# The impacts of climate change on global potato agriculture

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# Declaration

The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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# Abstract

It is vital that we develop our understanding of how crops will respond to climate change given the likely need to increase food production by 2050. The contribution of potatoes to the global food supply is increasing - consumption more than doubled in developing countries between 1960 and 2005.

Analyses of climate impacts on potato compared to other major crops are relatively rare. Studies involving biotic stresses in crop modelling are also comparatively rare - around 70% of models do not incorporate pest and disease damage. This thesis simulated abiotic and biotic impacts of climate change to 2050 to identify risks and opportunities for global potato agriculture. The GLAM crop model is used to assess abiotic impacts and the SimCastMeta model is used to assess the impacts of the most important global disease of potato, late blight *Phytophthora infestans*. A further analysis uses pesticide data as a proxy for pest pressures, showing that warming leads to pesticide increases in temperate areas.

GLAM is evaluated for potato simulation in two contrasting climates using data from Colombian regions and Aberdeen, UK. The model shows skill in simulating observed weather-yield relationships. National yield data are then used to test a global parameter configuration. Results show realistic planting dates and crop growth. Skill is low due to insignificant observed weather-yield relationships. Regional results show higher skill than global results, primarily due to more parameter detail.

Global model results show skill in reproducing observed yields in Europe. Elsewhere, correlations are generally positive but low. Future climate simulations show that yields are expected to increase in most cases, primarily as a result of $CO_2$ fertilisation, although the magnitude of increases are uncertain due to the uncertainties around future climate and $CO_2$ fertilisation. Temperature increases in some regions result in shorter durations and reduce yield increases. Late blight is predicted to increase more in temperate regions, particularly if adaptation to climate change is considered. Taken together, abiotic and biotic impacts show potential opportunities for potato agriculture in temperate latitudes providing pests and diseases can be sustainably managed.

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# Abbreviations

| **Acronym** | **Meaning** |
|---|---|
| AgMERRA | Agriculture Modern-Era Restrospective analysis for Research and Applications |
| AgMIP | Agricultural Model Intercomparison Project |
| CIAT | International Center for Tropical Agriculture |
| CMIP | Climate Model Intercomparison Project |
| $CO_2$ | Carbon Dioxide |
| CSA | Climate Smart Agriculture |
| DOY | Day Of Year |
| DSSAT | Decision Support System for Agrotechnology Transfer |
| FACE | Free-Air $CO_2$ Enrichment |
| FAOSTAT | Food and Agriculture Organization Corporate Statistical Database |
| GAP | Good Agricultural Practice |
| GCM | Global Climate Model |
| GDP | Gross Domestic Product |
| GLAM | General Large Area Model for annual crops |
| HI | Harvest Index |
| IAM | Integrated Assessment Model |
| IPCC | Intergovernmental Panel on Climate Change |
| ISI-MIP | Inter-Sectoral Impact Model Intercomparison Project |
| ISTG | Index for Stage of crop Growth |
| LAI | Leaf Area Index |
| MIDAS | Met Office Integrated Data Archive System |
| MIRCA | Monthly Irrigated and Rainfed Crop Area |
| MRL | Maximum Residue Limit |
| NWBDAYS | Number of days water balance is run before the start of the intelligent planting window |
| PAR | Photosynthetically Active Radiation |
| RAP | Representative Agricultural Pathway |
| RCP | Representative Concentration Pathway |
| RMSE | Root Mean Square Error |
| RUE | Radiation Use Efficiency |
| SEDAC | Socio-Economic Data and Applications Center |
| SLA | Specific Leaf Area |
| SRES | Special Report on Emissions Scenarios |
| STICS | Simulateur mulTIdisciplinaire pour les Cultures Standard |
| TE | Transpiration Efficiency |
| VPD | Vapour Pressure Deficit |
| $C_{\mathrm{YG}}$ | Yield Gap Parameter |

# Chapter 1

# Introduction

## 1.1 Motivation and overview

Increasingly, the focus and funding across various scientific disciplines is being aimed at real-world problems, such as the impacts of climate change on agricultural systems (Müller et al., 2017; Challinor et al., 2009b). It is widely reported that production has to increase substantially by 2050 to achieve global food security (e.g. Ramankutty et al., 2018; Godfray et al., 2010; Chakraborty and Newton, 2011). The extent of any required production increase depends on future socio-economic factors such as dietary choices, however (Tomlinson, 2013). Whilst access and the sustainability of food are also key to food security, production remains critically important (Godfray and Garnett, 2014). It is therefore vital that we develop our understanding of how crops will respond to climate change.

Potato production is rising globally, meaning that potatoes are likely to become an increasingly important part of the efforts to achieve global food security in the coming decades. The contribution of potatoes to the global food supply is increasing steadily in developing countries especially, with potato consumption more than doubling between 1960 and 2005 to over 100 million tonnes in India and China alone (FAO, 2005). More on where potatoes are grown and their importance for food security can be found in Section 1.4.

Studies concerning potato agriculture are relatively few in number compared to other major staple crops, maize, rice, wheat, sorghum and soybean. Global production of potatoes (327 million tonnes in 2005) is greater than that of soybean (215 million tonnes) and sorghum (60 million tonnes), approximately half that of wheat (627 million tonnes) and rice (634 million tonnes) and less than half that of maize (714 million tonnes) (FAO, 2005).

A Web of Knowledge search taken from Brown et al. (2011) of "Potato and (radiation interception or radiation use efficiency or photosynthesis or extinction coefficient or phyllochron or leaf appearance or leaf size or leaf area index or harvest index)" for the years 1950 to 2016 resulted in 7006 studies for potato. The same search for wheat, maize and rice yielded 27901, 18103 and 16357 studies respectively. When global production is weighted by the number of these studies, a striking picture develops - the relative number of studies on potato physiology and crop modelling is very low for its level of global crop production (see Figure 1.1). Reasons for this neglect could include the difficulties in observing below-ground physiology and the complexities of modelling a vegetatively propagated crop (Brown et al., 2011).

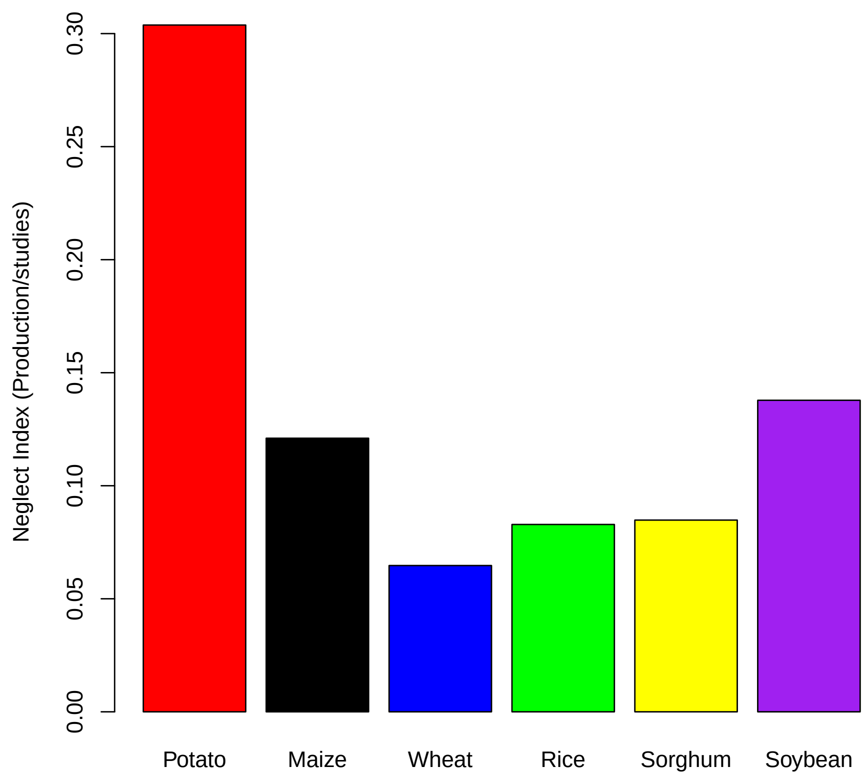



**Figure 1.1:** Figure relating the number of crop physiology and crop modelling studies to the level of global production over 1995 to 2005 for six major crops – the crop modelling "Neglect Index".

Biotic stresses (stresses to crops caused by other living organisms) are also neglected within the crop modelling community – around 70% of crop models do not incorporate pest and disease damage (Rivington and Koo, 2011). An understanding of the evolution of food systems is also needed, including adaptation to climate change and mitigation efforts, land use changes and socio-economic impacts. In order to make these comprehensive agricultural forecasts we need an understanding of how crops will respond to climate change, and in some cases this is still lacking.

This thesis primarily investigates how abiotic factors influence potato agriculture over the coming decades. It combines neglected areas of crop modelling in a framework designed to identify regions across the globe that present risks and opportunities for potato yields with climate change. The thesis also accounts for the impacts of a globally important disease of potato, late blight *Phytophthora infestans*, as well as a broader analysis of pest pressures and climate change using proxy pesticide data.

