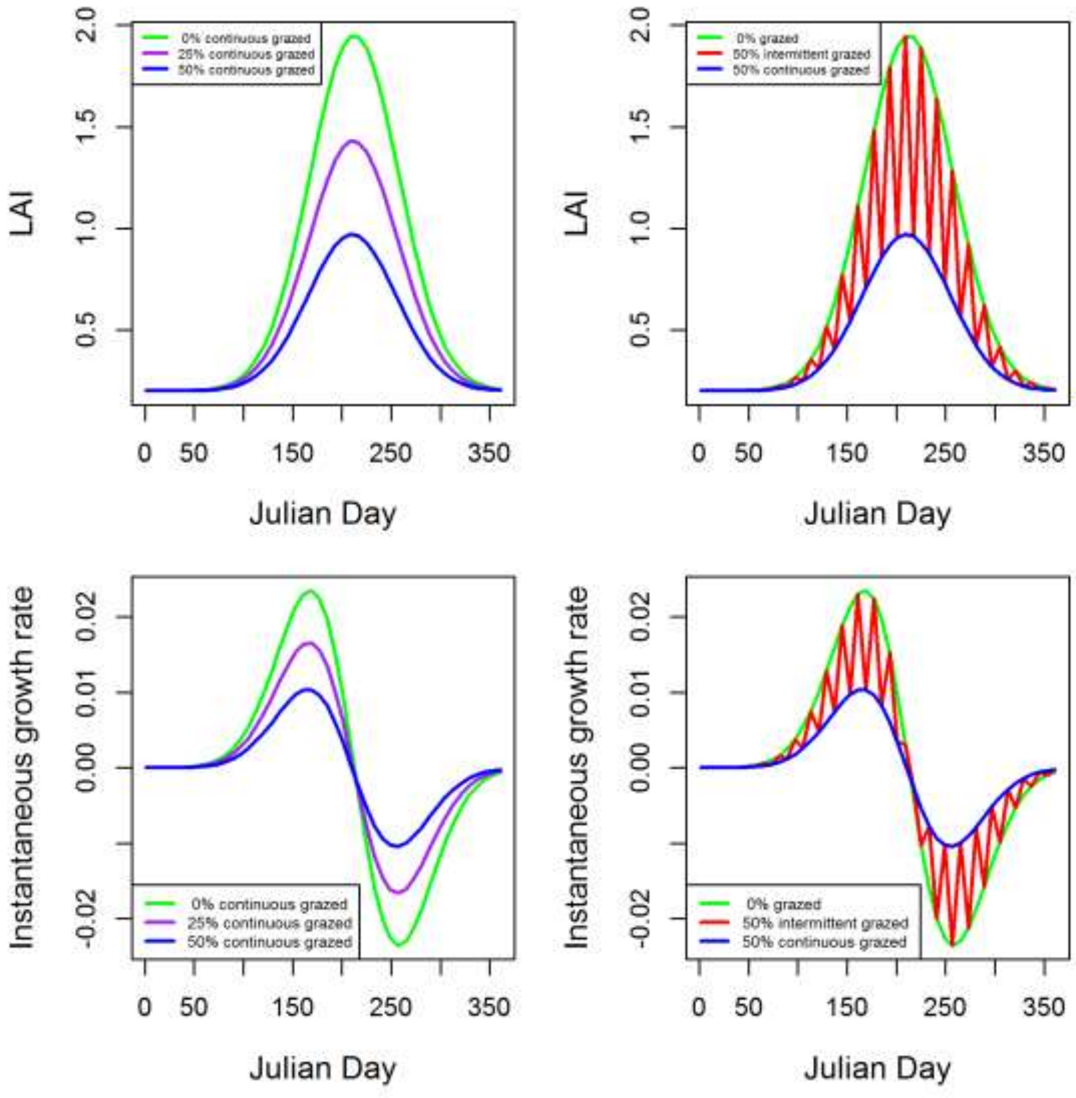


Figure 5.19: An example of the effect of grazing severity on the observed LAI and instantaneous net growth rate of LAI, with k1= 0.16, k2=0.0003, C=-14. The bottom two are L_t'

5.10 The uncertainty of the estimated grazing-led LAI changes

In Section 5.7.3, the results of grazing-led LAI changes were shown in Figure 5.14; however, the uncertainty of the estimated grazing-led LAI changes and the uncertainty of the improved LAI have not been quantified. This is important to quantify the accuracy of the estimated results. In this section, this thesis uses the summation of the three components of the uncertainty of the estimated grazing-led LAI changes to quantify the behaviour of the method in extreme cases; as a measurement of the uncertainty of the estimation, this allows a lower and upper bound on the actual implied errors of the final LAI to be derived.

5.10.1 Background noise and fitting goodness analysis

Both background noise and modelling error could contribute to the uncertainty of grazing-led LAI defoliation estimations. They can further affect the identification of different grazing types. The rest of this chapter will mainly analyse the background noise and the goodness of fit, which could affect the grazing-led LAI estimation.

5.10.1.1 Sensitive analysis of background noise:

Background noise is the stochastic fluctuation of the LAI value, best seen during the non-growth season. During that season it is a measurement of the difference between the observed LAI value ($LAI_{observed}$) and expected LAI value (LAI_{mode}). Due to the effect of measurement error of the satellite sensors and modelling error of the MODIS data (Tian et al., 2002), sometimes MODIS LAI values will deviate from their “true” value slightly. Nevertheless, the overwhelming majority of MODIS LAI values should be constant during the non-growth season. From Section 5.5, change detection results show the non-growth season is from observation numbers 1 to 14 and from 38 to 46[2]. For each possible non-growth season period, from 1 to a (a<= 14) and from b (b>= 38) to 46, the maximum background noise for each pixel is defined as:

$$Background\ noise_{max} = \max(\text{abs}(LAI_{observed} - LAI_{mode}))$$

where LAI_{mode} is the mode of observed LAI value from 2003 to 2014 during the non-growth season which is defined by a and b (start and end of the season). Notice here, modal value is used rather than mean value, for the modal value accounts for more than half of all the values.

The effect of the background noise will obviously be dependent on the value of a and b, between which the background noise is assessed; varying this is, therefore, a key sensitivity test. The maximum difference, mean difference, standard deviation and coefficient of variation are potential statistics we might use to evaluate the sensitivity of the background noise to the choices of a and b in defining the non-growth season; these are shown in Figure 5.20.

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[2] There are 46 observations every year, 1th observation means the first day of the year, the 2ed means the 9th day of the year and so on.

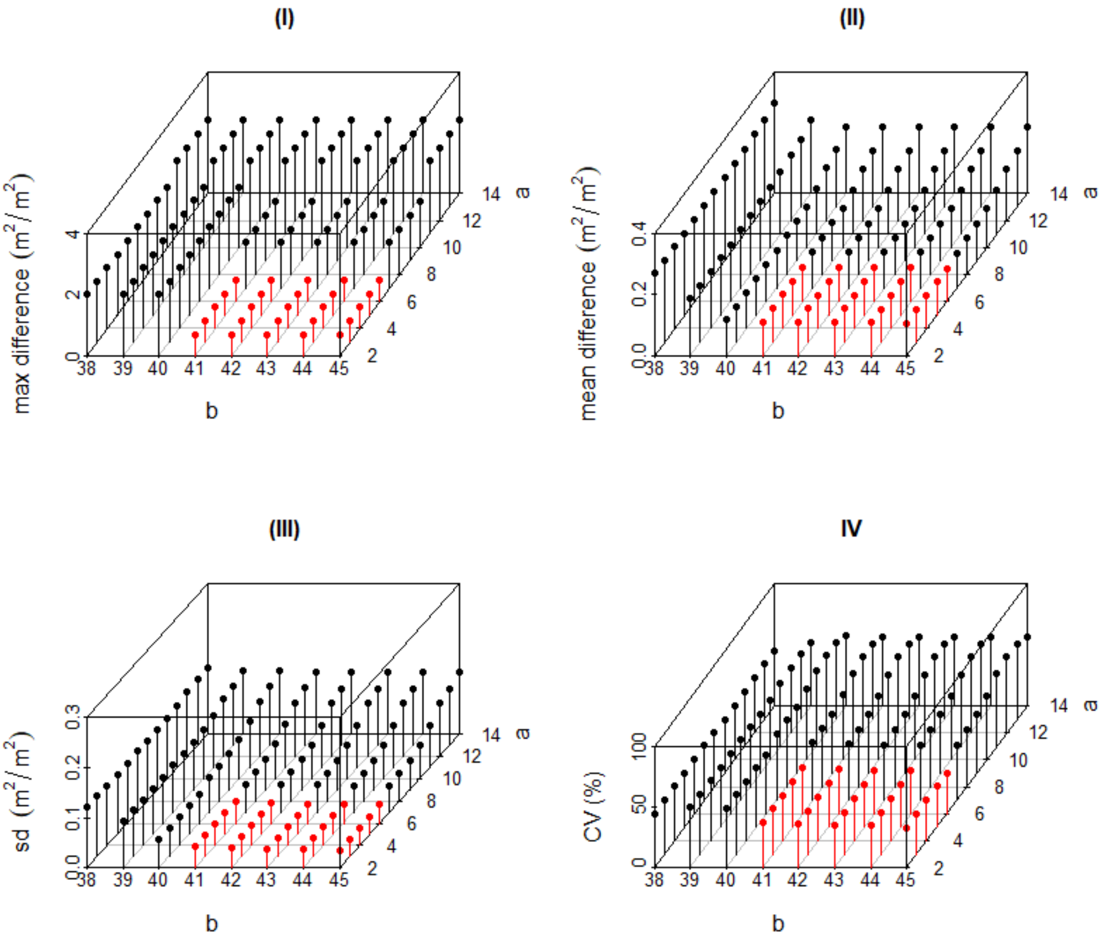


Figure 5.20: Sensitivity of a and b on MODIS LAI background noise during the non-growth season (I, maximum difference; II, mean difference; III, standard deviation; IV, the coefficient of variance), Zeku, 2003-2014.

As we can see from the figures, the maximum difference, mean difference, standard deviation and coefficient of variance tend to be fixed when the maximum of a is equal to 6 or less and the minimum of b equals 41 or bigger, that is, the background error estimation time period where the error is lowest is from 1 to 6 and from 41 to 46. The mean value of the background noise is 0.1128 m^2/m^2 with the standard variance of 0.3545 m^2/m^2. For each pixel, the background error estimation time period means the most stable and reliable representation for the winter non-growth period, and that sensitive test is to make sure the chosen time period is stable and reliable for all the pixels; in this way, the background noise can be calculated less affected by the individual phenological difference and the other mixed vegetation.

The results of the background noise are shown in Figure 5.21, where the maximum background noise is about 0.6 m^2/m^2, which is relatively small compared with the results of grazing-led LAI changes (see Figure 5.13).

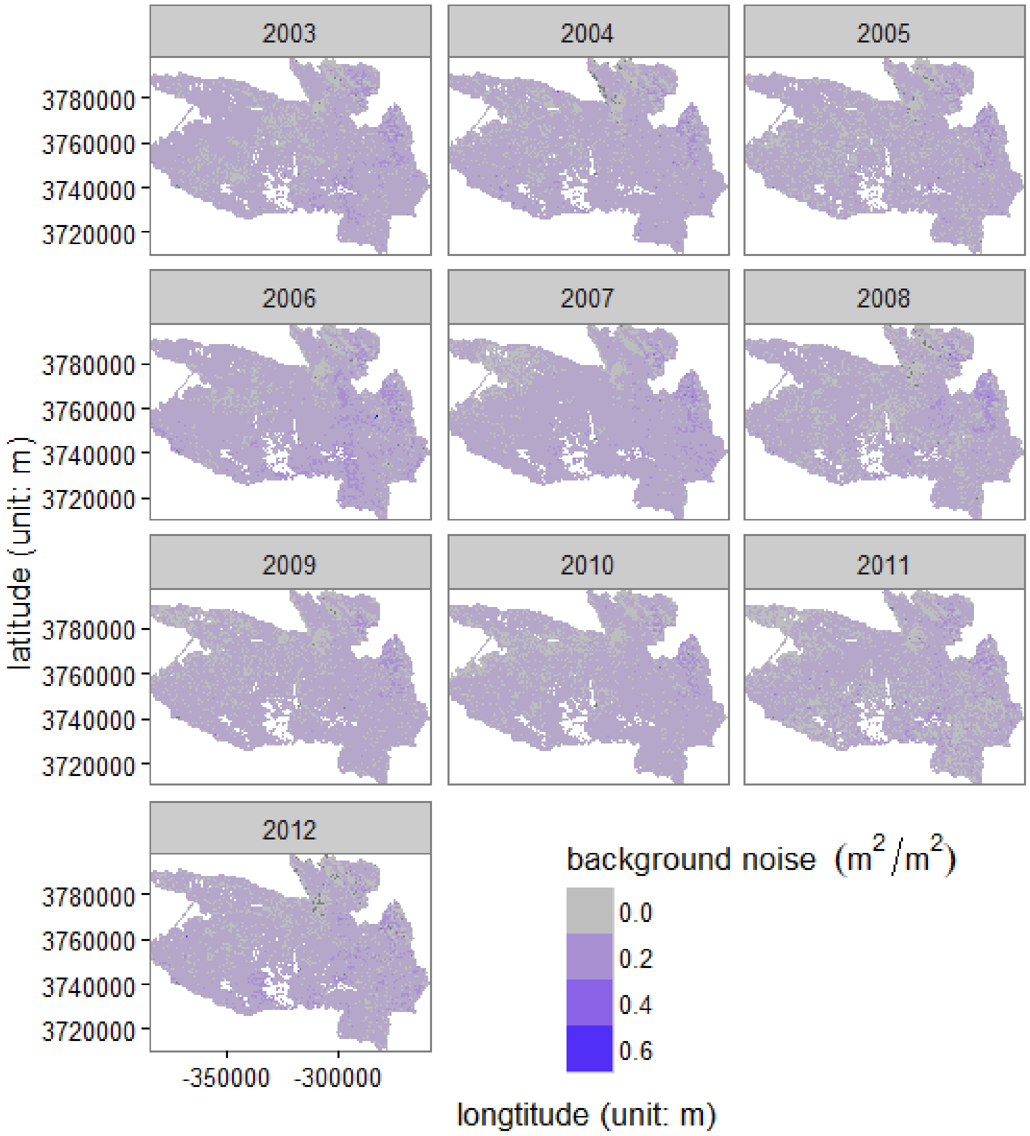


Figure 5.21: Background noise of MODIS LAI data during 2003~2012, Zeku, China

5.10.1.2 Goodness of fit

The estimation algorithm does cause an error when estimating the expected LAI. The statistics of the differences (absolute and squared) between measured and predicted values at sampled points are often used as an indicator of the performance of an inexact method (Li and Heap, 2011). As has been discussed in Section 5.7, RMSE is used to select the optimal neighbouring radius; here the RMSE is used to evaluate the estimation results, or more precisely, the model performance of our new growth function. RMSE has been used as a standard statistical measurement for model performance evaluations in both social and physical research (Babin and Boles, 1998; Landau et al., 2000; An et al., 2005). Another measurement, the mean absolute error (MAE) is also widely used in model evaluations. To simplify, if there are n samples of model errors e_i (e_i , i = 1, 2 . . . n). The RMSE and the MAE can be calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {e_i}^2}$$

Eq. 5-19

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |e_i|$$

Eq. 5-20

While they have both been used to assess model performance for many years, there is no consensus on which is the most appropriate. MAE gives the same weight to each modelling error e_i, while the RMSE penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values (by the squared operation on e_i). A comparison between MAE and RMSE has shown that RMSE is an inappropriate and misleading measure of average modelling error (Willmott et al., 2009), and therefore the MAE would be a better measure of average error and is unambiguous for the dimensioned evaluations and inter-comparisons of average modelling performance (Willmott and Matsuura, 2005). However, when the error distribution is expected to be Gaussian and, there are enough samples, the RMSE has an advantage over the MAE in illustrating the error distribution (Chai and Draxler, 2014). Figure 5.23 shows the distribution of the RMSE when fitting with the new growth function for each pixel, representing the difference between the fitted LAI and the observed LAI (MODIS “good quality” LAI). The average RMSE for each year ranges from 0.089 $\mathrm{m^2/m^2}$ to 0.11 $\mathrm{m^2/m^2}$ with the standard deviation ranging from 0.030 $\mathrm{m^2/m^2}$ to 0.036 $\mathrm{m^2/m^2}$. One sample T-tests show there are no significant differences in both the annual mean and standard deviation of RMSEs, indicating the fittings are stable across the years.

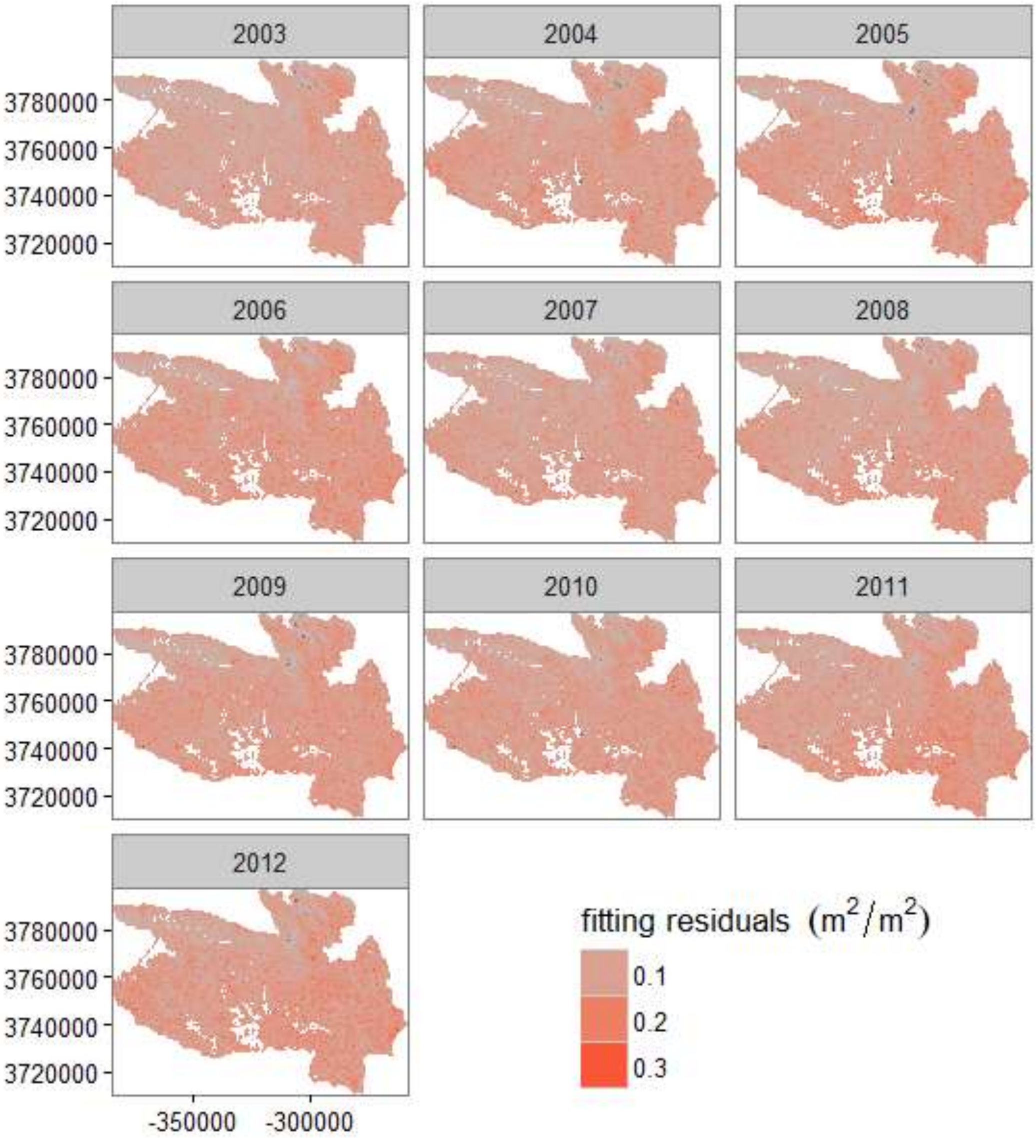


Figure 5.22: Fitting residuals of the new growth function against MODIS "good quality" data during 2003~2012, Zeku, China

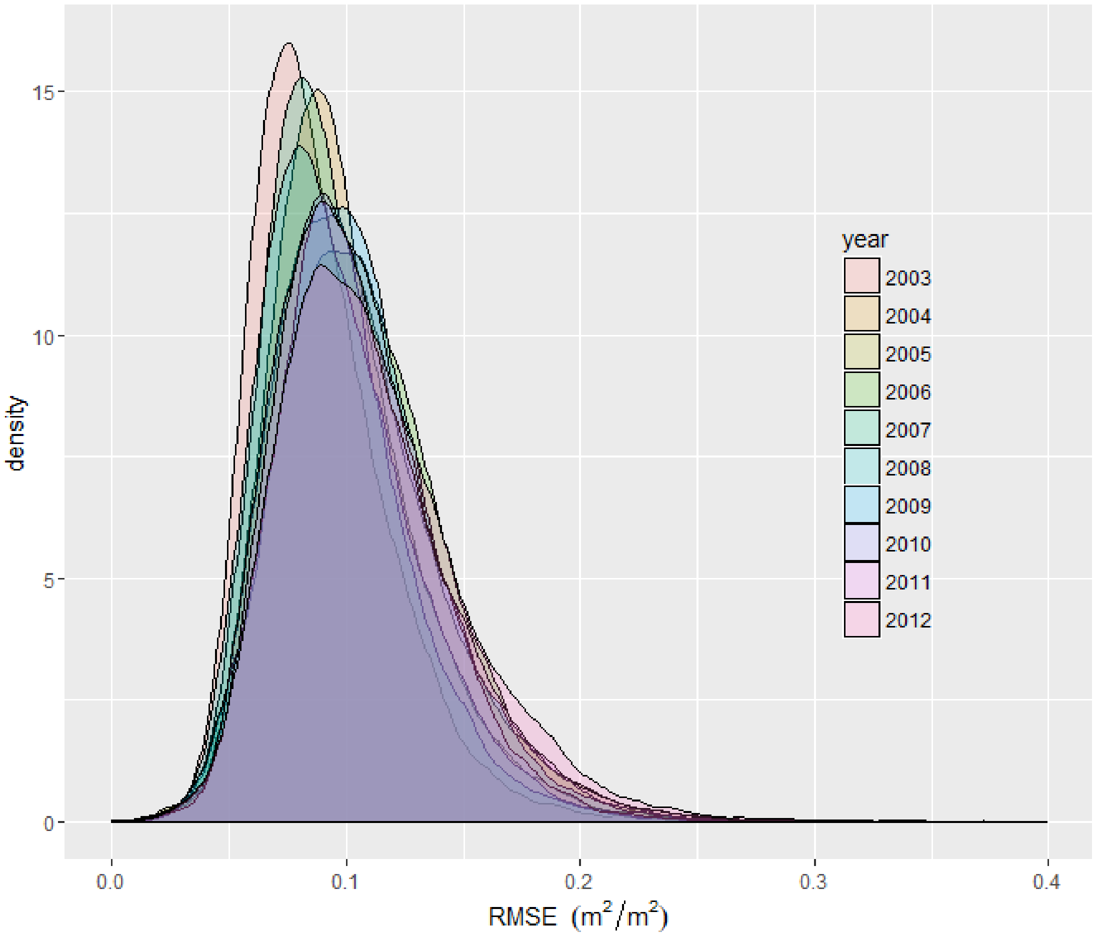


Figure 5.23: Distribution of RMSE using new growth function

5.10.2 The uncertainty of MODIS "good quality" LAI data

For each pixel, MODIS LAI was estimated associated with the day when the highest fraction of Photosynthetically Active Radiation (fPAR) value was observed during every 8-day period, and the fPAR was estimated based on daily surface reflectance data (Knyazikhin et al., 1999). Unfortunately, this date has not been recorded in the MODIS LAI dataset. In Section 5.6.3, we have used time difference as weight and assumed that the observing date of LAI is exactly the same as MODIS LAI recorded date (Julian day 1, 9…361). This assumption would affect the weight in calculating grazing-led LAI changes.

5.10.2.1 The uncertainty of date in MODIS LAI on the weight of time

This thesis, therefore, set up an uncertainty simulator, with the purpose of assessing the effect of the uncertainty of date in MODIS LAI on the weight of time. Taking assumed weight ($\frac{i-m}{n-m}$ in Section 5.6.3) for example, we assume r, i, m, n can be any day during the 8-day period in reality, the values of them are then randomised value between 0 and 1 (within 1 unit of 8-day period), we use 10000 iterations to recalculate the possible actual weight (possible MODIS weight), the mean and variance are plotted with regards to the different neighbourhood radius (Figure 5.24). Result shows on the average, the uncertainty of date in MODIS LAI has limited effect on the assumed weight. The variation of the weight in both assumed date and simulated random date has the same range, and are mainly caused by the position of left or right neighbourhood point (in 8-day period unit) within the optimal neighbourhood radius. The most obvious difference of the weight between the assumed date used in this chapter and the simulated random date during the 8-day period in Figure 5.24 is when optimal neighbourhood radius equals 1, the weight based on assumed date is a fixed at 0.5, while the weight of random simulated date ranges from about 0.3 to 0.7 (although the average value is also 0.5). This is because the left and right neighbourhood point is fixed when optimal neighbourhood radius equals to 1 for the assumed date we used in the estimation algorithm, while the randomly simulated date can be any day within the 8-day period. However, considering that the average optimal neighbourhood radius is 3 (Figure 5.17), and more than 99.5% of the optimal neighbourhood radius is bigger than 1, this effect has limited effect on the estimation of grazing-led LAI changes.

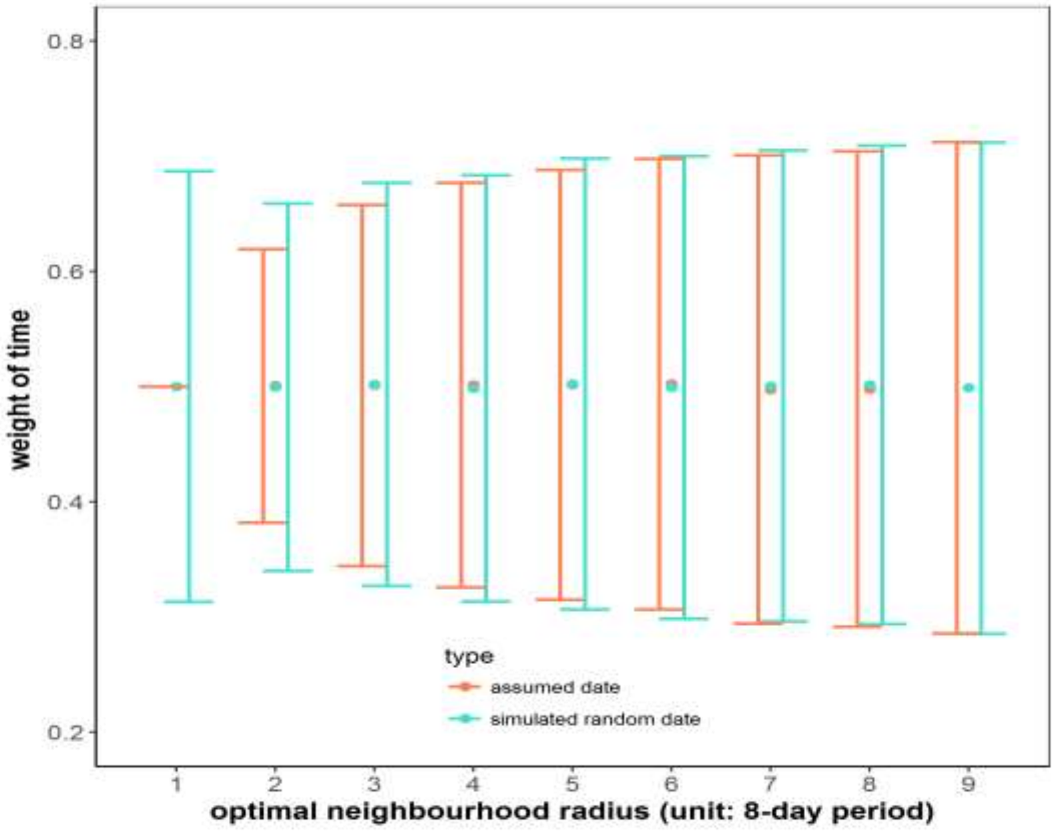


Figure 5.24: Uncertainty of the date recorded in MODIS LAI on the weight of the estimation of grazing-led LAI changes

5.10.2.2 The uncertainty of date in MODIS LAI on grazing-led LAI estimation

To further quantify the effect of uncertainty of date in MODIS LAI on grazing-led LAI estimation, an extreme situation analysis is carried out. The purpose of this extreme situation analysis is to explore the possible dates when extreme overestimating and underestimating of the grazing-led LAI changes might occur. An example of this extreme analysis theory is shown in Figure 5.25, where we have the following observations when the LAI value of a left neighbouring point is bigger than that of the right neighbouring point ($P_m > P_n$, see Panel A and Panel B in Figure 5.25):

- ✓ The preliminary estimation of grazing-led LAI change P_i would be smaller when the date of the left and right neighbouring point being closer to the first day in 8-days period;
- ✓ The grazing-led LAI change would be greater when the actual date of the estimation point (the point at date i) being closer to the first day in 8-days period.

Similarly, when $P_m > P_n$, see Panel C and Panel D in Figure 5.25, the following phenomenon is obvious:

- ✓ The preliminary estimation of grazing-led LAI change P_i would be greater when the date of the left and right neighbouring point being closer to the first day in 8-days period;
- ✓ The grazing-led LAI change would be smaller when the actual date of the estimation point (the point at date i) being closer to the first day in 8-days period.

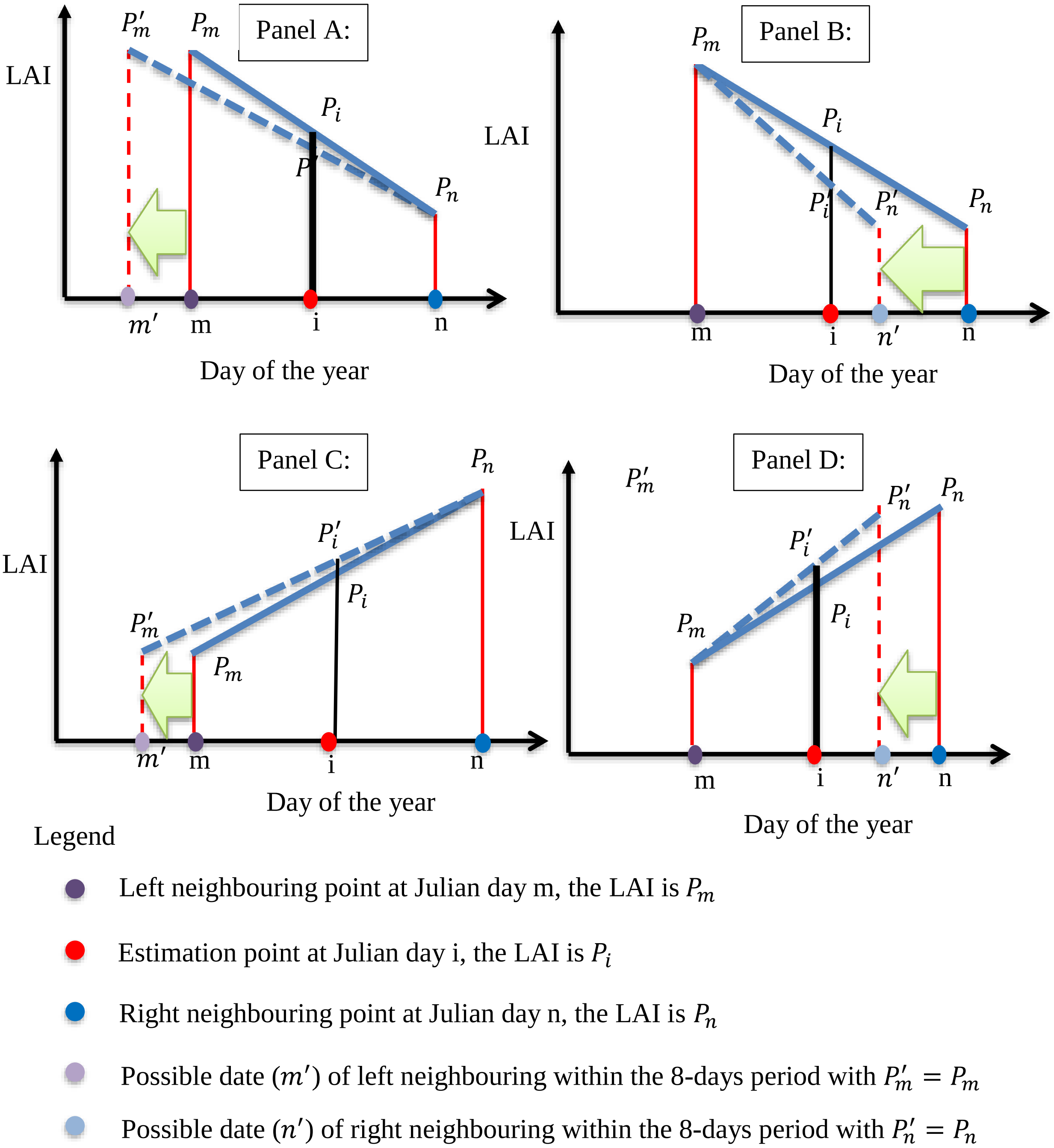


Figure 5.25: An example of the effect of the uncertainty of date in MODIS LAI on the estimation of grazing-led LAI change

Actually, for each estimation point, there are two extreme situations that the maximum and minimum grazing-led LAI changes can be estimated: the maximum grazing-led LAI changes can be calculated through:

- ✓ setting the date of right and left neighbouring point to the last day of the 8-days period (see Panel A and B in Figure 5.25) and, letting the date of the estimation point to be the first day of the 8-days period (if the LAI value of the left neighbouring point is bigger than that of left neighbouring point);
- ✓ setting the date of the right and left neighbouring point to the first day of the 8-days period (see panel C and D in Figure 5.25) and, letting the date of the

estimation point to be the last day of the 8-days period (if the LAI value of the left neighbouring point is smaller than that of left neighbouring point).

In the above two extreme situations, the maximum possible grazing-led LAI changes can be calculated. If this is the case in the real world, the grazing-led LAI changes estimated by equal days interval assumption (day 1, 9, 17…) were underestimated. In a similar way, the grazing-led LAI changes estimated by equal days interval assumption were overestimated when the minimum possible grazing-led LAI changes are the real case, which can be calculated by the following settings:

- ✓ setting the date of the right and left neighbouring point to the first day of the 8-days period and, letting the date of the estimation point to be the last day of the 8-days period (if the LAI value of the left neighbouring point is bigger than that of the left neighbouring point);
- ✓ setting the date of the right and left neighbouring point to the last day of the 8-days period and, letting the date of the estimation point to be the first day of the 8-days period (if the LAI value of the left neighbouring point is smaller than that of the left neighbouring point).

The underestimation error and overestimation error for each year at the pixel level, therefore, can be calculated by:

$$Error_{underestimation} = Extreme_{maximum} - Model_{asummed}$$

Eq. 5-21

$$Error_{overestimation} = Model_{assumed} - Extreme_{minimum}$$

Eq. 5-22

where $Model_{asummed}$ is the grazing-led LAI changes calculated by the equal days interval assumption during the year; $Extreme_{maximum}$ and $Extreme_{minimum}$ are the maximum possible grazing-led LAI changes and minimum possible grazing-led LAI changes estimated by the extreme situation analysis.

The spatial pattern of underestimation error and overestimation error are shown in Figure 5.26 and Figure 5.28. The maximum underestimation error reaches as high as about 9 m^2/m^2, and the minimum overestimation error is about -8 m^2/m^2. The maximum estimated grazing-led LAI change by equal days interval assumption is about 15 m^2/m^2 in Figure 5.11. However, when looking into the distribution of the underestimation error and overestimation error (see Figure 5.27 and Figure 5.29), the majority of the pixels have a relatively small absolute error. Further statistical analysis shows that 78.81% ~ 91.55% of the pixels with a possible underestimation error smaller than 1 m^2/m^2 from 2003 to 2012, and 92.35% ~ 97.70% of the pixels are possibly underestimated within 2 m^2/m^2 during 2003~2012. Similarly, 75.8% ~ 93.4% of the pixels are possibly overestimated within -1 m^2/m^2, and 92.92% ~ 98.82% of the pixels with a possible overestimation error within -2 m^2/m^2. The distribution of the overestimation error and overestimation error shows that the assumption of the equal day interval has a limited and relatively small impact on the estimation of grazing-led LAI changes. An overall uncertainty analysis which consists of the background noise (see Section 5.10.1), fitting residuals (also see Section 5.10.1), underestimation error and overestimation error, will be discussed below.

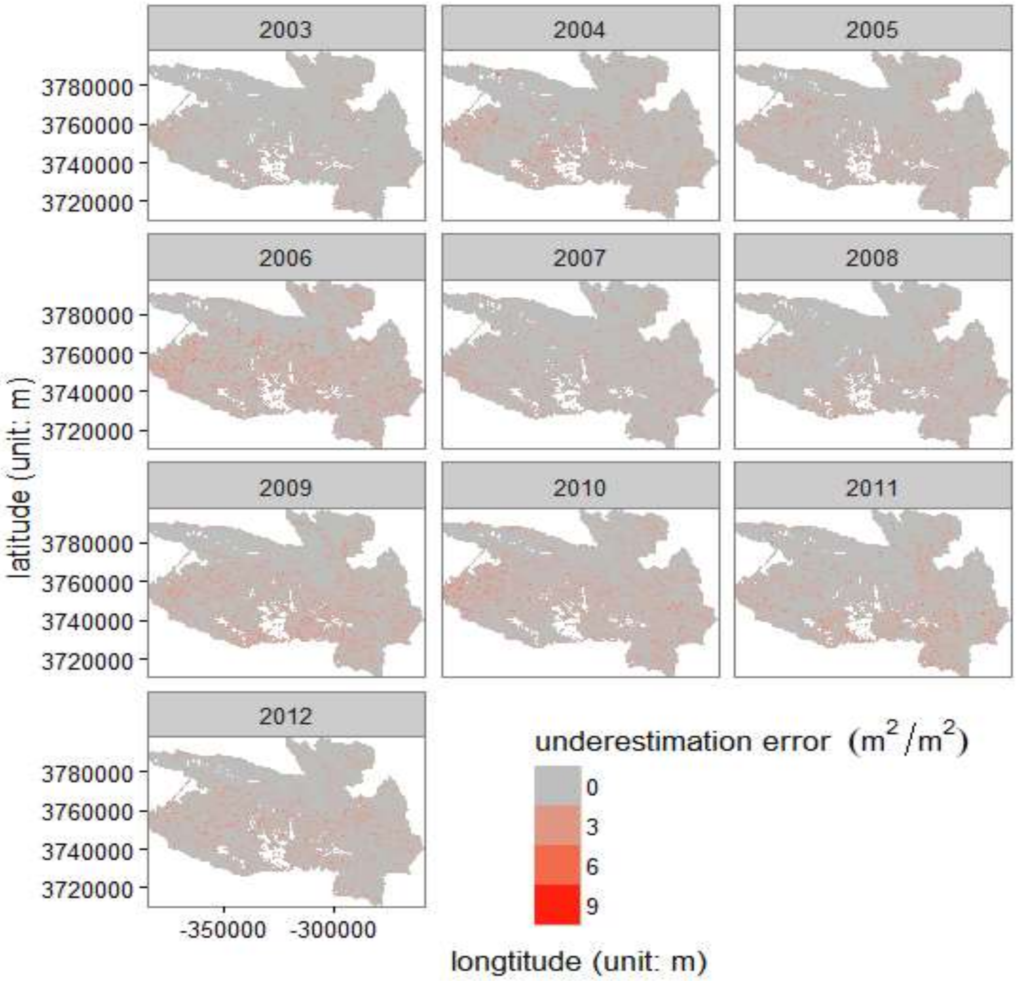


Figure 5.26: Underestimation error caused by equal days interval assumption during 2003~2012, Zeku, China

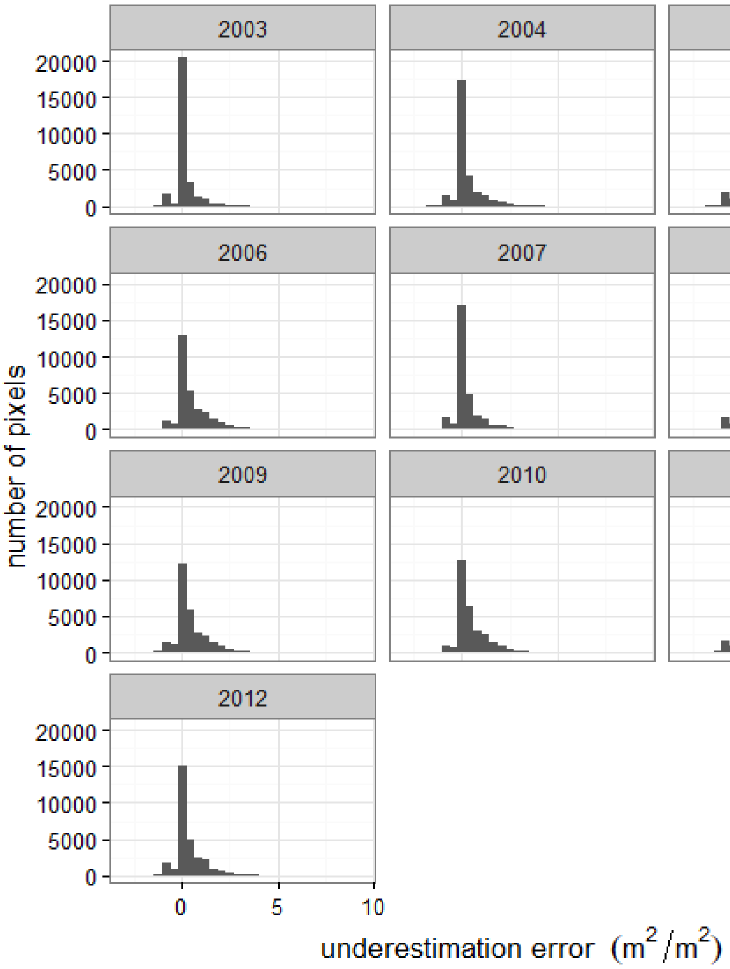


Figure 5.27: The distribution of underestimation error during 2003~2012, Zeku, China

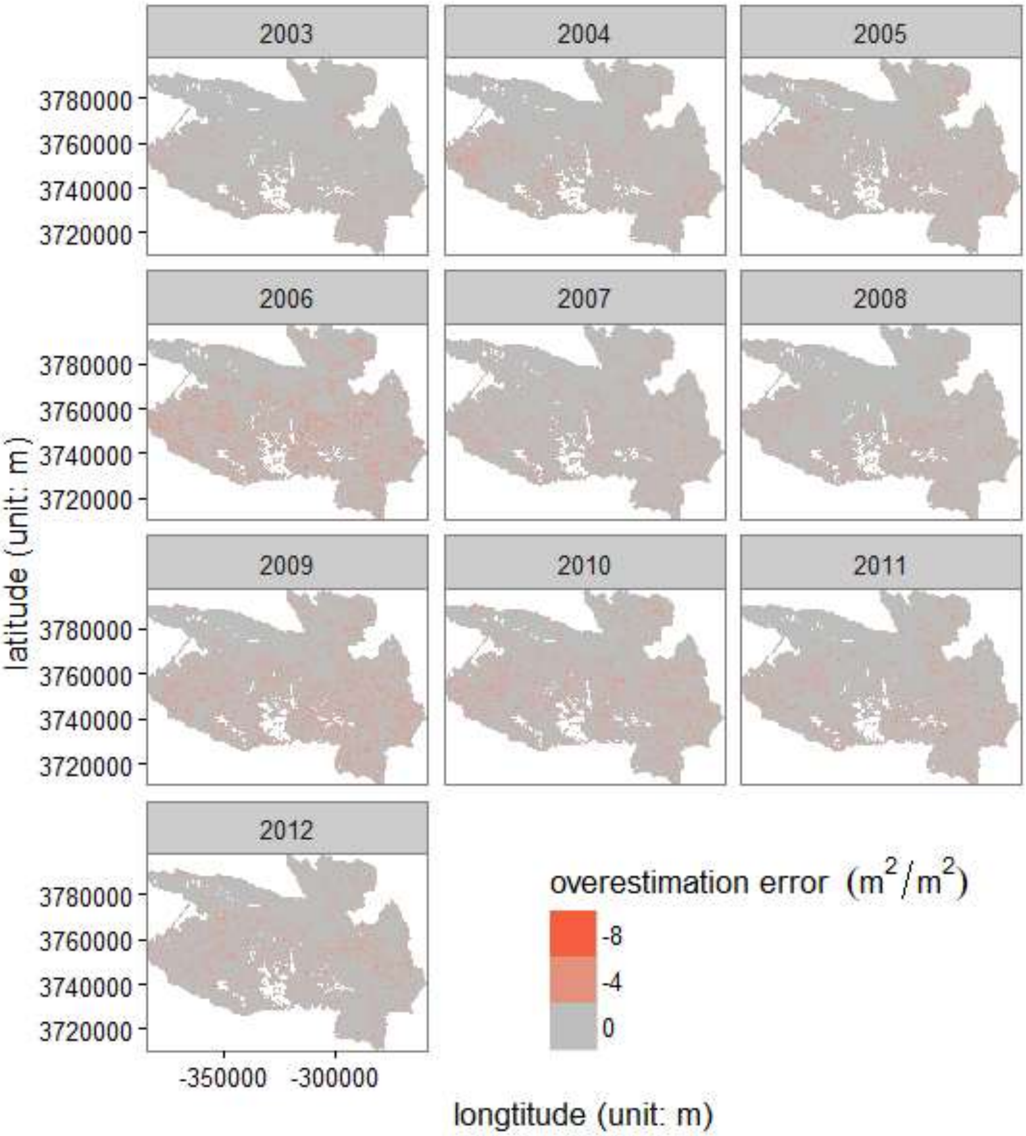


Figure 5.28: Overestimation error caused by equal days interval assumption during 2003~2012, Zeku, China.