This chapter introduces climate change and crops, the tools used to investigate them and potato agriculture specifically. Firstly, an overview of how climate change is predicted to impact crops through direct abiotic impacts is provided (Section 1.2.1). Section 1.2.2 then introduces crop biotic stresses: how climate change impacts pests and diseases (Section 1.2.2.1) and in turn how the crops themselves are affected by these changes to pests and diseases (Section 1.2.2.2).

The methods used to make these predictions are discussed in Section 1.3. Climate models are discussed in Section 1.3.1 – their structure (Section 1.3.1.1), how they simulate human-induced climate change (Section 1.3.1.2), ensembles of multiple models (Section 1.3.1.3) and the processing of output for use in crop models (Section 1.3.1.4).

Crop models are discussed in Section 1.3.2. Section 1.3.2.1 introduces different types of crop models and issues of appropriate model complexity and spatial scale. Section 1.3.2.2 gives a review of crop modelling from local to global domains. Section 1.3.2.3 provides a summary of how process-based crop models simulate crop growth and development. Section 1.3.2.4 details models of pests and diseases. Section 1.3.2.5 discusses some of the important uses of crop models, ranging from simulations that assess climate change adaptation to inclusion within broader food security assessments.

Potatoes are discussed specifically in Section 1.4, firstly providing an overview of global potato agriculture. Potato growth and development are then described (Section 1.4.1), before the projected impacts of climate change on potato agriculture are summarised (Section 1.4.2).

Thesis objectives are outlined in Section 1.5, along with the chapters that fulfil these objectives.

## 1.2 The impacts of climate change on food security

The earth has warmed on average globally from 0.72 - 0.85°C since 1850 (Stocker et al., 2013). This warming is unprecedented both in terms of its anthropogenic source (Shine and Sturges, 2007) and its speed; the current warming trend is the strongest of the last millennium (Jones et al., 2001).

With warming, species shift their distribution to match development and growth to appropriate temperature conditions (Chakraborty, 2013). Chen et al. (2011) found a median shift of species distribution of 16.9 km per decade, but there was substantial variation across taxa. Lowland forests are responding slower to warming than highland forests, for example (Bertrand et al., 2011). Without human intervention, such natural shifts to adapt to climate change do not occur in agricultural systems.

Climate change is expected to be harmful to food security, especially in areas that are already suffering from malnutrition (Wheeler and von Braun, 2013). Yields often display a negative response to rising temperatures (Challinor et al., 2014b), although technological improvements and potential increases in photosynthesis from increasing atmospheric levels of carbon dioxide ($CO_2$) may mitigate losses (Lobell and Field, 2007). Lobell et al. (2011) found that climate (primarily temperature) trends resulted in yield decreases for maize and wheat despite technology and $CO_2$ fertilisation gains.

Tropical countries are at greater risk from climate change as they face developmental challenges and generally use more traditional agricultural techniques (for example, relying on rainfed crops as opposed to irrigation – Portmann et al., 2010). A significant warming signal is also likely to emerge earliest in tropical countries (Mahlstein et al., 2011).

It is important to comprehensively examine agriculture in the context of climate change as well as just looking at abiotic impacts on crops (described below in Section 1.2.1). Multiple simultaneous climate shocks could lead to global food security crises (Homer-Dixon et al., 2015), and large scale holistic modelling efforts are needed that can coordinate risk assessments and food security policies worldwide (Challinor et al., 2017).

Section 1.2.1 outlines some of the projections for the abiotic impacts of climate change on crops. Section 1.2.2 discusses the biotic impacts of climate change specifically.

### 1.2.1 The impacts of climate change on crops

Given the likely need to increase food production, it is essential to quantify how a changing climate will impact yields. The distribution of temperature anomalies has shifted and broadened, meaning that more extreme climatic events and higher mean temperatures are now becoming increasingly likely (Hansen et al., 2012). In hotter conditions, crop yields often fall (Battisti and Naylor, 2009; Challinor et al., 2014a). Estimates of future hot seasons are therefore important for planning appropriate adaptation to climate change.

Challinor et al. (2014b) provide a meta-analysis of yield change with temperature, generally reporting losses even at small increases of temperature when no management adaptations to climate change are accounted for. At tropical latitudes, moderate temperature increases are more likely to be detrimental to crop yields with and without adaptation. This was in contrast to the 4th Assessment report of the Intergovernmental Panel on Climate Change (IPCC), when small yield increases were projected at low temperature increases (Easterling et al., 2007). As the bulk of the world's cereals come from low- to mid-latitudes, small to moderate increases in temperature are likely to severely hamper global food security, given the probable required increases in food production. Regionally, precipitation and $CO_2$ concentration changes will have large impacts on this general global trend. Temperature increases lead to yield reductions as a result of decreased crop durations (Hatfield and Prueger, 2015) and the impacts of heat stress (Challinor et al., 2010). Increasing precipitation can lead to more flooding of cropland, whereas water can become limiting (i.e. drought conditions) with decreasing precipitation (Saue and Kadaja, 2014).

Increasing $CO_2$ emissions are expected to result in an increase in crop yields due to increased photosynthetic activity or water use efficiency (Leakey et al., 2009). This could be counterbalanced, however, by increasing temperatures and changes to precipitation (Lesk et al., 2016; Lobell et al., 2014). Studies sometimes account for the impacts of climate change not only on mean yield levels but also on the variability of yields, with higher extreme yield years (i.e. more likely crop failure) usually predicted in the future (e.g.

Chavez et al., 2015; Challinor et al., 2010). In global analyses of major crops, warming usually leads to decreases in yields and $CO_2$ fertilisation to increases in yields, although results are crop, region and scenario-specific (Raymundo et al., 2017b; Deryng et al., 2014).

Crop-climate models are the primary tools with which estimates are made of climate change impacts on crop yields (see Section 1.3 for more information on how these work). For example, Lobell et al. (2011) used empirical modelling to quantify the impacts of temperature and precipitation changes on yield for four international staple crops from 1980 to 2008. Globally, wheat and maize production declined by 5.5 and 3.8% respectively, whereas soybean and rice showed no average decline. Climate impacts often exceed 10% of the rate of yield change from technological and management improvements, exerting a "drag" on yield improvements over time (Lobell et al., 2011).

Other studies take a mechanistic approach to model the impacts of climate on yield. For example, the General Large Area Model for annual crops (GLAM; Challinor et al., 2004) has been used for a variety of crops and regions to simulate the impact of climate on yield. Challinor et al. (2010), for example, found that crop failures of spring wheat in north-east China are due to become more frequent with increasing heat stress. Butterworth et al. (2010) used the crop simulation model STICS (Simulateur mulTIdisciplinaire pour les Cultures Standard) to simulate oilseed rape (*Brassica napus*) growth and yield. They predicted that oilseed rape yields will increase in Scotland and decrease in Southern England. Differences between statistical and process-based models are discussed in more detail in Section 1.3.2.

Agricultural adaptations (distinct from biological evolutionary adaptations) to climate change can be defined as activities that reduce negative or enhance positive impacts of climate change (Lobell, 2014) – the IPCC define adaptation as "the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (Field et al., 2014). Adaptations vary greatly in scope and design, from autonomous adaptations that involve small-scale incremental changes to larger scale and more transformative adaptations (Kates et al., 2012). Climate Smart Agriculture (CSA) aims to take into account not only adaptation but also mitigation to climate change, given the growing need to do both simultaneously (Harvey et al., 2014).

It is important to note that projections of climate change impacts on yields are uncertain due to various factors, including the input data used. Osborne et al. (2013) used 14 atmosphere-ocean global climate models (GCMs) to quantify the uncertainty in climate inputs. Soybean and spring wheat were simulated globally using GLAM under baseline and 2050 climatic conditions, using the A1B SRES emissions scenario (broadly a middle-of the road scenario, with high early emissions that peak mid-century before tailing off) along with different measures of adaptation. The spread of global yield change across GCMs and adaptation strategies ranged from 1 to -52%. There was no consistent pattern of impacts on yield across GCMs for crops and regions, highlighting the importance of accounting for GCM uncertainty. However, Asseng et al. (2013) found that the uncertainty associated with crop models was greater than that of the downscaled climate model projections. We therefore need to be careful in our use and interpretation of ensembles depicting large-scale impacts of climate change on crop yield.

### 1.2.2 Pests and diseases

Crop biotic stresses, or pests and diseases (hereafter collectively referred to as "pests") are a major limitation on crop yields in many parts of the world. Pests are incredibly diverse, with organisms from many taxa (including bacteria, viruses, fungi, oomycetes, insects and nematodes) contributing to agricultural losses. Fungi and oomycetes are among the most significant pest groups in terms of crop losses (Bebber and Gurr, 2015; Oerke, 2006). For example, the most significant global disease of potato (*Solanum tuberosum*) is the oomycete potato late blight (*Phytophtora infestans*) (Oerke, 2006). This thesis includes modelling aimed at assessing the potential for late blight to adapt to climate change and impact potato agriculture. Particular attention is therefore given to late blight in this section.

Section 1.2.2.1 discusses the impacts of climate change on pests. Section 1.2.2.2 then reviews the predicted impacts of pests on crops. Modelling of pests within crop-climate impacts science is detailed in Section 1.3.2.4.