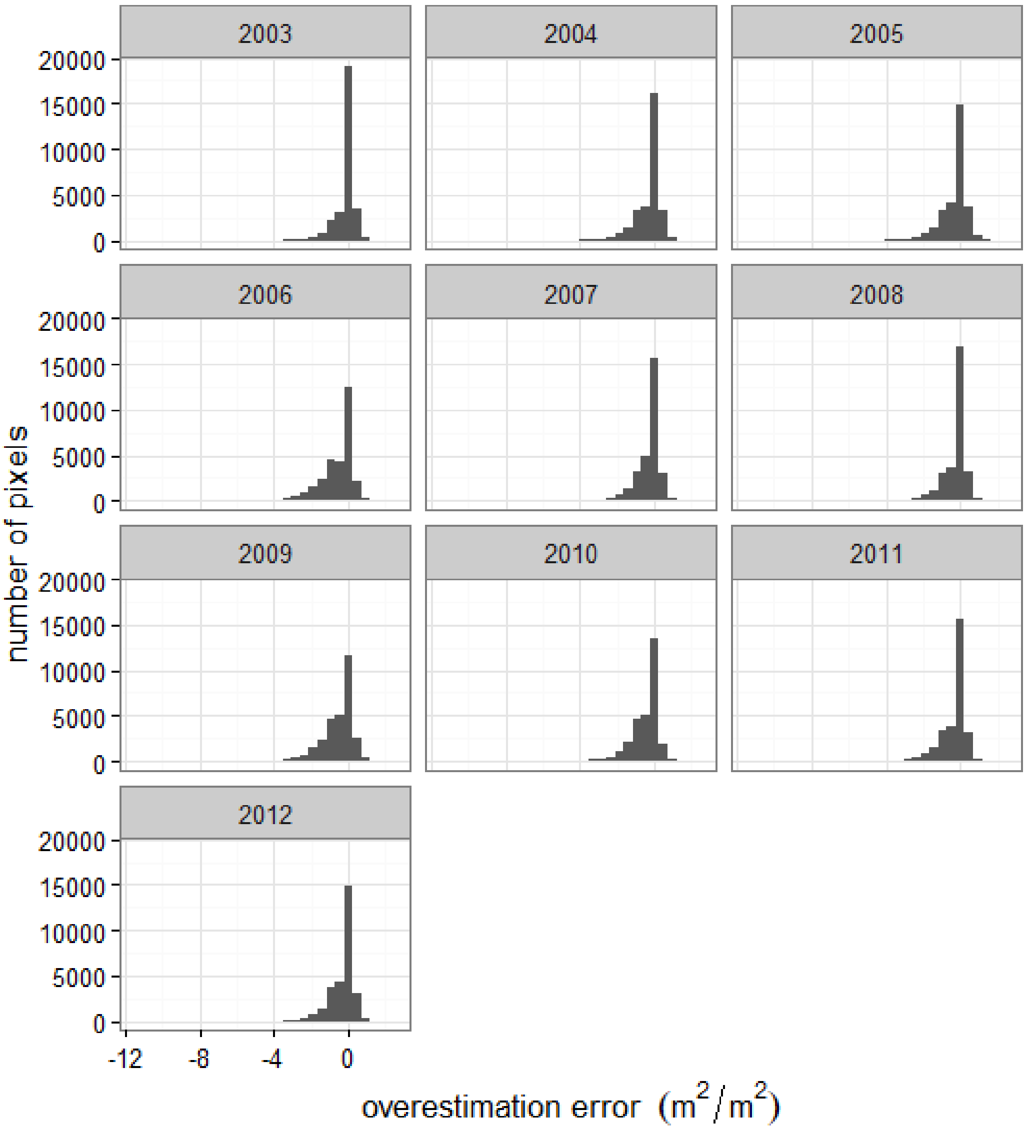


Figure 5.29: The distribution of overestimation error during 2003~2012, Zeku, China

5.10.3 The overall uncertainty of the estimated grazing-led LAI changes

The overall uncertainty of the grazing-led LAI changes estimated in this thesis can be quantified by the summation of the three components of the uncertainties:

$$Error_{overall} = Error_{noise} + Error_{fittingresidual} + Max(abs(Error_{underestimation}), abs(Error_{overestimation}))$$

Eq. 5-23

Where $Error_{noise}$ and $Error_{fittingresidual}$ are the background noise and the fitting residuals discussed in Section 5.10.1. They can be added up because they are all absolute values which represent different error components. $Max(abs(Error_{underestimation}), abs(Error_{overestimation}))$ means taking the maximum absolute value between underestimation error and overestimation error, as the grazing-led LAI changes can only be either overestimated or underestimated for each pixel.

The results of the overall error are shown in Figure 5.30, where the maximum overall error can reach as high as about 9 m^2/m^2, and the distributions of the overall error are within the error of error of 3 m^2/m^2 from 2003 to 2012. These are shown in Figure 5.31. A further statistical analysis of the overall error shows that 56.62% ~ 81.74% of the pixels have an overall error of less than 1 m^2/m^2; 86.37% ~ 95.93% of the pixels have an overall error of less than 2 m^2/m^2; and the percentage of the pixels with an overall error smaller than 3 m^2/m^2 is 94.98% ~ 98.90 % from 2003 to 2012. One the annual average, the overall error ranges from 0.59 m^2/m^2 to 1.08 m^2/m^2, and this is about 7.97%~12.34% of the estimated annual average of the grazing-led LAI changes (the average grazing-led LAI changes in Figure 5.14), and for the year 2011 (which will be used to quantify the input uncertainty in Chapter 7), it is about 10.26% of the estimated annual average of the grazing-led LAI changes. Those overall errors will further be used to quantify the upper and lower boundary of the estimation of grazing-led LAI changes, see Section 5.12, next.

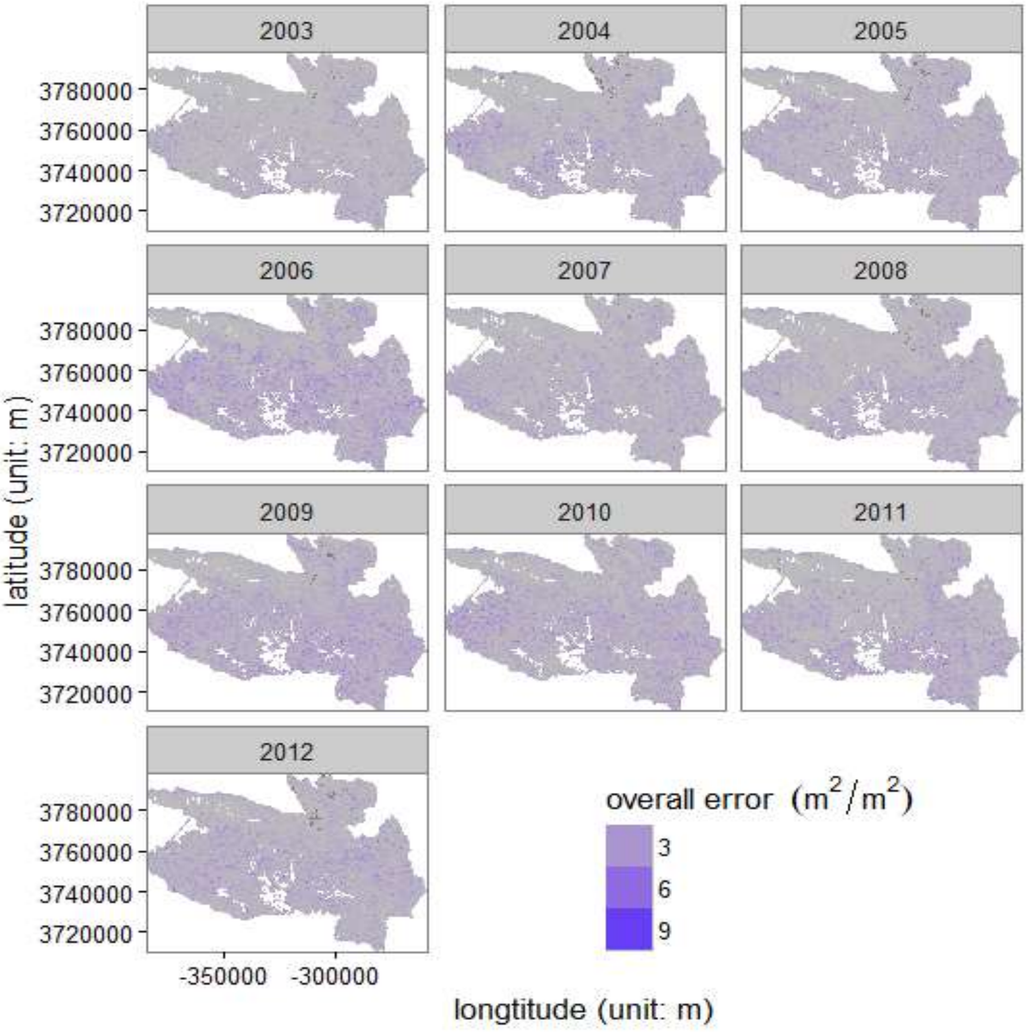


Figure 5.30: Overall error for the estimated grazing-led LAI changes during 2003~2012, Zeku, China

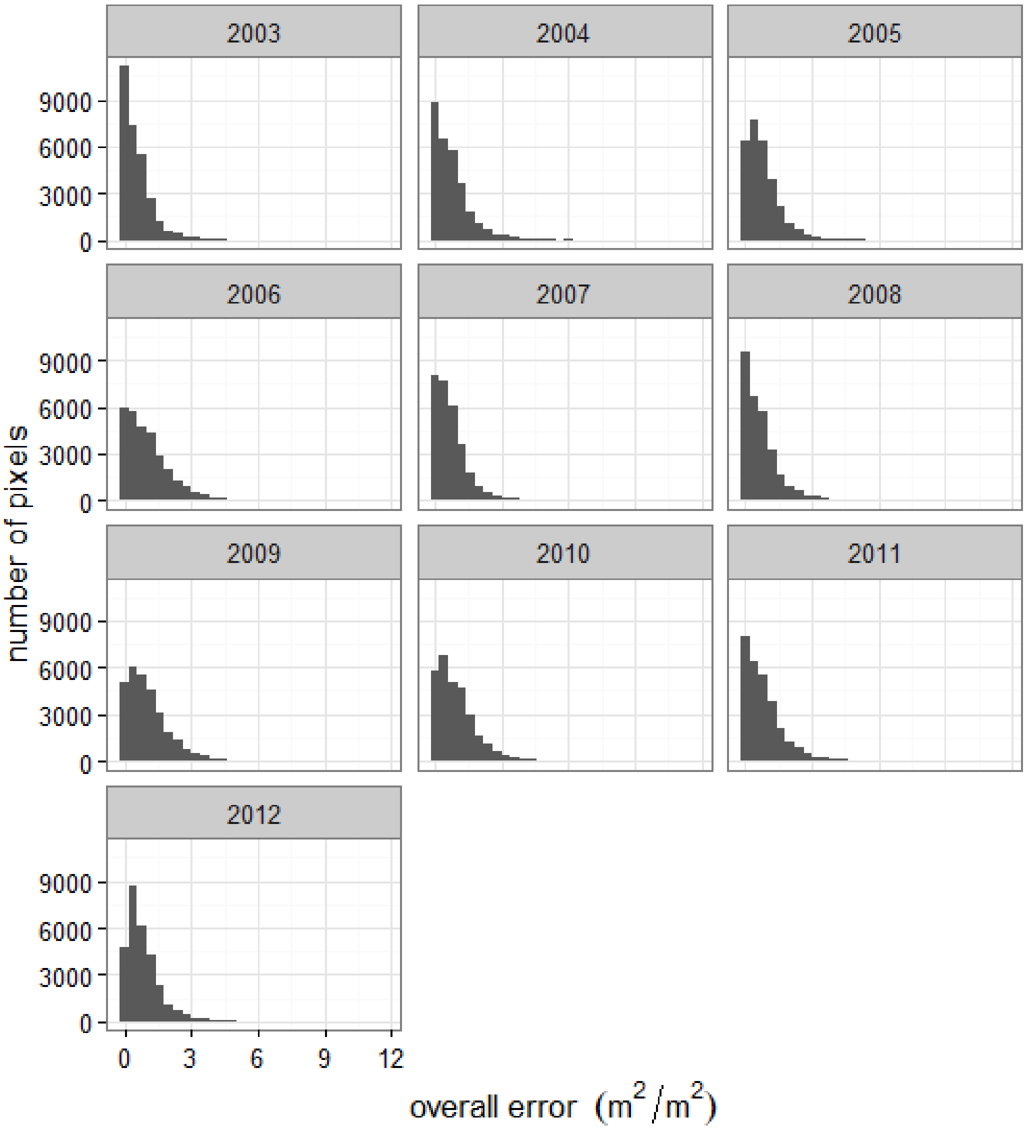


Figure 5.31: The distribution of the overall error of estimated grazing-led LAI changes during 2003~2012, Zeku, China

To this point, all the error components were quantified, and the overall error has been shown. The next section will discuss how to validate the estimation result of grazing-led LAI changes.

5.11 The uncertainty of the improved LAI

As mentioned in Step 4 of Section 5.6.4, the improved LAI can be derived from the new growth equation directly. There are 46 improved LAI images for each year, and due to the limited pages in this thesis, they are not visualized in GIS maps. Here, this thesis rather uses the average improved LAI of the whole region during 2003~2012 (see Figure 5.33).

In the same way, as the uncertainty of the estimated grazing-led LAI changes were quantified in Section 5.10, the uncertainty of the improved LAI is also quantified. The uncertainty of the improved LAI mainly consists of three parts:

1. Background noise. This is the same as has been calculated in Section 5.10.1;
2. The uncertainty of MODIS “good quality” data. This quantification is also the same as per Section 5.10.2, but that the underestimation and overestimation of the improved LAI are calculated directly rather than that of the grazing-led LAI changes;
3. The fitting residual of the new growth function. Underestimation and overestimation of the improved LAI have different fitting residuals. This thesis uses the biggest fitting residual of the underestimated improved LAI as the upper limit, and uses the smallest fitting residual of the overestimated improved LAI as the lower limit.

The overall uncertainty of the improved LAI is then the summation of those three components of the uncertainty. The uncertainty of the improved LAI is shown in Figure 5.33. We can visually see that the overall uncertainty of the improved LAI is quite fixed during the non-growth period, and the uncertainty of the improved LAI during the growth period is relatively smaller than that of the non-growth period.

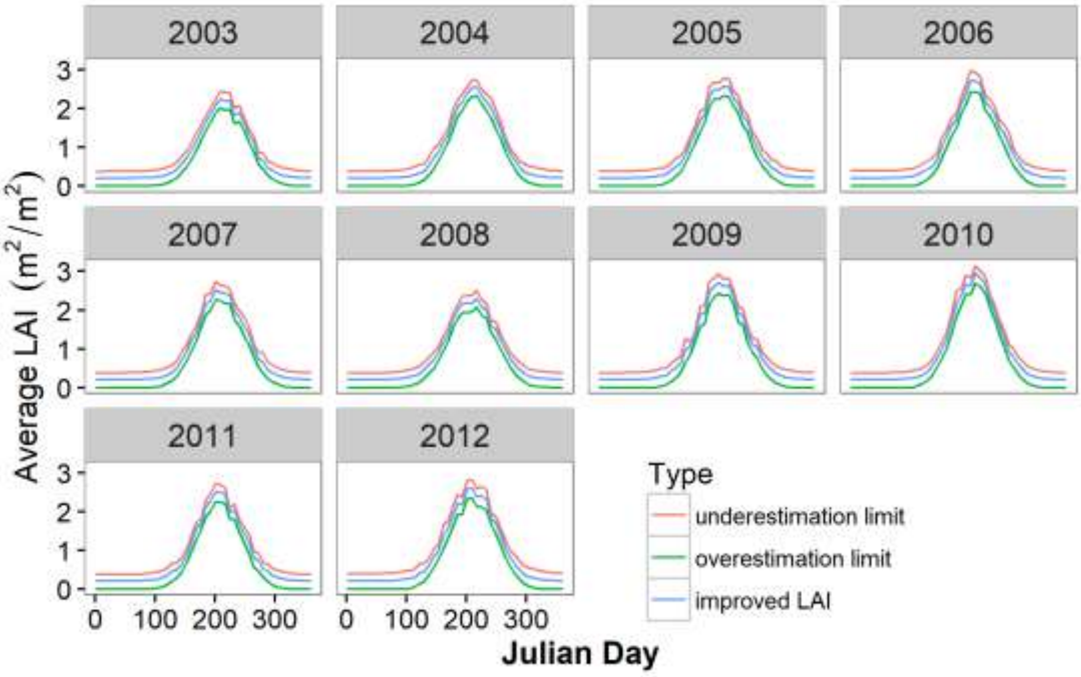


Figure 5.32: The average improved LAI of the whole region with underestimation limit and overestimation limit during 2003~2012, Zeku, China

To further investigate the uncertainty of the improved LAI during the growth period, and to compare with the degree of uncertainty of the estimated grazing-led LAI changes in the last section (Section 5.10), an average of the underestimation limit and overestimation limit are shown in Table 5.4. Although the highest underestimation rate and can reach 24.28%, and the biggest overestimation rate (absolute value) is 29.65% during the year, the maximum underestimation rate and overestimation rate are 14.48% and 18.71% respectively during the growth period (day 113¬289), which is at the similar level (within the range from 10% to 20%) for the uncertainty of the grazing-led LAI changes (the maximum uncertainty is 12.34%) during the growth period. The background noise and fitting residual of the estimated grazing-led LAI changes is the same as that of the improved LAI, but the effect of the uncertainty of the date in MODIS LAI data on the two is different, because the value of improved LAI and grazing-led LAI changes is different and therefore, the relative ratio of the uncertainty is different.

Table 5.4: The uncertainty of the improved LA during 2003¬2012

	unit	unit: m^2/m^2			unit: %	
type	Year	underesti-mation limit	overesti-mation limit	improved LAI	underesti-mation rate	overesti-mation rate
average LAI of the whole year	2003	0.91	0.51	0.73	24.28	-29.65
	2004	1.00	0.58	0.81	22.75	-28.01
	2005	1.03	0.60	0.84	22.59	-27.76
	2006	1.02	0.58	0.82	23.83	-29.71
	2007	0.98	0.57	0.80	23.09	-28.48
	2008	0.93	0.54	0.76	22.94	-28.88
	2009	1.03	0.61	0.85	21.91	-27.98
	2010	1.05	0.63	0.86	21.13	-26.97
	2011	0.95	0.54	0.77	22.39	-29.50
	2012	1.04	0.59	0.84	24.18	-28.89
average LAI of the growth period (day 113¬289)	2003	1.40	1.00	1.22	14.48	-17.89
	2004	1.57	1.15	1.39	13.38	-17.00
	2005	1.63	1.19	1.44	13.36	-16.81
	2006	1.61	1.15	1.41	14.13	-18.71
	2007	1.55	1.13	1.36	13.83	-17.29
	2008	1.46	1.07	1.29	13.52	-17.33
	2009	1.65	1.21	1.46	13.02	-17.16
	2010	1.69	1.25	1.50	12.54	-16.47
	2011	1.49	1.08	1.32	13.16	-17.94
	2012	1.64	1.18	1.44	14.29	-17.96

5.12 Validation of grazing-led LAI changes

The LAI should decrease proportionally to the amount eaten in grazing (Johnson et al., 2010). One direct way to validate the accuracy of grazed LAI estimation is to measure the on-the-ground LAI at both pre-grazing and post-grazing sites for every 8 days during the growth period. However, this requires continuous sampling on the same site for years. An alternative way is to compare with the total carbon mass consumption of the livestock for each year in Zeku. The total numbers of livestock recorded in the annual statistical yearbook are available from the Zeku Statistics Bureau. To calculate the livestock consumption, all the livestock including sheep (usually considered grazers on the ground), goat (usually considered browsers), yak and horse are converted to Sheep Unit (SU), then according to the SU conversion coefficient (Table 5.5), see NY/T 635-2002 NY/T635 (2002)), the carbon consumption is calculated during the grazing period for each year using the following formula:

$$\begin{aligned}\text{Raised Sheep Unit}\\ &= \left(livestock_{total_{start}} - livestock_{young_{start}}\right) * SUcoe_{mature}\\ &+ \left(livestock_{young_{start}} + livestock_{young_{increase}}\right) * SUcoe_{young}\\ &- \left(livestock_{total_{dead}} - livestock_{young_{dead}}\right) * SUcoe_{mature}\\ &* Coef_{die} - livestock_{young_{dead}} * SUcoe_{young} * Coef_{die}\end{aligned}$$

Eq. 5-24

$$\text{Carbon Mass} = \text{Raised Sheep Unit} * \text{GrassDryWeight}_{perSU}/0.5 * 155$$

Eq. 5-25

For each livestock type (sheep, goat, yak and horse), $livestock_{total_{start}}$ is the total number of livestock at the start of the year; $livestock_{young_{start}}$ is the number of young livestock at the start of the year; $livestock_{young_{increase}}$ is the number of livestock increased during the year; $livestock_{total_{dead}}$ and $livestock_{young_{dead}}$ is the number of total and young livestock dead separately during the year; $SUcoe_{mature}$ and $SUcoe_{young}$ is the SU convert coefficient for mature and young livestock (Table 5.5); $Coef_{die}$ is the percentage of livestock dead before the grazing period: here, we give this a constant value 0.5, assuming the number of dead livestock is evenly distributed during the year. In Zeku, the herders treasure the livestock as a fortune, and the livestock is mainly sold after the grass growth period according to our 2012 field survey. After calculating SU, the SU is converted to carbon mass using the second equation. A 0.5 multiplier accounts for the conversion from dry matter to carbon (Maselli et al., 2013), and 155 is the total grazing days during grass growth period according to Fan et al. (2010b) (Fan et al., 2010b). $\text{GrassDryWeight}_{perSU}$ is the dry grass consumed per SU, the value is 1.8 kg day^{-1} according to Fan et al. (2010a) (Fan et al., 2010a).

Table 5.5: Livestock convert coefficients:

	Mature (sheep unit)	Young (sheep unit)
Sheep	1	0.4*1
Goat	0.8	0.4*1
Yak	4.5	0.3*4.5
Horse	6.0	0.3*6.0

Year-round statistical carbon mass vs grazed LAI based leaf mass

To compare with the statistically calculated carbon mass, the grazed LAI are converted to carbon mass using (Johnson et al., 2010):

$$\text{LeafMass} = \text{LAI}/\sigma$$

Eq. 5-26

where σ is the Specify Leaf Area (SLA); we take the same value in the MODIS Biome-Property Look Up Table (BPLUT) (Running et al., 2000b). The following table (Table 5.6) shows the correlation matrix between the yearly time series of LAI based grazed leaf mass and the carbon mass calculated from raised livestock according to the statistics yearbook. The unit for carbon is 1×10^6 kgC. The herders would not sell the yaks until there was not enough feed from the grassland in Zeku, which is why we can see a correlation coefficient about -0.01 between raised yaks and estimated grazed carbon mass. However, the total number of sheep more accurately reflect the change in grassland provision, this is because sheep can be traded anytime and during any growth period as needed (the correlation coefficient is 0.59). The overall correlation between sheep units of actual sheep and estimated grazed leaf mass is 0.42, while the p-value of a paired T-test is 0.71 (with R-squared= 0.17), which indicates a consistent trend between estimated grazed amount of leaf mass and the statistically revealed consumed carbon mass over time.

Table 5.6: Correlation matrix among raised livestock and identified grazed leaf mass

	year	yak	horse	goat	sheep	total	leafmass
year	1.00	-0.78	0.82	-0.38	0.57	-0.50	0.28
yak	-0.78	1.00	-0.61	0.75	-0.68	0.84	-0.01
horse	0.82	-0.61	1.00	-0.49	0.32	-0.36	0.06
goat	-0.38	0.75	-0.49	1.00	-0.39	0.71	0.12
sheep	0.57	-0.68	0.32	-0.39	1.00	-0.22	0.59
total	-0.50	0.84	-0.36	0.71	-0.22	1.00	0.42
leafmas	0.28	-0.01	0.06	0.12	0.59	0.42	1.00

Note: leafmass is the converted carbon mass from grazing-led LAI changes

The overall error of the grazing-led estimation can be converted to the equivalent carbon through the same converting equation. The upper and lower limit of the grazing-led LAI changes are then can be calculated by adding and subtracting the converted leaf mass from the overall error map (see Figure 5.30). The relative error of the estimation of grazing-led LAI changes is evaluated by:

$$\text{Relative estimation error} = (LeafMass_{estimation} - CarbonMass_{statistical})/CarbonMass_{Statistical}$$

Eq. 5-27

Where $LeafMass_{estimation}$ is the leaf mass converted from grazing-led LAI change, $CarbonMass_{Statistical}$ is the livestock carbon consumption calculated from statistical data.

Table 5.7 shows the comparison of the converted carbon mass from grazing-led LAI changes and the total carbon mass consumption of the livestock from statistical data. The relative estimation errors range from -27.3% to 32.98% during 2003~2012 at the aggregated annual level. One cause of such high relative error can be sourced in the uncertainty of statistical data, where the total livestock structure data were only recorded at the end of the year, but the detailed data such as the number of young livestock and mature livestock sold, killed or naturally died during the grass growth period have not been recorded in the statistical data, this thesis can only make an evenly distributed assumption during the year when calculating. With more detailed ground measured and statistical data being collected in the future, the accuracy of grazing-led LAI changes can be improved. Nevertheless, the results of this chapter are the first attempt to quantify the per-pixel grazing information from remote sensing data, which will be useful for the large-scale grazing monitoring and further assessment of the grassland ecosystem.

Table 5.7: Comparison of converted carbon mass from grazing-led LAI changes and total carbon mass consumption of the livestock

year	SCC (10^6 *kgC*)	Leaf mass (10^6 *kgC*)	Leafmass Upper (10^6 *kgC*)	Leafmass Lower (10^6 *kgC*)	Relative estimation error (%)
2004	207.76	150.78	163.74	137.82	-27.43%
2005	204.87	221.35	235.00	207.70	8.04%
2006	209.51	236.73	254.97	218.50	12.99%
2007	196.23	174.75	187.29	162.21	-10.95%
2008	196.48	160.94	173.12	148.76	-18.09%
2009	206.31	274.34	292.03	256.66	32.98%
2010	189.25	239.02	255.32	222.71	26.30%
2011	185.11	149.27	163.57	134.98	-19.36
2012	206.09	250.74	265.02	236.47	21.67%
mean	200.18	206.43	221.12	191.75	–
Pearson correction value with SCC		0.420	0.416	0.424	--

Note: SCC means the converted statistical carbon mass
leafmass is the converted carbon mass from grazing-led LAI changes

5.13 Summary

Current reprocessing methods are focused on producing smoother and more spatiotemporally consistent LAI products by taking spatial, temporal, or hybrid combinations of weighted LAI. However, for grazing grasslands, the spatiotemporal weighted average LAI reprocessing methods diminish grazing information. In fact, for grassland vegetation, the temporal consistency is more important than the spatial consistency: every pixel is likely to have different conditions and/or different grazing patterns. This chapter considered the characteristics of grassland growth, developed a new exponential growth function under grazing to produce the final improved LAI data (after grazing or if grazing happens) and expected LAI data (before grazing or if no grazing happens), which is suitable for extracting grazing information effectively and consistently. This chapter developed a new growth grazing function with an estimation algorithm, to identify the grazing-led LAI changes for each pixel.

In this chapter, the main focus is on the estimation and fitting of the grazing-led LAI changes based on the MODIS LAI curve. The MODIS LAI does not account for the winter death and grazing of grasslands, so a new equation for growth curving fitting has been introduced and used for the production of improved LAI data. After that, a search algorithm has been developed to calculate the grazing-led LAI defoliation. The whole process is a series of algorithms consist of the calculation of initial background LAI, preliminary estimation of grazing-led LAI changes and expect LAI. Then the ratio of winter pasture area from household survey data was used to match up with the estimation results. Due to the limited summer/winter pasture map data, this thesis uses statistical aggregate data to validate the result. It shows that the estimates track the validation dataset consistently over time. The grazing-led LAI changes were calculated as the difference between improved LAI and expected LAI; then it was converted to leaf mass in this chapter. The carbon mass consumption of livestock during the grass growth period was calculated according to statistical yearbook data. Although the linear coefficient between grazed NPP estimated from this chapter and NPP consumption of livestock from the statistical yearbook is 0.42, the magnitude and the time trend show consistency with p-value = 0.71, indicating the new exponential growth function can be used to improved MODIS LAI data and to quantify livestock grazing. In addition, the possible overestimation error and underestimation error was quantified through an extreme situation analysis. Together with background noise and fitting residuals, the overall estimation error was calculated.

Another validation effort is to check the improved LAI produced in this chapter. To this end, in the next chapter, the improved LAI data will be used to calculate the Net Primary Productivity (NPP) using the light use efficiency with vegetation photosynthesis model (LUE-VPM). It is almost impossible to collect the grazing data before and after grazing over a sufficient time period in the field; however, given the requirement of grassland ecosystem monitoring work in China, grassland monitoring data is available, along with other data like *in situ* fresh weight, which is a crucial parameter for modelling grass growth under grazing. After converting the fresh weight sampling data to equivalent leaf mass, the LUE-VPM model is developed for such validation, and it is found that the improved LAI produced in this chapter is more accurate than the MODIS LAI with regards to NPP estimation.

Chapter 6 Grassland Productivity Sub-model

The productivity of the grassland patch is a key factor for the maximum number of livestock that can be raised on one specific land patch. It depends not only on the water and heat condition of the grassland, but also the grazing severity of the herbivores. These factors affect both the quality and quantity of grass (Briske et al., 2015). The chemical composition of pasture species has not been considered in this thesis due to the lack of relevant data. Only the quantity of grassland productivity is evaluated for each land patch. In Chapter 5, a grass status indicator, LAI, has been used to describe grazing during dynamic grass growth. The LAI is based on MODIS LAI dataset, and an improved MODIS LAI was produced by using a new growth function considering both senescence and grazing.

However, the accuracy of this improved MODIS LAI data has not been evaluated directly. Although the grazed LAI has been validated by the aggregated livestock consumption in Chapter 5, the accuracy of the improved LAI (LAI after grazing and with previous grazing effect) has not been evaluated, that is, whether the improved LAI has really been improved through the new growth function. This chapter, therefore, aims to validate the improved LAI. However, there is no available LAI data measured in Zeku. A survey that was done in 2016, the Livestock Husbandry Bureau of Zeku, has provided data for fresh grass weight from 15 sample sites collected in 2012. The validation work is then to convert MODIS LAI data and grass fresh weight data into a comparable unit. Thus, we need a Net Primary Productivity (NPP) model to calculate the NPP of the grassland (unit: gCm^{-2}) based on the improved LAI data, and then convert the in-situ measured grass weight data to carbon mass (unit: gCm^{-2}). In this way, the accuracy of the improved LAI can be evaluated indirectly.

NPP is defined as the net flux of carbon from the atmosphere into green plants (Odum, 1971). As an ecosystem structural and functional indicator, the amount of NPP is commonly used to measure the consumption of herbivory (Gignoux et al., 2001). NPP provides an energy and matter basis for ecosystems, it is also an important indicator showing the health of ecosystems and ecological balance, a key element for estimating carbon storage (which can be used as an indicator of the amount of forage grassland can provide (Fan et al., 2010a)) and the regulation of the ecological processes (Odum, 1971). Research has found the response of NPP to grazing intensity emerges as a complex result of both positive and negative, and direct and indirect, effects of grass productivity (Gignoux et al., 2001). Herbivores can maximize NPP (Luo et al., 2012), but high grazing intensity could strongly reduce the fraction of below-ground NPP (Gong et al., 2015).

There are numerous biomass estimation models at both global and regional scale, ranging from statistical models to process-based models and remote sensing based models. The purpose of this chapter is not to build a brand new NPP model, but to utilize the available high spatial resolution dataset to produce a highly reliable estimate of NPP. The Light Use Efficiency (LUE) model is widely used in NPP estimation (Xiao et al., 2004), and MODIS also used this model to produce their global 500 m and1000 m NPP data. The difference between the LUE model in this chapter and the conventional model used in the MODIS data is that the Vapour Pressure Deficit (VPD) attenuation scalar is replaced by a

Vegetation Photosynthesis Model (VPM) scalar due to data limitations (called “LUE-VPM” model for later reference).

Starting from a brief introduction of current NPP models, a detailed LUE-VPM model will be discussed that converts LAI to grass productivity. The grassland NPP that is calculated based on the improved MODIS LAI will be validated with the annual grassland monitoring data provided by the Zeku grassland monitoring station (a sector of Livestock Husbandry Bureau of Zeku), and be further compared with the MODIS NPP product. This process is essential to ensure the accuracy of the improved LAI product we have produced in Chapter 5.

6.1 Vegetation productivity models

Estimation of land productivity is crucial to the management of grassland grazing as well as allowing the quantification of the carbon balance for both regional and global sustainable grassland development. Essentially, there are four major categories of land productivity models: Canopy Photosynthesis Models (CPMs), Production Efficiency Models (PEMs), Ecosystem process models and statistical models. When data was limited, statistical models were prevalent, linking vegetation with climate factors. However, these are not suitable for large-scale spatial and/or pixel-specific modelling. In addition, the temporal resolutions are relatively low (usually, on a yearly basis) compared with the other three.

PEMs are based on the theory that the fraction of Photosynthetic Active Radiation (fPAR) absorbed by terrestrial vegetation can be derived from remote sensing data (Kumar and Monteith); for example, the Normalized Difference Vegetation Index (NDVI) recorded by the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) sensor (Anyamba and Tucker, 2005). Remote sensing based models have the advantage of near real-time, high spatial resolution and large-scale observation data, but these models are highly dependent on hard to estimate empirical parameter values such as radiation conversion efficiency, which is sensitive to the optical properties of the background environment and directional effects of the landscape (Myneni and Williams, 1994; Fensholt et al., 2004). Therefore, a predefined ‘conversion efficiency’ or an optimum value considering other environmental factors is used in NPP calculation. They are also called “diagnostic models” as remote sensing derived vegetation indices are employed in the calculation.

Ecosystem Process Models (EPMs) are “bottom-up” oriented – they are commonly modelled at the level of each ecosystem process: phenology, leaf thickness, minimum stomatal conductance, photosynthetic pathway, allocation, rooting depth based on the structural characteristics of the vegetation (Woodward and Cramer, 1996), then integrated through the canopy with biochemical fluxes (CO_2, water and energy exchange) (Cramer et al., 1999). However, such models are commonly complicated and involve lots of parameter estimation work. They either do not use PAR as an input, or are not able to provide the basis to compute fPAR. The following table (Table 6.1) shows some typical models of NPP simulation.

While in CPMs, the estimation process is basically the same as PEMs or EPMs, they are more focused on the leaf level plant photosynthesis, and usually integrated with the seasonal canopy dynamics (typically, LAI dynamics during the year) and biochemical exchanges. CPMs are called 'process models', because they evolved from ecosystem or crop models which have explicit processes for individual plant growth. The significant difference between CPMs and PEMs is that remote sensing measurements are not necessary for CPMs. For this reason, CPMs have the ability to produce results for future climate scenarios, and they are "prognostic models" as well (Ruimy et al., 1999a). However, CPMs depend highly on the vegetation seasonal parameters, which would be different across different vegetation types.

Table 6.1: Comparison of the broad features of the participating NPP models, modified from Cramer et al. (1999) and Ruimy et al. (1999a). Note: R, solar radiation; LAI; leaf area index; T, temperature; SW, soil water content; VPD, vapour pressure deficit; LeafN, leaf nitrogen; VegC, vegetation carbon; P, precipitation; AET, actual evapotranspiration; PET, potential evapotranspiration; S, soil inorganic sulphur; AWC, available water capacity.

	model	**temporal resolution as**	**calculated as**	**influenced by**	**Strategy**	**Key reference**
Statistical models	Miami	1 year	statistical	$\mathrm{NPP_T} = 3000/_{1 + \mathrm{e}^{(1.315-0.119}}$, ***Or,*** $\mathrm{NPP_r} = 3000(1 - \mathrm{e}^{-0.000654\mathrm{r}})$	Regression with temperature	(Lieth, 1975)
	Thointhwaite Memorial	1 year	statistical	$\mathrm{NPP} = 3000(1 - e^{-0.0009695(v-20)})$, $\mathrm{v} = \frac{1.05R}{\sqrt{(1+1.05R/L)^2}}$, $\mathrm{L} = 3000 + 25\mathrm{t} + 0.05t^3$	Regression with potential evaporation	(Lieth, 1975)
	CSCS	1 year	statistical	$\mathrm{NPP} = L^2 \cdot \frac{0.1 \cdot \sum \theta \cdot (K^6 + L(K)K^3 + L^2(K))}{(K^6 + L^2(K)) \cdot (K^5 + L(K)K^2)) } e^{-\sqrt{13.55+3.17K^{-1}-0.16K}}$, $\mathrm{L(K)} = 0.58802K^3 + 0.50698K^2 - 0.0257087K + 0.0005163874$	Classified by ecophysiological feature and regional evapotranspiration	(Lin, 2009)
	Chikugo	1 year	statistical	$\mathrm{NPP} = 0.29e^{-0.216 \times RDI^2} \times R_n$, $\mathrm{RDI} = \frac{R_n}{L \cdot r}$	Regression with radiation and radiative dryness index	(UCHIJIMA and SEINO, 1985)
	HRBM	1 month	NPP	NPP = f(T, P, AET/PET, CO_2, Fert)	regression of annual NPP on climate,	(Esser, 1994)

					seasonality driven by AET	
Production Efficiency Models (PEMs)	CASA	1 month	NPP	NPP = f($\boldsymbol{R}_s$, FPAR, T, AET/PET)	PEM, LUE derived empirically, applied to NPP	(Potter et al., 1993)
	GLO – PEM	10 days	GPP–R_A	GPP = f($\boldsymbol{R}_s$, FPAR, T, SW, VPD) R_A = f(Veg C, GPP)	PEM, LUE derived from a mechanistic model, applied to GPP	(Prince, 1991a)
	SDBM	1 month	NPP	NPP = f($\boldsymbol{R}_s$, FPAR, CO_2)	PEM, LUE derived empirically, applied to NPP	(Knorr and Heimann, 1995)
	TURC	1 month	GPP–R_A	GPP = f($\boldsymbol{R}_s$, FPAR) R_A = f(Veg C, T)	PEM, LUE derived empirically (global value), applied to GPP, environmental constraints applied to RA	(Ruimy et al., 1996)
Canopy Photosynthesis Models (CPMs)	FBM	1 day	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, SW, CO_2) R_A = f(Veg C, T)	leaf level photosynthesis model, C and H_2O balance integrated over the canopy, phenology internal	(Kindermann et al., 1993)
	PLAI	1 day	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, SW, CO_2) R_A = f(Veg C, T)	leaf level photosynthesis model, C and H_2O balance integrated over the canopy, phenology internal	(Plöchl and Cramer, 1995)
	SILVAN	6 days	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, AET/PET, CO_2) R_A = f(Veg C, T)	leaf level photosynthesis model, C and H_2O balance integrated over the canopy, phenology internal	(Kaduk and Heimann, 1996)
	KGBM	1 day	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, SW, VPD) R_A = f(GPP)	estimates LAI from water balance, phenology (= inactive period) from satellite	(Kergoat, 1998)
	BIOME3	1 month	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, AET/PET, CO_2) R_A = f(LAI, GPP)	simulates vegetation structure and physiological processes, coupled C and H_2O balance,	(Haxeltine and Prentice, 1996b; Haxeltine et al., 1996)

					phenology internal	
	CARAIB	1 day	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, SW, VPD, CO_2, O_2) R_A = f(Veg C, LAI, T)	leaf level photosynthesis model, C and H_2O balance integrated over the canopy, phenology internal	(Warnant et al., 1994)
	HYBRID	1 day	GPP–R_A	GPP = f($\boldsymbol{R}_s$, FPAR, T, SW, CO_2, N) R_A = f(Veg C, T, Veg N)	simulates vegetation structure and physiological processes, coupled C and H_2O balance, phenology internal	(Friend and Cox, 1995; Friend et al., 1997)
	SIB2	12 min	GPP–R_A	GPP = f($\boldsymbol{R}_s$, FPAR, LAI, T, SW, VPD, CO_2) R_A = f(GPP, T, SW)	SVAT model, coupled to GCM	(Randall et al., 1996; Sellers et al., 1996a; Sellers et al., 1996b)
Ecosystem process models	DOLY	1 year	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, SW, VPD, CO_2, Soil C & N) R_A = f(Veg C, T, Soil C & N)	simulates vegetation structure and physiological processes, coupled C and H_2O balance, RA and NPP annual	(Woodward et al., 1995a)
	CENTURY	1 month	NPP	NPP = f(Veg C, T, SW, P, PET, N, P, S)	mechanistic soil C and N model with above – ground vegetation processes, calibrated against observations	(Parton et al., 1993a)
	TEM	1 month	GPP–R_A	GPP = f($\boldsymbol{R}_s$, KLeaf, T, AET/PET, CO_2, N) R_A = f(Veg C, GPP, T)	mechanistic process model, using climate and soils data with a water balance algorithm to estimate NPP	(McGuire et al., 1995)
	BIOME – BGC	1 day	GPP–R_A	GPP = f($\boldsymbol{R}_s$, LAI, T, SW, VPD, CO_2, Leaf N) R_A = f(Veg C, T)	estimates LAI from water balance, no phenology	(Running and Hunt Jr, 1993)

6.2 NPP model selection

NPP is mainly affected by climate factors, so statistical models associate climate factors (precipitation, temperature, sunshine (Ye et al., 2013) and flux of radiation (Zhou et al., 1995), etc.) with plant dry matter production through a simple mathematical regression to estimate NPP (Lieth and Whittaker, 1975). The advantage of statistical models is the high availability of meteorological data, and that the result of them can truly reveal the climate-affected patterns of NPP, but NPP is also affected by other factors (e.g. soil conditions) therefore, this kind of model is too simple to represent the true NPP distribution. Physiological models consider the transformation mechanism of chemical energy from solar energy by plants, and canopy transpiration, as well as photosynthesis accompanied by soil and water effects (CENTURY 4.0 (Parton et al., 1993b), TEM 4.0 (McGuire et al., 1997), CASA (Potter et al., 1993)). Such models are important tools estimating NPP and predicting ecosystem or environmental change problems, but due to the complicated dynamic bilateral feedback of NPP with the environment, it is difficult to apply these models at different scales. Remote sensing based models are developing rapidly with remote sensing becoming increasingly popular. The basic theory is that different plants have different spectral reflectance and even the same plant has different spectral reflectance according to different growth stages (Li et al.; Field et al., 1995). The common assumption is that such models view above ground NPP (ANPP) as NPP and they have not taken full account of both turnover and below-ground NPP (BNPP) (Long et al., 1989).

To conclude, both PEMs and CPMs are the LUE based models, which concentrate on the conversion processes of solar radiation to carbon mass (or biomass). PEMs have the advantage of using remote sensing data to quantify fPAR; while CPMs consider the photosynthesis processes of vegetation leaves and the exchange of carbon and water, based on which the conversion of carbon mass from PAR can be calculated. Other ecosystem process models simulate the structure of vegetation and biogeochemical fluxes. Considering this, remote sensing based PEMs are more suitable for this thesis. The purpose of this chapter is to check whether the improved LAI produced in Chapter 5 is reliable. It is the most important input data we have to integrate into the final model.

In addition, MODIS NPP products were produced by the combination of PEM and an ecosystem process model (see Figure 6.1). By using the biome-specific ecosystem process model, BIOME-BGC, the maximum value for the conversion efficiency ε_{max} for each land type can be derived. However, while ε_{max} is the potential maximum convert efficiency for specific land type, the value of ε_{max} varies to different local environmental conditions (mainly temperature and atmospheric moisture). In the MODIS NPP algorithm, the Vapour Pressure Deficit (VPD) model was employed to calculate the final conversion efficiency ε :

$$\boldsymbol{\varepsilon = \varepsilon_{max} \cdot \mathrm{TMIN}_{\mathrm{scalar}} \cdot VPD_{\mathrm{scalar}}}$$

Eq. 6-1

$\mathrm{TMIN}_{\mathrm{scalar}}$ and VPD_{scalar} represent the constraint of minimum temperature and VPD. Both of the data were held by the Global Modelling and Assimilation Office of National Aeronautics and Space Administration (GMAO/NASA) at the daily scale.

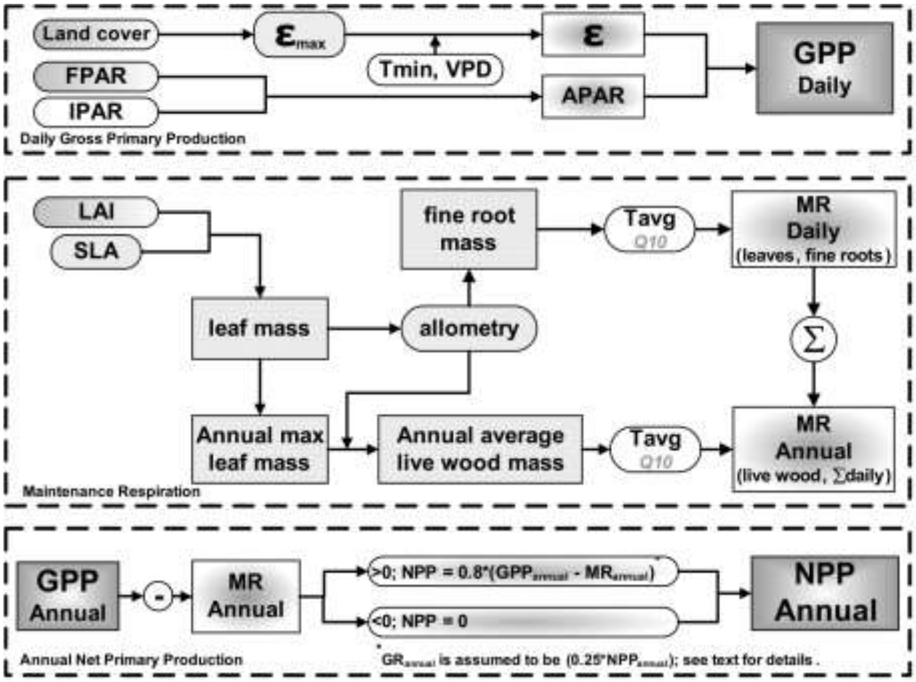


Figure 6.1: Flowcharts showing the logic behind the MOD17 Algorithm in calculating both 8-day average GPP and annual NPP, from Running (2015)

Unfortunately, the daily temperature and VPD data archived by GMAO/NASA are not publicly accessible, and most importantly, the spatial resolution (0.5 Latitude degree by 0.67 Longitude degree) of them (Zhao et al., 2006) is not enough to reflect the spatial heterogeneity of Zeku, which is an important factor that would affect the accuracy of any regional NPP calculation. Given these complexities, this thesis turns to the same algorithm as MODIS NPP, but instead of using LUE-VPD in calculating ε, an LUE-VMD model is selected as the best way forward, for the reasons that:

-The LUE model is one of the most widely used models in remote sensing based NPP estimation. MODIS itself published a global NPP dataset, with an 8-day period resolution, based on this model, with which we can easily compare our estimation;

-in Chapter 5, the LAI dynamic under grazing is analysed with remote sensing data; given this, the NPP estimation modelling is ideally done using a remote sensing based model;

-there are limited high spatial resolution climatic and planetary data for us to use to parameterize a process-based model (sadly, as the mechanism would be more clear if we could).

The following parts of this chapter will discuss the radiation, LUE and plant growth in detail. It will start with a Photosynthetic Active Radiation (PAR) estimation, then the VPM model and finally the NPP calculation.

6.3 General processes of LUE-VPM model

The LUE models are based on the rationale that daily photosynthesis is proportional to the Absorbed Photosynthetic Active Radiation (APAR) according to the Monteith theory (Monteith, 1972; Monteith and Moss, 1977), which proposed a linear relationship between aboveground photosynthesis and APAR for barley, potatoes, sugar beet, and apples in Britain. Later, a similar linear relationship has been found for cereals (Gallagher and Biscoe, 1978) and tropical trees (Harrington and Fownes, 1995). Thus, light use efficiency has been widely used to quantify the amount of APAR in energy units converted into vegetation biomass in carbon units (GPP) (Odum, 2013).

$$\mathrm{GPP} = \varepsilon \cdot \mathrm{APAR}$$

Eq. 6-2

where ε is known as light use efficiency (LUE), and it represents the conversion efficiency of solar radiation to carbon mass. A detailed theoretical analysis of Eq. 6-2 was discussed in Haxeltine and Prentice (1996a). The value of ε has been estimated both theoretically and experimentally for various species (Ruimy et al., 1994; Landsberg et al., 1997; Medlyn, 1998). It depends on the local environmental conditions: water, nitrogen, and temperature (Hunt Jr and Running, 1992; Wright et al., 1993; Ruimy et al., 1999b). MODIS NPP products (MOD17A2/A3) use temperature and moisture (VPD) as the two main constraint parameters to calculate ε (see Eq. 6-1). But as mentioned earlier in this chapter, a VPM model is used to calculate the value of ε. The other algorithms for NPP calculation are exactly the same as the MODIS NPP algorithms (see Figure 6.1). Before introducing these, a brief description of the APAR calculation (in Eq. 6-2) is presented first.

6.3.1 Quantifying the absorbed solar radiation for photosynthesis: APAR

Solar radiation is the key factor in vegetation growth, providing the essential energy for photosynthetic activities (Monteith, 1972). Solar radiation has a variety of wavelengths, but only the wavelengths between 0.4 μm and 0.7 μm can be used by vegetation for photosynthetic activities, that is, photosynthetically active radiation (PAR) (McCree, 1972). APAR (Absorbed PAR) describes the amount of PAR received by the vegetation canopy and used for photosynthesis. It varies with the change in day length due to axial tilt and the daily cloud over the aerosol attenuation of solar radiation (Odum, 2013), as well as the upwelling radiance reflected by the land surface (Roujean and Breon, 1995). Therefore, it is also an important component of any analysis of the global carbon balance through the estimation of vegetation photosynthetic carbon sink (Tucker et al., 1986). In addition, APAR implicitly indicates how much leaf area the vegetation (LAI) is exposed to absorb solar radiation, and it follows the form:

$$\boldsymbol{APAR = fPAR * PAR}$$

Eq. 6-3

where PAR is Photosynthetic Active Radiation (PAR), which is part of the solar radiation within the spectral range of 400-700 nm for vegetation photosynthesis, which controls the accumulation of NPP and the carbon fixation on the earth (Frouin and Pinker, 1995). It plays an important role in evaluating global productivity change and carbon balance (Li et al., 2015a) incoming photosynthetically active radiation. It is the potential radiation that could be absorbed to do photosynthetic work: not all this light is used, and fPAR is the Fraction of Photosynthetically Active Radiation absorbed by vegetation; the actual proportion used is known as the APAR.

Basically, all the methods of fPAR estimation are based on the relationship between vegetation indices and vegetation canopy properties. For example, fPAR was calculated by quantifying the linear relationship with the Normalized Difference Vegetation Index (NDVI) (Sims et al., 2006): FPAR = 1.24NDVI − 0.168; or the linear relationship with the Enhanced Vegetation Index (EVI) (Fisher et al., 2008): fPAR = 1.2EVI. The MODIS fPAR product has used a more advanced vegetation index, which consists of three or four wavelengths (Odum, 2013). Among all those calculations, the relationship between fPAR and LAI, which is known as Beer's law, is the most widely used one (Hu et al., 2013), which follows:

$$\boldsymbol{fPAR = 0.95(1 - exp(-k * LAI))}$$

Eq. 6-4

where fPAR is the fraction of incident PAR absorbed by the canopy, k is the light extinction coefficient, LAI is the one-sided leaf area per ground area. Similar to the other light use efficiency models, the light absorption here integrates leaf photosynthesis to the canopy (Ruimy et al., 1999b). The value for k is 0.5 in this thesis, which has been extensively validated for both herbaceous crops (Varlet-Grancher et al., 1980), forest (Jarvis and Leverenz, 1983) and grass (Zhang et al., 2014b).

6.3.2 Calculation of PAR from solar shortwave radiation

PAR is affected by atmospheric conditions (water vapour and ozone amounts, surface visibility, aerosol type and cloud optical thickness) (Frouin and Pinker, 1995) and radiation geometry (solar zenith angle) (Myneni et al., 1997b). However, numerous studies have confirmed there is a robust linear relationship between PAR and solar Shortwave Irradiance (SI) (Britton and Dodd, 1976; Papaioannou et al., 1993). Notice that, solar radiation is also called solar shortwave radiation compared with terrestrial radiation (longwave radiation) (Mani, 1980). Thus, PAR can be calculated by using SI at the top of the atmosphere and a conversion ratio, which can be expressed as:

$$\mathrm{PAR} = \varphi * \mathrm{SI}$$

Eq. 6-5

where φ accounts for the ratio of PAR to the solar shortwave radiation; SI stands for the solar shortwave radiation. Studies have found that the value of φ varied according to weather conditions. The early most commonly used value of φ was 0.44 (Moon, 1940). Under clear sky conditions, the value of φ changed from 0.47 to 0.5; while under cloudy or rainy conditions, the range was 0.47–0.59 (McCree, 1966).

In the Carnegie–Ames–Stanford Approach (CASA) model, φ is a constant value, which accounts for the fact that approximately half of the SI can be considered as PAR (Potter et al., 1993). For practical purposes, the ratio of photosynthetically useful radiation has been suggested to be half of the SI (Monteith and Reifsnyder, 1974). In Barrow, Alaska, the value was found to be 0.45, and similar results have been revealed in Jerusalem, Israel, and Rockville, Maryland, U.S.A (Goldberg and Klein, 1977), although the value ranged from 0.45 to 0.47 in Ultuna, Sweden (Rodskjer, 1983). The results for California State

University, Fresno site, indicated that φ varied from 0.458 in July to 0.446 in April (Blackburn and Proctor, 1983).

While in China, especially in the Qinghai-Tibet regions, the value of φ has been extensively investigated. A comparison of observed and modelled φ is shown in Figure 6.2. Although there are obvious seasonal differences in the ratio of PAR ("QP" in Figure 6.2) to SI ("RS" in Figure 6.2), the observed standard deviation is 0.004 at the monthly level with a mean value of 0.446 in Tibet (Li et al., 2010). The ratio ($^{Q_P}/_{R_S}$) of photosynthetically active radiation (Q_P) and global solar radiation (R_S) is not significantly different for each month. In this thesis, the value of φ is set to be 0.446, based on Li et al. (2010)'s observation.

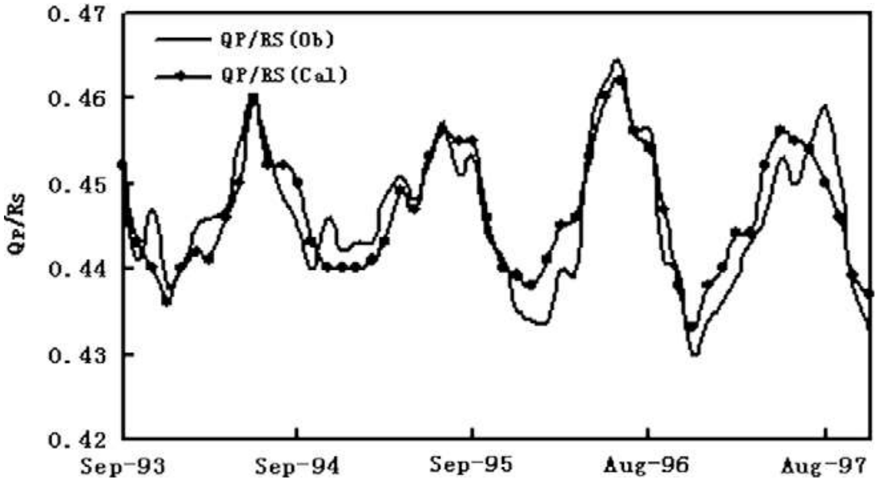


Figure 6.2: Monthly measured and modelled ratio ($^{Q_P}/_{R_S}$) of photosynthetically active radiation (Q_P) and global solar radiation (R_S), figure from Li et al. (2010)

Unfortunately, in the algorithm used for calculating the MODIS daily NPP (MOD17A2/A3) products, PAR is estimated in this manner (Eq. 6-5) from data provided by the Global Modelling and Assimilation Office in the National Aeronautics and Space Administration (GMAO/NASA). The spatial resolution of this shortwave radiance data is in increments of 2/3° latitude and 1/4° longitude (Masuda, 2004), which is not suitable for estimating NPP at a 463×463 m^2 spatial resolution. In addition, the MODIS method does not consider the shadow effect of hills' elevation on the total incoming shortwave radiation. This thesis uses a viewshed model developed by Fu and Rich (2002) to calculate the downward surface radiation for each day. The elevation data is from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) (ASTER, 2005) with a spatial resolution of 30m and resized to 463m (see Figure 6.3).

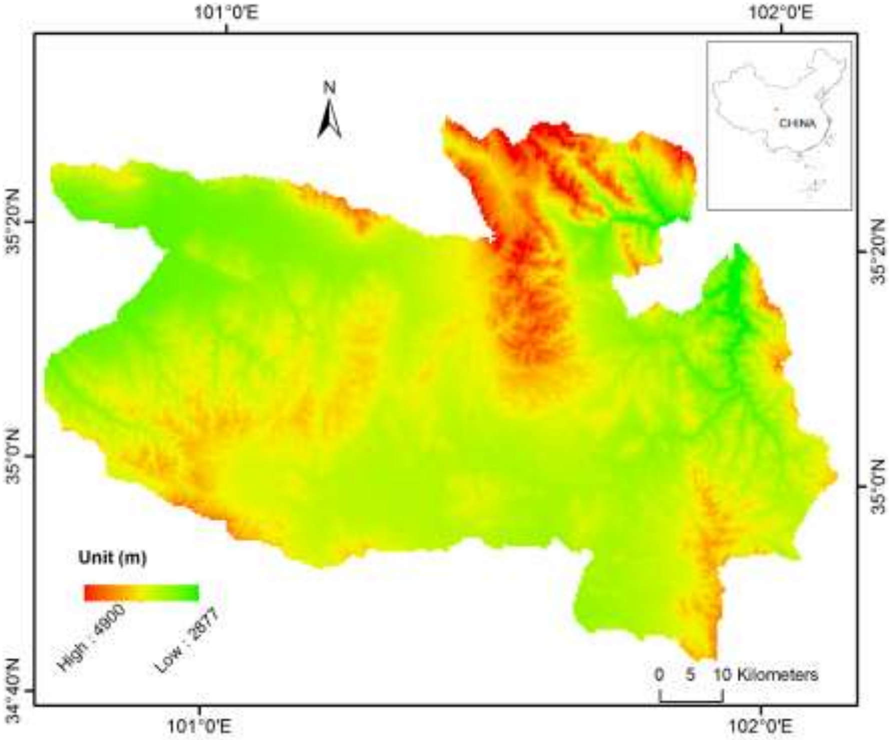


Figure 6.3: DEM of Zeku, China

Generally, when solar radiation travels from the sun through the atmosphere to the top of the canopy, it is inevitably affected by astronomical and meteorological factors (Brock, 1981). There are three components actually arriving at the top of the canopy: direct, diffuse, and reflected insolation. Direct radiation is the main component of solar radiation, it is not reflected or scattered and reaches the surface directly; while diffuse radiation is the second largest component, it is the scattered radiation that reaches the ground. Reflected radiation from surrounding landscapes (reflected from the ground onto the inclined receiver) generally accounts for a small proportion of total incident solar radiation and usually can be neglected (Hofierka and Suri, 2002). If both the diffuse and global solar radiation is known (diffuse ratio), the direct component of solar radiation can be obtained through simple subtraction (Tuller, 1976). However, the diffuse ratio varies inversely with cloudiness, the value of this ratio ranging from 0 to 0.35 has been observed (Tuller, 1976). In China, the value of the diffuse ratio for different regions are listed in Table 6.2. The diffuse ratio is set to 0.31(row “NC” in Table 6.2, means Northwest China region) in this thesis following the table (Fu et al., 2015).

Table 6.2: Sunny diffuse radiation percentage, from Fu et al. (2015)

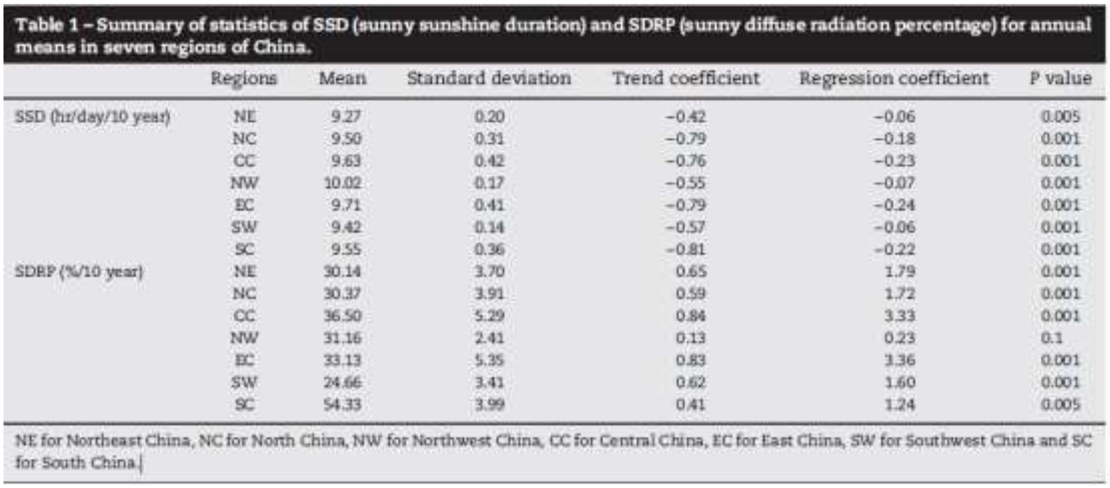


Table 1 – Summary of statistics of SSD (sunny sunshine duration) and SDRP (sunny diffuse radiation percentage) for annual means in seven regions of China.

	Regions	Mean	Standard deviation	Trend coefficient	Regression coefficient	P value
SSD (hr/day/10 year)	NE	9.27	0.20	−0.42	−0.06	0.005
	NC	9.50	0.31	−0.79	−0.18	0.001
	CC	9.63	0.42	−0.76	−0.23	0.001
	NW	10.02	0.17	−0.55	−0.07	0.001
	EC	9.71	0.41	−0.79	−0.24	0.001
	SW	9.42	0.14	−0.57	−0.06	0.001
	SC	9.55	0.36	−0.81	−0.22	0.001
SDRP (%/10 year)	NE	30.14	3.70	0.65	1.79	0.001
	NC	30.37	3.91	0.59	1.72	0.001
	CC	36.50	5.29	0.84	3.33	0.001
	NW	31.16	2.41	0.13	0.23	0.1
	EC	33.13	5.35	0.83	3.36	0.001
	SW	24.66	3.41	0.62	1.60	0.001
	SC	54.33	3.99	0.41	1.24	0.005

NE for Northeast China, NC for North China, NW for Northwest China, CC for Central China, EC for East China, SW for Southwest China and SC for South China.

Considering the effect of the solar altitude, atmospheric water vapour content, dust content, ozone content and any other radiation depletion, a transmission coefficient for direct and diffuse radiation have been proposed by Liu and Jordan (1960); it was also referred to as either the clearness index or cloudiness index. It is a very attractive parameter for estimating the response of solar radiation to different atmospheric conditions; using this the diffuse ratio can be calculated by using the global transmissivity of the atmosphere (Carroll, 1985). The transmissivity is set to 0.72 based on regional figures given by Pan et al. (2013) (see Figure 6.4), and the calculation interval is 30 minutes. Slope and aspect are from the DEM, and 32 different incident radiation directions are calculated.

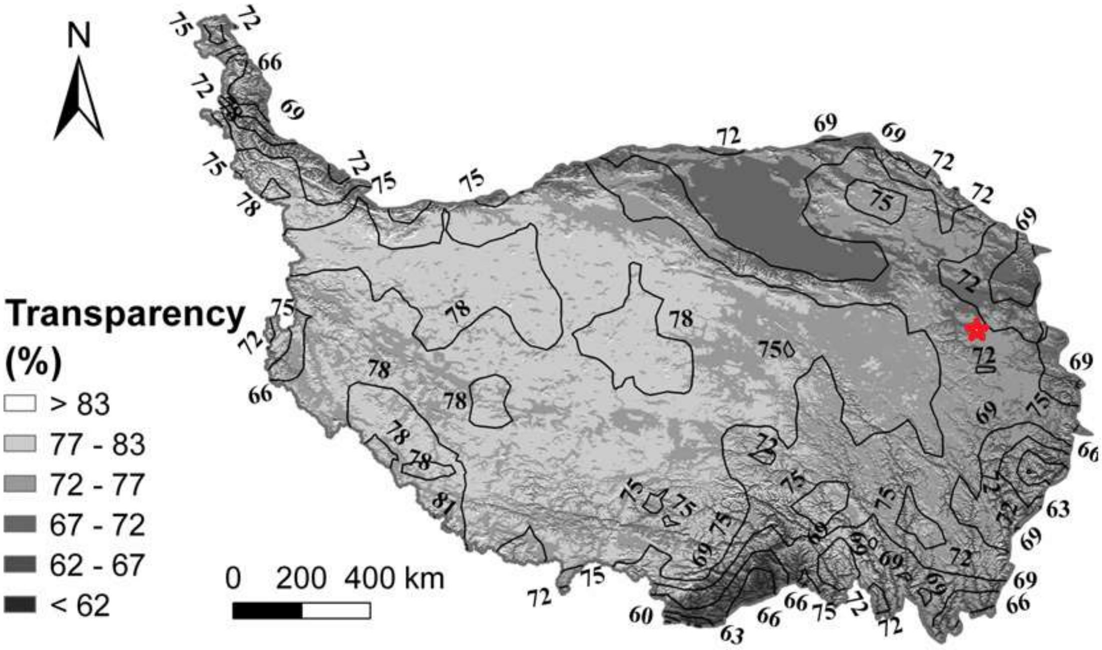


Figure 6.4: The spatial pattern of the atmospheric transmission coefficient under clear-sky conditions over the Tibetan Plateau, the labels are percentages. From Pan et al. (2013)

To summarise, the SI can be calculated by using the viewshed method, which includes two key parameters: diffuse ratio and transmissivity. The value of these two parameters were all referred to the current studies in the case study area. Then the PAR can be obtained through Eq. 6-5. The ratio for the PAR (φ) was derived from the study in Qinghai-Tibet region. According to Eq. 6-2, Eq. 6-3 and Eq. 6-4, the main difficulty for NPP estimation is the value of LUE for each pixel in Zeku. Due to the limited data accessibility and low spatial resolution of climatic data, instead of using VPD model, a VPM model will be used to calculate LUE (ε).

6.3.3 An alternative way of calculating LUE: VPM

The MODIS NPP algorithm uses the Water Vapour Deficit (VPD) model to calculate the scalars that attenuate the solar radiation. The main purpose of this calculation is to convert the maximum radiation conversion efficiency (ε_{max}) to the local instantaneous radiation conversion efficiency (ε) on a daily basis. The formula for the VPD model was shown in Eq. 6-1, where $Tmin_{scalar}$ is the scalar factor that reflects the effect of temperature on radiation conversion efficiency (the value range is from 0 to 1), and VPD_{scalar} reflects the effect of water on the radiation conversion efficiency (the value range is from 1 to 0). The default value of ε_{max} can be obtained from the Biome Property Look Up Table (BPLUT, see Table 6.3) (Running, 2015).

Table 6.3: Biome Property Look Up Table (BPLUT) for MODIS GPP/NPP algorithm (from MODIS data user guide, *: the constant $Q_{10} = 2.0$ is applied to fine roots and live wood, while for leaves, a temperature acclimation Q_{10} value is used as described in Equation)

Classification type	grass	Description
ε_{max} (KgC/m²/d/MJ)	0.00086	The maximum radiation conversion efficiency
Tmin_min (C)	-8.00	The daily minimum temperature at which $\varepsilon = \varepsilon_{max}$
Tmin_max (C)	12.02	The daily minimum temperature at which $\varepsilon = 0$
VPD_min (Pa)	650.00	The daylight average vapour pressure deficit at which $\varepsilon = 0$
VPD_max (Pa)	5300.00	The daylight average vapour pressure deficit at which $\varepsilon = \varepsilon_{max}$
SLA (LAI/KgC)	37.5	Projected leaf area per unit mass of leaf carbon
$Q_{10}{}^{*}$	2.0	Exponent shape parameter controlling respiration as a function of temperature
froot_leaf_ratio	2.6	The ratio of fine root carbon to leaf carbon
leaf_mr_base	0.0098	Maintenance respiration per unit fine leaf carbon per day at 20 ℃
froot_mr_base	0.00819	Maintenance respiration per unit fine root carbon per day at 20 ℃

However, the value of ε_{max} varies in different biome types and by local environmental conditions (Landsberg and Waring, 1997). The value of ε_{max} for grassland in the MODIS NPP products calculation is 0.00086 $gC/m^2/MJ$ (Running et al., 2000a), but one of the key uncertainties is the spatial and temporal variation of the daily ε_{max} value (Goetz and Prince, 1999; Turner et al., 2002). Therefore, in the NPP calculation, especially in regional or local areas (smaller scale calculations), the value of ε_{max} would be different (Goetz et al., 1999). In this thesis the value of ε_{max} is 0.0006 $gC/m^2/MJ$ when calculating the NPP based on ground measurement in Qinghai-Tibet (Li et al., 2012).

The main reason for choosing the VPM model is data availability. Since there is no access to the daily climatic data provided by GMAO/NASA, and the spatial resolution (0.5 Latitude degree by 0.67 Longitude degree) of GMAO/NASA climatic data is too low thus cannot be used. One pixel of GMAO/NASA data could cover all the area of Zeku and could result in the homogeneity of local ε, which is not true in reality. The China Meteorological Forcing Dataset (CMFD) (Chen et al., 2011) has provided high spatial resolution climatic data for every three hours from 1979 to 2012 (this is also the main reason for this thesis choosing 2003-2012 as a case study period; from 2003, the grasslands have also been contracted to individual households). By aggregating the three-hour temperature data to the daytime temperature data of CMFD, the effect of temperature on ε_{max} can be quantified. Basically, the VPM uses the following equation to calculate ε at the daily scale (Xiao et al., 2004):

$$\boldsymbol{\varepsilon = \varepsilon_{max} * T_{scalar} * W_{scalar} * P_{scalar}}$$

Eq. 6-6

where ε_{max} is maximum light use efficiency, and T_{scalar}, W_{scalar} and P_{scalar} are the downward-regulation scalars for the effect of temperature, water and leaf phenology on the light use efficiency of vegetation, respectively.

T_{scalar} is estimated at each time step, using the equation developed for the Terrestrial Ecosystem Model (Raich et al. 1991),:

$$\boldsymbol{T_{scalar} = \frac{(T-T_{min})(T-T_{max})}{(T-T_{min})(T-T_{max})-(T-T_{opt})^2}}$$

Eq. 6-7

where T_{min}, T_{max} and T_{opt} are minimum, maximum and optimal temperature for vegetation photosynthesis. If air temperature falls below T_{min}, when the temperature is beyond the minimum temperature for vegetation photosynthesis, the photosynthesis is at a low rate or there is no photosynthesis, and T_{scalar} is set to zero. The value of T_{min}, T_{min} and T_{min} are different according to the vegetation types. In the research of Qinghai-Tibet alpine ecosystems, the values for these three parameters are 0, 20 and 35 °C respectively (Li et al., 2007). In their research, the average daytime temperature during light periods was used instead of using the daily mean air temperature that is calculated as the average value between daily maximum temperature (generally daytime) and daily minimum temperature (night time) in calculating $\boldsymbol{T_{scalar}}$ (Li et al., 2007). They argued that the day time average temperature would better capture the temperature effect on $\boldsymbol{\varepsilon}$. But in this thesis, the average temperature is the average value during the whole day as it is the most commonly used way of calculating $\boldsymbol{T_{scalar}}$ (Xiao et al., 2004; Sannigrahi et al., 2016).

The main contribution of the VPM model is that it considers the effects of both water stress and vegetation phenology on ε. In the VPM, a water sensitive vegetation index (LSWI) was utilized to capture the effects of water stress and phenology on light use efficiency,

$$\boldsymbol{LSWI = \frac{\rho_{NIR}-\rho_{SWIR}}{\rho_{NIR}+\rho_{SWIR}}}$$

Eq. 6-8

where ρ_{NIR} is the surface reflectance band intensity between 841nm and 876 nm (near-infrared band), and ρ_{SWIR} is the surface reflectance band from 1628 nm to 1652 nm (short infrared band). Both of the data can be derived from the MODIS reflectance dataset MOD09A1 (Vermote, 2015).

Then, the effect of water on plant photosynthesis (W_{scalar}) can be calculated as:

$$\boldsymbol{W_{scalar} = \frac{1+LSWI}{1+LSWI_{max}}}$$

Eq. 6-9

where $\boldsymbol{LSWI_{max}}$ is the maximum LSWI within the plant growth season.

Finally, $\mathrm{P_{scalar}}$ is included in the VPM model to account for the effect of leaf phenology (leaf age) on photosynthesis at the canopy level:

$$\boldsymbol{P_{scalar} = \frac{1+LSWI}{2}}$$

Eq. 6-10

during bud burst to leaf full expansion $\boldsymbol{P_{scalar}}$ was set to be 1 after leaf full expansion.

6.3.4 Daily maintenance respiration

Maintenance respiration costs (MR) for leaves and fine roots are summarised in the flowchart Figure 6.1 and are also calculated on a daily basis. Leaf mass (kgC) is calculated as (Running, 2015):

$$\boldsymbol{Leaf\ Mass = {}^{LAI}/_{SLA}}$$

Eq. 6-11

where LAI is the leaf area index, and SLA is the specific leaf area (projected leaf area /Kg C).

Fine root mass is then estimated by:

$$\boldsymbol{Fine\ Root\ Mass = Leaf\ Mass * froot\_leaf\_ratio}$$

Eq. 6-12

Leaf maintenance respiration is calculated as:

$$\boldsymbol{Leaf\ MR = Leaf\ Mass * leaf\_mr\_base * {Q_{10}}^{(T_{avg}-20)/10}}$$

Eq. 6-13

T_{avg} is the average daily temperature (℃). Q_{10} describes the short term temperature dependence of the rates of biological processes widely used among biologists, which could affect the respiration of vegetation (Wager, 1941; Tjoelker et al., 2001b). Q_{10} is calculated through the equation which developed by Tjoelker et al. (2001a) :

$$\boldsymbol{Q_{10} = 3.22 - 0.046 * T_{avg}}$$

Eq. 6-14

Similarly, the maintenance respiration of the fine root mass can be calculated as:

$$\boldsymbol{Root\ MR = Root\ Mass * froot\_mr\_base * {Q_{10}}^{(T_{avg}-20)/10}}$$

Eq. 6-15

and finally, the net photosynthesis can be calculated:

$$\boldsymbol{PSNnet = GPP - Leaf\ MR - Root\ MR}$$

Eq. 6-16

In addition, for the energy cost for constructing organic compounds fixed by photosynthesis, which is empirically parameterized as 25% of NPP, the MODIS NPP algorithm simply uses a fixed percentage of NPP to calculate energy cost for constructing organic compounds fixed by photosynthesis, that is.

$$\boldsymbol{NPP = GPP - R_m - R_g = GPP - R_m - 0.25 * NPP}$$

Eq. 6-17

where R_m is the plant maintenance respiration, and $0.25 * NPP$ represents calculate energy cost for constructing organic compounds fixed by photosynthesis, therefore, the NPP can be calculated by:

$$\boldsymbol{NPP = 0.8 * (GPP - R_m)\ when\ GPP - R_m \geq 0, and}$$

$$\boldsymbol{NPP = 0\ when\ GPP - R_m < 0}$$

Eq. 6-18

To summarise, all the process for NPP estimation have been discussed in detail. They broadly followed the flow in Figure 6.1, but due to the data availability of climatic data and daily radiation data, the viewshed model and VPD model were employed to estimation solar radiation and the conversion rate of solar radiation to carbon mass on grassland. The rest of this chapter will show the results of the NPP calculations based on the improved LAI data produced in Chapter 5.

6.4 Improved and expected NPP of Zuku: new view of grazing effect on carbon fixation

Using the above estimation methods, the NPP after livestock grazing is shown in Figure 6.5. The LAI data for the calculation is the improved LAI data (improved by fitting with new growth function considering both the effect of the previous grazing and current grazing). The value of NPP ranges from 43.66 gCm^{-2} to 664.39 gCm^{-2}. the average NPP is 380.09 gCm^{-2} for the whole region. We can see obvious spatial heterogeneity in the NPP distribution, with the high productivity concentrating to the southeast of Zeku. The low productivity areas are mainly distributed in the northern mountainous areas (see DEM figure in Figure 6.3). Notice that there are some black points in the figures: these are the points where the improved LAI cannot be calculated (non-linear regression cannot find a solution for the new growth function). The total number of these black points is 45. Considering a total of 29423 pixels in Zeku, these black points have no noticeable influence on the NPP calculation. The spatial pattern is quite similar to that of Fan et al. (2010b).

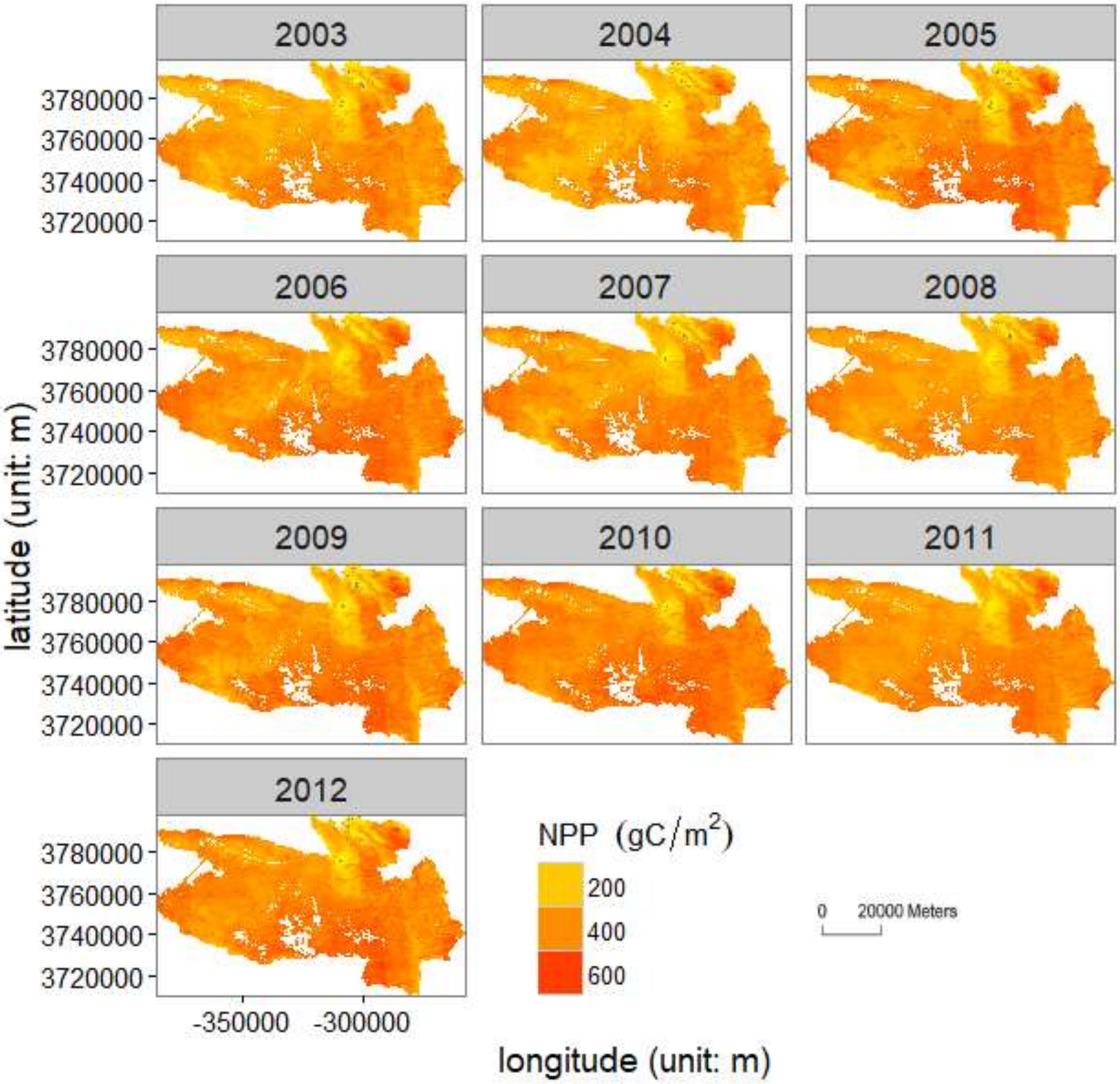


Figure 6.5: Improved NPP products, 2002~2012, Zeku (unit: gCm^{-2})

Similarly, the expected NPP can be calculated by using the expected LAI (the LAI value if the pixel has not been grazed) produced in Chapter 5. The calculation keeps all the other parameters the same, and changes the improved LAI to expected LAI. The aggregated annual NPP distribution is shown in Figure 6.6. On the whole, the spatial patterns have not changed compared with the improved NPP distribution. The minimum productivity is

45.79 gCm^{-2} and the maximum productivity reaches as high as 735.76 gCm^{-2}. On the average, the productivity is 405.58 gCm^{-2} from 2003 to 2012, which means that the effect of livestock grazing on the productivity is 25.49 gCm^{-2} in Zeku, accounting for 6.28% of the expected grassland productivity. This provides a new view in evaluating the effect of livestock grazing on grassland. Although a relatively high grazing pressure has been observed in Zeku (Fan et al., 2010b), the overall effect of grazing on the reduction of carbon fixation in Zeku by plants is 6.28%. Presumably, we cannot tell where the carbon goes—some as dung, some as cattle, some respired.

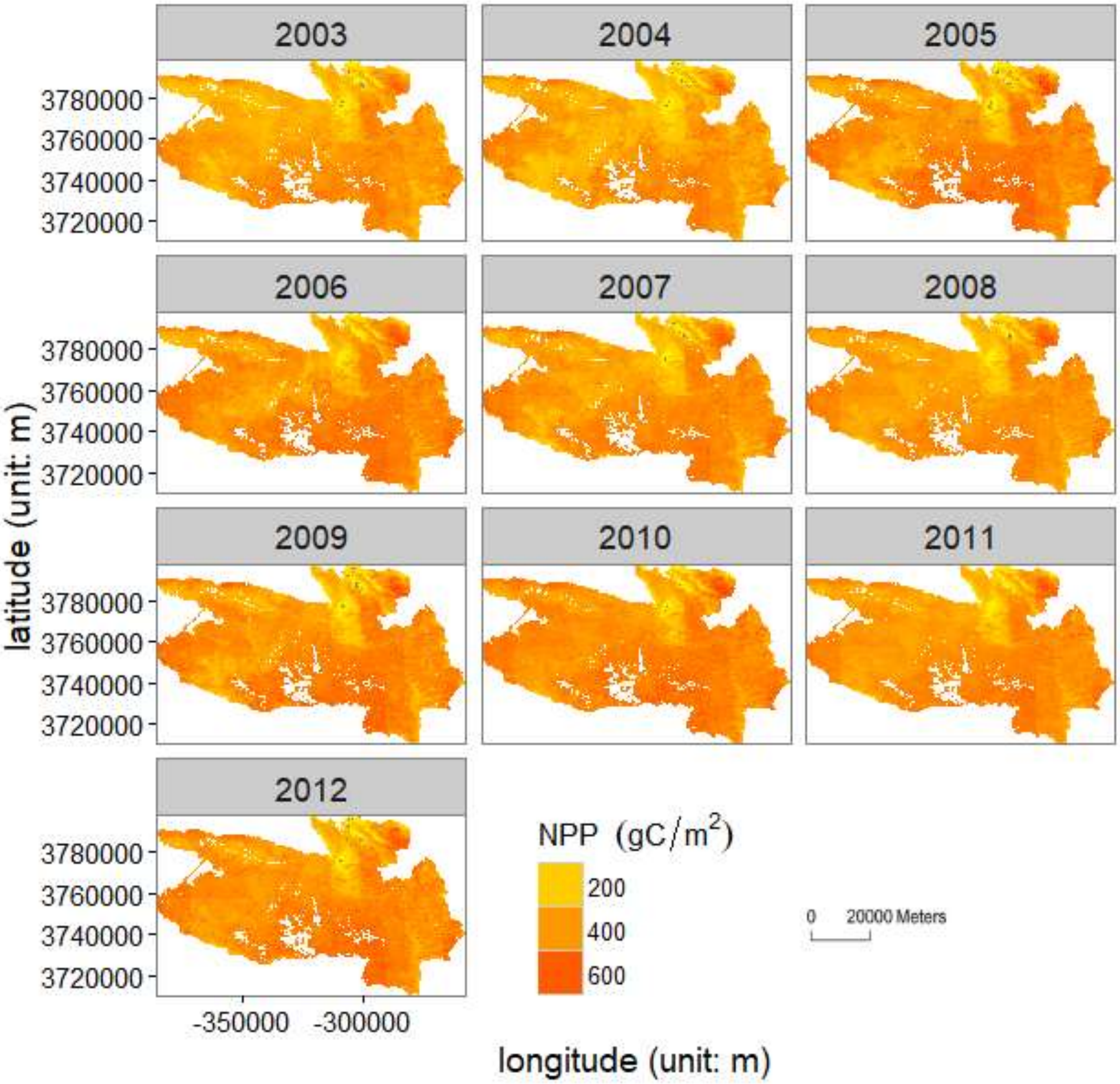


Figure 6.6: Expected NPP of Zeku, 2003~2012 (unit: gCm^{-2})

6.5 Validation of the improved NPP

This the Net Primary Productivity (NPP) produced by the improved LAI with *in-situ* measured grass weight data that were collected from the Grassland Livestock Bureau of Zeku. In order to validate improved NPP, the daily NPP calculated in this chapter needs to be aggregated to the exact sampling date (Table 6.5).

6.5.1 Estimate NPP based on the improved LAI with LUE-VPM

To convert the improved LAI to NPP this thesis here utilises the Light Use Efficiency (LUE) model which is widely used in NPP estimation, most specifically by MODIS, to produce their global 500m and 1000m NPP data. The difference between the LUE model in this thesis and the conventional model used in the MODIS data is the Vapour Pressure Deficit (VPD) attenuation scalar is replaced by a Vegetation Photosynthesis Model (VPM) scalar due to data limitations; for more information on the LUE-VPM construction, see (Xiao et al., 2004); the key parameters and datasets for models are shown in Table 6.4:

Table 6.4: Model parameters for NPP calculation

	MODIS (Running and Zhao, 2015)	LUE-VPM (Light Use Efficiency with Vegetation Photosynthesis Model)
Light Use efficiency (LUE)	Vapour Pressure Deficit (VPD)	Vegetation Photosynthesis Model (VPM) (Xiao et al., 2004)
Maximum radiation conversion efficiency (ε_{max}, $KgCm^{-2}/d/MJ$)	0.00086	0.00061(Li et al., 2012)
Photosynthetic Active Radiation (PAR) data	from Global Modelling and Assimilation Office (GMAO/NASA)	calculated by Area Solar Radiation (Fu and Rich, 2002)
the fraction of Photosynthetically Active Radiation absorbed by vegetation (fPAR) data	from MODIS fPAR	calculated with Beer-Lambert law (Ruimy et al., 1999b)

There are 14 national grassland monitoring sample sites in Zeku, 2012. The locations are shown in Figure 6.7.