#### 1.2.2.1 The impacts of climate change on biotic stresses

Species have to migrate, evolve or die in response to climate change (Chakraborty, 2013). Many pest species are expected to respond faster than their host crops to changing climate conditions because of large population sizes, short generation times and strong selection pressures (Bale et al., 2002). Aphids, for example, are an insect group expected to respond rapidly to climate change because of their short generation times and low developmental threshold temperatures (Harrington et al., 2007).

Late blight is an example of a fungal-like pathogen of global importance. Blight is appearing earlier in the growing season in response to increasing temperatures (Roos et al., 2011; Gregory et al., 2009). In addition, there is evidence of rapid spread of new varieties of late blight that have the potential to reproduce sexually and add to the evolutionary potential of the species (i.e. the adaptation potential of a species to respond to changing conditions) (McDonald and Linde, 2002; Cooke et al., 2012; Hwang et al., 2014; Roos et al., 2011).

Temperature is the most important environmental variable impacting insect development, abundance and persistence (Bale et al., 2002). In temperate regions it can be especially important; Svobodová et al. (2014b) showed that distributions of European corn borer (*Ostrinia nubilalis*), European grape vine moth (*Lobesia botrana*) and codling moth (*Cydia pomonella*) in southern Moravia and northern Austria are particularly determined by air temperature. In tropical regions, precipitation can be important in determining pest pressures, for example for pests of coffee in Zimbabwe (Kutywayo et al., 2013). Humidity is a primary determinant for the intensity of fungal pest outbreaks, with warmer and wetter conditions generally favourable for pests (Bebber, 2015; Sparks et al., 2011).

Pests colonise new areas as a result of both anthropogenic and natural means. As human societies become more interconnected, this anthropogenic dissemination of pests will likely increase (Bebber et al., 2013). For example, late blight has repeatedly been introduced by humans into non-native regions (Anderson et al., 2004).

Whilst the initial spread of pests is often the result of human intervention, climatic conditions are likely to determine whether or not a species can persist in a new area. Warming is predicted to result in an increasing latitudinal range of pests through the increasing availability of host crops, as well as through the direct effects on the pests themselves (Bebber et al., 2013; Anderson et al., 2004). Greater winter survival is often an important factor behind pests (especially insects) being able to survive at higher latitudes and thus extending their range (Bale et al., 2002). For pests where range expansion is limited by conditions for initial establishment, extreme conditions could make large shifts possible (Garrett et al., 2013). Bebber et al. (2013) calculate an average poleward shift of pests of $2.7 \pm 0.8$ km $yr^{-1}$ since 1960, although this is variable across pest taxonomic groups. Higher-latitude countries are more able to detect pest movement due to greater observational capacity (Bebber et al., 2014b). Therefore, in the absence of a climate-induced signal, we would expect a trend towards the equator (opposite of the observed poleward-trend).

There are two broad ways organisms can adapt to a changing climate: phenotypic plasticity and genetic adaptation. Phenotypic plasticity describes the ability of an organism to respond to environmental changes by changing its behaviour. In the context of climate change, this often manifests itself as range shifts (e.g. Bebber et al., 2013) and changes in seasonal cycles (e.g. for late blight - Gregory et al., 2009). Genetic adaptation (or evolution) describes adaptation through genetic changes by means of natural selection to better suit environmental conditions.

Crop pathogens have shown the potential to respond to host resistance (Gregory et al., 2009), and evolve resistance to pesticides (Maino et al., 2018) with short generation times and large populations aiding this process (Maino et al., 2018; Cable et al., 2017); pathogen evolution may be more rapid when large pathogen populations are present, so increased over-wintering and over-summering will also likely contribute as they lead to larger populations (Garrett et al., 2006). With respect to a changing climate, rapid evolution of genotypes more suited to warmer conditions has been reported for diseases in the past (e.g. for stripe rust, caused by *Puccinia striiformis*; Milus et al., 2006). The fungal pathogen *Batrachochytrium dendrobatidis* has shown evolutionary potential with different isolates showing adaptation to different environmental conditions (Fisher et al., 2009). Evolution could also accelerate with increased $CO_2$ due to enhanced host fecundity (Chakraborty and Datta, 2003). Warming has been linked with increasing rates of adaptation in bacteria (Davis et al., 2005). Another example of rapid pest evolution is provided by the redlegged earth mite *Halotydeus destructor*, where recent range expansions are outside of previous temperature limits (Macfadyen et al., 2018).

New clonal varieties of late blight are emerging (Gevens and Seidl, 2015; McDonald and Linde, 2002), with one clonal lineage having previously dominated the majority of blight populations (Goodwin et al., 1994). Different varieties have been shown to respond differently to temperature with respect to sporangial germination (e.g. Mizubuti and Fry, 1998; Danies et al., 2013) and lesion growth rate (Seidl Johnson et al., 2015). Mizubuti and Fry (1998) reported significant differences among lineages (US-1, US-7 and US-8) for sporangial germination at 15, 20, and 25°C, with this varying across lineages by approximately 35% at 15°C and 50% at 20°C. Sporulation rate was reported to vary by approximately 33% across US-22, US-23, and US-24 clonal lineages at 20°C (Seidl Johnson et al., 2015). Optimal temperatures for blight lesion growth rates were also found to vary on tomato leaves (tomato being closely related to potato) from 15.8 to 21.5°C. Indirect germination was faster for US-24 than that of three other clonal lineages studied by Danies et al. (2013); for example, after 30 minutes at 15°C, 13% of US-24 sporangia had released zoospores compared with 4% of US-23 sporangia. These studies collectively provide a body of evidence for a fitness advantage of certain genotypes at different temperatures. This results in adaptive advantages of certain varieties of blight in different areas – in other words, blight is better able to thrive in different temperature conditions and this results in some varieties being more virulent than others in different conditions. These studies do not usually feature changes to humidity, which is also important for blight populations (Bebber, 2015).

#### 1.2.2.2 The impacts of biotic stresses on crops

Global average yield losses to pests are 40% for potato, 28% for wheat and 37% for rice (Oerke, 2006). Losses tend to be higher in Africa and Asia compared to North America and Europe, although this is crop- and region-dependent – potatoes tend to follow this general pattern, however, with most high production countries having slightly lower losses due to better management of the crop (Oerke, 2006). Diseases account for much of these losses, with fungal diseases considered especially challenging to global food security and predicted to become even more so with climate change (Bebber and Gurr, 2015; Fisher et al., 2012). Pests are also increasingly saturating host crops across the world (Bebber et al., 2014a).

Whilst pests are expected to continue to spread geographically (see Bebber et al., 2013), it is uncertain how much of an impact climate change will have on the magnitude of pest attacks and therefore their impacts on crops. This is due to the huge diversity of crop-pest interactions with climate as well as a lack of data (Donatelli et al., 2017). Specific regional examples exist of predicted changes to pest distributions and in some cases yield changes, but global studies are lacking. For example, Van der Waals et al. (2013) projected the development rate of pests and pathogens of potato to increase through to 2050 in South Africa, meaning that pest pressures are predicted to increase.

Butterworth et al. (2010) looked at the influence of climate change on the yield of different cultivars of fungicide-treated oilseed rape when impacted by Phoma stem canker (*Leptosphaeria maculans*) using the STICS (Simulateur mulTIdisciplinaire pour les Cultures Standard) model and a weather-based regression model predicting pest severity. *L. maculans* is the most important disease of oilseed rape in England. Despite *L. maculans* being predicted to move north with warming temperatures, epidemics are not expected to significantly reduce future yields. Southern England, by contrast, is expected to see substantially reduced yields unless *L. maculans* epidemics are mitigated. Here, warming leads to yield losses from increased pest outbreaks, outweighing yield gains due to the increase in photosynthetic activity that results from increasing levels of $CO_2$. Some resistance genes are temperature-dependent, so it is important to identify crop varieties that will be effective under future climatic conditions in the UK. The differences in the results for Scotland and England demonstrate the complexity of the interactions between crop growth, climate and disease severity, and hence there is a need to model all of these things in concert.

Ideally, this requires data on all three aspects of pests, crops and climate change.

Whilst modelling provides the majority of information on the future influence of pests on crops (see Section 1.3.2.4), other studies use different methods to measure potential impacts. Schaap et al. (2011) used a semi-quantitative approach to measure the impact of changing climate extremes on impacts. Their framework utilises expert knowledge to define thresholds of climate that result in increased climate impacts, including pest damage. From the changing frequencies of these "climate factors", resulting economic losses are estimated. For example, as a result of sustained wet weather (defined as a period of at least 21 days with more than 0.5 mm precipitation on 75% of the days) being predicted to become less frequent, yield losses from *Phytophthora infestans* may fall. Increasingly warm and wet weather is predicted to result in an increase in *Pectobacterium carotovorum* incidence. Some studies use proxy data to predict changing pest impacts on agricultural systems. Warming is projected to increase pesticide costs and use in the United States by early and late 21st century, and therefore pest pressures are predicted to increase with warming (Ziska, 2014; Chen and McCarl, 2001).

In order to provide more precise estimates of the influence of climate on pests – and the subsequent impacts on yields – modelling is often our best option. In the majority of crop models, however, the impacts of pests on yield are not accounted for - Rivington and Koo (2011) found that c. 70% of crop models do not include the simulation of pest damage. See Section 1.3.2.4 for more details of pest modelling within crop modelling.