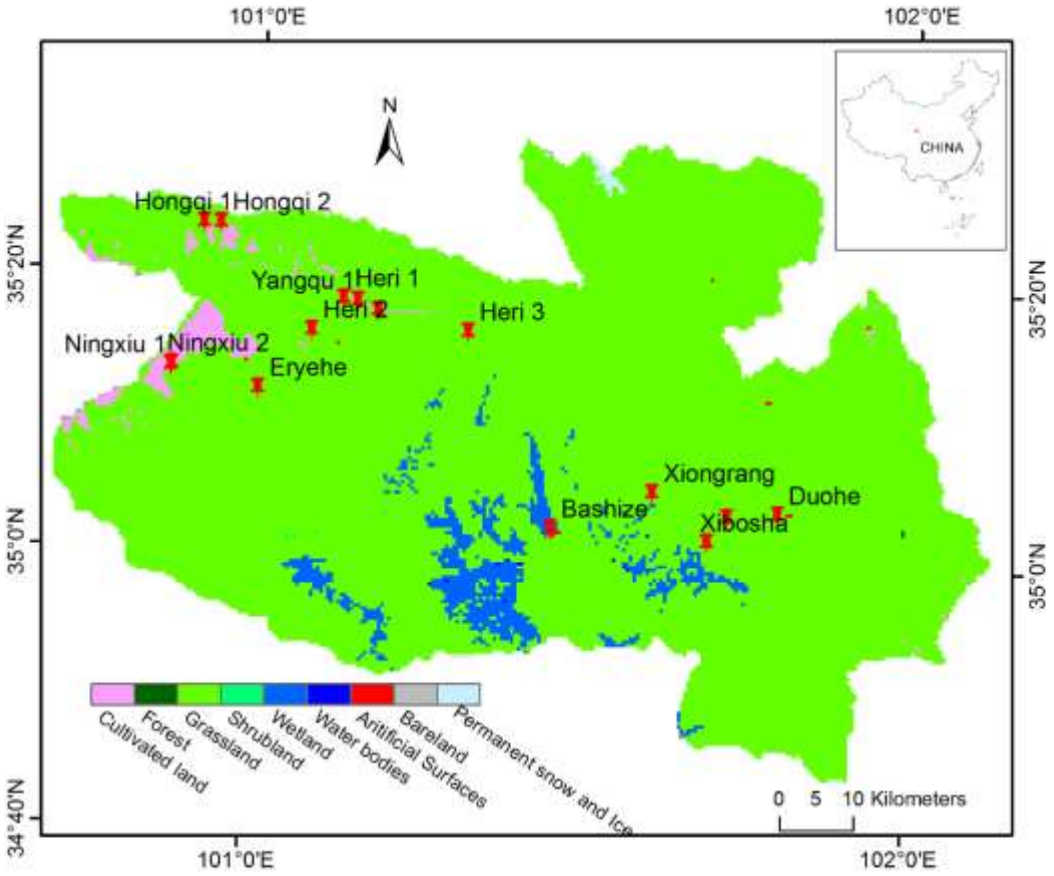


Figure 6.7: Locations of validation stations in Zeku, 2012

6.5.2 Modelling results vs MODIS NPP and in-situ measurements

For each sampling site, there are 4 samples, of which the size is 1m x 1m. Table 6.5 shows the average carbon of the 4 samples for each grassland monitoring site after converting from above ground fresh matter to whole plant carbon (column "Converted *in-situ* NPP"). Unfortunately, no information about the uncertainty of these estimates is provided. In comparison, this table also lists the MODIS NPP (column "MODIS NPP") and the NPP this thesis has estimated (column "LUE-VPM NPP (improved LAI)").

The NPP was calculated on a daily basis for our improved LAI (Table 6.5, column "LUE-VPM NPP (improved LAI)"). In order to compare with the *in situ* observed data (Table 6.5, column "LUE-VPM NPP (improved LAI)"; below), we aggregate the daily ANPP from the first day of 2012 to the date listed in Table 6.5 (column: "collecting time", these are the date when the fresh grass weight was measured). The original MODIS NPP product is in Table 6.5 (column: "MODIS NPP"). In addition, with the purpose of showing our improved LAI is better than the MODIS LAI, we calculated the NPP using MODIS LAI as well (column: "LUE-VPM NPP (MODIS LAI)"). However, before we can compare those results, the *in situ* grass weight (gm^{-2}) should be converted to grass mass (or NPP, gCm^{-2}), as described below.

The relation between aboveground dry matter (ADM) and NPP can be described as (Maselli et al., 2013; Running, 2015):

$$\mathbf{NPP} = \mathbf{DM} * (\boldsymbol{Root\_Leaf\_Ratio} + \mathbf{1}) * \mathbf{0.5}$$

Eq. 6-19

where the multiplier $(Root\_Leaf\_Ratio + 1)$ converts the above ground dry matter to whole plant dry matter (both above ground mass and below ground mass). This value is taken as 0.28 following Running (2015). The 0.5 multiplier accounts for the conversion from dry matter to carbon (Maselli et al., 2013). The ratio of dry matter to fresh grass in Zeku is 0.37 according to Lai et al. (2008).

Table 6.5: Validation with in-situ measured carbon mass (unit: gCm^{-2})

ID	longtitute	latitute	altitute	collecting time	Converted *in-situ* NPP	LUE-VPM NPP (improved LAI)	MODIS NPP	LUE-VPM NPP (MODIS LAI)
1	101.13	35.31	3482	2012-08-06	143.56	191.47	151.12	182.79
2	101.08	35.27	3495	2012-08-05	548.06	285.35	203.60	264.61
3	101.32	35.27	3636	2012-08-06	180.38	245.00	175.12	223.42
4	101.73	35.06	3617	2012-08-07	335.81	316.31	194.16	272.44
5	101.80	35.06	3549	2012-08-08	233.40	235.56	167.36	228.64
6	100.87	35.22	3371	2012-08-09	193.42	NA	194.96	NA
7	100.87	35.22	3380	2012-08-09	346.88	NA	183.36	NA
8	101.01	35.19	3511	2012-08-06	290.71	301.43	219.12	269.31
9	101.46	35.04	3671	2012-08-08	103.15	256.47	156.64	202.58
10	100.91	35.39	3411	2012-08-07	149.98	245.32	170.16	230.09
11	100.94	35.39	3420	2012-08-07	288.73	271.83	170.24	243.14
12	101.15	35.30	3481	2012-08-06	139.91	230.29	146.64	194.44
13	101.18	35.29	3524	2012-08-06	321.60	254.39	161.76	210.04
14	101.70	35.03	3619	2012-08-10	328.38	339.67	188.80	262.48
15	101.61	35.08	3789	2012-08-07	346.54	295.67	195.84	289.53
mean					262.32	266.83	176.97	236.42

The results of Tukey's honest significance test (TukeyHSD test) (Tukey, 1949) (Table 6.6) shows there is no significant difference between NPP calculated by LUE-VPM based on our improved LAI and converted *in-situ* measured carbon mass with a p-value equalling 0.998 (the RMSE between the two is 97.77 gCm^{-2}). Conversely, the p-value between converted *in-situ* measured carbon mass and the MODIS NPP product is 0.011 (the RMSE between the two is 133.98 gCm^{-2}), indicating the MODIS NPP product for Zeku is significantly different from the *in-situ* measured data. When keeping all the parameters of LUE-VPM the same, the p-value between converted *in-situ* measured NPP and the NPP calculated based on MODIS LAI is 0.760. In addition, from Table 4, the average converted NPP from *in-situ* measured data is 262.32 gCm^{-2}, while the NPP calculated by LUE-VPM based on our improved LAI is 266.83 gCm^{-2}, and if all the LUE-VPM parameters are kept the same, the average recalculated NPP by LUE-VPM based on MODIS LAI is 236.42 gCm^{-2}, which indicates that the improved LAI estimate has improved the accuracy of the NPP calculations on average.

Table 6.6: Multiple comparisons with one-way ANOVA test

(I) group	(J) group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
LUE-VPM NPP (improved LAI)	MODIS NPP	89.861*	26.350	.007	19.735	159.988
	Converted in-situ NPP	4.504	26.350	.998	-65.623	74.6301
	LUE-VPM NPP (MODIS LAI)	30.404	26.350	.658	-39.723	100.531
MODIS NPP	LUE-VPM NPP (improved LAI)	-89.862*	26.350	.007	-159.988	-19.735
	Converted in-situ NPP	-85.358*	26.350	.011	-155.485	-15.231
	LUE-VPM NPP (MODIS LAI)	-59.458	26.350	.123	-129.585	10.669
Converted in-situ NPP	LUE-VPM NPP (improved LAI)	-4.504	26.350	.998	-74.631	65.623
	MODIS NPP	85.358*	26.350	.011	15.231	155.485
	LUE-VPM NPP (MODIS LAI)	25.900	26.350	.760	-44.227	96.027
LUE-VPM NPP (MODIS LAI)	LUE-VPM NPP (improved LAI)	-30.404	26.350	.658	-100.537	39.723
	MODIS NPP	59.458	26.350	.123	-10.669	129.585
	Converted in-situ NPP	-25.900	26.350	.760	-96.027	44.227

*. The mean difference is significant at the 0.05 level.

Notes: Converted in-situ NPP is the converted NPP from the in-situ measurement of fresh grass weight;

MODIS NPP is MOD17A3H (MODIS collection 6 NPP), which is public free from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod17a3h_v006;

LUE-VPD (improved LAI) is the NPP calculated by Light Use Efficiency with Vegetation Photosynthesis Model based on improved LAI produced by this paper;

LUE-VPD (MODIS LAI) is the NPP calculated by Light Use Efficiency with Vegetation Photosynthesis Model based on MODIS LAI (MOD15A2H006, MODIS collection 6 LAI, which is public free from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod15a2h_v006).

6.6 The uncertainty of the NPP calculation

The LUE-VPM model was employed to calculate the NPP based on the improved LAI. However, the outputs of LUE-VPM depend on the model structure, input datasets, and the values of parameters describing the NPP, all of which affect the accuracy and reliability of the model output. Uncertainty will inevitably arise from the simplifications and abstractions of the real system used to create the models, as well as through the processes of data collection and the parameterization of the model {Bagnara, 2018 #1058}.

Imperfect simplification or abstraction of processes in a model leads to structural uncertainty. However, both the LUE model and VPM model have been widely used and validated worldwide; they have comparable consistency and can be assumed to reliably estimate the NPP with minimal structure uncertainty {Sannigrahi, 2017 #1056;Bao, 2016 #1057}. A multi-model comparison should be carried out in Zeku to quantify the structural uncertainty of LUE-VPM, but as it has been discussed in Section 6.2, the availability of data in Zeku region make further multi-model comparison extremely difficult. This is an important research area for future work that could be carried out when all of the datasets required for model parameterization are available (such as soil water content; vapour pressure deficit; leaf nitrogen; vegetation carbon; precipitation .etc., which have been listed in Table 6.1).

Inadequate information or knowledge of the values of parameters associated with the processes describing the system result in parametric uncertainty. The effect of the LAI change on NPP depends on many other factors, such as temperature, solar radiation, light use efficiency, leaf root ratio, etc. In this chapter, the values of those components were all derived from published literature or published datasets (see Section 6.3 for detail), but unfortunately none of these sources also published the uncertainty associated with their data. This makes it impossible to estimate parametric uncertainty meaningfully. More scientific effort on collecting site-specific values of parameters will be beneficial, but this would require collaboration among scientists from different research communities, and such an endeavour is well beyond the scope of this thesis.

The above-mentioned difficulties in quantifying uncertainty make it impossible to conduct a complete uncertainty analysis. Section 6.7 will further elaborate on these difficulties and the reasons that such an analysis is beyond the scope of this work. Instead, this section will use a numerical simulation approach to explore the relationship between LAI and NPP within the error range of the improved LAI in Zeku. The uncertainty of the improved LAI (produced in Chapter 5) is the main concern of this thesis as this uncertainty could propagate through the modelling process of LUE-VPM. Since no uncertainty estimates are available for the other parameters and the input data used in LUE-VPM for the Zeku region, the assumption here is all the other parameter settings and input data have no uncertainty (again, Section 6.7 will elaborate).

6.6.1 Numerical simulation for exploring the relationship between LAI and NPP using LUE-VPM model within the error range of the improved LAI

As it has been discussed in Chapter 5, the error range has been quantified along with the improved LAI based on the MODIS LAI product. However, the validation of the improved LAI in Section 6.5 would not be reliable if the uncertainty of the NPP is not accounted for. Figure 6.8, below, decomposes the estimation equations, showing how the Net Product Productivity (NPP), in equation 6.21 of Figure 6.8, can be estimated from the Leaf Area Index (LAI). As the NPP must be greater than 0 gCm^{-2}, the value of equation 6-21 should also be greater than 0 gCm^{-2}, and the monotonicity between LAI and NPP needs to be explored within such range. All the other input data and parameter values can be represented as two constant variables, *A* and *B*. These are shown in equation 6.21 in Figure 6.8, which expresses the relationship between LAI and NPP. Importantly, this relationship can take two forms, depending on the values of *A* and *B*. It can be either:

- non-linear but monotonic (see Figure 6.9) in the case that *A* is sufficiently larger than *B*; or
- non-linear and non-monotonic (see Figure 6.10) in the case that *A* is not sufficiently larger than *B*.

A feasible way to quantify the uncertainty of NPP caused by the LAI is to explore the real value of *A* and *B* in equation 6-21, and determine whether *A* is sufficiently bigger than *B*. In this case, the maximum and minimum improved LAI can be used to calculate the maximum and minimum NPP as the relationship between LAI and NPP in Zeku would be monotonic. If this were not the case and the result was non-monotonic, then the maximum/minimum NPP may not be calculated by giving maximum/minimum LAI. Such method will not work, and a more efficient exploration method should be developed to solve this problem, but it would be more complicated and time-consuming. We need to theoretically find all the extreme values of the NPP within the error range, and they may not locate at the points where LAI are the maximum/minimum, due to the non-monotonic relationship between LAI and NPP. It will be further discussed in Section 6.7.

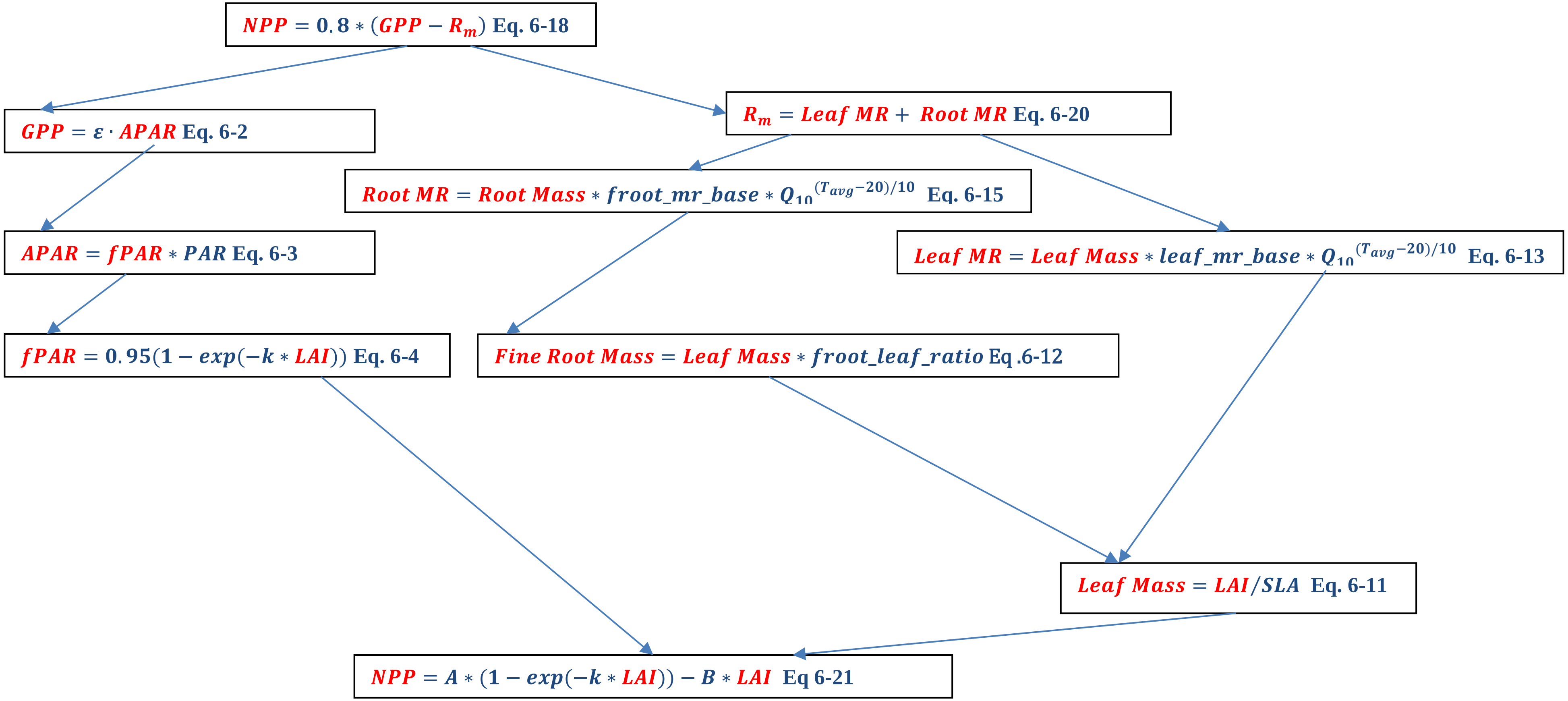


Figure 6.8: Decomposition of key equations for the NPP calculation in LUE-VPM

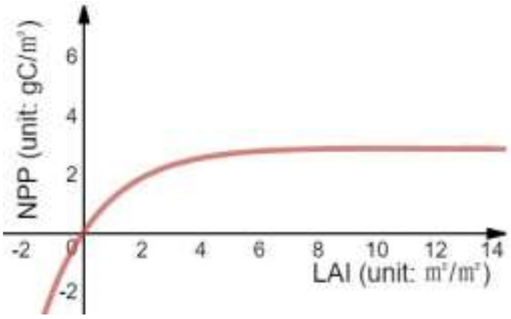


Figure 6.9: **An example of non-linear but monotonic relationship (NPP monotonically increase with the increase of LAI between 0 and 6 m^2/m^2) between LAI and NPP (the equation for the red curve is NPP=3*(1-exp(-0.5*LAI))-0.01*LAI)**

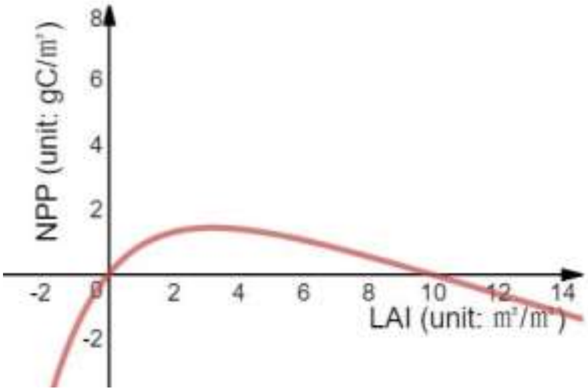


Figure 6.10: **An example of non-linear and non-monotonic relationship (LAI between 0 and 6 m^2/m^2) between LAI and NPP (the equation for the red curve is NPP=3*(1-exp(-0.5*LAI))-0.3*LAI)**

This section, therefore, uses a numerical simulation method to explore the relationship between LAI and NPP, that is, whether they are monotonic or non-monotonic. The process for this exploration is:

- for each data point during the year, the error range is equally divided into N segments (N=10 in this analysis, it can be any positive integer, and the bigger value of N, the better accuracy of the analysis);
- for each segment, a random number is produced within the upper and lower limit of the segment, and then this step is repeated M times (M=10 in this analysis, and also the bigger value of M, the better accuracy for the analysis);
- run the LUE-VPM to obtain the NPP output using LAI which has been randomly produced in the last step;
- check whether the NPPs based on the LAIs randomly produced in the same segment are all smaller or bigger than that in the next segment, and the overall trend for all the segment is increasing or decrease monotonically.

In this section, the relationship between LAI and NPP in Zeku is examined at both year-round NPP and stational NPP level. The year-round aggregated NPP is calculated by the summation of the daily NPP during the year for each pixel, and the regional average NPP is the mean NPP value for all the pixels in the whole region. The stational NPP is calculated by the summation of the daily NPP from the first day of the year to the sampling day of the year (see column “collecting time” in Table 6.5 for the exact date), with the purpose of giving the error boundary of the estimated NPP in Table 6.5.

The segments were produced within the error range of LAI from the lower limit to the upper limit, that is, the 10 randomly produced LAI values in the current segment were smaller than that of the next segment. The first 10 randomly produced LAI values within the lower and upper limit of the first segment (segment 1) were the smallest LAI value set among all randomly produced LAI values and then last 10 randomly produced LAI values made up the biggest LAI value set. For each pixel at the same time, the LAI values in segment 1 were smaller than that of segment 2, and the LAI values in segment 2 were smaller than that of segment 3, and that continues in the same way). The results will be discussed in the next two sections.

6.6.2 Result at the regional scale

The corresponding regional average NPP calculated by LUE-VPM based on the randomly produced LAI within the upper and lower limit of each segment for 2012 (in Section 6.5, the validation data was in 2012) is shown in Figure 6.11. The regional average NPP during the year monotonically increases within LAI values. The biggest NPP value calculated by the randomly produced LAI value within the lower and upper limit of segment 1 is smaller than the smallest NPP value calculated by the randomly produced LAI value within the lower and upper limit of segment 2, and that is true for all the two neighbouring segments, indicating “A” is sufficiently larger than “B” (see Eq 6-21 in Figure 6.8) at the regional average level.

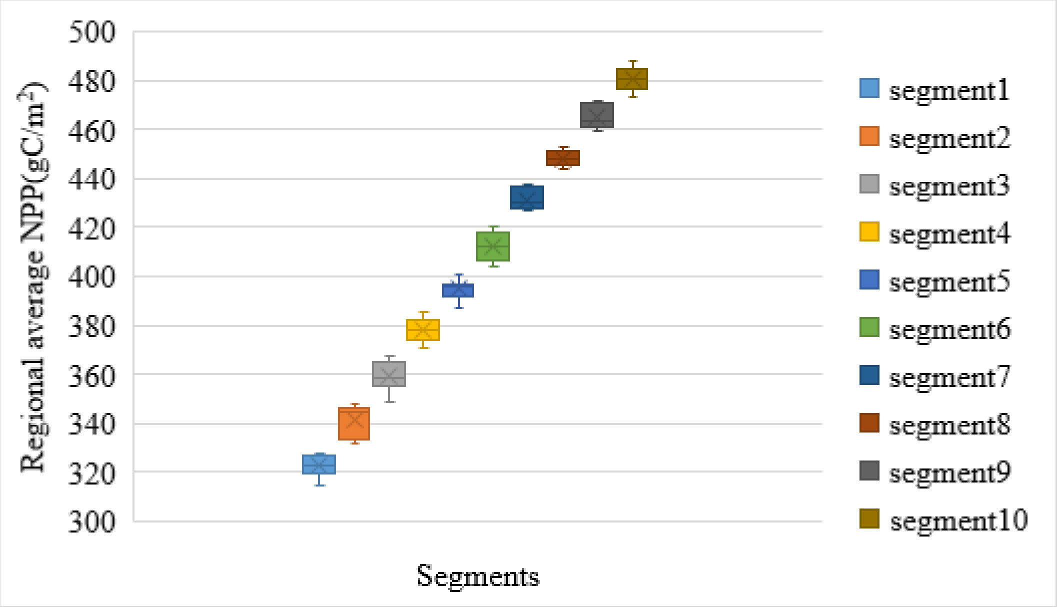


Figure 6.11: Boxplot of regional average NPP with 10 equally divided error segments within the error range of LAI in the year 2012

6.6.3 Results at the in situ grassland monitoring stations

However, the regional average trend for the NPP with the increment of LAI within the error range does not ensure a similar trend at the grassland monitoring station (pixel level). This section, therefore, examines the relationship at the 15 grassland monitoring stations. The name and identifications of the stations were shown in Table 6.5, and the spatial locations of the stations were shown in Figure 6.7. Similar to the validation process, the daily NPP values, that are based on a randomly produced LAI for each segment, are summated to the exact date when the in situ NPP was collected, and the specific dates were shown in Table 6.5.

The boxplot of NPP with 10 equally divided error segments within the error range of LAI in the year 2012 at 15 grassland stations is shown in Figure 6.12. There is an obvious increase trend in the NPP with the increase of the LAI (a larger number of segment identification means a greater value of LAI used in the NPP simulation). To summarise, both the regional aggregated NPP and the stational (pixel level) aggregated NPP shows a monotonic relationship between LAI and NPP within the error range of the improved LAI. This indicates A is sufficiently larger than B (also see Eq 6-21 in Figure 6.8).

Notice that a quite strong linear relationship between segment identification and NPP can be observed in Figure 6.12 and in Figure 6.11 (the horizontal axis is the numerical identification of the segment for both figures). This is possible because the variation of LAI is in a quite small range. In Table 5.4, the maximum underestimation error of the improved LAI was 24.18%, and the maximum overestimation error was 28.89% for the year 2012. These are quite small percentages compared with the possible LAI values (about 0 m^2/m^2 ~ 6 m^2/m^2 in Zeku). For example, for a point with a possible LAI value of 3 m^2/m^2, the upper and lower LAI value considering the uncertainty is 3.73 m^2/m^2 and 2.13 m^2/m^2, and this point can only either be overestimated or underestimated. This error range (2.13 m^2/m^2 ~ 3.73 m^2/m^2) is quite a small LAI range, and although the overall relationship between LAI and NPP is non-linear in Figure 6.9 or Figure 6.10, an obvious linear relationship between the two can be observed in a small value range of LAI.

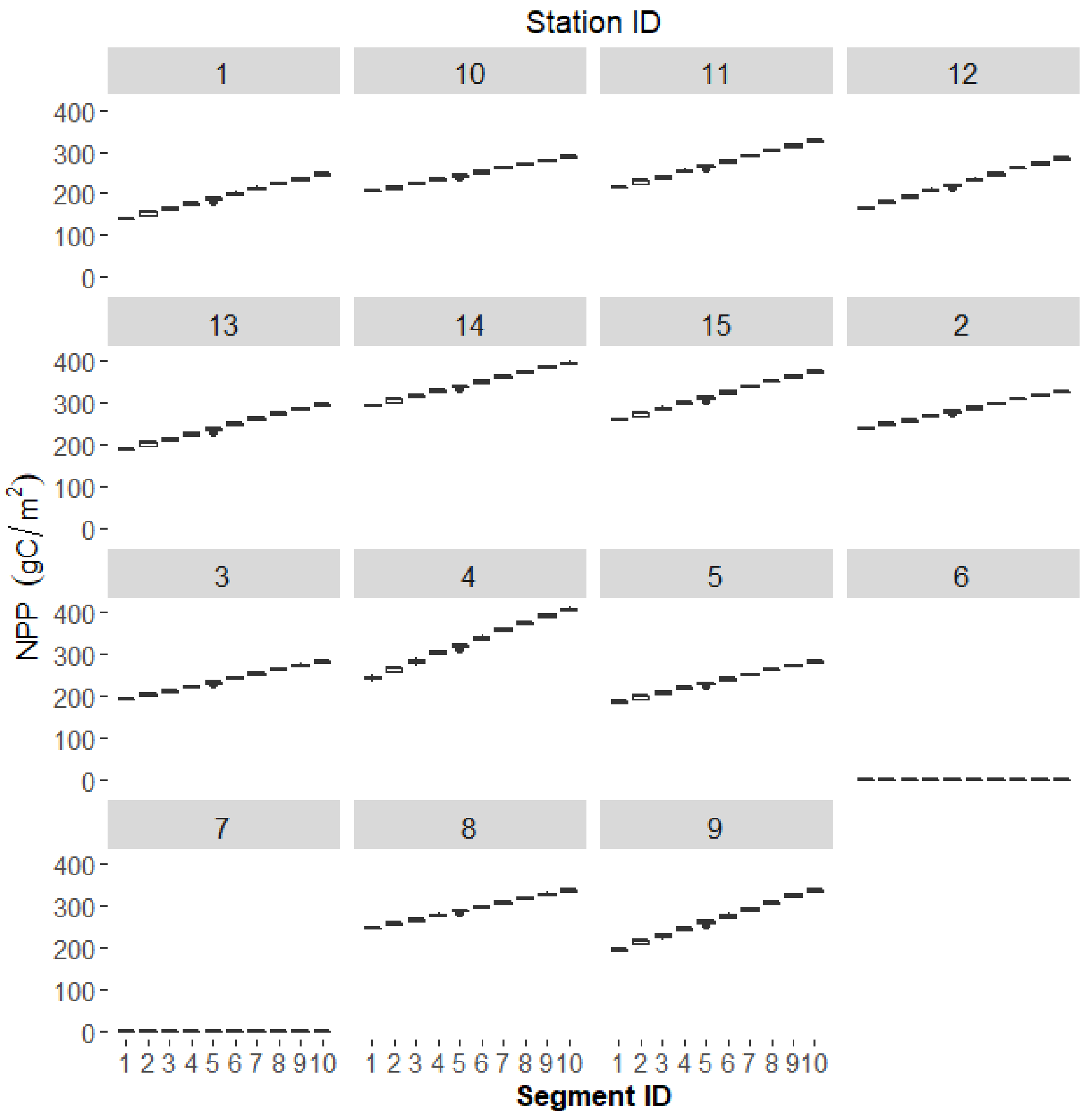


Figure 6.12: Boxplot of NPP with 10 equally divided error segments within the error range of LAI in the year 2012 at 15 grassland stations

In addition, the upper and lower boundary of NPP caused by the uncertainty of the improved LAI can, therefore, be calculated by setting the maximum and minimum LAI within the error range. The results are shown in Table 6.7, and it gives complementary information about the reliability of the validation results in Table 6-5. The relative maximum estimation errors are less than 32% for all the stations. The percentage of overestimation errors and underestimation errors listed in Table 6.7 are all the maximum possible error ratios; it would be very unlikely for the error to be this large in practice.

Table 6.7: Error range of NPP simulated in 2012 caused by the uncertainty of the improved LAI

ID	Converted *in-situ* NPP	LUE-VPM NPP (improved LAI)	Overestimation error	Underestimation error
1	143.56	191.47	32%	31%

2	548.06	285.35	19%	16%
3	180.38	245.00	25%	18%
4	335.81	316.31	27%	31%
5	233.40	235.56	24%	22%
6	193.42	NA	NA	NA
7	346.88	NA	NA	NA
8	290.71	301.43	21%	13%
9	103.15	256.47	28%	34%
10	149.98	245.32	19%	19%
11	288.73	271.83	25%	22%
12	139.91	230.29	32%	26%
13	321.60	254.39	30%	19%
14	328.38	339.67	16%	18%
15	346.54	295.67	15%	29%
mean	262.32	266.83	23%	23%

6.6.4 The spatial distribution of the uncertainty in NPP caused by the uncertainty of the improved LAI

Since there is a monotonic relationship between LAI and NPP using LUE-VPM in Zeku, the error limits of NPP can be calculated using the lower and upper limit of the improved LAI value. The maps of the lower and upper error boundary of NPP simulated by the improved LAI are shown in Figure 6.13 and Figure 6.14 respectively. For each pixel, the NPP is the summation of the daily NPP of that pixel during the year 2012. There is a similar spatial pattern of NPP in both Figure 6.13 and Figure 6.14, that is, the majority of the high productivity regions are distributed in the southeast part of Zeku, and we can visually identify that they are generally located in the low altitude area in Zeku (see Figure 6.3 for the DEM of Zeku). The regions with the lowest productivity are located in high mountainous areas.

In Figure 6.13, the lower limit of NPP in Zeku ranges from 0 gCm^{-2} to 570.92 gCm^{-2}, with the regional average of the NPP at 310.18 gCm^{-2}; while in Figure 6.14, the upper limit of NPP in Zeku varies from 0 gCm^{-2} to 759.49 gCm^{-2}, and the regional average of the NPP is 487.75 gCm^{-2}. The difference between the upper and lower limit of NPP is shown in Figure 6.15. The difference ranges from 0 gCm^{-2} to 427.54 gCm^{-2}, and the average difference is 177.57 gCm^{-2}. Compared with the NPP based on the assumption in Section 6.4 during 2012, of which the mean value is 407.78 gCm^{-2}, on the regional average, the overestimation error of NPP is 23.93%. This was calculated by:

$$Overestimation_{\text{Error}} = (NPP_{assumed} - NPP_{lower})/NPP_{assumed} \times 100\%$$

where $NPP_{assumed}$ is the NPP calculated under equal date intervel of LAI (see Section 5.10.2 in Chapter 5 for detailed information), and NPP_{lower} is the NPP with the smallest LAI within the error range. In a similar way, the average underestimation error of NPP is calculated and the error is 19.61%.

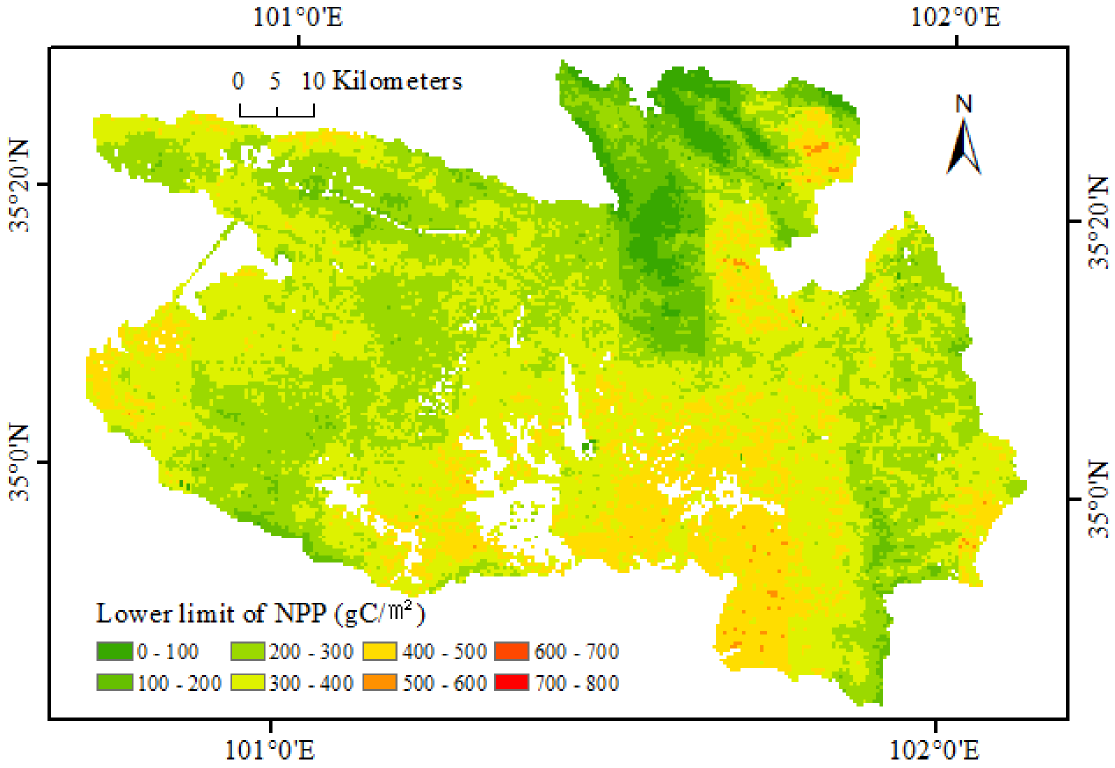


Figure 6.13: Lower limit of NPP (lower error boundary of NPP) by using improved LAI, 2012, Zeku, China

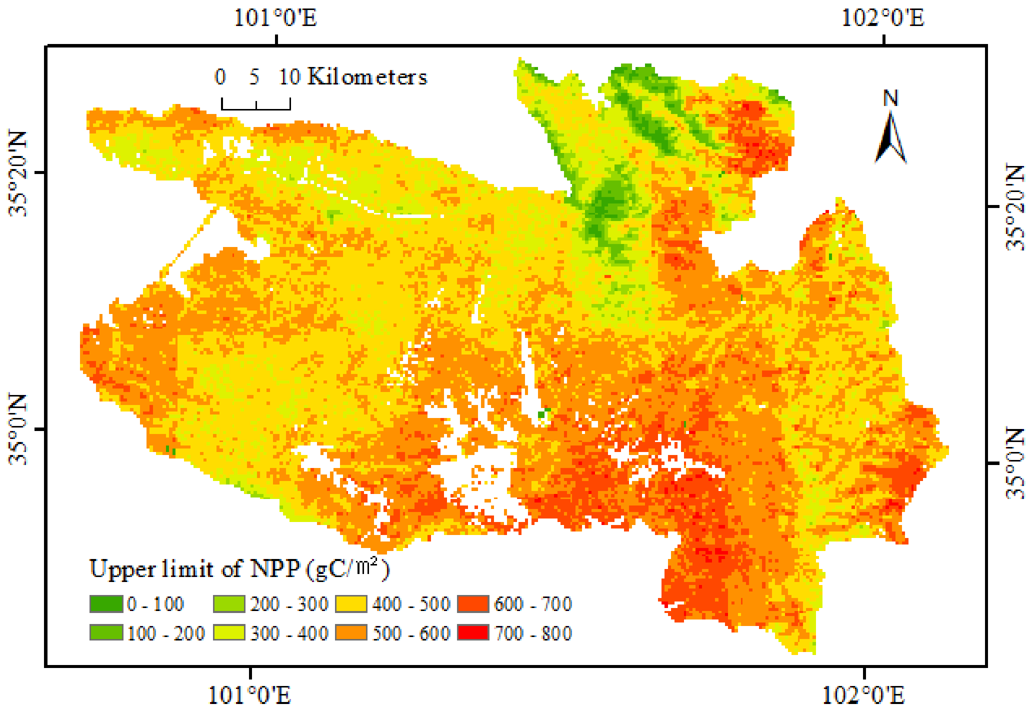


Figure 6.14: Upper limit of NPP (upper error boundary of NPP) by using improved LAI, 2012, Zeku, China

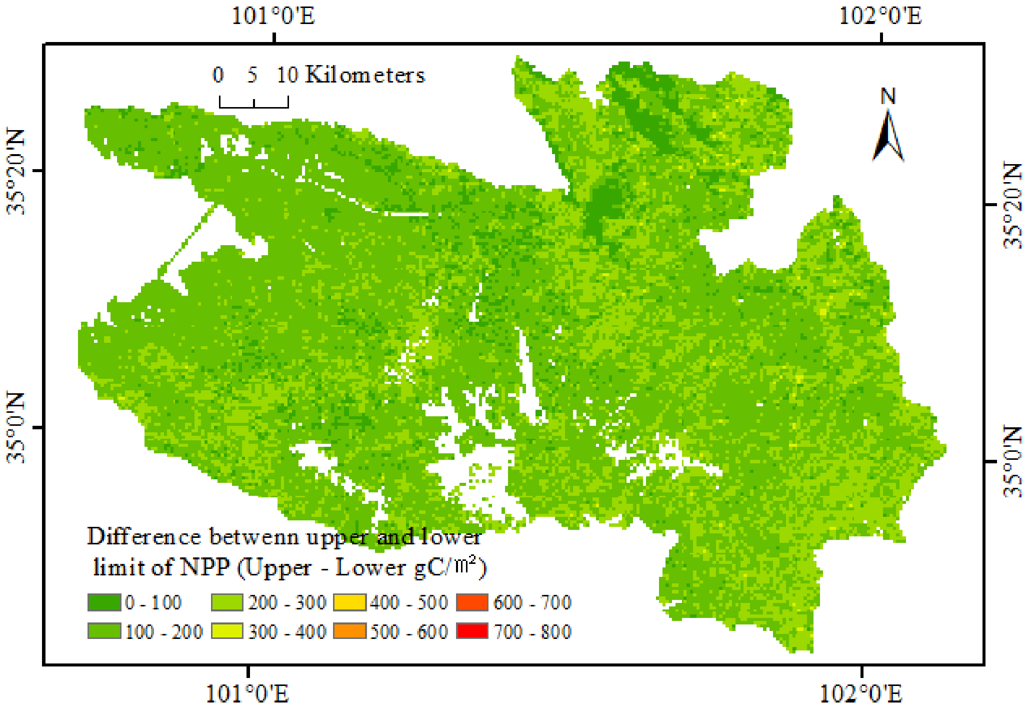


Figure 6.15: The difference in NPP estimation between the upper limit and lower limit of the improved LAI

6.7 Discussion

This chapter has modified the MODIS NPP estimation algorithm to calculate the grassland NPP of Zeku. In order to validate the modelling results, the improved LAI data was used to calculate the NPP using the LUE-VPM model. It is very difficult to collect real grazing data before and after grazing over a sufficient time period; however, given the requirement of grassland ecosystem monitoring work in China, grassland monitoring data is available, along with other data like in situ fresh weight which is a crucial parameter for modelling grass growth under grazing. After converting the fresh weight sampling data to equivalent leaf mass, the LUE-VPM model was validated, and found to be more accurate than the MODIS NPP estimations. The grazing-led LAI changes were calculated as the difference between improved LAI and expected LAI, then converted to leaf mass. The carbon mass consumption of livestock during the grass growth period was calculated according to statistical yearbook data. Although the linear coefficient between grazed NPP estimated from this paper and NPP consumption of livestock from statistical yearbook is 0.42, the magnitude and the time trend shows a great consistency with p-value = 0.71, indicating our new exponential growth function can be used to improve MODIS LAI data and to quantify livestock grazing.

The model is a simplification or abstraction of the real system. Due to an imperfect representation of the model structure, inadequate information or knowledge of the parameters or input data, and the uncertainty in measuring the observation data, output uncertainty exists in almost every model. A complete uncertainty analysis of the LUE-VPM should consider all sources of uncertainty that contribute to the modelling process and to the indicators or statistical properties of the model output. However, it is difficult to give a comprehensive uncertainty analysis of the NPP produced by the LUE-VPM. Although the uncertainty of the grazing-led LAI estimation has been calculated in Chapter 5, and the effect of such uncertainty has been clarified through a numerical simulation analysis, there are other components involved in the NPP calculation that may also affect the accuracy of NPP outputs. The source for those uncertainties includes: inaccurate assignment of the biological parameters (for example, seasonal difference in the value of light use efficiency); error in the remote-sensing measurement (uncertainty of surface reflectance data in VPM model); bias in in-situ measurement; and the structure uncertainty of the model. These were discussed in Section 6.6. This thesis is not able to determine the overall effect of all those uncertainties on NPP calculation because of a lack of data. Obtaining sufficient data would require a collaborative scientific effort from numerous different research communities.

Instead of conducting full uncertainty analysis, this chapter explored the uncertainty of NPP by analysing the extreme values of the NPP using a numerical simulation with random sampling. The upper limit and lower limit of the model can be derived easily by setting the model input to the maximum or minimum value within the error range. However, this is only feasible when there is a monotonic relationship between model parameters/inputs and model output (here, LAI was the input, and NPP was the output), as if the relationship is non-monotonic then this approach to estimating the uncertainty will not work. Section 6.6 showed that the relationship between LAI and NPP, when considering only the extreme (minimum and maximum) values of the improved LAI in Zeku, was monotonic both at the regional level and at the 15 measuring sites. Therefore an analysis of the extreme values of NPP was conducted, and the results showed that the estimated NPP values were not overly affected by the uncertainty in the LAI.

It is important to note that although there is a monotonic relationship between LAI and NPP at the regional level, as well as at the monitoring locations, this will not be the case for all the pixels. However, the presence of monotonic relationship at regional level indicates even if some pixels have a non-monotonic relationship between LAI and NPP at the pixel level, the effect of the monotonic relationship between LAI and NPP of the other pixels are big enough to diminish the effect of the non-monotonic relationship between LAI and NPP at the regional level. That is, they do not significantly affect the uncertainty of NPP calculated in Section 6.6 at the regional level. Increasing the number of segments within the LAI error range and increasing the number of sampling points in each segment will improve the reliability of the results in Section 6.4, but there is a comprise between computing cost and reliability. Nevertheless, 10 sampling points in each segment (10 segments for each LAI error range) means there is 100 sampling point within the error range of LAI for each pixel, and it is big enough to ensure the reliability of the result.

In addition, the monotonic relationship at the regional level might not be observed if the uncertainty of the other parameters and input datasets other than LAI change such relationship. That is, if the relationship between LAI and NPP at the regional level is non-monotonic, then the maximum/minimum NPP cannot be calculated by giving the maximum/minimum LAI. More comparison with the local convex and concave values for each pixel needs to be done. A more efficient sampling and analysis schema need to be adopted to well-represent the statistical properties of the data while requiring lesser combinations, but there is a compromise between the accuracy or confidence level of the analysis and the computational efficiency.

Nevertheless, the extreme value analysis here is sufficient to show that the grazing-led LAI changes estimated in Chapter 5 is reliable, and the improved LAI data is consistent with the *in situ* measured data. Theferore the next chapter will use the grazing-led LAI changes and the full-growth LAI as input datasets, with the purpose to explore the effect of different grazing strategies and institutional arrangements in Zeku.

Chapter 7 Agent-based modelling of grassland grazing-experimenting with real data

In Chapter 5, the grazing-led LAI changes (without the effect of previous grazing) and the full-growth LAI were estimated for each pixel based on “good quality” MODIS LAI product. Continuous, rotational and un-grazed pixels were also identified according to the frequency of the grazing-led LAI changes during the year. This was done at the resolution of remotely sensed data pixels (about 463×463 m^2), which can provide patch-specific information for the agent-based modelling of the grassland grazing system: grazing demands of livestock and grazing types of the patches (continuous, rotational and un-grazed). In this chapter and later, we will call pixels as patches – a term agent-based modellers are thought to be more familiar with.

This chapter presents an Agent-based Model of Grassland Grazing (ABMGG) that incorporates grazing information derived from remote sensing data. The results of applying the ABMGG to explore how different grazing strategies and institutional arrangements affect the LAI after grazing and degradation are presented. Section 7.1 details the general process of building an Agent-based Model (ABM). Section 7.2 provides a detailed description of the ABMGG developed. Section 7.3 focuses on evaluating ABMGG. Section 7.4 details the scenario of using the ABMGG to examine the effects of different grazing strategies and institutional arrangements on grassland in the case study area.

7.1 The general process of building an ABM

The whole process of developing, testing and applying a model consists of various parts, and the key design and development stages may be revisited repeatedly as a result of feedback. The applied modelling processes include model (re)design, (re)development, verification, sensitivity analysis, calibration and validation, (re)use (Railsback and Grimm, 2011). The aim of feedback and validation (where the model is tested and its performance measured) in this process is to make sure the model is fit for purpose (Wilensky and Rand, 2015). Model design is the first and the most important part, and it should be very clear what the main purpose of the model is. For an ABMGG, what kinds of agents should be included in the model? What are the behaviours and the interactions among the agents? Are there any adaptive, evolutionary or learning properties of the agents – in the way they make decisions? All those modelling related questions should be considered before any implementation. However, with consideration of more complexities, which are usually ignored in statistical or process-based models (variability among individuals, local interactions, complete life cycles, and in particular individual behaviour adapting to the changing internal and external environment), the costs of agent-based modelling increase. Therefore, when starting modelling, a trade-off between the costs and complexities needs to be considered. The first question of model design is then about how to describe such complex systems effectively. An Overview, Design, concept and Detail (ODD) protocol has been proposed by Grimm et al. (2006) to give a standardized way of describing such a complex system.

Model development considers what platform to use. One option is to choose a single computer programming language and may or may not involve utilising third-party libraries (things are written in a language, but not a core part of the language) to help build a model. Another option is to adopt an existing Agent-Based Modelling platform that might comprise several components that essentially run on a computer and allow a user to develop and run a model. Such a specialist platform may or may not, or may to a degree provide support for testing and validation. Many Agent-Based Modelling platforms are available, most of them (like programming well in any computer programming language) require a considerable amount of skill and knowledge to use well (Kravari and Bassiliades, 2015). Numerous ABM platforms exist, include: Agent Factory, Agent Builder, AgentScape, AGLOBE, AnyLogic, Cormas, ECHO, JADE, Madkit, MAGSY, MASON, MIMOSE, Cougaar, CybelePro, EMERALD, GAMA, JACK, NetLogo, Repast, SimAgent, SimPAck, StarLogo, Sugarscape, Swarm, SeSAm and FlowLogo (Castilla-Rho et al., 2015; Kravari and Bassiliades, 2015). A detailed comparison of these platforms can be found in Kravari and Bassiliades (2015). However, there is no single best platform for all modelling purposes because each one follows its own set of protocols for developing and encoding ABMs; some are efficient for parallel computing while others may be easier for establishing a prototype model. Therefore, selecting a proper platform is not only dependant on the aim of the model but also on modeller's programming expertise. According to Kravari and Bassiliades (2015) the main criteria for selecting a platform, however, include how the modellers could benefit more from the selected platform.

Model evaluation is an essential part of agent-based modelling to check the consistency and integrity after development; that is, the design, the entities, processes, and associated constraints and assumptions are implemented correctly, and it performs as expected. Usually, for a complex model, there is an inherent problem to make sure all the interactions and behaviours of agents are coordinated around specific constraints (Yilmaz, 2006). One commonly used method is checking the model's underlying mathematical and computational components do not fail by varying model configurations according to all foreseeable model inputs (Manson, 2003). For example, by varying the randomization technique used in the model, we can check how different randomization techniques could affect the agents' behaviours and model outputs. Castle and Crooks (2006) suggest that the process of evaluating the model can be segregated into three distinct activities: verification, calibration and validation.

Sensitivity analysis, calibration and validation are all about the further evaluation of the model, and these are the main process we will discuss later. For ABMGG, the modelling processes are listed in Table 7.1:

Table 7.1: The modelling process, measurement, techniques and data used for ABMGG

process	measurement	data
(1) verification	*R^2, t-test and RMSE, Chapter 5 vs simulated (2011)*	Grazing-led LAI changes and degraded patches

(2) Sensitivity analysis	PCC/PRCC, Simulated vs Chapter 5	Grazing-led LAI changes and degraded patches
(3) Calibration	ABC, Simulated vs Chapter 5 (2011)	grazing-led LAI changes and degraded Patches
(4) output validation	*R^2, t-test and RMSE (2012)*	Improved LAI Degraded patches

7.2 Description of ABMGG

The ABMGG model in this chapter does the opposite work to Chapter 5. The full-growth LAI and the grazing-led LAI changes are the input data sets for the ABMGG (see Figure 7.1). The purpose of ABMGG is to produce a similar curve to that of the LAI after grazing, i.e. the MODIS LAI (the LAI value with “good quality”). Although patches might not be grazed at exactly the same 8-day time period, the grazing frequency and the grazing-led LAI changes during the grass growing period (the non-growth period is not considered in the model) should be as similar as possible.

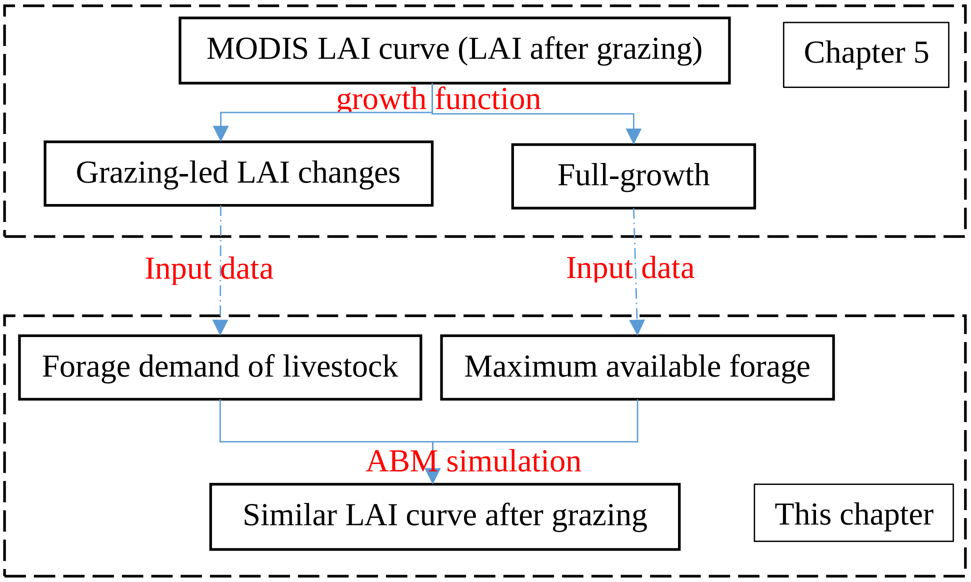


Figure 7.1: The patch-specific data source in the ABMGG

The ABMGG is designed for assessing the effects of different combinations of grazing strategies (un-grazed, continuous grazing and rotational grazing) and institutional arrangements (land market and grazing groups encouraged by the local government in Zeku) on grassland status. As was introduced in Chapter 3, there were two institutional arrangements in Zeku: group grazing and land market. Group grazing is a higher-level policy that would affect the herders’ grazing strategies: rotational, continuous and un-grazed (reserved land for winter feed or other purposes). The rotational grazing strategy is adopted for all the group grazing land (from the survey of the author in 2016), for example, the land patches in one grazing group may be divided into four or five sub-groups, with the livestock foraging on one sub-group and then moving to another sub-group. The land market is another form of group grazing. One herder rents or leases land from another herder at the beginning of the year, and then they can put some of their livestock on that rented land. This, in essence, is a kind of smaller scale group grazing, but in line with market demand. The relationship of these two institutional arrangements and three grazing strategies was shown in Figure 3.8.

In ABMGG, the herder agents in rotational grazing land patches form the grazing groups. The number of sub-groups is determined by the frequency of grazing-led LAI changes. Due to the limited data about the exact sizes and locations of grazing groups (although the aggregated statistics are known, see Table 7.7), the related parameters need to be analysed to make sure the modelling results are consistent with the grazing-led LAI defoliation derived from MODIS LAI (see the evaluation section of the model). At the beginning of each simulation year, three different grazing types are reinitialized. The grazing types of Zeku at 463x463 m^2 spatial resolution are based on the grazing-led LAI frequencies for each patch. Un-grazed patches are the pixels with 0 grazing frequency; rotational grazing patches are the pixels with grazing frequencies equal to 2 or bigger than 2; the rest of the patches are, therefore, the continuous grazing lands.

To demonstrate how these institutional arrangements and grazing strategies affect the grassland status (measured by LAI after grazing and by the number of degraded patches), this chapter first makes sure that the ABMGG output matches the remote sensing derived grazing pattern (the number of degraded patches) well, and then explores the impact of different combinations of group grazing, moving and marketing behaviours of herders on the model outputs. This section will introduce the ABMGG in detail; but firstly, how to simulate the LAI after grazing, which is the most important model output, will be explained.

7.2.1 The LAI after grazing in ABMGG

The LAI after grazing is the key proxy for evaluating grassland status after grazing. This thesis, therefore, explains how it will be simulated by the ABMGG before providing a detailed description of the ABMGG.

In this study, the LAI after grazing is the focus because:

- LAI after grazing is an indicator for the evaluation of grassland status, and whether LAI after grazing is significantly different under various grazing management scenarios will be explored through the ABMGG; and
- degraded patches are classified based on the ratio of LAI after grazing and full-growth LAI, and the number of degraded patches is another important concern in the evaluation of overall grassland status.

The patch-specific grazing-led LAI changes and the full-growth LAI were calculated based on the theory discussed in Chapter 5, that is, the grazing-led LAI changes were estimated for each pixel by equation 5-16 in Chapter 5. By setting the previous grazing effect, PB_t, and current grazing, PG_t, to 0, the full-growth LAI were calculated using the new growth-grazing function, that becomes:

$$\boldsymbol{L_{full\,growth} = L_m + L_0 e^{k_1 t - k_2 t^2 + C}}$$

Eq. 7-1

, where $\boldsymbol{L_{full\,growth}}$ is the theoretical LAI value without the effects of previous or current grazing; L_m is the background LAI, L_0 is the initial LAI, k1, k2 and C are the parameters describing growth and senescence of the grass, as estimated in Chapter 5. In Chapter 5, the grazing-led LAI changes were extracted through MODIS LAI, which were the LAI after grazing, and the full growth LAI can be produced through Eq. 7-1. In this chapter, the grazing-led LAI changes (direct changes in LAI caused by grazing) will be used as forage demand for every eight-day period for each patch, and the full growth LAI is used as the maximum available forage in each patch (Figure 7.1). The aim is to produce a similar LAI curve after grazing (by calibration) as it has been observed in the MODIS LAI (see Section 7.3). Then, a scenario analysis will be carried out in order to assess the effects of different grazing strategies and institutional management on grassland status (see Section 7.4).

This chapter, therefore, designs the agent landscape to match up with the MODIS LAI maps. Each land patch in ABMGG represents a grassland area of 463×463 m^2. For each continuous and rotational grazing patch, a livestock agent associated with it at the start of the year. The grass feeding demand for each livestock agent is the same as the grazed LAI calculated in Section 5.7.3, and this feeding demand is updated for each step. The maximum available forage for each land patch is represented by the full-growth LAI, which is calculated using Eq. 7-1. The grazing-led LAI changes were derived during the grass growing period from Julian day 113 to Julian day 289 (the days beyond this period during the year were not analysed in this thesis, as cattle tend to be fed with feed and the ground in the area is frequently snow covered).

In order to simulate the group grazing behaviour of the livestock in Zeku, all the rotational grazing patches are assigned with a group and sub-group identification. The livestock on the same group patch has the same group identification. The livestock can only move in and out of patches with the same group identification. For each step, the total grass feeding demand of the group is calculated by:

$$\boldsymbol{LDT_t = \sum_{i=1}^{m} LDI_{i,t}}$$

Eq. 7-2

, where $\boldsymbol{m}$ is the number of livestock agents in the group and $\boldsymbol{t}$ is the time step. $\boldsymbol{LDI_{i,t}}$ represents the grass feeding demand of the individual agent and, $\boldsymbol{LDT_t}$ is the total grass feeding demand of the group. For continuous grazing patches, m = 1, which means only one herder agent on the patch, and their livestock continuously graze on those patches.

For each rotational grazing patch in the sub-group, the LAI decrease caused by grazing is assumed to be proportional to its current available LAI, which means that selective foraging behaviour of the livestock is not considered in the model.

That is, the greater the currently available LAI of the patch, the bigger the LAI decrease caused by grazing. This can be expressed by:

$$\boldsymbol{LGI_{i,t} = LDT_t \times LCI_{i,t} / \sum_{i=1}^{n} LCI_{i,t}}$$

Eq. 7-3

, where $\boldsymbol{LGI_{i,t}}$ is the LAI decrease of a grazed patch in the sub-group $\boldsymbol{LCI_{i,t}}$ is the current LAI before current grazing of each patch in the sub-group; $\sum_{i=1}^{n} \boldsymbol{LCI_{i,t}}$ is the total available LAI in the sub-group and, $\boldsymbol{n}$ is the total numebr of patches in the sub-group. For continuous grazing patches, $\boldsymbol{LGI_{i,t}}$ is the LAI decrease of the individual patch, and is not affected by the other patches.

The current LAI before grazing ($\boldsymbol{LCI_{i,t}}$) for each patch is calculated as the subtraction of the effect of previous grazing on LAI from the full-growth LAI:

$$\boldsymbol{LCI_{i,t}} = L_{full\ growth} - \boldsymbol{LAI_{previous\ effect}}$$

Eq. 7-4

, where $\boldsymbol{LCI_{i,t}}$ is the current LAI before grazing, and $\boldsymbol{LAI_{previous\ effect}}$ is the previous effect on the LAI.

Finally, the LAI after grazing is calculated by taking the difference between the currently available LAI and the grazing-led LAI changes (the grazing demand on the LAI, or the effect of current grazing). The effect of current grazing is the total livestock consumption during the eight-day period, which can be calculated by Eq. 7-3. The livestock will eat forage production on grassland, and the LAI of the grassland will change accordingly. The effect of previous grazing is calculated through averaging previous LAI after grazing and full-growth LAI from the next iteration (average of the two neighbouring LAI time-series). At the beginning of each simulation year, the effect of both previous and current grazing is 0 (no grazing happening); while for continuous or rotational grazing patches where previous grazing has occurred, the effect of previous grazing can be calculated by:

$$\boldsymbol{LAI_{previous\ effect} = L_{full\ growth} - (LAI_{after\ grazing-1} + LAI_{full\ growth+1})/2}$$

Eq. 7-5

, where $LAI_{after\ grazing-1}$ is the $LAI_{after\ grazing}$ value at its previous iteration and; $LAI_{full\ growth+1}$ is the $L_{full\ growth}$ value at the next iteration. At the beginning of each simulation year, the effect of both previous and current grazing is 0 (that is, $LAI_{previous\ effect} = 0$, no grazing happening). The rest of work is then to make sure that $LAI_{after\ grazing}$ derived from the ABMGG matches with $L_{observed}$ derived from the MODIS LAI dataset, and to examine how $LAI_{after\ grazing}$ changes with different policy scenarios.

One model iteration (step) accounts for eight days of simulated time (this is the temporal resolution of the MODIS LAI data). Simulations last for 46 time steps, representing the years for which data are available (2011). The livestock owned by herder agents moves from one sub-group of patches to another sub-group of patches and the livestock grazes on the patch that they are on at each time step for rotational grazing patches. For continuous grazing land, once livestock enters the land patch, they do not move to other land patches. The LAI will decrease accordingly after livestock grazing, with the LAI after grazing for each patch at each time step being calculated by (variables introduced in Eq. 7-3 and Eq. 7-4):

$$\boldsymbol{LAI_{after\ grazing} = LCI_{i,t} - LGI_{i,t}}$$

Eq. 7-6

Now the LAI after grazing can be simulated through ABMGG. This section is an introduction to the key process of the ABMGG. A detailed Design, concept and Detail (ODD) and Decision (ODD+D) description of the ABMGG, where each part of the model is introduced in a standardised way.

7.2.2 Detailed ODD+D description of ABMGG

As mentioned earlier in this Chapter, the ODD protocol is a standardised way of describing ABMGG. This thesis employs an Overview, Design, concept and Detail (ODD) and Decision (ODD+D) protocol to describe the agent-based model, ABMGG. The protocol is widely used in social and ecological studies (Polhill et al., 2008; Müller et al., 2013). The detailed ODD+D descriptions of ABMGG will be discussed, following the guiding questions proposed by Müller et al. (2013).

7.2.2.1 Overview

Purpose

The model aims to reproduce the leaf area index (LAI) after grazing based on the full-growth LAI and the grazing-led LAI changes. Specifically, the model attempts to produce the same number of unaffected, slightly-, medium- and severely-degraded patches, the regional average of the mean and variance of the grazing-led LAI changes of the patches. The model is intended to be useful for researchers and policy-makers who are interested in grassland management (macro policies).

Entities, state variables and scales

There are two types of entities in ABMGG. Firstly, herder agents represent resource users. They are not the real herders, but the representatives of the grazing-led LAI changes (without the effect of the previous grazing) observed in MODIS LAI. There are three types of herder agents according to their grassland management types:

- grazing herders (sedentary or continuous) agents, whose livestock cannot move among land patches;
- group grazing herder agents who have joined the group at the beginning of the year and can move their livestock from one land patch to another land patch within the group;
- land market herder agents who can lease/rent land from/to the other herders. These are randomly chosen from sedentary grazing herder agents.

Another type of entity in ABMGG is the grassland patch, which represents the available forage for grazing (measured by LAI). The variables associated with herder agents and land patch agents are shown in Table 7.2. The names of the variables are all self-explanatory, and all the parameters are classified into three types:

- patches related variables;
- herders related variables; and
- global variables.

The land patch related parameters are mainly used to present the dynamics of the LAI and the group grazing information. With livestock moving between sub-groups, the dynamic of grazed LAI can be simulated to match the grazing intensity and grassland status after grazing. Due to the limited data about the exact sizes and locations of grazing groups, the number of sub-groups they have and within which radius they would form a group, all these related parameters need to be analysed to make sure the modelling results can reveal the grassland status observed in MODIS LAI.

Table 7.2: Key parameters in ABMGG

type	Variable	value	explanation
land patches	lai_current_fullgrowth	Chapter 5	A theoretical full-growth LAI if there is no grazing (calculated from new growth function detailed in Chapter 5.
	lai_right_fullgrowth	Chapter 5	the full-growth LAI for the next time step.
	lai_current_grazed	state variable	the LAI actually being "grazed" (grazing-led LAI change without the effect of the previous grazing).
	lai_current	state variable	the LAI after grazing. It will be affected by the previous grazing ("lai_current_previous") and current grazing ("lai_current_grazed").
	lai_current_previous	state variable	the effect of the previous grazing on the current LAI.
	lai_left	state variable	the LAI after grazing of the previous time step (one step before current time step).
	lai_type	Chapter 5	the grazing types of the land patches (un-grazed, continuous and rotational).
	group_id	random	all the rotational grazing land patches will form a local grazing group within the radius, and the locations of the groups are randomized. The land patch agents in the same group will be assigned a same group identification number.
	sub_group_id	random	Each grazing group has a certain number of sub-groups, and the land patch agents in the same sub-group will be assigned a same sub-group identification number.

	SU_patch	Chapter 5	all types of land patch agents have a certain unit of livestock, which denoted by grazing-led LAI changes (without the effect of the previous effect) derived from MODIS LAI. They are used to represent the grass forage demand of livestock.
	cell_size	463m×463m	the spatial resolution of the model. It represents the size of one land patch in reality.
herders	id_livestock	state variable	from which land patch the livestock comes. This association is initialized at the beginning of the year. It is a "pointer" to a land patch agent and does not change during the year.
	SU_livestock	Chapter 5	They are the same as "SU_patch" for land patch agents. For each time step, the "SU_patch" will be updated, and then, "SU_livestock" will also be updated as the same as "SU_patch" through association "id_livestock".
	group_id_livestock	random	these are the same as the land patch agents, and they are initialized at the start of the year after creating livestock agents on each land patch.
	sub_group_id_livestock	random	these are the same as the herder agent.
	destination	Random	the destination for the next move of a rotational grazing livestock agent. It is also a "pointer" to a land patch agent but changes at each step during the year.
Global	radius	6	the radius of the grazing groups. It indicates the "size" of the grazing groups.
	number_participant	40	the minimum number of herders in a grazing group.
	number_sub_group	3	the average number of sub-groups in a grazing group.
	lease_percentage	16%	the percentage of continuous grazing patches being rented to the other herders.
	prolonged_snow_prob	0.01	the probability that prolonged snow occurs.

The administrative boundary of Zeku is initialized by the land patches where "lai_current_fullgrowth" does not equal to "NaN"; it is a little bit smaller than the actual administrative boundary due to the presence of non-grass patches or area with no data. Each land path agent occupies a cell of 463m × 463m in the real world. The locations and spatial reference are kept the same as remote sensing data; each time step represents an 8-day period. There are 46 time steps during the year, and the model assumes that the prolonged snow happens randomly during the year.

Process overview and scheduling

At the beginning of the year, the following process will be executed. The detailed description and decision-making process will be discussed later in Table 7.3.

- Store "lai_left" for each step;
- Update the full-growth LAI for each step;
- Update land types (un-grazed, sedentary and rotational grazing land) and create livestock annually;
- Update grass forage demand for the land patch agents and their associated livestock agents;
- Form the grazing groups;
- Divide sub-groups;
- Update the current LAI considering the effect of the previous grazing;
- Build Leasing/renting relationships.

During grass growth season (step 16-37, which refers to day 121~289), four processes will proceed:

- Simulate the effect of prolonged snow on LAI dynamics;
- Livestock grazing;
- Update LAI after grazing;
- Nothing happens outside of the grass growing season.

7.2.2.2 Design concept

Theoretical and Empirical Background

The decision-making of the herders is not based on theory. However, the empirical background of this model is the grass regrowth under different combinations of grazing strategies and institutional arrangements. Rotational grazing patches will see a higher regrowth rate than that of continuous grazing patches (if they are in the same condition) due to the rest period of rotational grazing at the individual species level (Thornley and Johnson, 1990).

In addition, macro policies such as institutional arrangements (group grazing), to some extent, may further amplify this effect by making the size or scale of rotational grazing larger. Thus, accurate simulation of the LAI after livestock grazing is highly depended on the moving behaviours of livestock and the interactions between livestock and grassland. These two key features play to the innate advantages of agent-based modelling for modelling the grassland grazing system. Therefore, the following theories are included in the model:

- grass growth function based on MODIS LAI data (see Chapter 5);
- social-ecological approach to the study of grazing grassland management (Wang et al., 2013).

The ABMGG assumes that the livestock on the sedentary grazing patches do not move to the other patches; all the herder agents on the rotational grazing patches will join a local grazing group and all the livestock on a group grazing land (owned by group grazing herder agents) will move from one sub-group to another to simulate the herders' rotational grazing strategy. Once herders have joined a grazing group at the beginning of the year, they will not quit or change to another grazing group. According to field surveys in 2012 and 2016, the herders usually have been contracted to the grazing group for the whole year, and no one quits or changes group during the contracted year. The locations of grazing groups and the sub-groups are randomized due to the lack of such information. The total number of grazing groups was 338 in the year 2011. Although accurate locations can improve the accuracy of the model, randomized locations can be used if they can reveal the overall grazing patterns (grazing intensity and grassland status) with considerable uncertainties, which will be discussed in the model evaluation section later.

The decision-making process underlying the model is to make sure the model output (grazing intensity and grassland status) is consistent with what has been derived from MODIS LAI. The total number of grazing groups and the average number of sub-groups in one grazing group are provided by Grassland and Livestock Bureau of Zeku. The full-growth LAI and the per-pixel grazing-led LAI changes (with the effect of the previous grazing) are based on the results of Chapter 5. The full-growth LAI and the per-pixel grazing-led LAI changes are at the individual level; the average number of sub-groups is at the group level; while the total number of grazing groups is at the system level (the whole case study area).

Individual Decision-Making

In ABMGG, all herder agents are forced to behave in a predetermined way: the livestock on a sedentary grazing land cannot move to the other land patches (at the individual level). The livestock on a group grazing land will have to move from one sub-group to another sub-group. The order of visiting sub-groups is randomized. This behaviour is at the grazing group level. Compared with continuously grazed land patches, rotationally grazed patches have a “rest” period, which can change their grassland status. The total available forage (indicated by LAI) for grazing should be greater than that of the forage needed. During the model evaluation, they make decisions based on this pre-defined rule.

The adaptive behaviours of the herders are not considered in the model. The rotational grazing herder agents can only move their livestock within the spatial boundary of the group. The full-growth LAI and the grazing-led LAI changes (without the effect of the previous grazing) are updated at every step. The parametric and stochastic uncertainties are quantified through Approximate Bayesian Computation with multiple parameter sets and repeated model executions, and the input uncertainty is quantified through an extreme situation analysis. These uncertainty analyses will be discussed in the model evaluation section later.

Learning

Individual learning is not considered in the model.

Individual Sensing

The herder agents sense all the endogenous state variables of patches (listed in Table 7.2) without error. The rotational grazing herder agents can additionally perceive the “group_id_livestock” , “sub_group_id_livestock” and “SU_livestock” of the other rotational grazing herder agents without error. Only the herder agents in the same group know the LAI before grazing of other agents in that group. The cost of cognition and the costs of gathering information are not considered.

Individual Prediction

Because the full-growth LAI and grazing-led LAI changes (without the effect of the previous grazing) are direct from the results reported in Chapter 5, the prediction of grass growth is not explicitly considered in this model.

Interaction

There are direct interactions both with the land patch agents (through grazing) and among the herder agents (through grouping), which depend on the group identification and sub-group identification. The first type of interaction is between livestock and grassland: livestock will eat forage on grassland, and the growth of grassland LAI will be changed accordingly. Similar to the grazing-led LAI change estimation algorithm in Chapter 5, the LAI before grazing can be calculated as the average of its left and right time neighbours, and the LAI after grazing is the difference of LAI before grazing and grazing-led LAI defoliation. Another is interaction among herders: the herders can join a grazing group or lease land to the others. The subdividing of their group grazing lands affects the LAI after grazing (for land patch agents), they are imposed in a predefined order.

Collectives

Collective behaviour is considered in the model. Herders in one group will move from one sub-group patches to the other sub-group patches during the grass growing period. By forming the grazing group and subdividing of the grazing group, the LAI decreased proportionally to the available forage of individuals. In such way, the collective behaviours of herders are simulated in the model.

Heterogeneity

The agents are heterogeneous with regards to the following state variables:

- group identification;
- sub-group identification;
- full-growth LAI;
- LAI before/after grazing;
- livestock unit;

The (decision) processes are the same for the agents with the same grazing type, but due to their heterogeneous attributes, different grassland degradation patterns emerge.

Stochasticity

Stochasticity is used to represent two sources of variability in livestock movement that are too complex to represent mechanistically.

- although the selective instinct of livestock could affect their moving behaviours, the livestock just move randomly to the sub-group patches (in pre-defined random order);
- the second stochasticity is where the prolonged snow would happen during the modelling steps. This is an unpredictable extreme climate event. An overall possibility of a prolonged snow event is represented by parameter “prolonged_snow_prob”;

In addition, since the spatial boundary of the grazing groups and sub-groups is not available, another stochastic element is the locations of the group and subgroups (they are randomized).

Observation

LAI after grazing and grazing-led LAI changes are collected for each time step. The simulated grazing-led LAI changes (mean and variance) and the grassland status (the number of no-effect, slightly, medium and severely degraded patches) will be evaluated in Section 7.3.

7.2.2.3 Details

Implementation Details

The model is implemented using NetLogo 6.0.3 with the GIS extension and R 3.3.3. The source code is free for research purpose, and the website is: http://modelingcommons.org/browse/one_model/5706#model_tabs_browse_info

Initialisation

The model world is initialized with the same spatial boundary of the grassland in Zeku. At the beginning of a simulation year, three different grazing types of the patches are reinitialized: un-grazed, sedentary (continuous) grazing and rotational grazing; then the full-growth LAI and the forage demand on each land patch is loaded; the grazing groups and sub-groups are formed randomly thereafter, which are varied among simulations due to the random location of the grazing groups and sub-groups. The other initial state of the model is the same among the simulations. The grazing groups, sub-groups and leasing-renting relations are formed based on the aggregated statistical properties (the total number of grazing groups, the average number of sub-groups in the group and the percentage of leasing-renting land patches). The other initial values are chosen from the grazing information derived from MODIS LAI (see Chapter 5).

Input Data

There are three main input data sets:

- full growth LAI, which changes for each time step;
- “SU_livestock” is updated for each time step; and
- the grazing types which update at the start of the year.

The full growth LAI can be calculated from the new growth-grazing function by setting the previous grazing effect PB_t and current grazing PG_t to 0. We can also calculate the LAI consumption based on the estimated grazed LAI. In order to simulate the group grazing behaviours, and because there is no spatial boundary data for the grazing groups and herders, the ABMGG does not aim at producing the results of exactly the same grazing amount and grazing frequency at the exactly grazing time point, but rather by producing the same grazing pattern: i.e. the same grazing intensity and grassland status. In ABMGG, grazed LAIs (demand of livestock) are updated at the same grazing-led LAI changes (without the effect of previous grazing) as estimated in Chapter 5.

Submodels

The detailed submodels and processes are listed in Table 7.3. There are three parameters related to the group rotational grazing:

- "number_participant";
- "number_sub_group";
- "lease_percentage".

one related to land market:

- "lease_percentage"

and one related to exogenous disturbance

- "prolonged_snow_prob"

Their values are given in Table 7.2.

Table 7.3: Details of the implementation of the model processes.

Process	Variable involved	Description	Formalization
1. Store LAI after grazing of the previous step	State variable *("lai_left")*	for each land patch at each time step, the LAI after grazing (even if it has not been grazed) will be stored before updating any other values of the land patch agent. It is used to calculate the effect of the previous grazing on the current LAI.	*ask patches* *[set lai_left ai_current]*
2. Update full-growth LAI	The full-growth LAI *("lai_current_fullgrowth" and* *"lai_current_fullgrowth_right")*	The theoretical LAI if there is no grazing. it is input data for ABMGG from an external file.	Using NetLogo GIS extension to read the external file.

3. Update land types	The grazing type of land patch agents *("lai_type")*	At the start of a simulation year, three different grazing types are reinitialized. The grazing types of Zeku at 463x463 m^2 spatial resolution are based on the grazing-led LAI frequencies for each patch. The un-grazed patches are the pixels with 0 grazing frequencies; while the rotational grazing patches are the pixels with grazing frequencies equal to 2 or bigger than 2. The rest of the patches are therefore continuous grazing lands.	This information is a pre-produced map derived from the results of Chapter 5.
4. Update forage demand of the livestock	The forage demand of the livestock owned by herder agent (*"SU_patch" and "SU_livestock"*)	The livestock forage demand is measured by the grazing-led LAI changes (without the effect of the previous grazing) during the year. For each time step, "SU_patch" will be updated and then the associated livestock will update "SU_livestock", the values of the two are exactly the same.	These are also the pre-produced maps.
5. Form the grazing groups	The size of the group ("*radius*"); The number of herders in the group ("*number_participant*"); The group identification of	All the rotational grazing land patches will have to join the local grazing groups. The locations of the grazing groups are randomized.	Ask *number_participant* herder agents to form the group.

	the land patch (“*group_id”*)		
6. Divide sub-groups;	The group identification of the land patch (“*group_id”*) The sub-group identification of the land agents (“*sub_group_id”*) ; The number of sub-groups *(number_of_sub_group).*	The land patch agents in one grazing groups are divided into sub-groups.	Ask *number_participant/number_sub_groups* herder agents *to form a sub-group.*
7. calculate the effect of the previous grazing	The full-growth LAI *(“lai_current_full growth”, “lai_right_fullgrwoth” and “lai_current_previous”).*	The effect of the previous grazing is the difference between full-growth LAI and the expected LAI (with the effect of the previous grazing but without the effect of current grazing).	See Eq. 7-5
8. Build Leasing/renting relationships	The percentage of leasing/renting herders *(“lease_percentage”);* The livestock consumption demand *(“SU_livestock”).*	This is a simplified land market behaviour. Randomly select the same percentage of the herder agents to form such relationships.	Ask *lease_percentage*total_number_herders* continuous grazing herder agents change *SU_livestock*
9. The effect of prolonged snow	The probability of prolonged snow (“*prolonged_snow_prob*”); The current LAI *(“lai_current”).*	The model assumes prolonged snow only happens on rotational grazing patches and causes a random LAI loss (an addition decrease on “lai_current” of continuous grazing patch leads to the grazing frequency greater than 1, which is not true for	Ask *prolonged_snow_prob * (count patches with [lai_type = 2])* *[set lai_current random lai_current]*

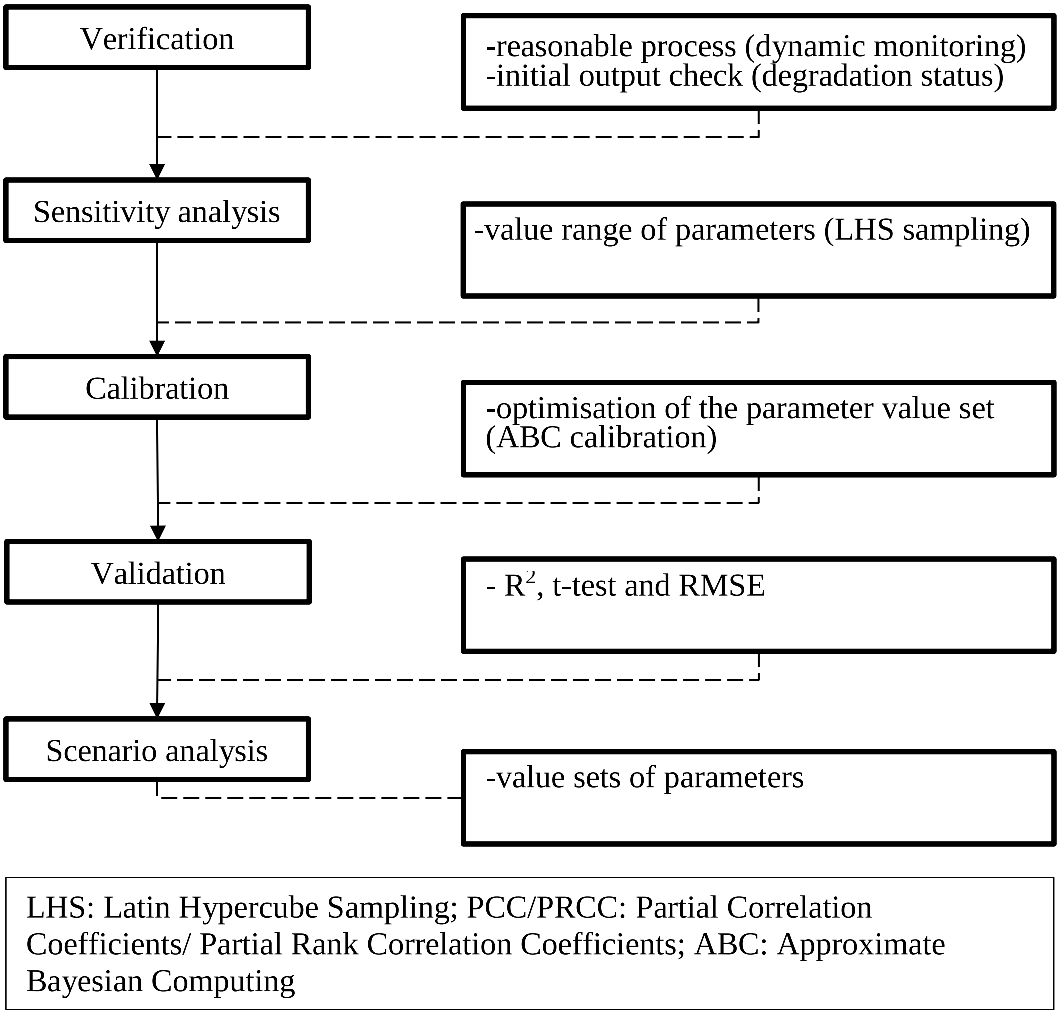
		continuous grazing patches)	
10. Livestock grazing	The livestock consumption demand *("SU_livestock");* Current LAI *("lai_current")* The identification of patches *("group_id" and "sub_group_id")* The identification and destination for next move of herder agents *("id_livestock", "group_id_livestock", "sub_group_id_livestock"* and *"destination")*	The LAI of the land patches will decrease directly on continuous grazing patches, and the livestock will not move to the other patches; For rotational grazing patches, the livestock will move from one sub-group to another sub-group in a randomly pre-defined order. The LAI of the patches in the subgroup will decrease proportionally to the current LAI.	See Eq. 7-2, Eq. 7-3 and Eq. 7-4
11. Update LAI after grazing	The full-growth LAI *("lai_current_full_growth");* The full-growth LAI for the next time step *("lai_right_full_growth");* the LAI for previous time step *("lai_current_previous");* LAI after grazing *("lai_current");* Grazing-led LAI changes *("lai_current_grazed").*	For un-grazed and sedentary grazing patches, the LAI change is the same as that observed in remote sensing. For rotational grazing patches, the LAI value depends on the number of livestock standing on a patch. The LAI is calculated by considering the effect of current grazing and the effect of the previous grazing.	See Eq. 7-6
8. All the other steps during the	The current LAI (*"lai_current")*	The effect of grazing is ignored during this period.	Ask patches

year: nothing happens (not considered in ABMGG)			[set LAI after grazing to full-growth LAI; set grazing-led LAI changes to 0]

7.3 Model evaluation

This section discusses the evaluation of ABMGG. The verification of the model is presented in Section 7.3.1, followed by a subsection that focuses on sensitivity analysis to identify the effect of the parameter value changes on the model output (Section 7.3.2). After calibrating the ABMGG with an Approximate Bayesian Computing method (Section 7.3.3 and Section 7.3.4), the model validation work is then carried out (Section 7.3.6). Section 7.3.5 presents the uncertainties of the ABMGG. Finally, a scenario-based analysis is employed to assess the different combinations of grazing strategies and institutional arrangements for Zeku in Section 7.4, where the uncertainty of the results of scenario analysis is also discussed.

After building the ABMGG, the rest of the work is to make sure it works reasonably well; that is, to ensures the parameter values, interactions, process and output are working in the same manner as the real grassland grazing system, thereby allowing the policy assessment to proceed. In fact, the process of policy assessment is intimately tied to the validation and scenario analysis of the ABMGG (Figure 7.2). The evaluation process consists of model verification, a sensitivity analysis and model calibration. Following the evaluation, the policy scenario analysis proceeds through the analysis of the outputs by changing the value sets of the model parameters. This chapter will now explain each of them.



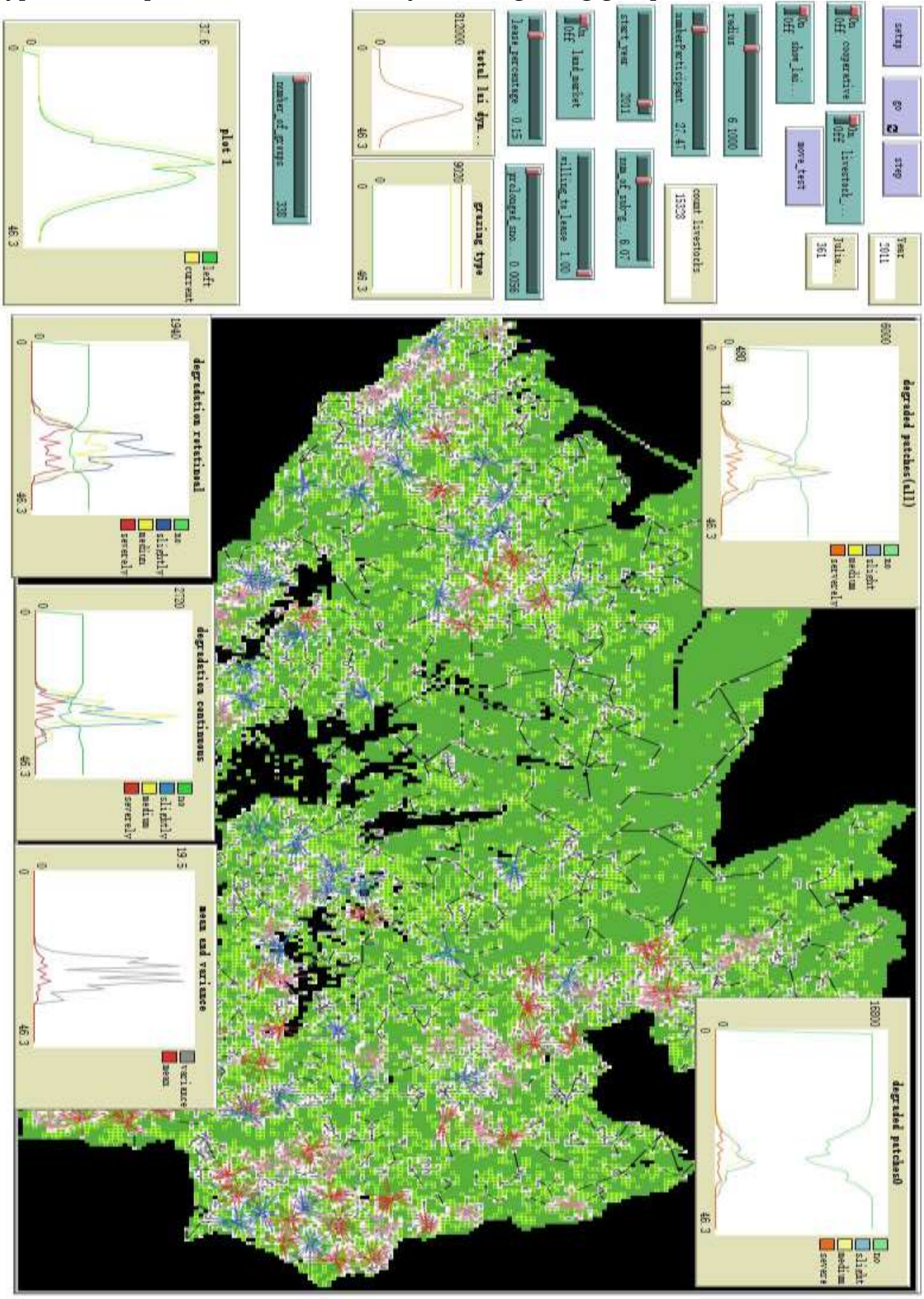
LHS: Latin Hypercube Sampling; PCC/PRCC: Partial Correlation Coefficients/ Partial Rank Correlation Coefficients; ABC: Approximate Bayesian Computing

Figure 7.2: The processes of model evaluation and scenario analysis

7.3.1 Model verification

Verification is an essential part of developing the ABMGG to ensure that the model processes have been accurately implemented such that the model behaves as it is expected to (Ormerod and Rosewell, 2009; Arifin et al., 2011). The main behaviour in ABMGG is livestock grazing according to different grazing types. That is, a herder agent of sedentary grazing type will not move to any patches during the simulation process. Randomly moving herders (herders that do not form grazing groups; they are used just for comparison purposes with the group moving herders) will move to their neighbouring patches randomly. While the group moving herders will move to their sub-group areas one by one, they are quite similar to the industrialized farms, the land in one group will be divided into several subgroups and the livestock will graze on the subgroups one by one. When the land market feature is on, the herders will find a landlord to rent land from at a certain probability.

Figure 7.3 shows the interface of ABMGG. The moving behaviours can be visually examined. The monitoring of the model results can be through either spatial maps or time-series graphs, which plot the indicators over the time of the model run. The large output extent is able to display the spatial maps of LAI after grazing, grazing types of land patches and the randomly formed grazing groups.



cooperative On/Off
livestock_... On/Off
show_lai... On/Off
land_market On/Off
radius 6.1000
numberParticipant 27.47
start_year 2011
lease_percentage 0.15
num_of_sub-g... 6.07
willing_to_lease 1.00
prolonged_sno... 0.0056
number_of_groups 338
count livestocks 15328
Julia... 361
Year 2011

Figure 7.3: Snapshot of the ABMGG

Another step of the ABMGG verification is to assess whether the simulation outputs fall within a reasonable range compared with the real data, which means whether ABMGG can produce the same grazing intensity and grassland status. Note that un-grazed patches are excluded in the test because they would produce almost identical LAI values as the MODIS LAI. Hence the grazing-led LAI defoliation would be 0, which would significantly improve the results of statistical tests.

Only time steps between 16 and 37 for the simulated year are tested because these are the grass growth period. In addition, the LAI would be the same in winter when MODIS LAI cannot tell the difference between grazed and un-grazed land. The model was run 50 times for the year 2011 to generate the average outputs for each step.

Figure 7.4 shows the average grazing-led LAI changes (without the effect of the previous grazing) simulated by ABMGG. The standard deviation of 50 simulated runs is also shown in this figure. Within all the simulation steps, the standard deviations are quite small, which indicate the stochastic uncertainty of the model output is quite small; and generally, a bigger standard deviation of the grazing-led LAI changes can be observed in the time steps with a higher average value of grazing-led LAI changes. This is expected as the stochastic setting in the ABMGG (for example randomised locations of grazing groups) affect the grazing-led LAI changes, and a higher grazing intensity would generate a bigger variance of the model output.

In addition, we can see that the average simulated grazing-led LAI changes (without the effect of the previous grazing) are systematically higher than the grazing-led LAI changes (without the effect of the previous grazing) derived with MODIS LAI product. The main reason is that, for some of the grazing groups, the number of sub-groups was bigger than the actual number of sub-groups (unfortunately, the number of subgroups for each grazing group is not available at the time of writing). This may lead to the total grazing demand (represented by LAI) in the group was even greater than that of the total available forage of the sub-group; when the livestock moved in that sub-group, they only ate the maximum available forage rather than the actual grazing demand of the forage (it was bigger than the maximum available forage). Nevertheless, the R^2 between simulated and observed grazing-led LAI changes is 0.996, and the p-value of the T-test is 0.88, which indicates that they are statistically similar.