## 1.3 Crop-climate modelling

### 1.3.1 Climate models

This section introduces climate modelling and how climate model output is prepared for use with crop models, as used in all the analyses of this thesis. Historical (or baseline) climate data are used in all analysis chapters in this thesis. Future climate data are used in Chapters 6 and 7.

Climate models, such as Regional or Global Climate Models (RCMs or GCMs), can be used as a source of climate information for crop models. Given that our climate is changing, it is not reliable to extrapolate current trends to predict climate change. Empirical models do not allow the complex interactions of systems to be represented which are necessary for such predictions – numerical (process-based) simulation models, however, allow surrogates of the climate system to be tested and the uncertainty associated with these predictions to be measured (Lobell and Burke, 2010).

Subsections that follow describe firstly climate model structure (Section 1.3.1.1), model forcing (Section 1.3.1.2), model ensembles (Section 1.3.1.3) and lastly downscaling and bias correction for use in conjunction with crop models (Section 1.3.1.4). For more details on crop modelling, see Section 1.3.2.

#### 1.3.1.1 Climate model structure

Climate models vary in complexity. Simple energy-balance and statistical models approximate the trajectory of global mean temperature or radiative forcings (e.g. Aldrin et al., 2012). GCMs partition the layers of the atmosphere, the surface of the earth and the ocean into grid boxes. They describe how climatic variables change in each grid box over time. Climate simulations often begin at pre-industrial times and can simulate climate until the end of the 21st century and beyond.

As scientific understanding of the climate improves we can simulate a greater number of processes mechanistically. However, limitations in the resolution of GCMs (due to computational limitations) are important in the sense that local climates cannot always be represented accurately. Many processes in the climate system take place at scales finer than are represented in GCMs. Approximations of these processes are then necessary, which leads to much of the uncertainty associated with GCMs. Examples of these processes are cloud formation and precipitation. Precipitation results from small-scale convective processes that are increasingly being simulated explicitly rather than parameterised empirically (Fosser et al., 2017). Continental-scale temperatures are treated with higher reliability than those of smaller scales due to averaging over areas reducing internal variability and increasing agreement between models (Räisänen, 2007).

In the fifth assessment report of the IPCC, GCMs operate at a typical spatial scale of around 200 $km^2$, which is too coarse a spatial scale to explicitly represent cloud formation (Stocker et al., 2013). Such GCMs still need to represent the large-scale effects of clouds, so parameterisations are used in an attempt to answer questions such as what proportion of the box is covered by cloud, as well as the effect of this cloud on temperature and precipitation. These parametrisations all have associated levels of uncertainty. Different GCMs have been developed that vary in scale, as well as which processes are explicitly represented (e.g. the carbon cycle). More significant differences between models arise when models approximate processes, such as cloud formation (Stocker et al., 2013).

#### 1.3.1.2 Climate model forcing

External forcings can be used to simulate the impacts of various factors on the climate system. Some of these forcings are "natural" as opposed to anthropogenic. Volcanic eruptions are an example of a natural forcing; these result in aerosols reaching the stratosphere, which shield the earth from solar radiation and hence have a temporary cooling effect (Robock, 2013). Fischer et al. (2014) showed that models are surprisingly consistent in their response to forcings, with internal model variability providing more uncertainty.

Increasing concentrations of greenhouse gases are an important anthropogenic external forcing. Such anthropogenic forcing is included in GCMs using scenarios of socio-economic and technological changes (Stocker et al., 2013; Moss et al., 2010), called Representative Concentration Pathways (RCPs). Climate model simulations are usually referred to as "projections" rather than "predictions" as they are contingent on these scenarios (Lobell and Burke, 2010). Greenhouse gases force a GCM system into trends, such as increasing temperatures with rising $CO_2$.

#### 1.3.1.3 Climate model ensembles

Within a single model, "perturbed-physics experiments" are used to explore within-model uncertainty across parameter space (as in Stainforth et al., 2005). An ensemble of different GCMs can be used to develop a sense of structural uncertainty. It is the differences between models in terms of what processes are included and how they are represented that makes analysing groups of models for climate change projection so essential. The cause of the spread of model results within ensembles will vary, but is often down to differences in model resolution and model formulation, or differences in climatic noise, which can be quantified by looking at within-model ensembles of different initial conditions.

Ensembles can quantify parameter uncertainty using one model (Challinor et al., 2009c) and model structural uncertainty using many models (as demonstrated by Rosenzweig et al., 2013). Climate ensembles refer to directly comparable simulations as they use the same protocols to carry out simulations. These simulations are generated using some or all of multiple climate projections, multiple climate models and multiple configurations of the models.

The Climate Model Intercomparison Project 5 (CMIP5; Taylor et al., 2012) is an example of such a climate model ensemble. It is a coordinated climate modelling framework designed to provide accurate climate modelling forecasts – a climate multi-model ensemble. It allows us to examine model differences in poorly understood feedbacks - in particular, the carbon cycle and cloud formation. It also helps to determine why similarly-forced models produce different responses. The emissions scenarios outlined in Moss et al. (2010) allow the assessment of different policy actions on future climate scenarios using an ensemble of model simulations.

The models selected in ensembles are themselves important (assuming access to all models is not available); the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) data of 5 bias-corrected GCMs (Hempel et al., 2013) represent a globally-coherent data set that is a reasonable subset of the CMIP5 ensemble, as demonstrated by McSweeney and Jones (2016). They found that many more models would have to be included in an ensemble to offer significant improvement in terms of representing the CMIP5 ensemble. These data are used in the climate change analyses of Chapters 6 and 7.

#### 1.3.1.4 Climate model output processing for crop modelling

There are issues with using GCM output as crop model input, whether for historical or future climates. The spatial scale of grid cells in climate models is typically larger than that of crop models, leading to a need for the downscaling of the climate output. Regional dynamical models can be nested into global models, or statistical downscaling can be used. For both this dynamical and statistical downscaling, spatial detail is added to model output, but it is often essentially interpolation (Baron et al., 2005). Whilst dynamical downscaling has been shown to reproduce small-scale extreme events more accurately, the uncertainty associated with the GCM results is also inherently associated with the regional output (Lobell and Burke, 2010). In order to characterise this uncertainty, downscaling from ensembles of GCMs is possible (Jones and Thornton, 2013), as well as comparisons between different downscaling methods. Additional sources of uncertainty in such climate projections (aside from parameter and structural uncertainty) come from emission uncertainty and natural variability in weather processes (Lobell and Burke, 2010).

The reliability and realism of climate outputs also needs to be considered. Different GCMs can predict different absolute changes in temperature, as well as different responses to increasing anthropogenic forcing. There are various ways of dealing with these biases. The raw GCM daily output can be used for impacts studies. This is simple but can be subject to the aforementioned biases; parameter calibration in crop models can help to deal with both this climate model bias and other factors such as the yield gap between potential and actual yields (Challinor et al., 2005b). The aforementioned dynamical downscaling may be used to help correct bias, although it does not completely eliminate bias as regional climate model boundary conditions are biased. Weather generators typically involve fitting an empirical model to daily observations. Monthly mean data from GCMs are then used in conjunction with the empirical model to produce future daily weather forecasts. This approach assumes that the empirical model produces the correct variability ranges (Hawkins et al., 2013b). The “Delta” method involves adding the monthly mean change in climate from GCMs to daily observations (not using a weather generator).

Ho et al. (2012) suggest output correction for climate change projections fall into two categories: “bias correction” and “change factor”. Bias correction adjusts the projected GCM output using the differences in the mean and variability between output and observations. Change factor uses the output baseline values subtracted from future simulated values, which are added to the present day observed values. Bias correction assumes model discrepancy stays constant in time; change factor assumes that the change in distribution from the past to future model simulations is the same as the distribution change from the past to future observations. These two methods can lead to significant differences in terms of climate output and therefore the climate impacts results. This is an additional source of uncertainty in climate and impacts modelling. For all of these methods, the choice of GCM is important. How to downscale the GCM data, and whether the variability of the data (as well as the mean) should also be calibrated, are important questions (Hawkins et al., 2013b).

In order to effectively deal with these biases (and to account for uncertainty), a range of models are likely to be of use for bettering our understanding of the processes involved in simulating crop yields, or for helping us quantify uncertainty (see Section 1.3.1.3).

Reanalysis data sets use observational and GCM output data to create data sets that can be used as baseline period crop model inputs. As opposed to other climate data sets, particular efforts are made to bias-correct agricultural areas and reproduce the climate variables that crops are known to respond to. These include biases in mean growing season precipitation and temperature and the frequency and sequence of rainfall events. Examples of such data sets are the Princeton data (Sheffield et al., 2006) and the AgMERRA data (Ruane et al., 2015), which are described in Chapter 3. Ruane et al. (2015) compared different reanalysis data sets to find that AgMERRA performs comparably well and as such is well suited for global climate impacts studies.

### 1.3.2 Crop models

This section describes the structure and use of crop models. The GLAM-crop model is used throughout this thesis (Chapters 2 to 6). Crop models are tools that are used to assess the impacts of environment and management factors on development, growth and yield. Crop management includes choice of crop cultivar, sowing date, fertiliser and irrigation levels. Environmental factors include temperature, day length, solar radiation, precipitation and biotic stresses.

Section 1.3.2.1 discusses different types of crop models, including issues of spatial scale and appropriate complexity. Section 1.3.2.2 details the uses and differences associated with crop modelling across different spatial domains. Section 1.3.2.3 then looks at the fundamentals of how process-based crop models simulate growth and development. Section 1.3.2.4 discusses modelling of biotic stresses in crop model frameworks. Section 1.3.2.5 covers different applications of crop models, including the impacts of climate change, adaptation and use within broader modelling ensemble studies.

#### 1.3.2.1 Crop modelling approaches and scales

Crop models vary a great deal in terms of the processes they aim to simulate and the spatial scales at which they operate. These models primarily aim to simulate crop growth and development in response to climate, with adaptation to climate change also commonly simulated. Methods range from empirical models to process-based numerical simulations. Process-based models themselves vary a great deal, from relative simplicity (such as GLAM, Challinor et al., 2004) to more detailed models (e.g. DSSAT, Jones et al., 2003). There is often overlap between empirical and process-based models, given that processes are sometimes described empirically within the latter (Challinor et al., 2009a).

Empirical (or statistical) crop models (e.g. Schlenker and Lobell, 2010; Lobell et al., 2008) have the advantage of being applicable over large spatial scales and can represent crop yields in response to both biotic and abiotic realised conditions (Estes and Beukes, 2013). The validity of such models when using data outside the range from which they were fitted can be questionable – both in terms of time and space. Statistical models run the risk of overtuning if using limited data and should not be used to make predictions outside of the explanatory data range of historical data, without assumptions concerning the linearity of crop responses outside of this range (Lobell et al., 2008). This most often arises when looking at the impacts of climate projections on crop yield (Challinor et al., 2009a).

Process-based simulations (e.g. Brisson et al., 1998; Challinor et al., 2004) examine the response of crop yield to predominately abiotic factors. This sometimes involves tuning to take into account a yield gap, which represents the gap between potential and actual yields. This gap is made up of the impacts of pests, diseases and non-optimal management (Jagtap and Jones, 2002; Challinor et al., 2004). Other models only simulate potential yields (e.g. see Hijmans, 2003).

In a report based on data gathered using an online questionnaire (Rivington and Koo, 2011), 57% of crop models were described as process-based whilst 14% were empirical. Empirical models were found by Estes and Beukes (2013) to project larger yield losses than process-based models with climate change. The majority of these differences were attributed to the water use efficiency gains simulated by process-based models under conditions of elevated $CO_2$. A meta-analysis looked at the differences in results between process-based and empirical models (Challinor et al., 2014b), and concluded that near-term (to 2020) yield losses were greater using empirical models, although when looking at longer-term changes there was broad agreement between the two. Other studies confirm that statistical and process-based studies are likely best used for different purposes, crops and regions - e.g. Watson et al. (2015) showed that a process-based model (GLAM - Challinor et al., 2004) was more resilient to precipitation errors than an empirical model (Hawkins et al., 2013a). Errors in simulating temperature relationships were more of a problem for the process-based model, however.

Large-area crop modelling seeks to combine the advantages of process-based models with those of empirical models. That is, to simulate crop yields under changing climates over large areas with a relatively low input data requirement (e.g. GLAM; Challinor et al., 2003, 2004, and as used throughout this thesis). Models should be complex enough to capture the response of the system to the environment but not so complex as to include parameters not directly estimable from available data. The appropriate degree of complexity for these models is largely determined by both the spatial scale at which the weather-crop relationship is apparent and the output variable of interest. The larger the spatial scale, the more aggregation of environmental variables will be needed to model crop yield (Challinor et al., 2009a). Challinor et al. (2003) set out a framework for a combined seasonal weather and crop forecasting system, using the example of groundnut yield in India. The relationships between crop yield and climate variables were tested at different spatial scales. The scale of GCMs was found to be appropriate for crop modelling (around 100-200 $km^2$).

All crop models are prone to errors and uncertainties associated with climate model output. Some process-based crop models (for example CROPGRO - Boote et al., 1998) use a more detailed mechanistic approach, often at smaller spatial scales; a detailed picture of the biophysical processes associated with climate change can hence be built up for a specific region, but there is a danger of overtuning if the modelling framework is overly complex. Yield can, for example, be dependent on many variables such as soil, crop type and management practises. Such models can be useful for informing the adaptation of the local management of farms but are of limited use across large spatial domains (and possibly for teasing out general patterns) due to their inherent specificity. They may also rely on the downscaling of climate data, which adds to analysis uncertainty. See Section 1.3.2.2 for more on crop modelling across large and small domains.

The spatial resolution of the model determines the spatial scale of processes it can represent. Only processes that function immediately below the output variable of interest (usually yield in the case of crop models) should be simulated, as only these processes are of immediate relevance in producing output (Sinclair and Seligman, 2000). This also helps avoid overparameterisation, which can lead to large errors and increase the risk of overtuning a model to one environment. To help avoid overtuning, parameters should whenever possible be based on observations, i.e. be empirically testable (or semi-empirically, for example a water stress index that is empirically related to yield). With a lack of observed data, models risk reproducing yield without correctly representing the processes involved (through many unconstrained parameters). The parameters obtained for one climate should not be used for another; a climate could change temporally with climate change or spatially when looking at another geographic area (Challinor et al., 2004), and varieties may differ across regions.

#### 1.3.2.2 Spatial domain of crop models: from field-scale to global

Crop models are used across a variety of spatial extents, ranging from the farm level to global simulations (Ewert et al., 2011). This section will introduce the uses and challenges of crop modelling across these different scales.

Global studies are defined as those with full global coverage (e.g. Chapter 6 of this thesis), and regional studies as those with limited geographic extent, such as the province or county scale (e.g. Chapter 3 of this thesis; Challinor et al., 2014a). Local studies are typically defined as being site-specific or at the field scale. It is common for crop models to be used at a different spatial scale to that which they have been designed and calibrated for, however (Ramirez-Villegas et al., 2015). See Section 1.3.2.1 for more on the appropriate spatial scales of crop models.

Global studies typically use globally-consistent input data and assumptions concerning parameter configurations in order to provide assessments of uncertainty and crop model comparisons (e.g. Müller et al., 2017; Deryng et al., 2014; Osborne et al., 2013). They do not usually involve model parameter optimisation across different regions in any great detail. Such calibration of parameters for global studies is computationally limited, the data are often lacking that enable calibration across regions and confident evaluation (Müller et al., 2017; van Bussel, 2011), and this kind of optimisation may be undesirable when trying to achieve a consistent model set up to evaluate models across a large range of environments. Management and phenology parameter information is lacking across larger scales, and evidence suggests these can improve model skill (Adam et al., 2011; van Bussel et al., 2011).

Global gridded crop models provide comprehensive coverage, although there are usually large challenges for calibration and quality control of inputs (Ruane et al., 2017). Müller et al. (2017) propose using the best model for each region/crop as a benchmark to assess how well models are performing, given the lack of quality observational data in some cases. Other studies assess how particular model components such as heat stress can impact results across different models at the global scale (Mistry et al., 2017). It is important to recognise that the appropriate spatial scale to model some processes is larger than others - for example, modelling the impacts of El Niño lends itself to larger scale modelling (Iizumi et al., 2014).

Regional studies use detailed analyses with more data and specific knowledge to better inform policy decisions (e.g. Lv et al., 2013). When regional parameter information is limited, parameters can be optimised to represent crops in specific environments. Examples include optimising parameters that adjust mean yield levels across a region (Challinor et al., 2004) or optimising phenology parameters to simulate realistic crop durations (Nicklin, 2013). Regional impacts models provide assessments of the impacts of climate change or evaluation of model skill to see if accurate representation of the regional inter-annual variability in observed yields is feasible.

It is difficult to evaluate model performance using national scale yield data alone (van Bussel, 2011), although this is often done in global studies as little else is available, especially for potatoes (Raymundo et al., 2017b). For regional studies, more detailed information is likely to be available to researchers. Certain areas show that there are drivers of yield other than the direct impacts of weather variables (such as technology and management changes and biotic stresses), resulting in an improved understanding of model performance in regional studies. In contrast, variability in year-to-year data can average out across large areas (van Bussel, 2011), leading to lower correlations with weather variables and hence poorer model results. It is often difficult to ascertain the exact cause of poor model skill in global studies (Challinor et al., 2018).

Aggregation of data inputs is often necessary to model at global scales (Ewert et al., 2011). These inputs include weather, soil, sowing and yield data. In some cases, aggregation has been shown to have a limited impact on results at large scales (van Bussel et al., 2011) but other studies show its importance in impacting results – soil aggregation uncertainty can be significant relative to other sources of data uncertainty, for example (Folberth et al., 2016).

Ruane et al. (2017) provide a summary of strengths and weaknesses of crop modelling at different extents. The most common type of site-based modelling can effectively characterise specific agricultural systems but may fail to cover the diversity seen across large areas. Global gridded studies can provide broad assessments but lose regional detail. The combined use of regional and global studies can help inform both approaches – regional studies to help improve global simulations in specific areas, and global results to put regional studies into a broader context. An example of the latter could include an assessment of how important a region is for broader food security, both now and with climate change. Figure 1.2 summarises strengths and weaknesses of these crop modelling domains.