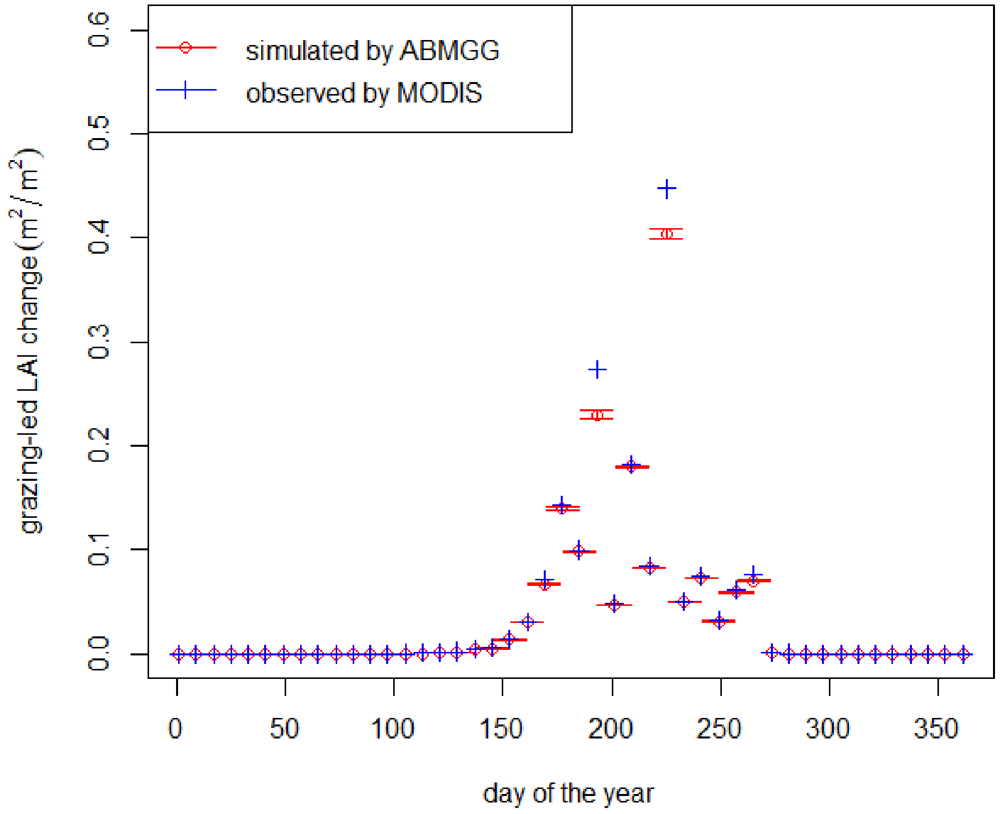


Figure 7.4: Simulated and observed grazing-led LAI changes (without the effect of the previous grazing), 2011

The numbers of degraded patches are the important aspect of evaluating the grassland status, and they are simply calculated according to the Chinese national criteria of “Parameters for degradation, sandification and saltfication of rangelands” (Su et al., 2003). By definition, if a decreased LAI is less than 10% of expected LAI, it will be classified into unaffected grassland type (“no effect” in this thesis), which means the patch has not been degraded. If it is between 10% and 20%, the land patch then is classified into the slightly degraded type; The medium degraded land patch indicates a decrease of LAI between 20% and 50%, while that of severely degraded land exceeds 50%.

Figure 7.5 shows the number of degraded patches for each time step of the year 2011 under these four degradation criteria. The ABMGG has underestimated the number of unaffected patches but overestimated the number of degraded patches for the other three types of degradation. Three goodness-of-fit indicators are shown in Table 7.4. The R^2 between simulated and observed numbers of degraded patches are all bigger than 0.6. The p-values of the t-test for the number of unaffected, medium and severely degraded patches are all bigger than 0.01, indicating that they are statistically the same on the average. However, the p-value of the t-test for the number of slightly degraded patches is smaller than 0.01, which means the average of the number of slightly degraded patches is statistically different. One reason for the discrepancies between statistics of model output with observed data is the inaccurate setting of the grazing groups and sub-groups. The ABMGG used randomised locations of the grazing groups rather than the actual locations, and the livestock moved from one sub-group to another sub-group in a random order. Even if they were to eat the same amount of grass forage, the LAI after grazing would be different due to the differences in full-growth LAI for the land patches. These model discrepancies can be decreased or even eliminated by using accurate grazing group and sub-group information and the grazing order (or behaviour) within the sub-groups. On the whole, although there are differences in the number of degraded patches, and the simulation results did not hit the exact points of MODIS LAI observed ones at an individual perspective, the ABMGG has behaved as expected and the model output matched with observed data (except for the number of slightly degraded patches). In addition, such discrepancies can also be decreased by calibration with the observed data, which will be illustrated in Section 7.3.3.

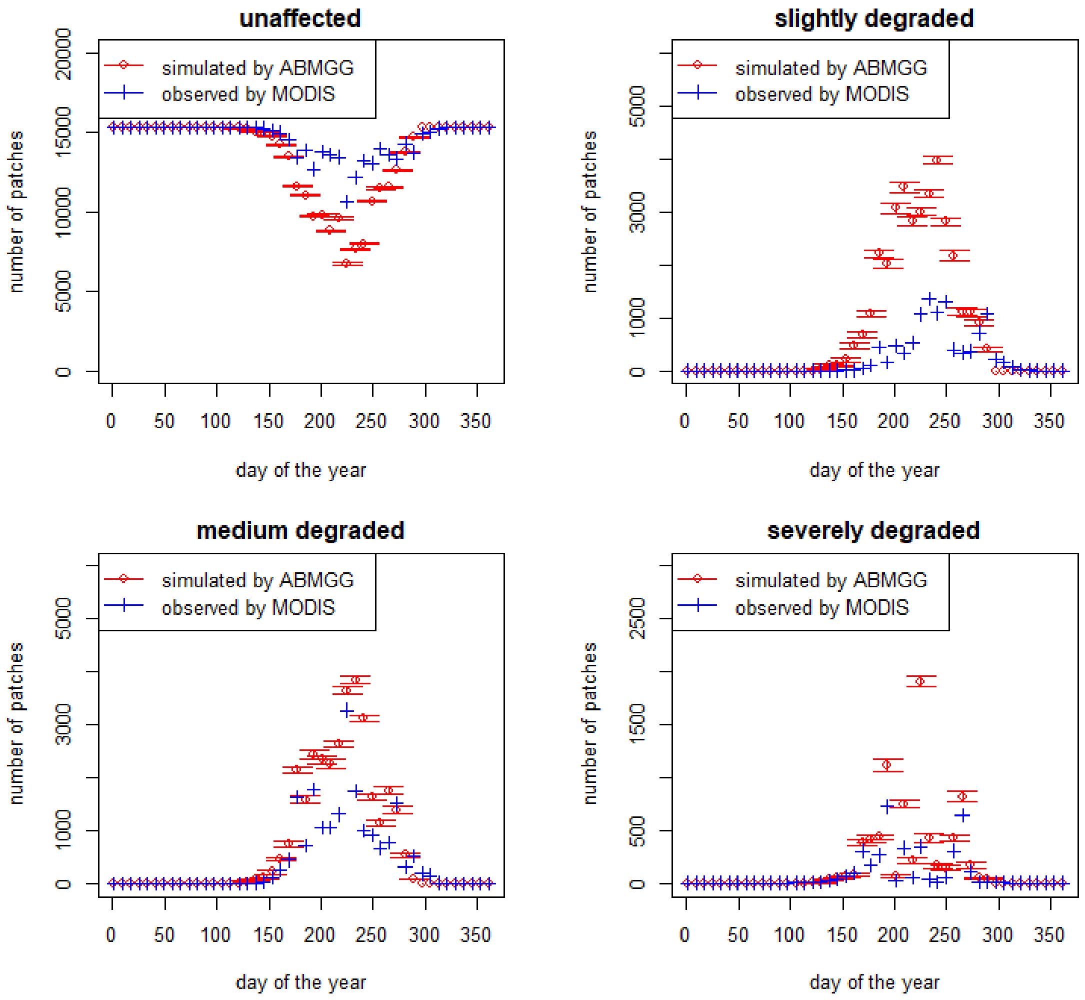


Figure 7.5: Simulated and observed number of degraded patches for each step of the year 2011

Table 7.4: Goodness-of-fit measurements of the modelling results

Type	**R^2**	**T-test (P-value)**	**RMSE**
Unaffected	0.8623	0.0234	1842.3160

Slightly degraded	0.6089	0.0062	1072.2240
Medium degraded	0.8362	0.1674	615.0182
Severely degraded	0.6512	0.1563	260.1417

7.3.2 Sensitivity analysis

For agent-based modelling, sensitivity analysis is commonly carried out to explore the effect of a model's parameters on the model outputs. This analysis is essential for identifying the most important parameters for the model before it is calibrated or used in scenario analysis. One widely used approach in sensitivity analysis is to change one parameter at a time, while keeping all other parameter values constant (Thiele et al., 2014). However, this approach is oversimplified as it leaves out possible interactions among input parameters (Ten Broeke et al., 2016). Therefore, cross-variation systematic sensitivity analysis should be conducted to understand dynamics in the real world system that are described by ABMs (Ten Broeke et al., 2016).

Typically, there are three different approaches: screening, local and global sensitivity analysis (Saltelli et al., 1993; Thiele et al., 2014). Screening methods are designed to explore a large set of parameters with wide value ranges and usually are computationally efficient. They are very fast in identifying the important parameters but cannot quantify importance. Local sensitivity analysis can deliver more detailed information about such importance by changing the values of parameters to a certain percentage. However, interactions between parameters are ignored; the results may be totally different if another set of parameter values were chosen. In a global sensitivity analysis, the importance of parameters is quantified by exploring the full range of their possible values against each other. The defect with global sensitivity analysis methods is they are usually computationally expensive.

The global sensitivity analysis techniques are chosen for ABMGG as there are few uncertain input parameters. The technique for global sensitivity analysis of ABMGG is the Partial (rank) correlation coefficient (PCC/PRCC), which is used to measure the relationship and the strength of the relationship of the input parameters (Saltelli et al., 1993; Manache and Melching, 2008). PCC can be used for the measurement of linear relationships, and PRCC is used for the measurement of non-linear but monotonic associations.

Figure 7.6 shows the results of the PCC/PRCC analysis of ABMGG. For the average values of grazing-led LAI changes in the bottom left figure, the PCC/PRCC results show that they are only monotonically correlated with the number of sub-groups. The same is true for the variance of the grazing-led LAI changes. As it had been explained in Section 7.3.1, the main reason for this is the randomized locations of grazing groups and the setting of the average of the number of sub-groups. For some of the grazing groups, a larger number of sub-groups than the actual number may cause insufficiently available forage for livestock grazing, and therefore, the grazing-led LAI changes would be smaller than the observed ones. The calibration work would be helpful to prevent the simulated grazing-led LAI changes being fundamentally different with the observed data, as only the parameter values which produce the smallest difference between model output and observed data could be selected as valid settings. This will be introduced in the next sections.

The other four parameters do not have a strong correlation with the mean or variance of the grazing-led LAI changes, and this indicates they are non-linear and non-monotonic. Since the radius of the grazing group, number of participants in the group and lease percentage are grazing strategy and institutional arrangement related parameters, and their value would affect the size of grazing groups and the scale of land market, this non-monotonic relationship indicates that different grazing strategies or institutional arrangements cannot significantly change the grazing intensity in ABMGG. It is expected that the grazing intensity should at least keep statistically the same as the observed data, and this is the premise for the scenario analysis later in Section 7.4.

There is basically no relationship between the numbers of degraded patches (four categories) and the number of participants in the groups and lease percentage. The relationship between the number of degraded patches and the radius varies according to the standard of degradation. Radius has a weak positive linear relationship (PCC < 0.5) with the number of medium and severely degraded patches, and a strong negative linear relationship (PCC < -0.5) with the number of unaffected patches, but a strong negative linear relationship (PCC > 0.5) with the number of slightly degraded patches.

The number of sub-groups has a similar relationship with the number of slightly, medium and severely degraded patches, that they have a strong linear but monotonic (decreasing) relationship (PCC and PRCC < -0.8). There is a strong positive linear relationship between the number of sub-groups and the number of unaffected patches (PCC and PRCC > 0.8). In addition, the probability of prolonged snow has a weak negative linear relationship with the number of unaffected patches, and a weak positive linear relationship with the number of slightly and medium degraded patches, but a strong linear and monotonic (increasing) relationship with the number of severely degraded patches. This is expected as the prolong snow was simulated as an exogenous variable to decrease the LAI randomly, and the number of unaffected patches should increase with the increase of the probability of prolonged snow; while the number of slightly, medium and severely degraded patches would increase.

To conclude, the relationship between input parameters and model outputs are revealed through the PCC/PRCC analysis. The grazing strategies and institutional arrangements do not have a significant effect on the mean value of the grazing-led LAI changes; the influence of different grazing strategies and institutional arrangements related parameters varies against the degradation criteria. Based on those analyses, although the number of sub-groups has a strong linear and monotonic relationship with the numbers of degraded patches (four categories), the relationship between the values of the parameters and the statistical properties of the model output are not linear and monotonic, which means the maximum values of the parameters will not produce the maximum statistical properties of the model output. This thesis, therefore, needs to calibrate the model with a method dealing with such non-linear and non-monotonic relationship, which will be illustrated next.

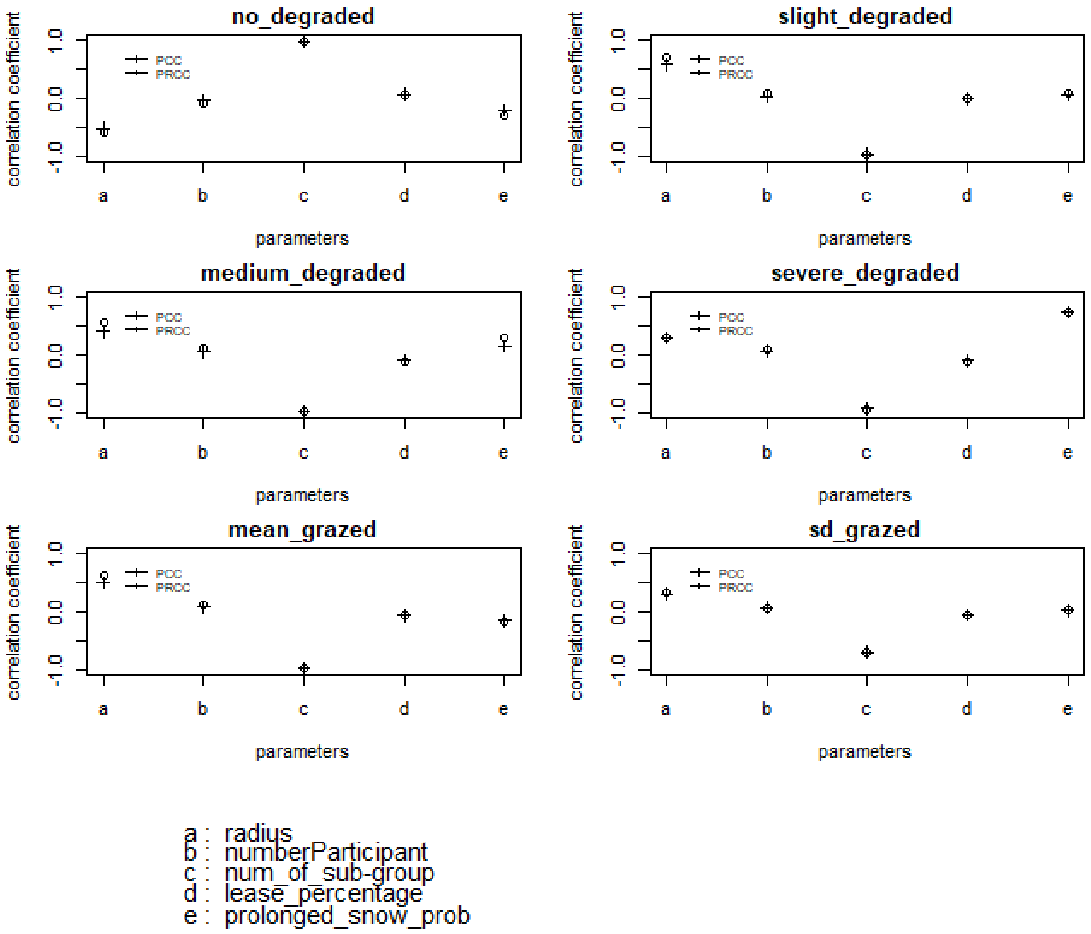


Figure 7.6: PCC/PRCC sensitivity analysis of ABMGG

7.3.3 Model calibration with Approximate Bayesian Computing

The next step is the calibration of the model. In this stage, an optimisation of the parameters used in the model will be involved. Generally, there are two different ways of fitting the modelling parameters to real-world data. Best fit strategies try to find a parameter set that leads to the lowest difference between observed data and simulated results. However, models usually have more than one criterion that needs to be fitted, and even the parameter set that best fits one criterion may not be able to reproduce the observed pattern that fits embodies a fit for all the other criteria. For ABMGG, the fitting criteria consist of not only grazed LAI measurements (mean and variance) but also degraded related patch measurements (no effect, slight, medium and severe). In addition, the strength of each criteria importance should be considered before aggregating them into one criterion when using best-fit strategies for ABMGG.

Categorical calibration methods are used in a situation where a range of plausible parameter values is defined for each calibration criteria, rather than one single value (compared to best-fit strategies). The aim of categorical calibration is therefore to find a parameter set that meets all predefined criteria. In this thesis, multiple fitting criteria is used with best fit calibration. Approximate Bayesian Computing (ABC) is particularly well suited for implementing this optimisation as ABC not only provides the best parameter value estimation but also gives the uncertainty with consideration of correlations between parameters (Csilléry et al., 2012a). Rather than estimating the exact maximum likelihood through statistical summaries and simulations, ABCs calibrate a model by forming the posterior parameter distribution which is closest to the real world data (Thiele et al., 2014). The basic idea of ABC methods can be described as (Wilkinson, 2013):

$$\pi(\theta|D) = \frac{\pi(D|\theta)\pi(\theta)}{\pi(D)}$$

where $\pi(\cdot)$ represents different probability densities, and $\pi(\cdot\,|\,\cdot)$ is the conditional probability densities; θ accounts for the parameter sets to be calibrated; D denote the real world observation data; $\pi(\theta)$ means the prior distribution of the parameter sets; $\pi(D|\theta)$ is the probability of the true value under the model given parameter values. $\pi(\theta|D)$ is the posterior distribution, and $\pi(D)$ is the evidence for the model. The calibration is then used to calculate posterior distribution based on the true value distribution of parameter sets.

Suppose that a parameter named θ_i needs to be calibrated, the first step of ABC calibration is to produce a sample of θ_i of size j; for each parameter sample value $\theta_{i,j}$, the relevant result of model simulation is represented by $sim_{i,j}$. Then the Euclidean distance d_i can be used as a measurement of the statistical differences between $sim_{i,j}$ and actual data obs_i (van der Vaart et al., 2015):

$$d_i = \sqrt{\sum_j \left({sim_{i,j} - obs_j}\Big/_{sd(sim_j)} \right)^2}$$

If d_i is smaller than a given threshold value, which is determined by the tolerance rate (the percentage of accepted simulation, that is, how many simulations are sufficiently realistic) in ABC, the parameter set will be added to the accepted parameter value sets. A smaller value of tolerance would lead to a better approximation (d_i is smaller) of the true posterior distribution. Therefore, tolerance can be regarded as a determinant of the accuracy of the algorithm. Usually, the value of this tolerance can be calculated by cross-validation of the parameter sets (see detail in Section 7.3.3.2).

All the accepted parameter values thus form a distribution that represents the best estimation of the parameter values. This distribution can be further improved by incorporating the relationship between sim_i and $\theta_{i,j}$; local linear regression (Beaumont et al., 2002) and neural networks (Csilléry et al., 2010) are commonly used for this improvement:

$$\theta_i = f(sim_i)$$

where $f(\cdot)$ is linear or other advanced methods describing the relationship between simulation results and parameter values. Details can be found in Csilléry et al. (2012b).

7.3.3.1 Latin Hypercube Sampling for parameter value sets

An efficient method to reduce the number of parameter sets but still be able to scan the parameter space in a systematic way is Latin Hypercube Sampling (LHS) (Stein, 1987), which is widely used in the model sensitivity analysis (Marino et al., 2008), calibration (Ciampaglia, 2013) and uncertainty analysis. LHS is a stratified sampling method without replacement, which partitions each parameter distribution into certain intervals of equal probability, and selects one parameter value from each interval. The interval sizes are determined by the probability density distribution of the parameters. For ABMGG, the value ranges of parameters are listed in Table 7.5. The radius of a grazing group is usually 1km or 2 km from the survey (see Chapter 3), that is 2 or 5, patch distance for ABMGG. To make sure the calibration includes some larger grazing groups, the maximum value of radius is taken as 10 (4.6 km in the real world; a greater radius value than 10 is fine, but the trade-off between the cost of computing and maximum value should be considered). The number of participants in one group is the minimum number of herders in a grazing group. The average number of herders in a grazing group can be calculated by dividing the total number of rotational grazing patches by the number of grazing groups (it is from the survey, and the number of grazing group was 338 in 2011), and the results is 21; this thesis, therefore, set the calibration range to 10~45. A bigger number of the minimum number of herders in a grazing group is fine, but the efficiency of the calibration should be considered; in addition, the herders in the ABMGG will find the closest grazing groups to join in if they cannot be assigned to a grazing group randomly, and if the minimum number of herders in a grazing group is too big, it may cause the intersection among grazing groups, which is unlikely to happen in the real situation according to the field survey by the author in 2016. For the number of sub-groups, the rotational grazing patches should have at least 2 sub-groups (otherwise it will be continuous grazing patch or un-grazed patch), the maximum is 22 because it is big enough to encompass all situations. From the survey, we just have one fixed number of lease percentage, which is about 15%. This value range extends to 10~20% in the calibration. Unfortunately, we have not got the prolonged snow data, but in the neighbouring (Maqing) County, the probability is 0.27%. Therefore this calibration chose 0.1~1% as a value range for the prolonged snow probability.

Table 7.5: The prior distribution of the parameter values in ABC calibration

parameters	Value range	Distribution
radius	2~10	uniform
num_participant	10~45	uniform
num_sub_group	2~22	uniform
lease_percentage	5~20%	uniform
prolonged_snow	0.1~1%	uniform

7.3.3.2 Cross-validation for ABC tolerance selection

The tolerance value determines how many simulations should be accepted, and how to get a good tolerance value is then the next challenge for the ABC calibration. Cross-validation methods provide an alternative way to evaluate the accuracy of the tolerance value when there is not enough data to distinguish the accuracy of different tolerance values (Kohavi, 1995; Csilléry et al., 2012a). Here, 5 different tolerance values are tested: 5%, 10%, 20%, 30% and 50%. The summary statistics are shown in Table 7.6:

Table 7.6: Summary statistics of the results of cross-validation for model parameters

tolerance / **parameters**	**5%**	**10%**	**20%**	**30%**	**50%**
radius	1.0133	0.9566	0.9858	0.9794	0.9892
num_participant	0.983	0.9912	0.9719	0.981	1.0121
num_sub_group	0.0265	0.0314	0.0436	0.0646	0.1785
lease_percentage	0.9985	0.9936	0.9974	0.9972	0.9984
prolonged_sonw	0.4268	0.5803	0.7977	0.9224	0.9767

A simulation is selected repeatedly to be a validation simulation, while the other simulations are used as training simulations. The error of this “leave-one-out” cross-validation shows the tolerance value 20% is more suitable compared with all the other values. The modelling error of “radius” is decreased and then increased with the tolerance value varying from 5% to 20% and being fixed around 0.98 when tolerance value exceeds 20%, while the error of “num_participant” , “lease_percentage” and “prolonged_snow” were all increase when tolerance value exceeding 20%. The error of “lease_percentage” under is not sensitive to the value of the tolerance rate and it is fixed to about 0.99. A bigger value of the tolerance rate is fine, but there is a compromise between the value and the accuracy of the calibration results. Usually, the smaller the tolerance rate, the higher the accuracy of the calibration results, but also the higher cost of the computing time.

7.3.3.3 ABC calibration results

The final step of ABC validation is to generate a parameter set that produces the best-matched simulation result against the remote sensing derived data. In Section 7.3.1, the comparisons of ABMGG results show the simulated number of unaffected, medium and severely degraded patches match with the remote sensing derived data, but the simulated number of medium degraded patches was statically different from the remote sensing derived one. The ABC calibration results aim therefore to find a parameter set that produces a match as similar to the remote sensing derived data as possible for all the calibration years. The ABMGG focus on producing a similar grazing intensity and the grassland status, and the calibration year used is 2011. The numbers of degraded patches, mean and variance derived from MODIS LAI data are shown in Table 7.7. Notice that the un-grazed patches are excluded, and the numbers of degraded patches were also calculated for the continuous and rotational grazing pixels by comparing the rate of LAI after grazing to full-growth LAI with the degradation standard.

Table 7.7: Number of degraded patches, mean and variance of grazing-led LAI changes derived from remote sensing data

output	value	unit
no_degraded	12804	-
slight_degraded	752	-
medium_degraded	1474	-
severe_degraded	268	-
mean_grazed	0.077	m^2/m^2
var_grazed	0.0680	-

The posterior distributions of ABC calibration are shown in Figure 7.7. There are 2000 LHS sampling parameter value sets. The ABC calibration, therefore, needs to run the model for 2000 times and repeat 10 times for each parameter value set to get the mean value of statistical properties of the model output. This can produce more robust results compared with single run with each parameter value set due to the stochastic settings in the ABMGG, of which only 20% of the running can be accepted (see tolerance rate selection for detail). The posterior distributions are all based on these 400 accepted simulations. These distributions provide not only the best-matched parameter value sets but also upper and lower confidence boundaries, which would be helpful in producing a confidence band for the ABMGG.

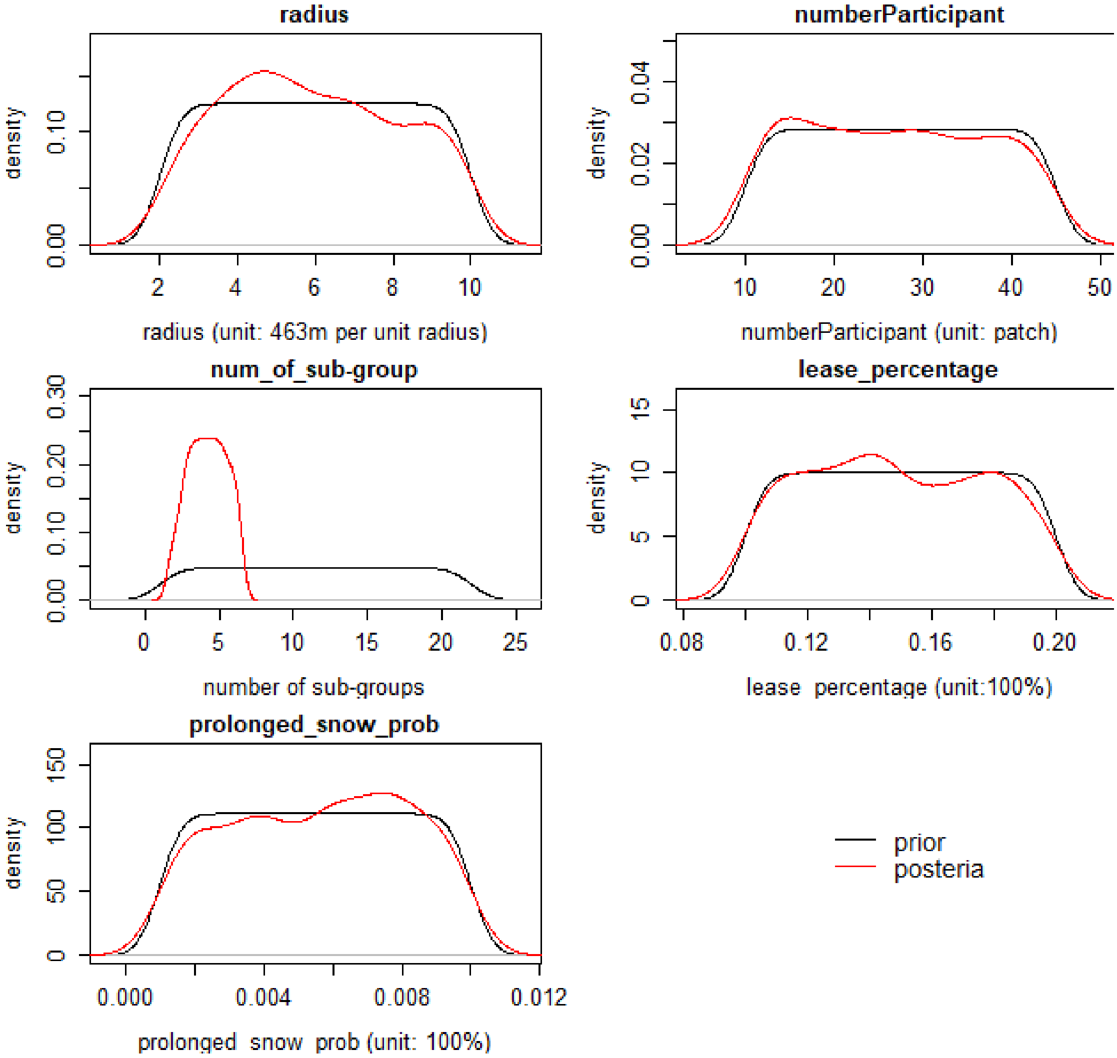


Figure 7.7: Posterior distribution of the parameters using ABC

In addition, the estimation of posterior distributions can be improved by local linear regression, but it is not suitable for this research as there is no obvious linearity among parameters. Figure 7.8 shows the joint posterior density between all the parameters. The Pearson’s product-moment correlation test shows the correlations among parameter are all smaller than 0.2, which indicate there is no significant linear relationship among the parameters. This thesis, therefore, does not need to incorporate with the linear relationship between the parameters.

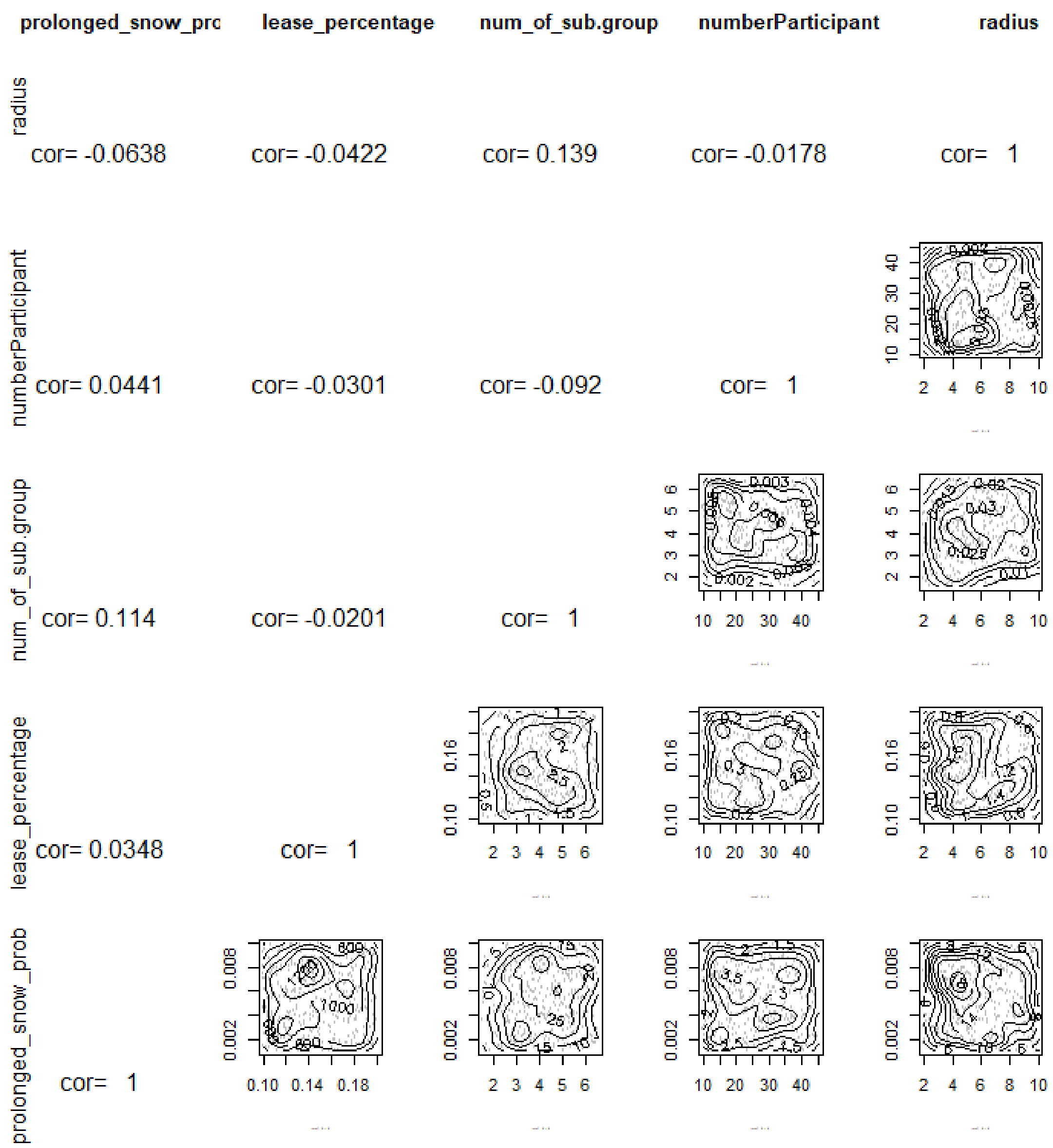


Figure 7.8: Joint posterior distribution between parameters: top-left part shows the Pearson's product-moment correlation test value; the bottom-right part shows their joint density counterplot

The preferred parameter selection of ABC calibration in Table 7.8 is the mean of the posterior parameter distribution. Commonly, mean or mode values of posterior parameter distribution can be selected as the best match parameter value set as well depending on different modelling purposes; and in the R “abc” package, the median absolute deviation is used as a robust unbiased estimation of the standard deviation, and it is more resilient to outliers in the data (Csilléry et al., 2012b). However, this thesis uses the mean value of the posterior parameter values as the calibration results as it is more convenient and common to visualise the uncertainty with the mean value. The model results produced by the other posterior values of the parameters, therefore, can be expressed as the uncertainty of the model.

Table 7.8: Posterior distribution characteristics for all the parameters after ABC calibration

	radius	*num_participant*	*num_sub_group*	*lease_percentage*	*prolonged_snow*
Min.:	2.011	10.055	1.585	0.100	0.001
5 % Perc.:	2.566	11.770	2.065	0.105	0.002
Median :	5.733	26.838	4.212	0.146	0.006
Mean:	5.939	26.797	4.203	0.149	0.006
Mode:	4.690	15.139	4.185	0.140	0.007
95 % Perc.:	9.615	42.962	6.269	0.195	0.010
Max.:	9.973	44.989	6.495	0.200	0.010

7.3.4 Evaluation of the calibration results

The evaluation of the calibration results is to make sure the performance of the ABMGG has been improved. Using the mean values of the selected parameters listed in Table 7.8, the R^2 between simulated and observed grazing-led LAI changes is 0.978, and the p-value of the T-test is 0.66, which indicates they are still statistically similar. However, this result does not ensure the same grassland status under the degradation standard, and therefore, the goodness-of-fit measurements and the spatial pattern of the grassland status should be evaluated to ensure a successful calibration.

Similar to the model verification, three goodness-of-fit indicators have been employed to evaluate the calibration results. As it is shown in Table 7.9, the R^2 and the p-value of the t-test between simulated degradation status and that observed in MODIS LAI for each degradation type has increased, while the RMSE has decreased. This indicates that the calibration has improved the overall model accuracy. However, the R^2 and the p-value of the t-test for slightly degraded patches are still relatively low. As was mentioned in Section 7.3.1, such discrepancies between simulation results and the observed data can be improved by more accurate and explicit information and knowledge on, for example, grazing groups and sub-groups.

Table 7.9: Goodness-of-fit measurements before and after calibration

	Type	**R^2**	**T-test (P-value)**	**RMSE**
Before calibration	Unaffected	0.8623	0.0234	1842.3160
	Slightly degraded	0.6089	0.0062	1072.2240
	Medium degraded	0.8362	0.1674	615.0182
	Severely degraded	0.6512	0.1563	260.1417
After calibration	Unaffected	0.8667	0.05023	1445.2860
	Slightly degraded	0.6459	0.0131	920.7647

Medium degraded	0.9112	0.1983	388.6010
Severely degraded	0.7589	0.1943	158.2865

Another aspect of the evaluation work is to compare the spatial pattern of the degradation status. In this section, the spatial maps of the four degradation types will be displayed directly. Since the simulated degradation maps were all produced through an average of 50 repeated simulations, the standard deviation of the numbers of degraded patches is shown alongside the average numbers of degraded patches.

The maps of the number of degraded patches are shown in Figure 7.9, Figure 7.10, Figure 7.11 and Figure 7.12. Notice that the un-grazed patches identified in Chapter 5 are filled with black colour, and these are the patches where no grazing happen in both observed data from remote sensing and the model output of the ABMGG. The values on the maps are the counts of the patches which have been identified as specific degradation types during the year (there are 46 time steps in total for the year). In addition, the relative estimation error ratio at the patch scale can be represented by the ratio of the difference between the simulated and observed number of degraded patches to the observed number of degraded patches. Four descriptive statistics (maximum, minimum, mean and standard deviation) of the relative error are shown in Table 7.10.

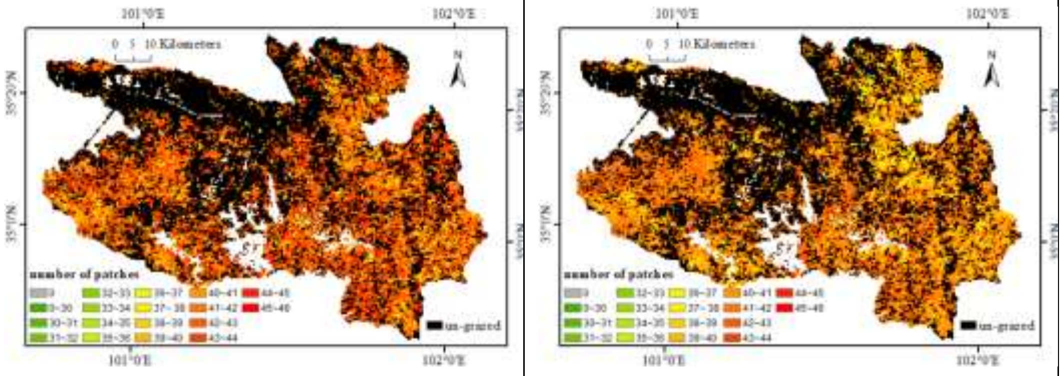
Table 7.10: Descriptive statistics of the relative error of the model

	Minimum	**Maximum**	**Mean**	**Standard Deviation**
Unaffected	-0.178	0.257	-0.037	0.043
Slightly degraded	-0.950	3.480	0.503	0.849
Medium degraded	-0.970	2.880	-0.013	0.538
Severely degraded	-1.000	0.899	-0.315	0.281

An obvious decrease (an overall decrease in redness) in the simulated average number of unaffected patches in Figure 7.9b can be seen compared with that in Figure 7.9a, and more specifically, in Figure 7.9d, where the differences between the two show that the majority of the difference is negative, which mean the ABMGG has underestimated the number of unaffected patches. This is consistent with the results of the top-left plot in Figure 7.5, where the simulated numbers of unaffected patches were systematically smaller than that of the observed data. In addition, as listed in Table 7.10, the average relative error ratio is -3.7%, which also indicates the ABMGG has slightly underestimated the number of unaffected patches on the average.

a, observed number of the unaffected patches

b, simulated average of the number of the unaffected patches



c, simulated standard deviation of the number of the unaffected patches

d, differences between simulated and observed number of unaffected patches

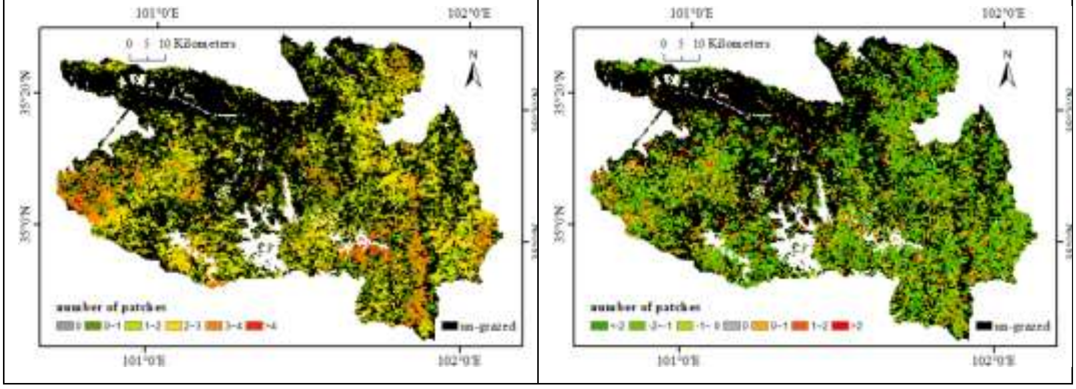


Figure 7.9: Spatial maps of the simulated and observed number of unaffected patches

Contrary to the number of unaffected patches, there is an obvious increase (an overall increase in redness) in the simulated average number of slighted patches in Figure 7.10b can be seen compared with that in Figure 7.10a; and in Figure 7.10d, the differences between the two show that the majority of the difference is positive, which indicates the ABMGG has overestimated the number of slightly degraded patches. This is more visually obvious in the results of the top-right plot in Figure 7.5, where the simulated numbers of slightly degraded patches were significantly bigger than that of the observed data. As it is shown in Table 7.10, the average relative error ratio is 50.3% for the simulated number of slightly degraded patches, and this implies the number of slightly degraded patches was largely overestimated.

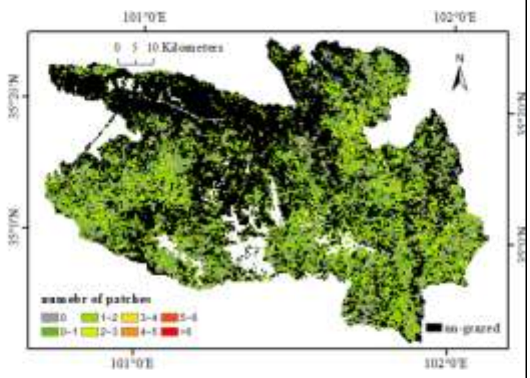
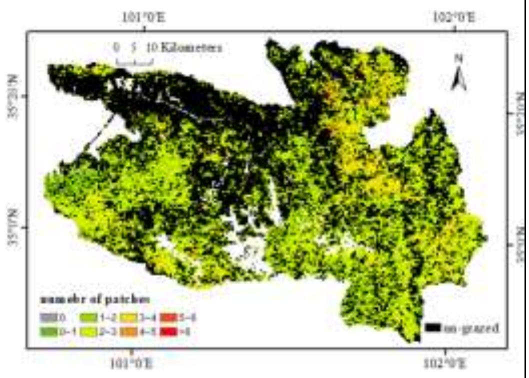
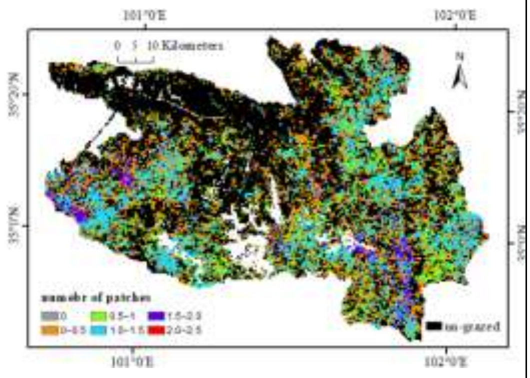
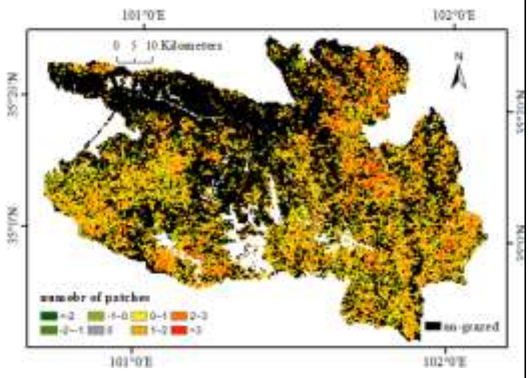
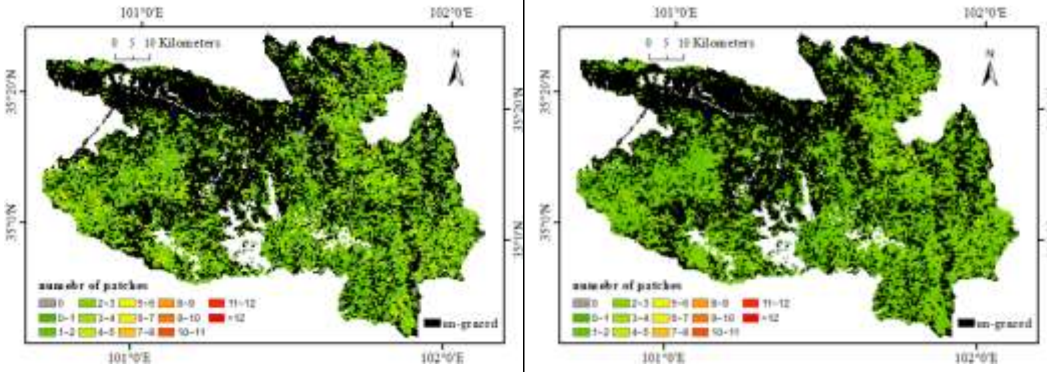
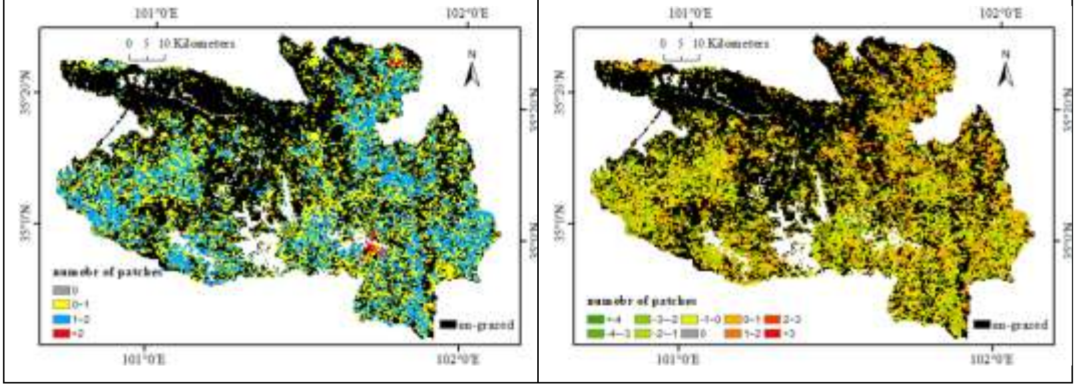
a, observed number of the slightly degraded patches  	b, simulated average of the number of the slightly degraded patches 
c, simulated standard deviation of the number of the slightly degraded patches  	d, differences between simulated and observed number of slightly degraded patches 

Figure 7.10: Spatial maps of the simulated and observed number of slightly degraded patches

The comparison of the spatial maps of the observed and simulated number of medium degraded patches shows (see Figure 7.11a and Figure 7.11b) there is no obvious overall increase or decrease pattern; this can be further confirmed through Figure 7.11d, where the overestimated and underestimated number of medium degraded patches are scattered on the land, and we can hardly verify the overall pattern (decrease or increase) through visual interpretation. The further descriptive statistics in Table 7.10 shows the average relative error ratio is -1.3% for the simulated number of slightly degraded patches, which means the ABMGG has slightly underestimated the number of medium degraded patches.


a, observed number of the medium degraded patches

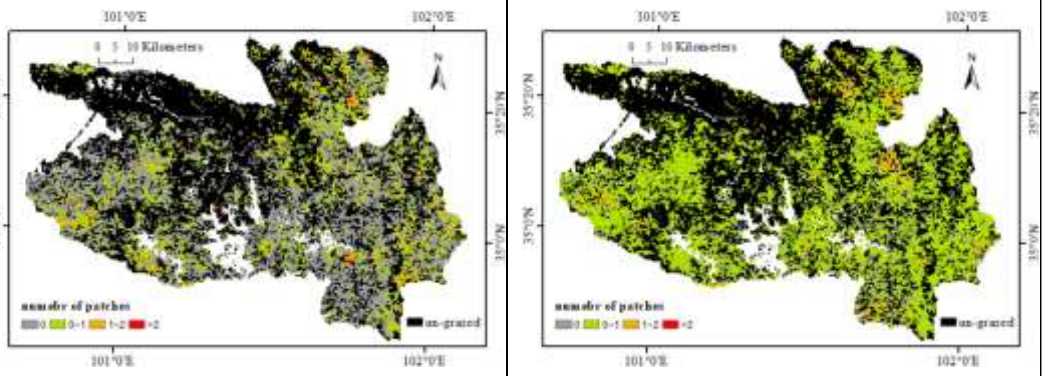
b, simulated average of the number of the medium degraded patches


c, simulated standard deviation of the number of the medium degraded patches

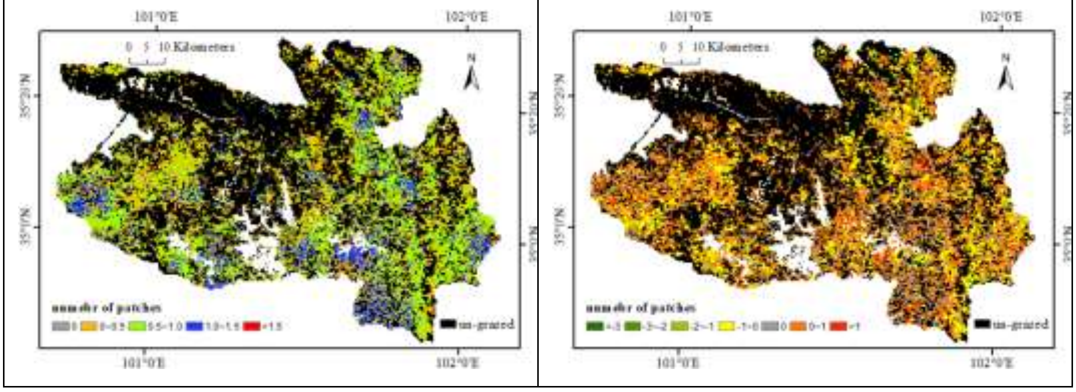
d, differences between simulated and observed number of the medium degraded patches

Figure 7.11: Spatial maps of the simulated and observed number of medium degraded patches

For the number of severely degraded patches, there is an obvious increase (an overall increase in redness) in the simulated average number of unaffected patches in Figure 7.12b can be seen compared with that in Figure 7.12a. We can also see that the overwhelming positive differences between the simulated number of severely degraded patches and the observed number of severely degraded patches are shown in Figure 7.12d. This is also can be seen from the bottom-right plot in Figure 1.4, where some of the simulated numbers of unaffected patches were much greater than that of the observed data. However, the average relative error ratio for the number of severely degraded patches in Table 7.10 is -31.5%, which suggests a contrary result. This is because the average relative error ratio here is the mean value of the relative error ratio for all the severely degraded patches. Although most of the number of severely degraded patches have been overestimated, the relative error ratio is relatively smaller than that of the underestimated patches; and therefore, a negative average relative error ratio presents.


a, observed number of the severely degraded patches

b, simulated average of the number of the severely degraded patches


c, simulated standard deviation of the number of the severely degraded patches

d, differences between simulated and observed number of the severely degraded patches

Figure 7.12: Spatial maps of the simulated and observed number of severely degraded patches

The spatial maps of the standard deviation in Figure 7.9c, Figure 7.10c, Figure 7.11c and Figure 7.12c show a quite similar spatial pattern, which presents quite similar "clusters" at the current classification. A further detailed spatial pattern analysis can be helpful to understand the spatial distribution of these standard deviations, but this is beyond the topic of this research.

The goodness-of-fit measurements in this section have examined the improvement of the model output at the regional level through model calibration, and the comparison of the simulated and observed spatial distribution of the number of degraded patches further explored the model validity. However, the spatial maps displayed in this section were the results of 50 repeated simulations, which is useful to explain the uncertainty caused by the stochastic setting in the ABMGG; the parametric uncertainty, however, needs to be additionally clarified to ensure the model output being within a reasonable range.

7.3.5 The uncertainty analysis of the ABMGG

The uncertainty of the ABMGG consists of 3 parts:

- stochastic uncertainty, which can be quantified by repeated simulations and it has been presented in Section 7.3.4;
- parametric uncertainty, which typically can be evaluated through model calibration and the result of the parametric uncertainty will be discussed in this section; and
- input uncertainty, which will be explored after the validation section.

The parametric uncertainty can arise from imprecise settings of the parameter values. In the calibration section (Section 7.3.3), only the parameter value sets producing the results of the closest distance with observed value were selected as the posterior distribution of the parameter values. The parametric uncertainty, therefore, can be described by the model outputs with those selected parameter values.

Figure 7.13 shows the distribution of the model output before and after calibration within the parameter space, which contains a set of all possible combinations of values for all the different parameters in the ABMGG. The red lines were additionally drawn on those figures indicating the observed results by MODIS LAI, which were listed in Table 7.7. We can see that the observed values are all included in the range of the simulated results selected by ABC calibration, except the number of slightly degraded patches, which was discussed in Section 7.3.4, that was systematically overestimated by the ABMGG.

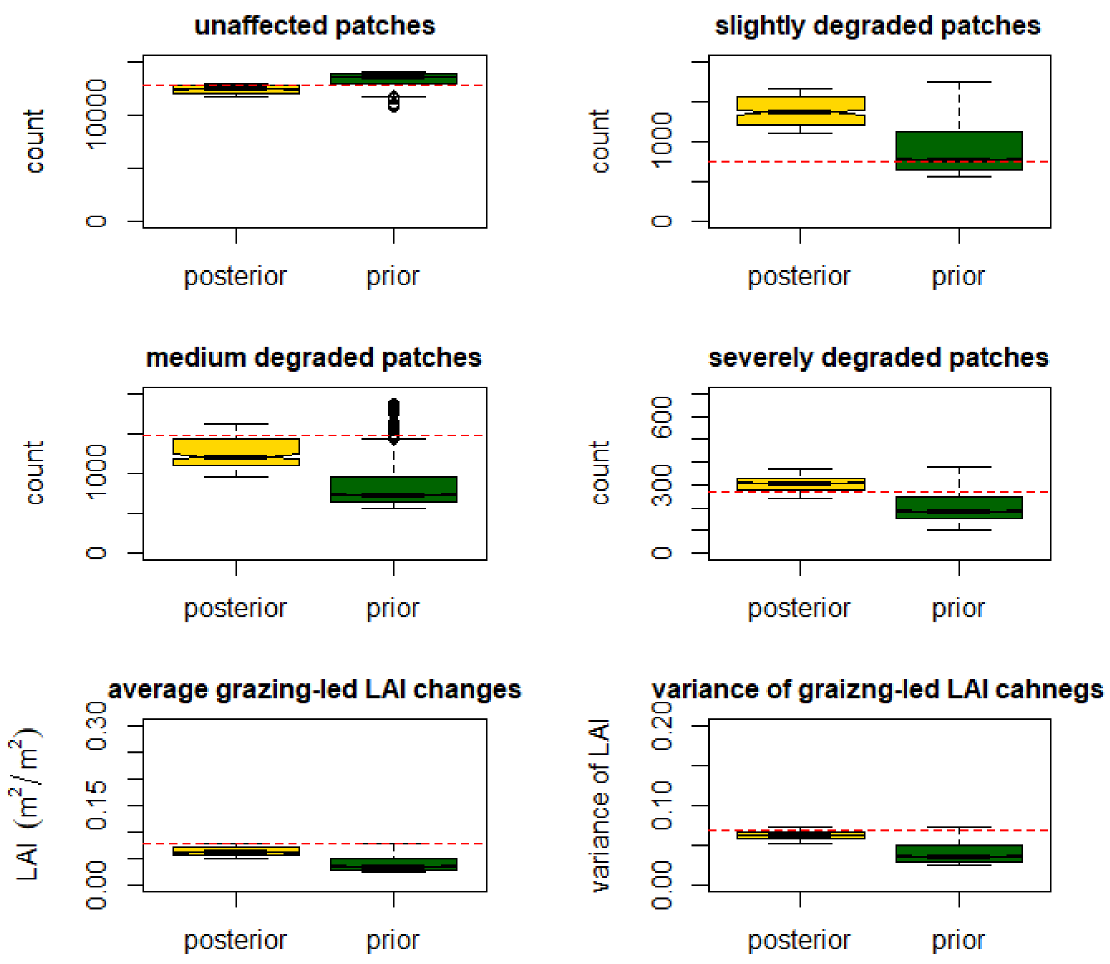


Figure 7.13: Comparison of the prior and posterior distribution of the model outputs

In addition, the descriptive statistics of the four degradation types selected by ABC are shown in Table 7.11, where the specific uncertainty boundary can be seen more clearly. The coefficients of variation (CV) of the four model outputs are all smaller than about 0.15, which indicate the parametric errors are distributed relatively close to the estimated mean value of the model outputs. Up to this point, the parametric uncertainty of the ABMGG has been illustrated; the next section will validate the calibration results with the input data from a different year.

Table 7.11: Descriptive statistics of the parametric uncertainty of the simulated grassland status

Type	**Mean**	**SD**	**CV**	**Max**	**Min**
Unaffected patches	12379.6	392.2	0.031	12988.4	11736.9
Slightly degraded	1373.6	175.8	0.128	1672.6	1097.0
Medium degraded	1241.7	182.3	0.155	1629.9	951.2
Severely degraded	303.9	29.7	0.098	367.6	239.8

7.3.6 Validation with model output

The final stage of making sure ABMGG can represent the grazing system correctly is the validation of the model outputs. Validation of agent-based models is one of the most difficult problems during the modelling process (Rand et al., 2003). The behaviour and structure generated by agents interacting are very hard to predict (Bankes, 2002). Where agents make decisions based on pre-defined rules, this can lead to the modelling results being extremely sensitive to initial settings or such pre-defined rules (both agents and their environment). In addition, due to the stochasticity and uncertainty in agents' decision-making and interactions, one may have multiple emergent patterns when running the model many times.

The aim of building ABMGG is to ensure the simulated grazing-led LAI changes, and the grassland status matches remote sensing derived data; then the "what if" assessment can be done by changing the grazing strategies and institutional arrangements. It is not a predictive model; that's why we cannot validate the model with predictive results. In previous sections of this chapter, the behaviours of herder agents and grassland patches are verified. The stochastic and parametric uncertainties of the ABMGG have been quantified, and the values of the parameters were optimized as well by ABC calibration.

The validation in this section is then to examine whether the calibration is good by: was it over-fitted for other years when using the parameter values after calibration? The validation year is 2012 because the grazing groups and sub-groups information were based on the information collected for the year 2011, and it was in the same five-years' plan period (12th five-year plan, 2011~2015). The policies on grazing strategies and institutional arrangements were more relatively stable and coherent during the same five-year plan period. In addition, the year 2012 was just one year after 2011, the parameter values of the model would be more likely to be the same. The model was configured using the parameter value set from the ABC calibration (see Table 7.8). The model runs 50 times for the year 2012.

Figure 7.14 shows the simulated and observed grazing-led LAI changes for each time steps during 2012. The R^2 between the two is 0.97, and the p-value of the t-test is 0.63, which indicates the observed and simulated grazing-led LAI changes are similar. The further comparison of the grassland status is shown in Figure 7.15, where the mean and variance of the number of the degraded patches for 50 repeated simulations are plotted along with the observed ones. An obvious underestimation of the number of unaffected patches presents on the top-left figure of Figure 7.15; while for the numbers of slightly and medium degraded patches, the ABMGG have overestimated them.

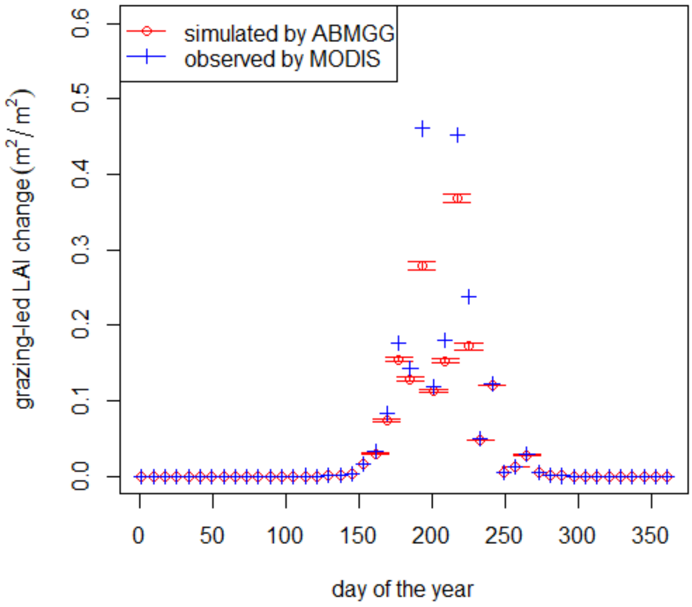


Figure 7.14: Simulated and observed grazing-led LAI changes in the validation year, 2012

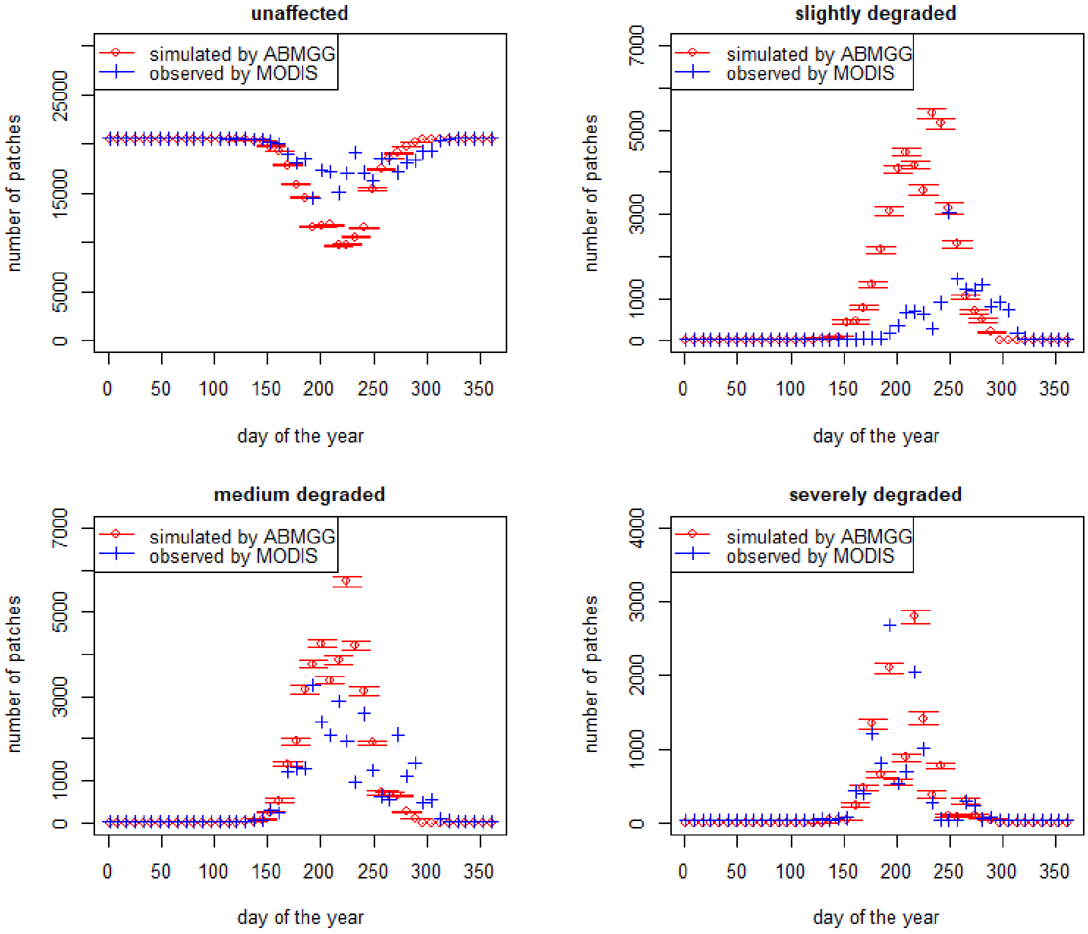


Figure 7.15: Simulated and observed numbers of the degraded patches, 2012

The results of more detailed goodness-of-fit measurements are shown in Table 7.12. Similar to the results of goodness-of-fit measurements in the calibration section (see Table 7.9), the ABMGG again failed to match the number of slightly degraded patches with the observed ones. This is a systematic defect of the ABMGG caused by the insufficient information on grazing groups and sub-groups, and the model randomly assigned the locations of the grazing groups and sub-groups. Such patch-specific information is still not available in the study area. Nevertheless, the R^2 for the other three in Table 7.12 are all bigger than 0.68, and the p-value of the t-test are all bigger than 0.05, which show they are statically similar. This can ensure the model has not been overfitted through modelling calibration.

Table 7.12: Goodness-of-fit measurements of the validation results

Type	**R^2**	**T-test (P-value)**	**RMSE**
Unaffected	0.6828	0.0948	2532.5360
Slightly degraded	0.1811	0.0216	1559.1990
Medium degraded	0.6882	0.3903	944.0199
Severely degraded	0.8850	0.9238	197.0047

7.4 Scenario analysis: the effect of different grazing strategies and institutional arrangements on grassland

Up to this point, this thesis has discussed the methods by which the ABMGG was evaluated, through calibration and validation against remote sensing derived data. In this section, the aim of the scenario analysis is intended to explore the potential outcomes of the combination of different grazing strategies and institutional arrangements at the study site. The experiments in the scenario analysis simulate how the number of degraded patches changes under different strategies. Are the current grazing strategies and institutional arrangements the best choice, or is there an alternative?

7.4.1 Scenario definitions

To evaluate the effect of grazing strategies and institutional arrangements on the number of degraded patches, eight experiments will be conducted in order to answer these questions, involving varying the behaviour of the herder agents. The combinations of all these rules are listed in Table 7.13. The grazing-led LAI changes for different scenarios are classified into four types (notice that rotational and continuous grazing patches are the grazing types of the patches, which have been defined before the model running and they remain unchanged during the simulation year):

- group rotational grazing: assumed for TTT (current choice scenario. This is a way of naming the scenarios according to the behaviour of herders, see Table 1) and TTF (no market scenario). The grazing-led LAI change for each patch depends on the proportion of currently available LAI on the patch to the total available LAI of the sub-group (see Section 7.2.1). This is affected by the grazing demand in the group and the number of sub-groups in the group;
- group continuous grazing: assumed for TFF (group continuous grazing without market scenario) and TFT (group continuous grazing with market scenario). The grazing-led LAI change for each patch depends on the proportion of currently available LAI on the patch to the total available LAI of the whole group. This depends on not only the total grazing demand in the group but also the total available forage in the group;
- regional random moving grazing: assumed for FTT (random moving with market scenario) and FTF (random moving with market scenario). The grazing-led LAI change is the same as the grazing demand; the livestock moves randomly on all rotational grazing patches, and
- regional continuous grazing: assumed for FFT (regional continuous grazing with market scenario) and FFF (regional continuous grazing without market scenario). The grazing-led LAI change for each patch depends on the proportion of currently available LAI on the patch to the total available LAI of all the rotational grazing patches. This is affected by not only the total grazing demand in all the rotational grazing patches but also the total available forage in all the rotational grazing patches.

Table 7.13: Combinations of different grazing strategies and institutional arrangements

ID	grouping	moving	marketing	explanation
TTT	√	√	√	**Current choice scenario (group rotational grazing scenario)**: parameter values exactly the same as the validation experiment (mean value of parameter values after calibration). Grazing groups are formed on rotational grazing patches, and the livestock can move from one sub-group to another sub-group during grass growth period; herders on the continuous grazing patches can rent/lease land from/to other continuous grazing herders.
TTF	√	√	×	**No market scenario**: similar to TTT, but there is no leasing/renting behaviour among continuous grazing herders.
TFF	√	×	×	**Group continuous grazing without market scenario**: grazing groups are formed on rotational grazing patches, but livestock owned by the rotational grazing herders

				cannot move from one land patch to another, and they continuously graze on the land in the group; there are no land market behaviours.
FFT	×	×	√	**Regional continuous grazing with market scenario**: herders can lease/rent land from other herders on continuous grazing lands; there are no grazing groups, and the livestock does not move among patches; herders on the continuous grazing lands can lease/rent lands.
FTT	×	√	√	**Random moving with market scenario**: there are no grazing groups, but the livestock owned by rotational grazing herders can move randomly among all the rotational grazing patches;
TFT	√	×	√	**Group continuous grazing with market scenario**, it is similar to TFF, but the herders on the continuous grazing lands can rent/lease lands from the other continuous grazing herders.
FTF	×	√	×	**Random moving without market scenario**: similar to FTT, but the herders on the continuous grazing lands can rent/lease lands from the other continuous grazing herders.
FFF	×	×	×	**Regional continuous grazing without market scenario**: there are grazing groups on the rotational grazing patches, and also no leasing/renting behaviours of the herders on continuous grazing patches.

Note: √ means scenario include that behaviour while × not

These eight combinations form the policy scenarios based on the grazing strategies (continuous and rotational grazing) and institutional arrangement (land market) in Zeku. The most significant advantage of ABMGG is that it is able to gain a quantified assessment of possible grazing strategies and institutional arrangements. For each scenario, the model was run for 50 replicates to capture the uncertainties. Through different scenario analysis using ABMGG, the LAIs after grazing and number of degraded patches according to the Chinese Criteria of Grassland Degradation (Su et al., 2003) can be obtained. The results can be used as a policy tool to assess the impact of policies on the grassland grazing system, and to pinpoint the possible optimal one when keeping the other parameter values the same. The time scale is the year 2011 for the assessments.

7.4.2 Results of scenario analysis

The regional average (continuous and rotational grazing patches) of the LAI after grazing is shown in see Figure 7.16. The average LAIs after grazing under FFF (regional continuous grazing without market scenario) and FFT (regional continuous grazing with market scenario) are the highest among all the scenarios; TFT (group continuous grazing with market scenario) and TFF (group continuous grazing without market scenario) give the lowest average LAIs after grazing among all the scenarios. The standard deviation of the 50 simulations for each scenario is too small to be presented in Figure 7.16, and does not significantly affect the statistical analysis later.

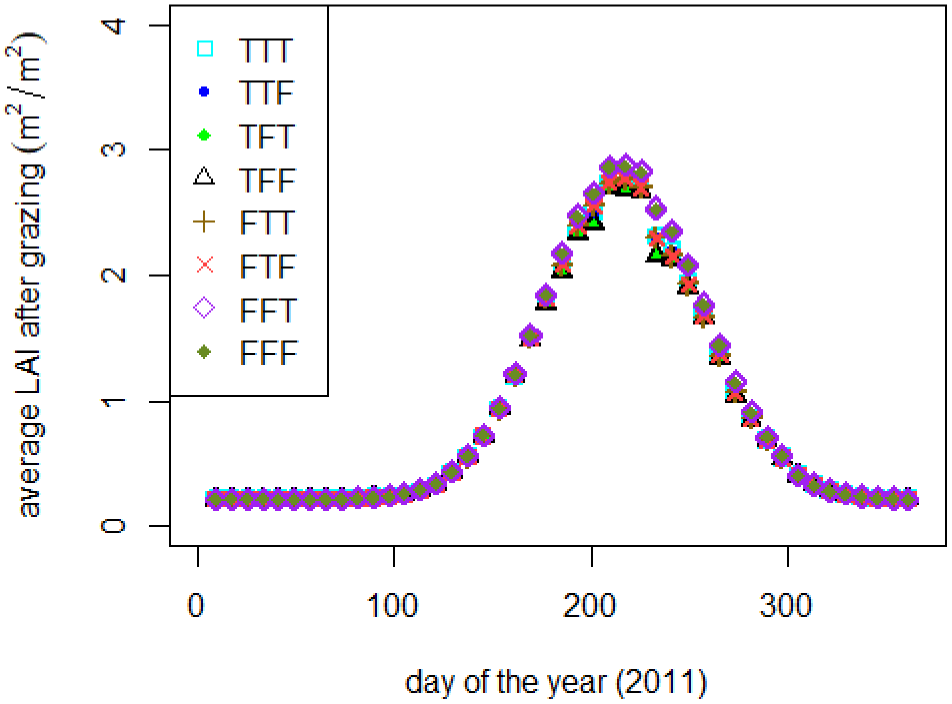


Figure 7.16: The LAI after grazing for all the combinations of grazing strategies and institutional arrangements (see Table 7.13 for the meaning of the legend)

Since the t-test can report the significant level of the difference, but is only suitable for two-sample comparisons; in order to know whether these differences among the eight scenarios are statically significant, Tukey's honest significance (TukeyHSD) test is employed. It was designed for multiple comparisons (more than three samples). The results of the TukeyHSD test are shown in Figure 7.17. All the differences in the LAI after grazing are relatively low, and the TukeyHSD test shows they are statistically the same (Figure 7.17), where the zero difference line (red vertical line) is within the range of all 99% confidence levels of the difference pairs (horizontal red line segments). This is similar to previous studies (Woodward et al., 1995b; Jerrentrup et al., 2015) that showed that different grazing strategies or institutional arrangements could not improve or decrease the productivity of the grassland (herein, the productivity of the grassland is represented by the LAI) significantly.

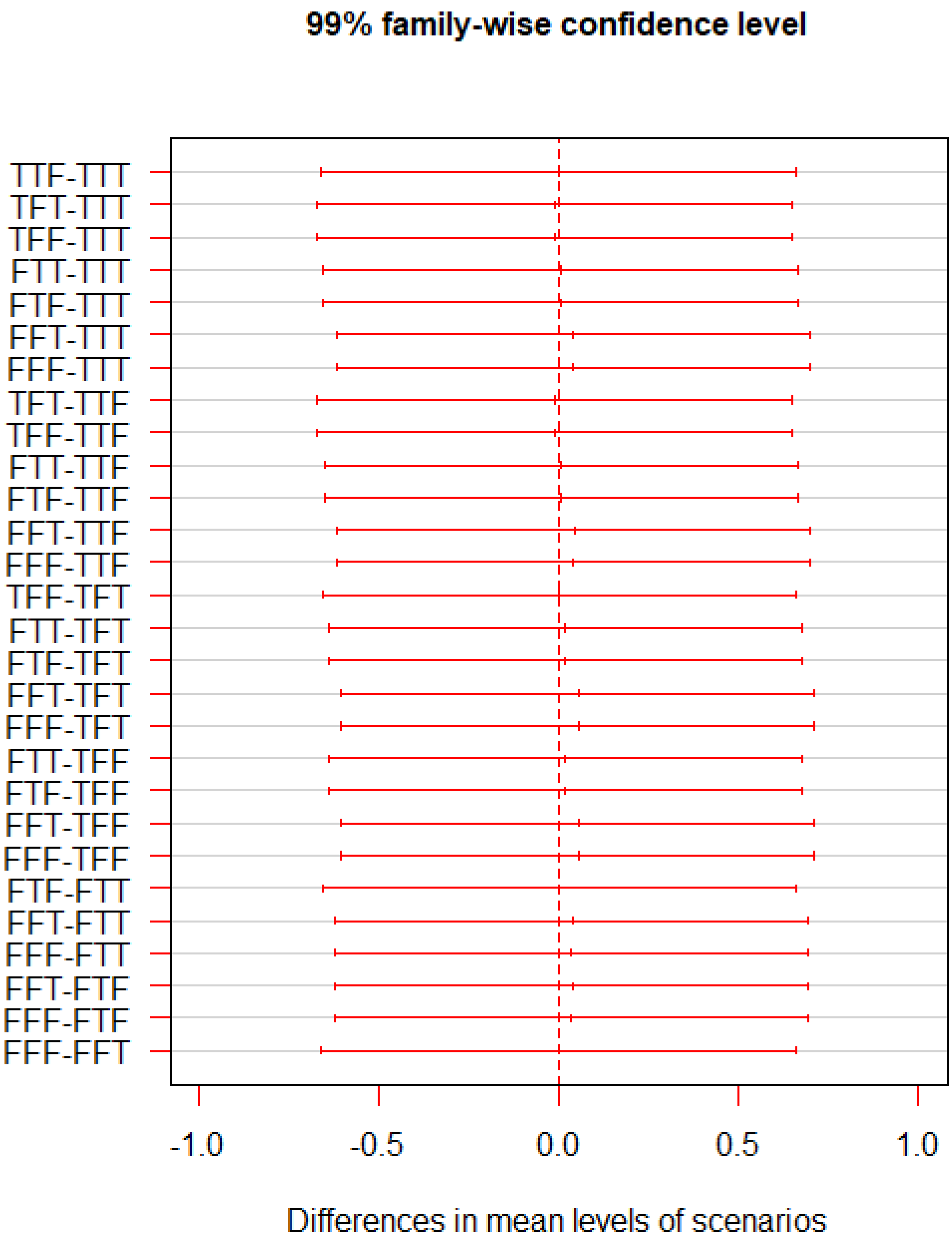


Figure 7.17: Results of the TurkeyHSD test for the average LAI after grazing under 8 scenarios

Another important output of the ABMGG is the number of degraded patches, which are calculated for each time step for all 50 replicates. The mean values for each time step are plotted against the current choice scenario (Figure 7.18). The standard deviations of those 50 simulations, however, are too small to be presented in Figure 7.18, indicating that the stochastic uncertainties in the ABMGG have a limited effect on the results of scenario analysis.

The boundary of the effects of these scenarios can be seen clearly in Figure 7.18. In Figure 7.18-A, FFT and FFF have the largest number of unaffected patches when the regional continuous grazing strategy exists, and the number of unaffected patches in FFT is a little bit larger than that of FFF due to the positive effect of the land market on the number of unaffected patches. This phenomenon can be seen from FTT and FTF, TFT and TFF, TTT and TTF as well. The moving behaviour can positively affect the number of unaffected patches as seen from the comparison of TTF~TFF and TTT~TFT, where the number of unaffected patches on group rotational grazing patches is larger than that on the group continuous grazing patches; however, when such comparison extended to the regional scale, for example, FFT~FTT and FFF~FTF, an obvious negative effects of the moving behaviours on the number of unaffected patches appear, that the number of unaffected patches on the regional continuous grazing lands are much larger than that on the patches with livestock randomly moving in the region. All the scenarios are better performed compared with the group continuous grazing without market scenario (TFF) and group continuous grazing with market scenario (TFT) with regards to the number of unaffected patches.

For the number of slightly degraded patches (Figure 7.18-B), FFT and FFF have a smaller number than that of the other scenarios, both of them involve the regional continuous grazing behaviour. While the number of slightly degraded patches of TTT and TTF is larger than that of FTT and FTF, but they are much smaller than that of TFT and TFF, which means the group rotational grazing strategy performed better than the group continuous grazing strategy, but worse than the regional continuous grazing strategy and regional randomly moving strategy. The institutional arrangement of the land market has a negative effect on the number of slightly degraded patches, which can be seen from FFF~FFT, TTT~TTF, FTF~FTT and TFF~TFT.

Scenario FFF and FFT still have the smallest number of medium degraded patches among all the scenarios (Figure 7.18-C), and scenario TFF and TFT have the largest number of medium degraded patches, but there are some model results where a smaller number of medium degraded patches (compared with current choice scenario, TTT) emerge within the range of about 0~2000. This is more obvious for scenario FTF and FTT, under which lots of model outputs have a smaller number of medium degraded patches (also compared with current choice scenario, TTT) within the range about 0~4000; This indicates that the regional continuous grazing strategy has a negative effect on the number of medium degraded patches, while the group continuous grazing has a positive effect on the number of medium degraded patches.

It is interesting to see almost all the scenarios have a smaller number of severely degraded patches than that of the current choice scenario except scenario FTT and FTF (Figure 7.18-D), indicating that the regional randomly moving strategy performs worse than that of the other strategies in terms of the number of severely degraded patches. FFT still has the smallest number of severely degraded patches for all the steps during the simulation. TFT and TFF have a little bit larger number of the severely degraded patches than that of the FFF and FFT, but there is an obvious smaller number of severely degraded patches than the current choice scenario.

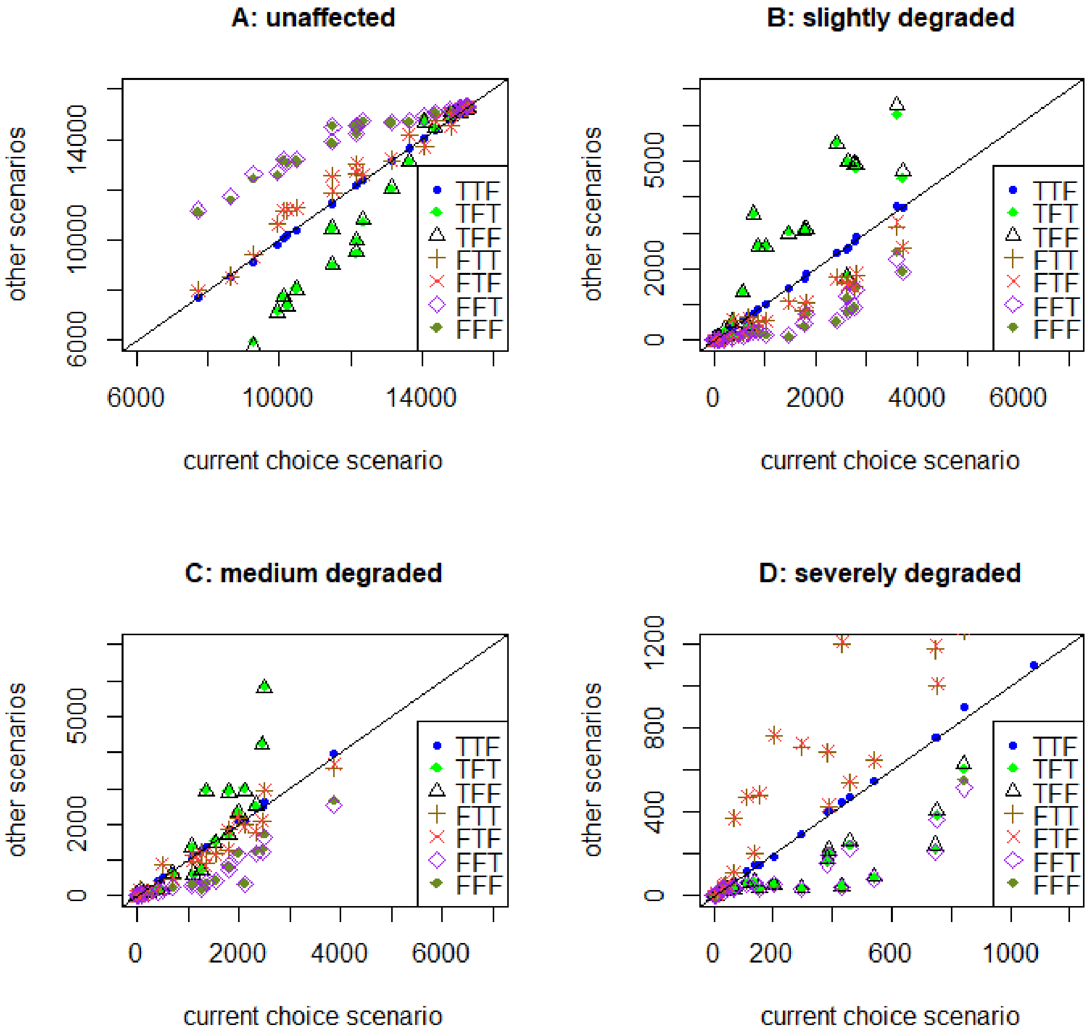


Figure 7.18: Number of degraded patches of current choice scenario plotted against other scenarios simulated by the ABMGG

Overall, the regional continuous grazing scenarios (FFF and FFT) produce the smallest average number of severely degraded patches and the largest number of unaffected patches. The land market could have a positive effect on the number of unaffected patches, but a negative effect on the number of slightly, medium and severely degraded patches, which indicates that appropriate land market strategy could improve the grassland status under grazing, as it produces fewer slightly, medium and severely degraded patches, and greater number of unaffected patches.

Group continuous grazing scenarios (TFF and TFT) can produce a smaller number of severely degraded patches than that of the current choice scenario (TTT), but they also produce a higher number of the slightly and medium degraded patches, and a smaller number of unaffected patches than the current choice scenario (TTT).

Regional randomly moving scenarios (FTT and FTF) produce the largest number of the severely degraded patches compared with all the other scenarios, but they also produce a smaller number of the slightly and medium degraded patches, and a greater number of unaffected patches compared with the current choice scenario.

To conclude, under current grazing intensity in Zeku, regional continuous grazing appears to be the best choice, as it can produce a greater number of unaffected patches and a smaller number of slightly, medium and severely degraded patches. However, such continuous grazing assumes that all the land patches are being grazed proportionally according to their available forage. This is a quite strong assumption that all the livestock are also distributed proportionally, according to the available forage of the land patches, which is quite difficult to manage in reality. One of the key parts in grassland management is to manage the heterogeneity (both grass resources and herbivores) of the grassland (Stewart and Pullin, 2008; Bonari et al., 2017). although regional continuous grazing scenario could reduce such heterogeneity, there are also other difficulties such as dealing with the local land tenure systems across villages in the whole region.

Group continuous grazing is worse than the current choice with regard to the grassland status, indicating a rotational grazing strategy is more suitable than continuous grazing at the group level for Zeku. That is, compared with group continuous grazing, group rotational grazing with the land market (current choice scenario, TTT) is a reasonable choice, with regard to fewer slightly, medium and severely degraded patches, and more unaffected patches. This ‘reduces’ the spatial heterogeneity of forage distribution. Livestock on low productivity land with a relatively high stocking rate can move to high productivity land rather than continuously graze on one land. This also supports field experiments in north-central Texas, USA, where evidence suggested that, for large paddocks, rotational grazing allowed recovery from, and reduced degradation caused by, patch overgrazing (Teague and Dowhower, 2003).

Compared with standard rotational grazing, grasslands of intensive rotational grazing with a greater number of subdivisions have longer resting periods preserving storage biomass more close to maximum yield, and therefore can maintain higher stocking rates (Savory and Parsons, 1980; Barnes et al., 2008; Teague et al., 2011; Jakoby et al., 2014). The rotational grazing strategy increases income and improves rangeland conditions, but might demand high management costs (Beukes et al., 2002) and the risk of forage shortage if livestock stocking rates are too high (Hart et al., 1993).However, although rotational and continuous grazing strategies may have little effect on the frequency, severity or variation of grazing-led grass defoliation (Hart et al., 1993) and its botanical composition (Taylor, 1989) if the stocking rates remain the same. This research reports similar results (see Figure 7.16 and Figure 7.17), the degradation structure of the land would change with different grazing strategies and institutional arrangements (Figure 7.18).

In addition, macro-level policies can affect the grassland system. Research on the institutional arrangements targeting grazing removal on grasslands, which have largely been implemented in Sanjiangyuan, China (Wang et al., 2010b; Lu et al., 2015), suggests the policy run the risk of exacerbating both poverty and degradation (Yeh, 2009). Land market institutional arrangements can aggregate grazing land into larger units, which can better achieve an efficient allocation of grassland resources and economies of scale in livestock production (Gongbuzeren et al., 2016). The complex and comprehensive nature of the impact of different grazing strategies and institutional arrangements (Briske et al., 2015) on the ecological, socio-economic and climatic conditions (Campbell et al., 2006) of grassland systems should be considered before selecting robust management strategies and institutional arrangement.

Up to this point, the effects of different grazing management scenarios under current grazing intensities have been explored. Due to the relatively small stochastic uncertainties in the number of degraded patches (four types), only the mean values of the 50 replicants were presented in Figure 7.18, and this did not affect the results of scenario analysis. However, as it has been discussed in Section 7.3.5, the parametric uncertainties can also affect the model outputs, and therefore, to assure the conclusions discusses in this section, a further analysis about the error propagation through parametric uncertainty in the parameter values is carried out.

7.4.3 The parametric uncertainty of the scenario analysis

The parametric uncertainty analysis here aims to explore whether the changes in parameter values could change the effect of grazing strategies and institutional arrangements reported in the last section. It is impossible to examine the number of degraded patches from all the possible parameter values after calibration (see Table 7.8 for the ranges of parameter values), and instead, this thesis examines the two extreme situations: 5% and 95% percentile of the parameter values after calibration.

Similar to the scenario analysis, for both of the parameter value set, the ABMGG is repeated 50 times for each of the scenarios. The average numbers of degraded patches (four types) for each time step are plotted against the current choice scenario (TTT).

The results are shown in Figure 7.19 and Figure 7.20, where a similar pattern of the number of unaffected, slightly, medium and severely degraded patches among the scenarios are presented. This means the parametric uncertainty of the ABMGG does not fundamentally change the results of scenario analysis.

However, only examining those two extreme parameter value sets does not ensure the scenario analysis can produce the same results for the other valid parameter value sets. Ideally, such examination should cover all the possible parameter value sets, but as it clarified at the start of this section, the aim is to explore whether the changes in parameter values could change the effect of grazing strategies and institutional arrangements on grassland status. Simply running the model with all the possible parameter value sets can only quantify the uncertainty for each scenario. Such uncertainties are not useful for the examination of the effect of parameter value change on the grassland degradation status among scenarios; as the uncertainties of the scenarios are based on all the possible parameter value sets, but the effect of the parameter values on the grassland status is based on one specific combination of the parameter values, which is one of the possible parameter value sets. The error range of the former would be much larger than that of the later, and therefore, this thesis chooses those two extreme parameter value sets as an example of the parametric uncertainty analysis for the scenario analysis.