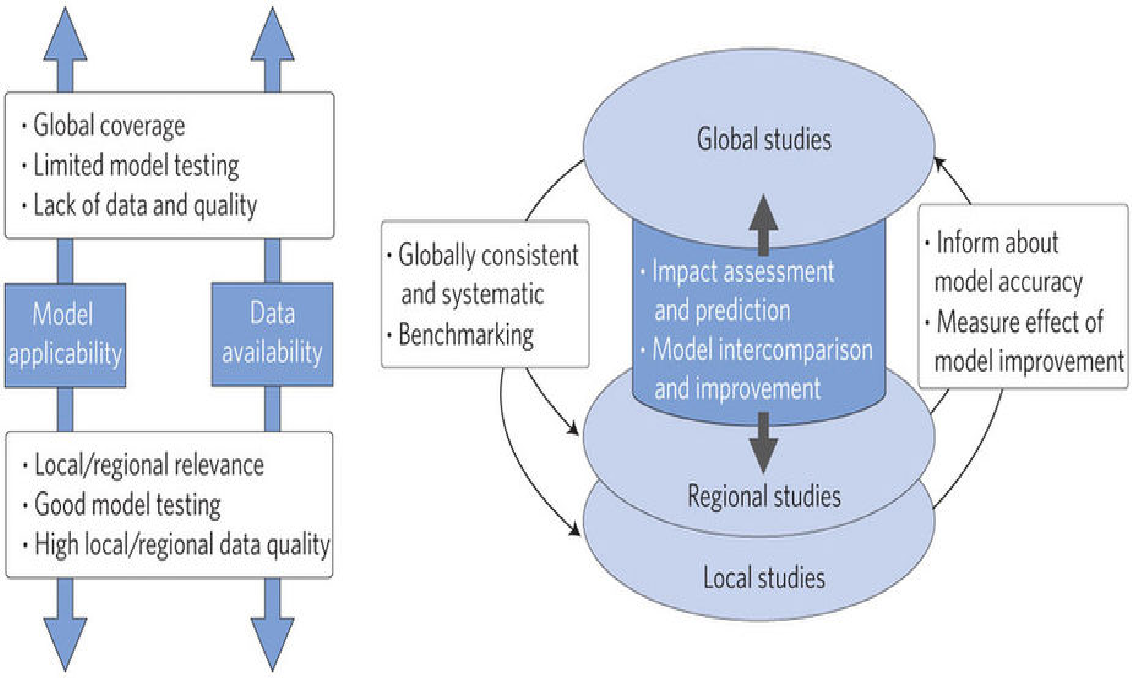



**Figure 1.2:** Proposed coordination of modelling improvements using different spatial modelling domains, including strengths and weaknesses of local to global studies. Taken from Challinor et al. (2014a).

Integrated Assessment Models (IAMs) provide coordinated and comprehensive evaluation of key climate responses from local to global scales, featuring crop modelling as well as socio-economics (Ruane et al., 2017). They combine detailed site-based studies with gridded global analysis. Baseline responses generated by gridded models can initially be compared against the corresponding site-based simulations to assess methodological uncertainty and calculate bias-correction factors. These studies are still not common in the climate impacts community, however.

To summarise, global studies can produce a single consistent evaluation, but the data are often lacking that would enable us to see if there are losses of information from the regional to global scale. Such losses could include management information, parameter knowledge and input data detail. There is a resulting danger that seemingly robust global simulations will lack regional skill, leading to misinformation at the policy level. In-depth analyses have rarely been performed that investigate these differences (Challinor et al., 2014a). Zampieri et al. (2017) provide an example of a regional and global comparison, but focus on yield anomalies rather than assessing model skill. Chapter 5 of this thesis compares the model skill of the regional and global simulations that are outlined in Chapters 3 and 4 respectively.

#### 1.3.2.3 Modelling crop growth and development

Genetic, environmental and management factors drive crop growth and development. Plant growth can be described as the increase of biomass that results from the difference between the gain and loss of environmental resources (Hay and Porter, 2006). Growth refers to the increase of biomass of the plant, which ultimately comes from photosynthesis. This process uses solar radiation to convert $CO_2$ and water into carbohydrates and oxygen. There are three photosynthetic pathways, C3 and C4 and CAM. Most crops (including potato) use the C3 pathway, which is predicted to lead to more $CO_2$ fertilisation than the other pathways as $CO_2$ is less saturating in baseline conditions (Leakey et al., 2009). Crop growth can be limited by water and nutrient availability as well as by temperature. When water is limiting, transpiration and photosynthesis are reduced, resulting in lower biomass accumulation.

Temperature is the environmental variable most important in determining crop development (also known as phenology), driving the crop from a vegetative to a reproductive state (Chujo, 1966). Temperature also has an effect on respiration rates and the translocation of assimilates, but less so on photosynthesis, even at light saturation (Grace, 1989).

Process-based crop models generally aim to quantify environmental effects on plant physiological processes, and need to account for both growth and development, as well as partitioning to yield. Rates measure how a quantity changes over time and are crucial in models. Integrating a rate over time yields the quantity amassed during the time period elapsed. For example, thermal time (or degree days) is used to assess the rate of crop development. This is a more nuanced alternative to simply using a number of days in each developmental stage. The optimal rate of crop development is associated with a certain temperature, with no development above or below crop-specific limits.

Equation 1.1 describes the basic elements of a crop model simulating the yield $Y$ over the thermal time when water and nutrients are non-limiting from sowing $s$ to harvest $h$, as described in Hay and Porter (2006):

$$Y = \int_{Tt=s}^{Tt=h} Q\, RUE\, f(L)\, g(W)\, \mathrm{d}t \tag{1.1}$$

where Q is the amount of photosynthetically active radiation incident on the crop, RUE is the radiation use efficiency, $f(L)$ is a function of the leaf area index of the crop (as a leaf canopy is needed to intercept and absorb radiation) and $g(W)$ is the harvested fraction of the total dry matter produced by the plant. More layers of detail can be added to this basic model, such as substituting RUE with mathematical descriptions of photosynthesis and respiration, the constraints of production caused by a lack of nutrients and water, or the impacts of pests, diseases and competing plants. Evapotranspiration can be modelled simplistically using empirical relationships (Priestley and Taylor, 1972) or using more data-intensive methods (Allen et al., 1998). Chapter 2 gives an example of a description of a process-based model of medium complexity – GLAM-potato.

#### 1.3.2.4 Modelling pests and diseases in crop-climate modelling

Traditionally, the growth and development of crops and pests have been modelled in two distinct scientific communities. Whilst much modelling knowledge and expertise is now available, linking these two fields usually leads to over-simplifications of one or both areas (Donatelli et al., 2017). It is important to define clear research objectives in any modelling study and for different objectives different modelling approaches will be prioritised and desirable, leading to further potential simplifications.

A common way that pests are modelled is to simulate their distribution based on climate variables, often predicting future distributions from extrapolations of current relationships (Svobodová et al., 2014a; Kocmánková et al., 2011; Herrera Campo et al., 2011). Variants on statistical distribution models include those making use of remote sensing (Mahlein et al., 2012) and those including the simulation of pest phenology (Trnka et al., 2007). Pest severity can also be linked to climate using statistical models (Sparks et al., 2011; Butterworth et al., 2010 – see the late blight modelling in Chapter 6).

Kutywayo et al. (2013) examine species distribution models of the African coffee white stem borer (*Monchamus leuconotus*) in Zimbabwe to quantify their distribution and how climate change will impact this distribution; the coffee white stem borer is the most serious coffee pest in Zimbabwe. Models predict that the borer will become more common by 2080, although one region shows a predicted decline. Precipitation-related variables are shown to be the most important predictors of borer distribution.

Extrapolations of pest distributions and impacts based on current climates could be of little use as observed distributions of pests say little about future potential distributions under novel climatic conditions (Conn et al., 2015). Warming could lead to a tipping point at a temperature threshold for a pest species, changing the nature of the temperature-pest relationship (Lenton, 2013; Salis et al., 2016). These extrapolations also fail to account for pest evolution in response to the changing climate.

Knape and de Valpine (2011) advise caution when using climate variables to predict population dynamics and structure. They suggest that the effects of variation in climate on population dynamics are complex. As a result, specific knowledge of a system is needed to identify the environmental variables important in modelling dynamics. Without this knowledge it becomes easy to statistically over-fit models of population structure to weather variables. Hence, they recommend limiting analysis of the impact of climate on populations to just a few judiciously-chosen variables. For example, Svobodová et al. (2014b) showed that distributions of European corn borer (*Ostrinia nubilalis*), European grape vine moth (*Lobesia botrana*) and codling moth (*Cydia pomonella*) in southern Moravia and northern Austria are particularly determined by air temperature. Sparks et al. (2011) relate late blight intensity to temperature and relative humidity.

Another common method used in pest modelling communities is that of decision support systems that assess the impacts of climate change on practical applications, for example the frequency of pesticide applications (Sparks et al., 2011, 2014). Some studies go further and use assessments of pest intensity to estimate yield losses (Dillehay et al., 2005).

Less commonly, pests are simulated as part of a crop-climate modelling framework (Rivington and Koo, 2011). Reasons for the scarcity of pest damage functions in crop models include the inherent complexity of processes and a lack of data with which to evaluate modelling efforts (Donatelli et al., 2017). These complexities include linking pest damage to pest abundance, multiple pest species dynamics and pest-crop interactions with climate (Donatelli et al., 2017).

Crop pests have been included in crop models using a variety of techniques, however. These are often dependent on the spatial scale of the analysis. Some use a data-intensive, small-scale, process-based framework to simulate the impact of pests upon the organs of the plant that are in direct contact with the pest (for example Kropff et al., 1995). Yield then reduces as a result of damage to, for example, the leaf area. Others, like Challinor et al. (2004), scale the yield down via a yield gap parameter that not only accounts for the impact of pests but also non-optimal management. This approach is more suited to larger scale modelling as it does not rely on extensive pest input data. Others do not attempt to include the impacts of pests on crop yield, as in den Hoof et al. (2011). In some cases, the models make the decision not to include the impacts of pests as they are deemed insignificant, perhaps given local pesticide usage (Brisson et al., 2003).

Kropff et al. (1995) describe detailed methods to input pest damage in crop models using "coupling points". Coupling points in pest-crop modelling can be at the level of resource capture (light, nutrients or water), the process level (photosynthesis, respiration or translocation) or at the state variable level (biomass, leaf area etc). Damage mechanisms include resource stealing, stand reduction (killing plants in the canopy) and assimilate sapping. Damage levels can be hard to define for certain pests as they can damage the crop in multiple ways simultaneously – late blight, for example, damages potato leaves, stems and tubers.

The simulation of pest impacts in coupled pest-crop models also requires data on the various mechanisms of pest damage, for example the quantification of the relationship between leaf blast severity and photosynthesis levels (Bastiaans, 1991). In CERES-rice, for example, 20 coupling points were used to implement these damage mechanisms, including leaf and assimilate consumption (Pinnschmidt et al., 1995). A module was developed in the model to read in pest data and compute the damage impacts at the coupling points. Such approaches can be simplified by defining guilds of pest damage, thus accounting for the diversity of pests within a model (Rabbinge and Rijsdijk, 1982). These remain data-intensive processes, however. In InfoCrop (Aggarwal et al., 2006), pest population dynamics are not simulated; pest incidence has to be provided directly as input data.

The most advanced pest models used to estimate pest damage on crops are those that simulate pest population dynamics and hence the severity of pests within a region explicitly (e.g. Wiman et al., 2014). Predicting these dynamics is complicated, however. Such information on pest dynamics is derived from observed data, or parametrised using expert knowledge. Single species are most often simulated as opposed to multiple species (e.g. Hegazi et al., 2015); such interactions can quickly become overly-complex for the likely appropriate level of complexity of the model.

Regardless of the method used to model the impacts of pest pressures, data limitations are often a problem (Donatelli et al., 2017), making large scale analyses hard to evaluate. Some studies use surrogates for pest pressures to help get around this problem. Garrett et al. (2013) estimate a conduciveness to pest attack as a result of climate inputs. Chen and McCarl (2001) relate the cost of pesticides to weather variables as a surrogate for changing pest pressures in the United States for different crops. Ziska (2014) similarly relate minimum temperature data to pesticides to assess climate change impacts of pests on soybean in the mid-western United States. Chapter 7 of this thesis features a global analysis relating pesticide use to climate change. In general, small-scale analyses for specific crop-pest interactions are feasible if data are available (e.g. Butterworth et al., 2010), but global scale analyses on broader pest-crop systems are lacking.

Further complexities and challenges to the crop-pest modelling community include accounting for uncertainty from climate change projections and the impacts of agricultural adaptation strategies (Newbery et al., 2016) – Gouache et al. (2013) providing one of few examples where climate model uncertainty is taken into account. The use of model intercomparison groups such as the Pest and Disease Modelling Intercomparison Project (PeDiMIP - part of AgMIP) are in their infancy but may help with the sharing of expertise and data across modelling disciplines (Donatelli et al., 2017), potentially leading to improved global pest impact assessments.

#### 1.3.2.5 Crop model applications

Impacts on mean yields have traditionally been the focus of climate impacts studies (e.g. see Challinor et al., 2014b). Increasingly, however, studies aim to quantify the impacts of inter-annual variability and extremes on food systems (Ewert et al., 2015; Chavez et al., 2015). Such studies often focus on stresses such as heat stress, flooding and droughts to crop yields as opposed to mean impacts such as duration changes (Lesk et al., 2016; Lobell et al., 2014; Deryng et al., 2014; Challinor and Wheeler, 2008; Challinor et al., 2005a). The methods used to assess extreme impacts are often different to those used in more traditional climate impacts studies. These include the use of agroclimatic indices (Trnka et al., 2011) and machine learning techniques (Chavez et al., 2015). Indices have the advantage of requiring fewer assumptions and data than analogous modelling studies, however they can be of limited use when extrapolating results for future climates (Challinor, 2011) and are usually not used to calculate yields.

Challinor et al. (2018) suggest other improvements for the targeted use of crop models, including the use of more diverse modelling approaches and outputs, better use of stakeholder knowledge for framing of analyses and greater clarity of assumptions used in studies. It is also important to recognise the improvements still needed for individual crop models (Müller et al., 2017) – Wang et al. (2017), for example, show that improving temperature response functions increases model skill in wheat simulations.

Increasingly, studies take into account uncertainty in results (e.g. yield projections) using multiple models. Full quantification of uncertainty would require responses to future atmospheric and climatic conditions, the response of agriculture to these projections, and non-climatic drivers (Challinor et al., 2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP) is used for agricultural model intercomparison and climate change impacts, using inputs from multiple crop and economic modelling groups (Rosenzweig et al., 2013). Osborne et al. (2013) quantify the uncertainty in climate inputs using a 14 member ensemble of GCMs. Asseng et al. (2013) show that the uncertainty associated with crop models can be greater than that of downscaled climate model projections. Maiorano et al. (2017) found that crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles, resulting in fewer models being required in multi-model impact assessments.

Part of the uncertainty in future climate impacts is associated with the extent to which we can adapt to climate change. Crop models can be used to explore a range of adaptation scenarios to help us quantify this uncertainty. These range from studies assessing small in scope, incremental adaptations, such as changing planting dates and crop varieties (Shin et al., 2017), to more transformational adaptations, such as changing cropping systems (Rippke et al., 2016; Kates et al., 2012). Some studies go further by looking at the timing of important climate change impacts and adaptations rather than looking at impacts between fixed time slices (Challinor et al., 2016).

Most modelling studies feature only incremental adaptations (Challinor et al., 2014b) and there are a lack of adaptation options included in most modelling studies (Beveridge et al., 2018; Challinor et al., 2018). The benefits of adaptation are often overestimated, however, as studies do not account for technological changes in the baseline climate (Lobell, 2014). The third side of the Climate Smart coin (the others being production and adaptation) is mitigation to climate change, which is commonly not accounted for in crop modelling studies (Challinor et al., 2018). Typically, mitigation in crop production can be achieved through better soil management in cropping systems, reductions in fertiliser use and through preventing the loss of high carbon ecosystems in establishing new agricultural areas (Harvey et al., 2014).

Integrated Assessment Models (IAMs) aim to model not just abiotic climate impacts on yields but socio-economic scenarios and changes in land use (e.g. see Ruane et al., 2017). Representative Agricultural Pathways (RAPs) provide additional information that can be used for agricultural impact assessments, using plausible future biophysical and socio-economic conditions to carry out climate impact assessments for agriculture (Antle et al., 2017). Crop models are important tools within these modelling frameworks.

Regardless of the crop modelling application, past trends due to technological changes should be accounted for as models rarely simulate these factors directly (and we do not know if such trends will continue). There are numerous statistical techniques available to deal with technology trends, the most common of which is to detrend using the (often linear) relationship between observed yields and time. However, if outliers are present in the time series then the assumptions of ordinary least squares regression can be violated (Finger, 2013). In such cases, so-called robust regression techniques are statistically sounder (Finger, 2010; Claassen and Just, 2011; Ye et al., 2015).

## 1.4 Potato agriculture

Potato is the most important non-grain crop and 4th most important crop in terms of global production (FAO, 2016) – maize, wheat and rice have approximately double the production of potatoes globally. 2009 was "International Year of the Potato" (Lutaladio and Castaldi, 2009), resulting in the Food and Agriculture Organization (FAO) recommending potatoes as an important food security crop in the context of uncertainties in food supply, a growing population and an increasing demand for food. Many economically-developing areas with high populations (such as large areas of India and China) overlap with potato cultivation and rely on potatoes for an increasingly large proportion of their calories, meaning that there is potential for potatoes to help combat food poverty (Devaux et al., 2014).