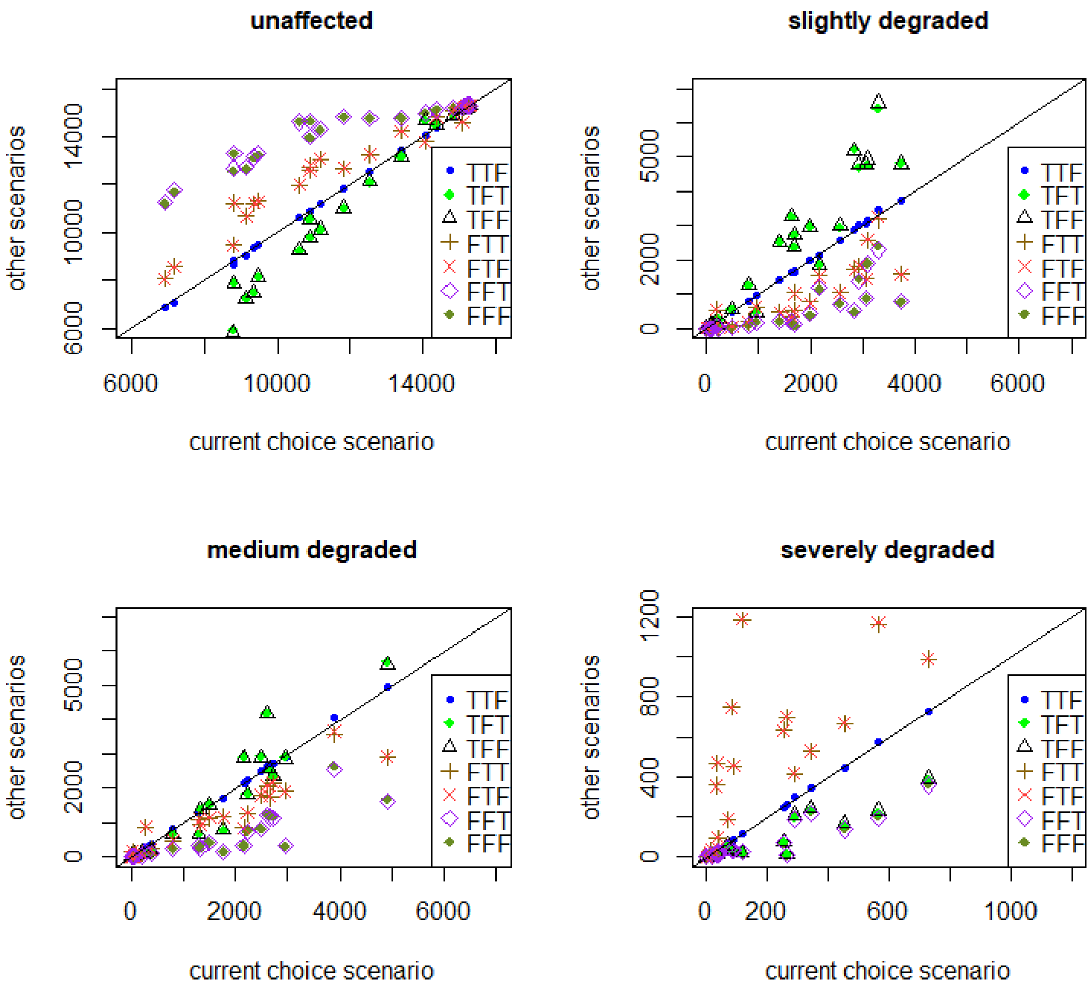


Figure 7.19: Number of degraded patches of current choice scenario plotted against other scenarios simulated by the ABMGG with parameter values from 5% percentile of the parameter values after calibration

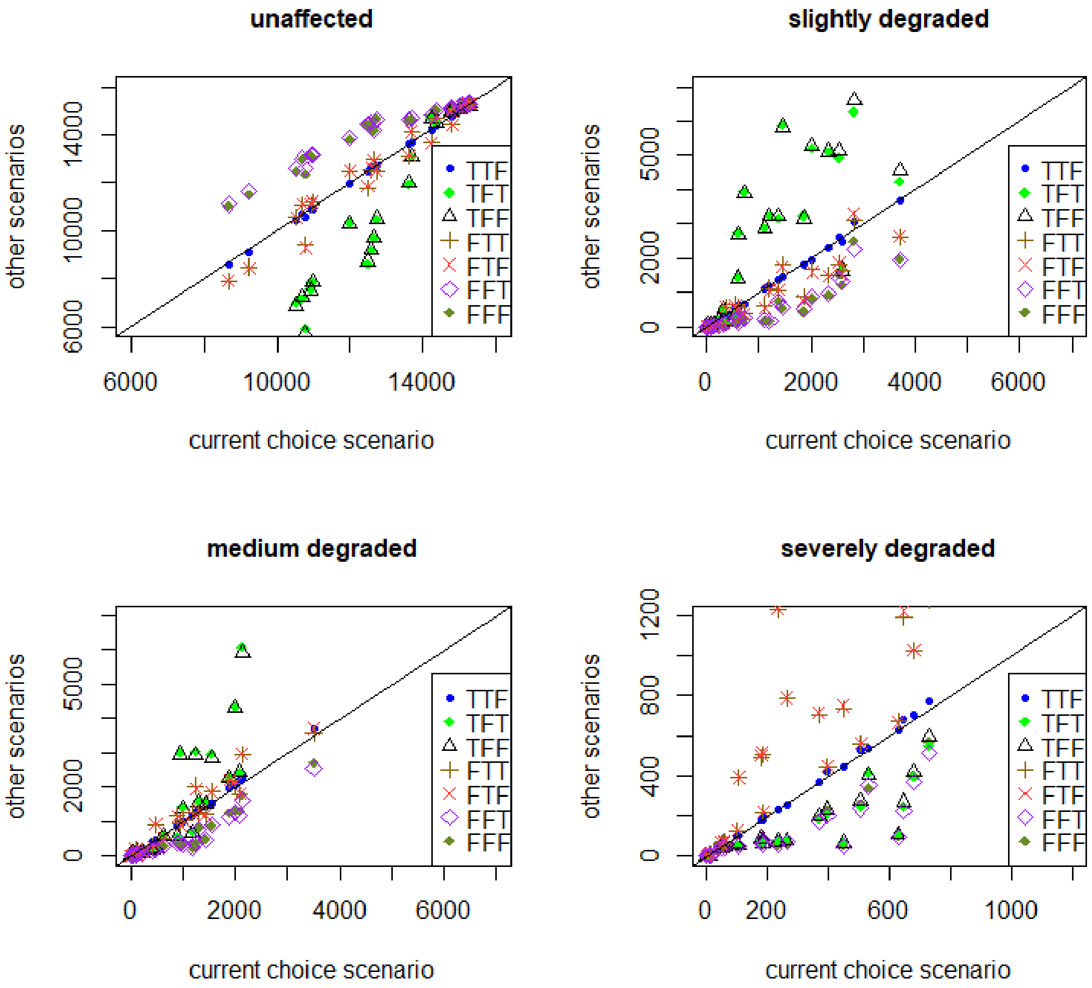


Figure 7.20: Number of degraded patches of current choice scenario plotted against other scenarios simulated by the ABMGG with parameter values from 95% percentile of the parameter values after calibration

7.4.4 Input uncertainty of the scenario analysis

As mentioned in Section 7.3.5, the last part of the uncertainty in the ABMGG is the input uncertainty. In Chapter 5, it was estimated that the relative error for the estimated average of the grazing-led LAI changes was about 10.26% for the year 2011. This chapter used grazing-led LAI changes as an input for the livestock consumption demand. Such uncertainty in the grazing-led LAI changes can propagate through the modelling processes and affect the final output of the model. In addition, the grazing intensity is a key factor that affects grassland status. The input uncertainty in this section is also related to another important research question: how the grazing intensity could affect the grassland status.

This section, therefore, aims to explore the effect of input uncertainty on the results of scenario analysis. In the ABMGG, and additional global parameter “overall_error” is designed to quantify such effects. It is a ratio of the input uncertainty of the grazing demand. Since the relative error for the estimated average of the grazing-led LAI changes was about 10.26%, this section, therefore, sets the "overall_error" to -10.26% and 10.26% respectively to cover the lower and upper error boundary of the input data. The ABMGG is also running 50 times for each of them, and the average number of the degraded patches (four types) are plotted against that of the current choice scenario. Due to the quite small standard deviation of the 50 repeated simulations in the number of the degraded patches, they are not plotted out, and they do not affect the comparison results later.

The results of the input uncertainty analysis are shown in Figure 7.21 and Figure 7.22. Again, a quite similar pattern of the number of the degraded patches (four types) emerges (compared with the scenario analysis results presented in Section 7.4.2, and also the parametric analysis results presented in Section 7.4.3) at both 10.26% of the average underestimation error in input data and 10.26% of the average overestimation error in input data. One of the reasons for such a small change in the number of degraded patches caused by input uncertainty is that, as it has been reported in Chapter 6, the loss of grassland productivity caused by grazing was only 6.28% of the expected grassland productivity, and 10.26% of the uncertainty in the input data still results in a relatively small proportion of the grazing intensity change. Nevertheless, the results in Figure 7.21 and Figure 7.22 indicate that the results of the scenario analysis in Section 7.4.2 are stable and robust to the uncertainty in input data.

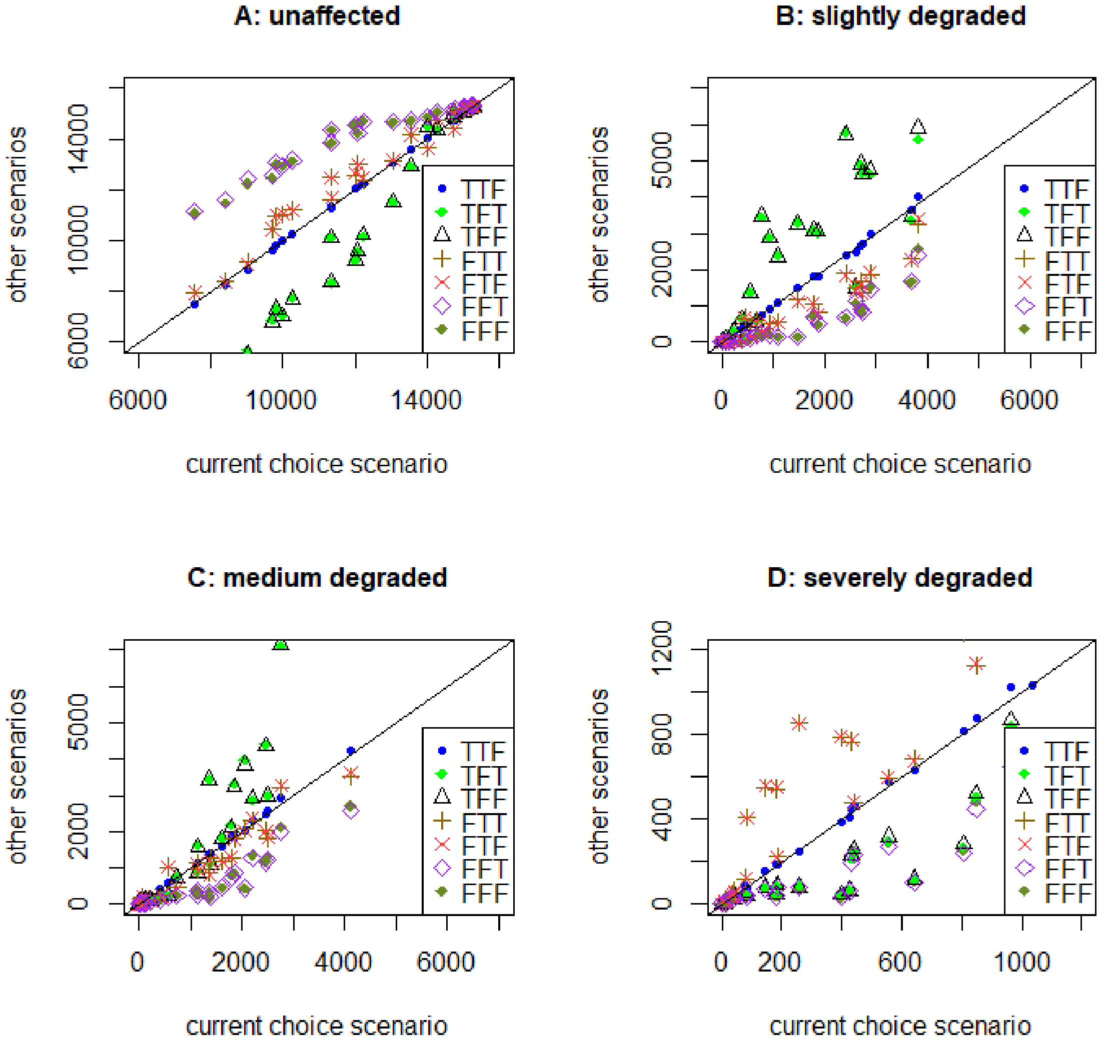


Figure 7.21: Number of degraded patches of current choice scenario plotted against other scenarios simulated by the ABMGG with 10.26% of the average underestimation error in input data

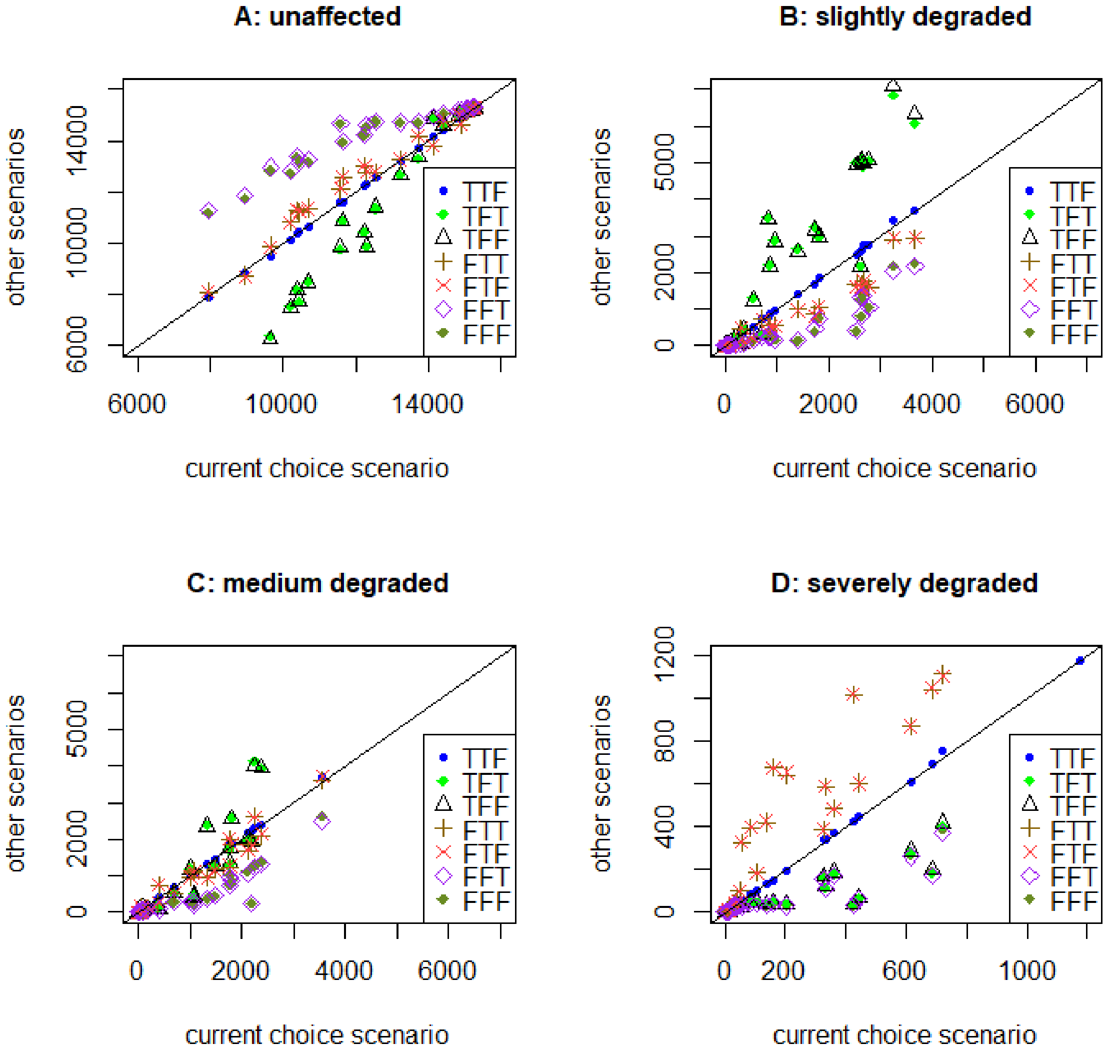


Figure 7.22: Number of degraded patches of current choice scenario plotted against other scenarios simulated by the ABMGG with 10.26% of the average overestimation error in input data

7.5 Discussion

Policy assessment is critical for successful policy development and implementation, especially in the complex grassland grazing system. However, assessment of such natural resource related policies has usually been neglected, and a substantial gap is emerging between theory and practice (Wallace et al., 1995), which may lead to unsuccessful or harmful policy implementations (Sallis et al., 1998; Sarewitz et al., 2000). An example can be seen in the effect of long-term exclusion policies, which have been implemented to improve grassland productivity, but in fact have caused the loss of plant cover and diversity in arid regions (Oba et al., 2000). The same is true for institutional changes in Inner Mongolia, where market and protection policies have actually suppressed local incentives for grassland conservation (Robinson et al., 2017).

Existing methods and models for the assessment of the coupled human and natural system have not provided an integrated evaluation which is sensitive to household decision-making, policy/institutional arrangements and natural constraints (Bellamy et al., 2001). The bottom-up agent-based model presented in this section accounts for the heterogeneity in grassland resources, individual herder' decision-making and plant-livestock interactions. After calibration with real grassland situations, the ABMGG has the capability to assess the effect of different policies on grassland status. This provides a new perspective through which to undertake policy assessment for grassland management.

A novel agent-based model that has been integrated with near real-time remote sensing data for the assessment of various grazing policies has been presented. In this chapter, the ABMGG has been evaluated through model verification, sensitive analysis, calibration and validation, then different combinations of grazing strategies and institutional arrangements were assessed under various criteria. Although there are some drawbacks, the ABMGG is an ideal methodology for the grassland grazing system that is characterized by individual interactions and contains hierarchical grazing strategies and institutional arrangements. There were eight combinations of grazing strategies and institutional arrangements. The model was able to estimate the number of degraded patches based on the individual level interactions under those combinations.

It was found that different grazing management scenarios have no effect on the LAI after grazing; that is, different grazing management scenarios could not significantly improve or decrease grassland LAI. This is similar to findings from previous studies (Woodward et al., 1995b; Jerrentrup et al., 2015), suggesting that grazing intensity, rather than grazing strategy, is the main factor in changes in grassland productivity. Importantly, however, the grassland *status* was different under those scenarios. Although the regional continuous grazing scenario performed best, with the more unaffected patches and fewer slightly, medium and severely degraded patches, compared to the other scenarios, the proportionally spatial distribution assumption of the livestock grazing intensity to the available forage on the patches in regional continuous grazing scenario could make it quite difficult to be implemented, due to potentially high managemental cost. Compared to the group continuous grazing scenario and regional randomly moving scenario, the group rotational grazing (current choice scenario) was a reasonable grazing management implementation in Zeku; it is a group level management strategy, which involves subdividing of the land patches in the groups.

Although spatial pattern analysis or spatial statistics could help the researchers to reveal different information embedded in the results, due to the fact that the unaffected patches will only occur on the un-grazed land patches in the simulation, and the slightly, medium and severely degraded patches will only happen on the continuous or rotational grazing patches, whose topological locations play an important role in the spatial pattern of the grassland status; in addition, there are 46 time steps during the year, and they have different spatial distribution of the grassland degradation. To analyse the time series changes of the spatial distribution of the grassland degradation during the year is quite difficult and unnecessary as this section seeks to quantify the overall effect of each grassland management scenario. Instead, this section uses the occurrence frequency of the degradation during the year for each land patch to represent the spatial distribution of the grassland status. The spatial difference can be interpreted directly from those frequency maps. In addition, this section also illustrated three components of the uncertainty in the ABMGG. The results of error propagation and uncertainty analysis in this section showed the reliability of the ABMGG, which was robust and accurate for the number of unaffected, medium and severely degraded patches, but it overestimated the number of slightly degraded patches due to lack of patch-specific information on the location of grazing group and sub-groups, as well as the grazing behaviour of the livestock.

Validation of the agent-based model is one of the most difficult problems during the modelling process (Rand et al., 2003). The behaviour and structure generated by agents interacting can be very hard to predict (Bankes, 2002). Firstly, agents making decisions based on pre-defined rules rather than gradual monotonic data series can lead to the modelling results having extreme sensitivity to initial settings (both within agents and their environment). Secondly, due to the stochasticity and uncertainty of agents' decision-making and interactions, one may have a wide spectrum of emergence end results when running the model many times. In both cases, here, this section has good pixel scale constraining LAI data with which to limit the model and calibrate it accurately. Given this, indicative "what if" assessment can be done by changing the grazing strategies and institutional arrangements.

One of the key difficulties in agent-based modelling of policy assessment is effective calibration. ABMs are usually used to simulate non-linear dynamic systems with different initial settings (Waldrop, 1993). Effective calibration requires a wealth of high-quality data, but, unfortunately, empirical data which describes the behaviours of the agents is usually scarce (Windrum et al., 2007). Therefore, the calibration of ABM is often considered a major point of weakness with ABM that needs to be improved (Phan, 2007; Crooks et al., 2008). In addition, agent-based models for the human and natural systems often involve numerous parameters and therefore calibration requires the searching of extremely large parameter spaces; even on the most powerful computing systems available, the time requirements can be unacceptable (Malleson, 2010). In this paper, the Approximate Bayesian Computing (ABC) calibration method was used with the assistance of Latin Hypercube Sampling (LHS), which substantially decreased the time cost of calibration. Nevertheless, it still took 10.5 days for 20000 model runs (Windows 10 Education; Inter Core i7-4710MQ @ 2.5GHz; 8 GB RAM, 64-bit Operating System). In ABC calibration, a larger sample size means higher accuracy (van der Vaart et al., 2015), there certainly exists some calibration schema or methods yet to be developed to improve the calibration efficiency.

Chapter 8 Conclusions

8.1 Introduction

The research in this thesis is theoretically and methodologically innovative. There are only limited published researches that assess different grazing management approaches based on natural grass growth under grazing and macro-grazing strategies, especially the spatial explicitly assessment. The main difficulty is, in essence, the lack of patch-specific grazing and management information. Hitherto, it has been regarded as almost impossible to collect this data for each land patch at a regional or global scale over a long time period; and this is especially true with regards to the status of grassland before and after grazing. Extracting such information is the basis for any further research, and it is the biggest methodological challenge for researchers. In addition, how to build a model that reflects the real-world situation, and to integrate all of the necessary components into the model, has been a theoretical challenge for grassland grazing modelling. The grassland grazing system is a complex system. The complexities consist of the natural growth of grass, the population dynamics of the livestock, the herbivore-vegetation interactions and the constraints of herders' grazing strategies and wider institutional arrangements. To what degree these complexities should be included in the model should be considered as the first priority, but in turn, they are highly dependent on data availability.

This chapter will sum up the main research findings and highlight the extent to which the research aim and objectives have been met. Then the contributions of this research will be listed. After this, a critique of the research methods and the limitations of this project will be discussed thoroughly, based on which some recommendations for future work will be summarised. Finally, this chapter ends with some concluding remarks.

8.2 A summary of the research findings

The overall aim of this research was to establish an agent-based model that incorporated grazing information derived from remote sensing data in Zeku, with the purpose of assessing various grassland management scenarios. To accomplish this aim, five research objectives needed to be accomplished. In this section, a discussion about the extent to which they have been accomplished by the main body of the research will be carried out.

Objective 1: review, discuss and critique the grassland grazing literature and analyse the current theories and system complexities in the grazing system in order to identify those that should be employed in the model

This objective was accomplished in Chapter 2 through a review of the literature on modelling the complexities as well as the current modelling paradigms used to research grassland grazing systems. The grassland grazing system is not only affected by livestock grazing, which may be indirectly determined by the grazing strategies and institutional arrangements, but also by the local climate, radiation conditions and even extreme events (for example, prolonged snow). To model such a complex system, the overall modelling paradigm will need a variety of different modelling theories. Chapter 2, therefore, demonstrated that it is extremely important to understand that the grassland grazing system is a complex, dynamic and unstable system.

Before reconciling the equilibrium and non-equilibrium paradigms, Chapter 2 reviewed the grassland modelling literature with the purpose of determining what kinds of complexities were indispensable in order to describe the individual-level dynamics of the grazing system. With respect to individual grassland patches, research pointed to the importance of the interaction between vegetation and herbivores, as it is the important lower-level factor that changes the growth of grass. The spatiotemporal heterogeneity of the vegetation and distribution of herbivores were also found to have an effect through the selectivity of herbivores and floristic composition of grasslands. They were mainly determined by the local natural conditions, but in the livestock grazing dominated regions, the dynamic of the livestock population was also controlled by the herders' willingness and power to gain from grassland and the social-economic demands of livestock production. Chapter 2 and Chapter 3 also reviewed the grazing strategies and institutional arrangements that are used to manage grassland grazing, which would further affect the status of grassland by changing the grazing intensities. Those complexities, along with grassland grazing modelling paradigms, form the basic theory on which the model is based.

Objective 2: review, discuss and critique the modelling techniques and data availability for the grassland grazing system to highlight the necessity of the techniques used for this research and to guide the model development process

One of the main research findings in this thesis was that the heterogeneity of individual forage and livestock distributions, vegetation-herbivore interactions and grazing management strategies should be considered when assessing the overall status of grassland in grazing systems. Also, all the complexities that were discussed in Chapter 2 are based on the individual interactions among herders, livestock and the grasslands and, as such, should not be modelled by a constant fixed rate. Chapter 2 introduced empirical and process-based modelling techniques that could, to some extent, overcome some of those problems but it was found that they were not able to fully account for the mechanisms (herders' grazing strategies and institutional arrangements) behind the individual vegetation-herbivore interactions.

Agent-based modelling proved to be the most suitable way to deal with these problems, and the few published agent-based grassland grazing models were critiqued. The use of agent-based modelling in grazing system analysis appeared in studies of animals' behaviours (Topping et al., 2003; Dumont and Hill, 2004b), but they were typically simple rule-based, spatially explicit models that did not consider the interactions between livestock and vegetation. Milner (2006) improved this and built the first agent-based grazing model for grassland in Kazakhstan, which included both household decision-making and vegetation-herbivore interactions. However, the effect of different grazing strategies and institutional arrangements was ignored (Milner-Gulland et al., 2006). Wang (2013) further enriched the field by incorporating social mechanisms and institutional arrangements in their study of Mongolian grasslands, but the absence of the real productivity and livestock grazing data in the model make the results less convincing (Wang et al., 2013). The effect of grazing has usually been ignored or simply represented by a fixed rate for all patches. This becomes the main impediment for further individual level grassland grazing modelling. Janssen et al. (2000) have built an adaptive agent model, but like many other ABMs in modelling grassland grazing systems, the grazing intensity data used in the research was actually the regional average intensity (at property scale). Such data used in the model led to the ignorance of the spatial heterogeneity of the grassland resource, which could produce a false expression of the plant-herbivore interaction due to the different grazing intensities in the different places of the property. Yet for this reason, the spatial distribution patterns of the vegetation have not been reported in many ABMs of the grassland grazing systems.

Chapter 2 also elaborated the advantage of agent-based models in modelling vegetation-herbivore interactions and herders' decision-making. Along with remote sensing (one of the key research findings in this thesis, see next), agent-based modelling is the most suitable technique for the further assessment of grassland status based on individual interactions and decision-making.

Objective 3: Develop a new method to derive information about grass growth and the effect of grazing from remote sensing data

Remote sensing, as a widely used grassland monitoring technique, has been used in quantifying grazing intensities (Kawamura et al., 2005) and the impact of grazing on pasture biophysical properties (Numata et al., 2007; Eddy et al., 2017), but unfortunately, all the grazing-related information has previously been aggregated to the regional level as a whole for further analysis. LI *et al*. (2007) and Gómez (2017) used pixel-based analysis of grazing intensities based on vegetation index (VI) fluctuations caused by grazing (Gómez et al., 2017b; Li et al., 2017), but again, did not attempt to estimate the amount of the grass that was eaten by livestock. On the other hand, the current reprocessing methods for remote sensing data were designed to smooth the outputs through spatial or temporal averaging techniques. This makes them unsuitable for grazing information extraction, where grazing-led unusual fluctuations need to be retained during estimation. Sakamoto (2016) used the Normalized Difference Vegetation Index (NDVI) data as a source of an indicator of the grass forage distribution, and applied an agent-based model to simulate the behaviours of the pastoralists, in order to explore the dynamics of vegetation and livestock. However, the model results have not been validated due to the lack of data, and the *ad hoc* assumptions of the behaviours of the pastoralists (for example, grazing range, frequency and carrying capacity) make it difficult to be applied to new conditions. Chapter 2 and Chapter 5, therefore, explained the feasibility of remote sensing in the more spatiotemporal specified extraction of grazing information. No other techniques that can derive the grazing information for each grassland patch are as convenient as remote sensing related techniques.

A novel grass growth function has been derived with consideration of both plant senescence and grazing-led defoliation based on the conventional exponential growth function. It is a year-round grass growth under grazing function rather than a predictive plant-livestock interaction function. This new growth-grazing function was not used in isolation to estimate the growth of grass under grazing; it was accompanied by a grazing-led LAI changes estimation algorithm, which was used to estimate the values of parameters in the new growth function. Using this new growth function, it was possible to account for a large degree of the complexities that Chapter 2 has pointed to. By filling the “gaps” of MODIS LAI data caused by clouds or uncertainties within the MODIS algorithm, two products were produced: improved LAI (LAI after grazing) and expected LAI (LAI before grazing). The grazing frequencies and grazing types were also identified. The validation of these results consisted of two parts: Chapter 5 reviewed the accuracy of estimated grazing-led LAI changes through an LUE-VPD model. Chapter 6 has a detailed description of the validation of the improved LAI by comparison with the statistical data. The validation results showed a great spatiotemporal consistency with both *in-situ* data and statistical data and, therefore, this new growth function can be used in deriving grazing information based on remote sensing data. This is a novel contribution to the field.

Objective 4: Design and build an agent-based model that can account for the different grazing strategies and institutional arrangements and use remote sensing data as an input

Chapter 4 translated the complexities reviewed in Chapter 2 into a prototype model based on the grazing profiles of grazing system in Zeku. Chapter 3 elucidated the livestock grazing and grassland distribution profiles, land tenure system and three grazing strategies and two main institutional arrangements in the case study area. These features of the grassland grazing system in Zeku provided a modelling basis for conceptualising the key components of the prototype model. Chapter 4 began with an explanation of how different modelling paradigms and system complexities could be represented in a conceptual model. Three key features of the environment were represented through available forage, seasonal forage growth rate and degraded status. Chapter 4 also showed three conceptual models: a sedentary grazing model, land market model and EAHEC model. The herders in those three models were differentiated by the grazing strategies and institutional arrangements. The behaviours of agents change according to their initial decision-making when degradation occurs. To compare the output performance of these three grazing systems, Chapter 4 concluded with an assessment of the livestock and forage dynamics, net income of herders and number of degraded patches in these three conceptual models.

Building upon these three conceptual models in Chapter 4 and the grazing information derived from remote sensing in Chapter 5, Chapter 7 developed an agent-based grassland grazing model (ABMGG) which was parameterized with real grazing and grassland forage data. The key parameter in the ABMGG was the leaf area index (LAI). The overall purpose of Chapter 5 was to derive the grazing-led LAI changes based on the remaining LAI (improved LAI), but the key issue for Chapter 7 was calibration: how to generate similar grazing patterns for each pixel as compared to the real grazing patterns (as remote sensing observed grazing-led LAI changes) through the full-growth LAI. For the un-grazed patches, the grazing pattern produced by ABMGG would be exactly the same as we could observe from the improved LAI (there are no grazing activities happening for un-grazed patches in ABMGG). For continuous grazing patches, the simulated grazing-led LAI changes were the same as those derived from remote sensing data, as the time, frequency and quantity of grazing-led LAI changes were the same. However, for rotational grazing patches, the difficulty was how to form the grazing group reasonably so that it matched up with the grazing frequencies and grazing quantities for each grassland patch. This required a piece of detailed survey information on the grazing profiles and grazing groups. Chapter 3 reviewed the results of the survey in 2012 and 2016 with respect to grassland productivity, livestock and the grazing group profiles of Zeku. Then Chapter 7 technically documented the final model. The parameterized ABMGG in Chapter 7 was able to incorporate the paradigms and complexities discussed in Chapter 2 and later implemented in Chapter 4, and formed a solution that is able to account for the dynamics of the grassland grazing system based on individual decision-making and grazing management strategies.

Objective 5: Assess different management scenarios after making sure the model has the ability to simulate the grassland status under grazing based on current grazing strategies and institutional arrangements

Before carrying out an assessment, an essential part of the modelling endeavour is to make sure the model behaved as it was expected to. That is, the design, the entities, processes, and associated constraints and assumptions are implemented correctly. This is the critical step for any complicated model that involves numerous parameters, which could potentially or indirectly affect model outputs. Chapter 7 evaluated ABMGG through systematic testing and validation with the real-world data from Zeku. The evaluation began with a verification to track the key outputs of the models, along with the sensitivity analysis of the parameters, and was able to determine that the ABMGG was able to produce acceptable results in simulating real group grazing behaviours. The rest of the evaluation work was then to calibrate ABMGG to the remote sensing observed grazing patterns by an Approximate Bayesian Computing schema. The validation of ABMGG was to see whether the calibrated model was over-fitted to the data; this thesis used R2, t-test and RMSE to quantify the overall model accuracy, where an obvious improvement of the model accuracy could be seen when comparing the model outputs before calibration and after calibration. In addition, the stochastic, parametric and input uncertainty of the ABMGG were analysis by repeated simulation, calibration with Approximate Bayesian Computing (ABC) method and numerical simulation, and they have been extensively discussed in Chapter 7 to evaluate the accuracy and credibility of the ABMGG.

To fully accomplish the final aim of this thesis, the various grazing management scenarios that were tested with the model were discussed in Chapter 7. The most significant advantage of agent-based modelling is that it is able to gain a quantified assessment of possible grazing strategies and institutional arrangements and to pinpoint the possible optimal strategy when keeping other parameter values the same. There were eight combinations of grazing strategies and institutional arrangements. The model was able to estimate the number of degraded patches based on the individual level interactions under those combinations. This analysis has not considered the effect of scales of the economy which may further decrease the number of severely degraded patches by with good grassland management. It was found that different grazing management scenarios could not significantly improve or decrease grassland productivity. That is, different grazing management scenarios had no effect on the average LAI after grazing. This is to be expected as animals always have the same energy requirements, regardless of the quality of patches, and therefore, the total amount of LAI devoured would be the same. However, the assessments highlighted that the rotational group grazing was a reasonable choice in terms of the obvious smaller number of degraded patches; although the regional continuous grazing scenario produced the smallest number of degraded patches, the assumption of the same percentage of available forage being grazed was quite difficult to be implemented in reality. These results can be used as a policy tool to assess the impact of policies on the grassland grazing system.

8.3 Limitations of the research

Although the five research objectives have been achieved through the employment of the new growth function, the development of the model and its application in the scenario analysis of grazing management, there are still some limitations to this research.

The effect of cell size

The spatial resolution of the LAI data used in this research is 463×463 m^2. As was mentioned in Chapter 7, a rotational grazing patch at a higher spatial resolution may appear as a continuous grazing pattern at a lower spatial resolution patch size, for example where the sub-division of a farm cannot be observed from remote sensing. That is, although the pixels are rotational grazing pixels in reality, they still have the possibility of being classified into continuous grazing pixels from a remote sensing perspective if the spatial resolution is lower than the farm size. Given the fact that the majority of the farm sizes in Zeku are smaller than 0.33 km^2, only spatial resolutions of remote sensing smaller than 0.33 km^2 can be used for rotational grazing pixel identification and grazed LAI estimation. This is the main reason why 1 km×1 km MODIS LAI was not used in this thesis.

At the time of writing, the highest spatial resolution LAI data are the 463m MODIS LAI version 6 products, which are about 0.21 km^2. This is similar to the size of the household average summer farm size (0.20 km^2); therefore, the sub-divisions of the summer pasture of the household cannot be observed from remote sensing. However, when grazing groups are formed, the group grazing grassland size would be much larger than the spatial resolution of the MODIS LAI data. Sub-division of the group grazing grassland for rotational use can be identified from remote sensing. Unfortunately, the higher spatial resolution LAI data have not been published, and there is no ideal method that can be used to identify the household level rotational grazing patterns.

In addition, the cell size will further affect the assimilation of the survey and statistical data at the patch unit. Here, this includes the radius of the grazing group, the number of participants in the group, as well as the spatial resolution of climatic and radiation data. A mismatch of the spatial resolution is a common problem in agent-based modelling when incorporating pixel-level remote sensing data and regional or community level statistical data. How to ensure the change of spatial resolution does not induce further uncertainties into the model is the next challenge for modellers.

Data scarcity and uncertainty

Chapter 4 has presented an advanced agent-based model of grassland grazing, that accounts for the four main aspects that drive the system. However, the data for the parameter parameterizations were still insufficient, and uncertainties still exist in some key parameter values, as discussed in Chapter 7. In this thesis, there are three types of data related to those problems: 1) household social-economic data, which includes: the price of selling or buying livestock; the kinship of the herders (Wang et al., 2013); the cost of renting land; the cost of joining or leaving grazing groups;

and the boundary of the summer/winter pastures for each household and grazing group. Lacking that information, the social-economic outcomes cannot emerge from the individuals' behaviours, which is why the social-economic performance of the grazing system has not been included. 2) species-specified biophysical data, which involves the value for potential light use efficiency (ε_{max}), specified leaf area (SLA) and the leaf-root ratio, which are all highly dependent on the vegetation types and could further affect the accuracy of Net Primary Productivity (NPP) estimation. The use of an empirical value for a broader vegetation type will introduce uncertainty. 3) high resolution climatic and Photosynthetic Active Radiation (PAR) monitoring data, which consist of the daily temperature data and ground measured PAR data. When lower spatial resolution input data have been used for a higher spatial resolution model, the spatial heterogeneity of the model is affected reducing the model accuracy. The modelling work therefore needs to be able to cope with such scarce or uncertain data by dynamic data assimilation or calibration (see next—the calibration schema).

In Chapter 5, the uncertainty of the grazing-led LAI changes was quantified by an extreme situation analysis. Also, the uncertainty of the improved LAI estimated in Chapter 5 can propagate through a Light Use Efficiency with Vegetation Photosynthesis Model (LUE-VPM) in Chapter 6. The error boundary of the Net Primary Productivity simulated by the LUE-VPM was quantified considering the error range of the improved LAI estimated in Chapter 5. However, as it has been discussed in Section 6.7 of Chapter 6, the other sources of uncertainties in the parameters and input datasets (for example, the uncertainty of daily temperature data) used in the LUE-VPM were not given. Obtaining such uncertainty information would require a collaborative scientific effort from numerous different research communities, especially when the model is used in a new condition that the error range of the parameter values would be different.

The calibration schema

One of the key difficulties in agent-based modelling is effective calibration. ABMs are usually used to simulate non-linear dynamic systems with different initial settings (Waldrop, 1993). Effective calibration requires a wealth of high-quality data, but unfortunately, empirical data which describes the behaviours of agents is always scarce (Windrum et al., 2007). Therefore, the calibration of ABM is often considered a major weakness of ABM that needs to be improved (Phan, 2007; Crooks et al., 2008). In addition, agent-based models for human and natural systems often involves numerous parameters and therefore calibration requires the searching of extremely large parameter spaces; even on the most powerful computing systems available, the time requirements can be unacceptable (Malleson, 2010). In this thesis, the Approximate Bayesian Computing (ABC) calibration method was used with the assistance of Latin Hypercube Sampling (LHS), which substantially decreases the time cost of calibration. Nevertheless, it still took 11 days for just 20000 model runs[3]. In ABC calibration, a larger sample size means higher accuracy (van der Vaart et al., 2015); there certainly exists some

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[3] The machine used in this thesis is: Windows 10 Education; Inter Core i7-4710MQ @ 2.5 GHz; 8 GB RAM, 64-bit Operating System.

calibration schema or methods yet to be developed to improve the calibration efficiency.

8.4 Recommendations for Future Work

The ABMGG can be further developed in several ways to improve upon the limitations discussed above. One means of improvement would be through integration with other models such as climate models, solar radiation models, vegetation distribution models, productivity models and even economic models. However, such integration should be followed with caution because the "more is different" (Anderson, 1972). The more detailed the components in the model, the less relevant the science behind the overly detailed structure of the model (Anderson, 1972). In addition, replacing simple abstracted parameters in the current ABMGG model with more complex sub-models would dramatically increase the complexity of the overall model, which would surely be more computationally expensive to evaluate. Therefore, the more simple and feasible ways to extend the current work in the future would be:

Firstly, a predictable growth function under grazing should be developed based on the new growth function introduced in this thesis. That is, the long-term effect of grazing on the growth of grass should be considered (a multi-year' growth function rather than current year-round growth function). This could improve the usefulness of the new growth function in the field of grassland grazing management, but this also requires extensive comparison experiments in different grassland types.

Secondly, this research specifically calls for studies on social-economic data assimilation (Anderson and Kellam, 1992) in agent-based modelling, as human's decision-making depends on his/her social-economic status and even on the cultural or psychological difference, which all change with time and condition. The spatial and temporal scale of the social-economic or psychological data can be considered dynamically.

Thirdly, one direction might be to create the individual herder agents rather than abstract herders for each grassland patch. The behaviours of agents in this thesis are estimated from the regional aggregated statistical properties, but this could hide the influence of kinship, community and the individual interactions among herders, which are important elements of the complexities of the grazing system. Another contrary direction might be the scaling up the agents and patches and embedding them in a broader context, for example, to explore the effect of grazing and grazing management practices/policies on the landscape scale ecosystem functions.

Fourthly, the bilateral feedbacks of vegetation and the livestock under grazing was not considered in the ABMGG**.** However, such bilateral feedbacks may change the long-term dynamics of both vegetation and the herbivores. In addition, the decision-making may also have multiple feedbacks on the vegetation, herbivore and the other agents. The bilateral and multiple feedbacks should, therefore, be considered in future work.

Fifthly, the composition of vegetation on the grassland needs to be considered. The livestock has the selective behaviour of the grass species, and the favourite species on the land may be more frequently visited by the livestock. In addition, the vegetation composition is also determined by the natural conditions as well as the grazing management practices. It is an evolution and co-evolution process among vegetation, herbivore, natural conditions and the human.

Seventhly, the multi-spatial and multi-temporal and multi-source remote sensing data can be used to derive the grazing information in more detail. For example, the vegetation structure and composition (Wachendorf et al., 2018)and the livestock moving behaviours (Steenweg et al., 2017). In addition, there are researchers using the Unmanned Aerial Vehicle (UAV) to map the heterogeneity of the grazing pasture (Kawamura et al., 2016), which provides a new source of the data at high spatial and temporal resolution.

Sixthly, the ABMGG can be improved by incorporating the learning behaviours of the agents. That is, the model can evolve by changing the grazing strategies and institutional arrangements and producing the best combinations of grassland management practice dynamically.

Eighthly, the ABMGG can be applied to different places if the information on local management practices is available, and more case studies should be carried out in different regions and/or under different grazing management strategies where the model parameters could be further validated. The scenarios are common practice in grassland management practices. More cross sites analysis should be carried out in the future to evaluate the flexibility of the model.

In addition, the error propagation and uncertainty analysis are essential to make sure the model is reliable. For agent-based modelling, the errors from individual agents or the parameters could propagate through multiple level interactions, and the final outputs of the models may have quite large uncertainties that even reach the unacceptable level. In addition, the effect of errors from individuals, parameters, input data or the model structure may suppress or diminish the effect of each other, the overall effect of the all the errors may be smaller than the individual ones. Current methods for the uncertainty analysis are mainly computational, e.g. sampling from the parameter space to see how the results change with the parameter values. The consideration of spatial and temporal heterogeneity of the entities and their relations in the ABMs should be considered in future work. However, as mentioned earlier in this chapter, the full uncertainty analysis of the model needs a collaborative scientific effort from numerous different research communities, especially when the parameter values are highly site-specific or scale-dependent.

8.5 Concluding Remarks

The contribution of this research to grassland grazing management can be summarised through three main components: a new growth function under grazing that considers both growth and senescence of grass with an estimation algorithm; a LUE-VMP model to estimate NPP for improved LAI validation; a novel agent-based model that has been integrated with near real-time remote sensing data for the assessment of various grazing management strategies. Although there are some drawbacks, agent-based modelling is an excellent methodology for grassland grazing systems that are characterized by individual interactions and contain hierarchical grazing strategies and institutional arrangements. It is suggested that the ABMGG can be further developed by improving the data quality and considering of vegetation composition and evolution/co-evolution with livestock, human and the environment. Also, it is important to address the error propagation and uncertainty of ABM. In addition, by involving multi-spatial and multi-temporal and multi-source, adapting and learning in the grazing strategies and institutional arrangements, the ABMGG would be able to produce the optimal grazing management practices, which are important tools for the sustainable development of the grazing system for both herders and policymakers.

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