Potatoes are an especially important source of food security and income in the developing world (Lutaladio and Castaldi, 2009). Potatoes are important for local food security in many developing regions as they are not globally traded as much as major cereal crops due to higher post-harvest losses, resulting in prices being determined primarily by local production costs (Oerke, 2006; Lutaladio and Castaldi, 2009). In addition, smallholders can increase household income from planting potatoes as they are also used as a cash crop in many regions, further alleviating food poverty (Devaux et al., 2014). Potato production in Asia has increased due to both increasing yields as well as more growing area (FAO, 2016). African countries have increased production primarily from increasing potato growing areas (FAO, 2016).

Potatoes are a nutrient-rich crop (Lutaladio and Castaldi, 2009). The potato yields more nutritious food more quickly on less land and in harsher climates than any other major crop, with high harvest index values meaning a very high fraction of dry matter goes to the tubers (Ivins and Bremner, 1965). Potatoes are a good source of vitamin C, B1, B3 and B6, as well as minerals such as potassium, phosphorus, iron and magnesium (Burlingame et al., 2009).

Potatoes are grown over a wide latitudinal range (Hijmans, 2001) across more than 100 countries (FAO, 2016) – see Figure 1.3 for maps of potato growing area and irrigation levels (Portmann et al., 2010). Temperature often limits potatoes to being grown at higher elevations in hotter countries, with it being a common lowland crop only in temperate areas – tuber growth is inhibited above 33°C (Timlin et al., 2006; Wolf et al., 1990; Ingram and McCloud, 1984). For respectable yields, over 500 mm of water is required over a typical growing season of 120 to 150 days (FAO, 2016).

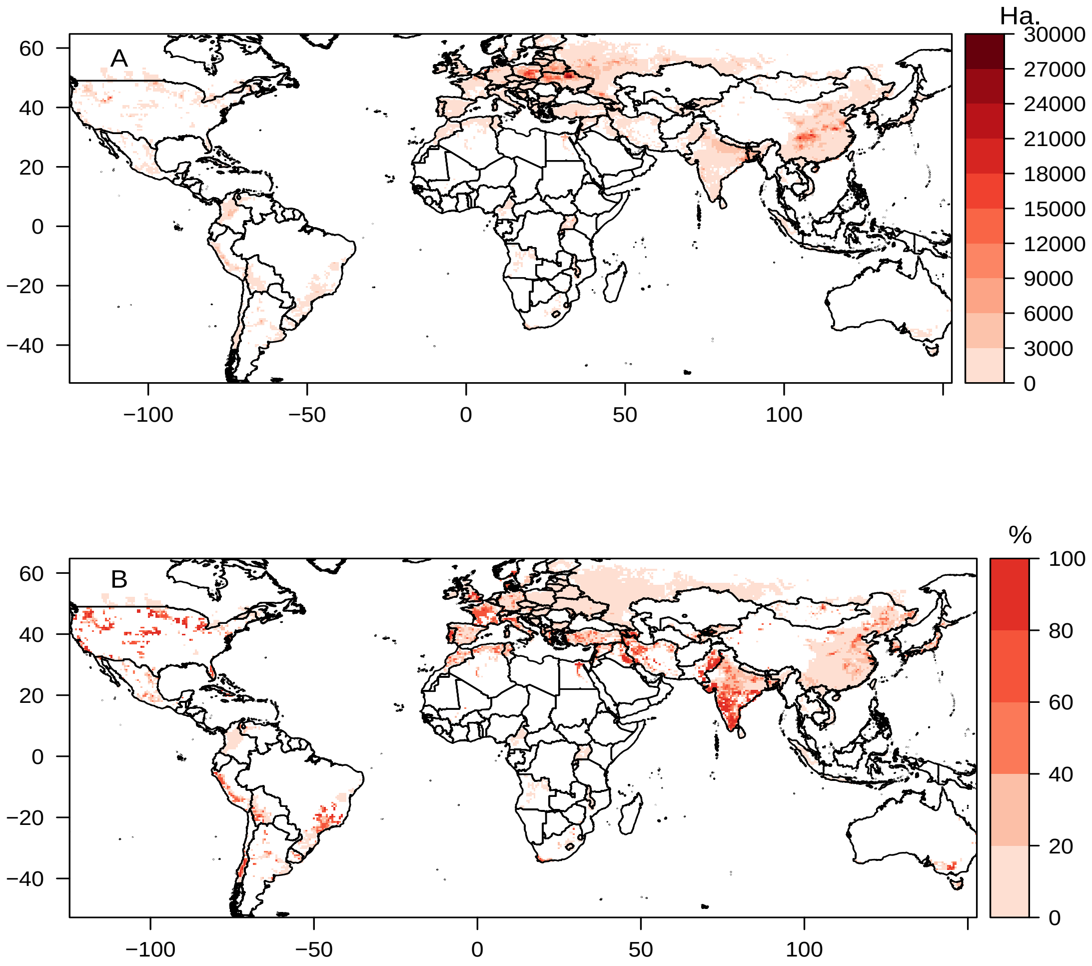



**Figure 1.3:** A. Potato growing area per grid cell (Ha) and B. percentage of irrigation per grid cell for the baseline climate based on MIRCA data (Portmann et al., 2010).

Global production is skewed towards the northern hemisphere and especially Europe, which claims around 50% of global growing area (Hijmans, 2001; Birch et al., 2012). Globally, potato production has increased by about 20% since 1990, but production is still 50% below that of wheat, maize and rice (FAO, 2016). Asia is now catching Europe up as a major global producer (Birch et al., 2012), with India, Bangladesh and China increasing potato yields and area grown (Hijmans, 2001). The contribution of potato to food supply is increasing steadily in developing countries especially, where potato consumption has more than doubled between 1960 and 2005 to 22 kg per capita per year (FAO, 2016).

Around 10% of the potato tubers produced annually are used for propagation rather than consumption (McKey et al., 2010). Consequently, there is greater competition between potato tubers used as seed (see Section 1.4.1 below) and those used as food compared with sexually reproducing crops. Seed potatoes are typically the most expensive input to potato cultivation (FAO, 2016).

In North America and Western Europe, yields often exceed 40 Tonnes/Ha, but in developing countries yields are commonly half of this amount (FAO, 2016). Higher yields in developed countries are due to favourable climates, higher levels of mechanisation, higher-yielding and pest-resistant varieties, more irrigation, better pest management schemes and more use of pesticides and fertilisers (Lutaladio and Castaldi, 2009).

Potato irrigation water demand and water use is similar to other crops, typically needing at least 500 mm of water in the growing season (FAO, 2016), however potatoes are a water-efficient crop, meaning that more yield per water used is achieved compared to other major crops (Hay and Porter, 2006). Irrigation is important for potatoes in certain areas, but the majority of global potato growing area is rainfed (Portmann et al., 2010). In order to achieve the highest yields, soil moisture should not go below the field capacity of a sandy soil, especially during tuber bulking stages (FAO, 2016). In high yielding temperate countries such as the UK, irrigation is used to supplement rainfall and increase yields, with over half of the growing area of England and Wales irrigated to some extent (Daccache et al., 2011a). In countries at lower latitudes such as Colombia, the growing season coincides with the rainy seasons and production is rainfed (CIP, 2009).

Potatoes are particularly vulnerable to pest attack compared to other major crops, due to vegetative propagation, diverse pest species and high post-harvest losses (Oerke, 2006). Global average yield losses to pests are around 40%, compared with 28% for wheat and 37% for rice (Oerke, 2006). Diseases alone account for 21% of potato losses. Pesticide use is therefore high, and increasing in the developing world (Handford et al., 2015). Most of the current widely-cultivated potato varieties are susceptible to late blight (Forbes, 2012), resulting in disease management relying heavily on fungicides. Yield losses from late blight can be as high as 30% (Dowley et al., 2008). Late blight causes such substantial yield losses by damaging most parts of the plant – the leaves, stems and tubers (Hwang et al., 2014).

### 1.4.1 Potato development and growth

Potatoes typically develop from seed tubers, which are a potato tuber from which the plant vegetatively grows – potatoes are rarely grown from true seeds (Harris, 1992). Potatoes propagated from true seed as opposed to seed tubers tend to have lower yields, smaller tubers and are more susceptible to pests and diseases (Burton, 1989).

The physiological age of the seed tuber influences the timing of phenological development as well as final yields (Hay and Porter, 2006). A physiologically-older seed tuber (e.g. a seed kept in storage for a long period) will typically have a faster developmental cycle (quicker canopy development, tuber initiation and senescence) at the expense of reduced yield due to a reduction of overall light interception (Hay and Porter, 2006). Dormancy of seed tubers ends when temperatures exceed 2-4°C, depending on the variety (Harris, 1992). Once planted, the seed tubers sprout when temperature conditions are favourable for crop development. Growth can be limited when the soils are poorly aerated or heavily compacted leading to poor aeration, but potatoes can grow in a wide variety of soil moistures (Harris, 1992). However, a volumetric soil water content of 15 to 25% is desirable (Van Loon, 1981).

Flowering often has no effect on tuber initiation and is absent in some cultivars (Sands et al., 1979). Potato development is driven mainly by temperature, but photoperiod also plays a key role in the time taken from emergence to tuber initiation (Gayler et al., 2002; Streck et al., 2007). Photoperiods below a critical threshold hasten tuber initiation. Potatoes typically senesce their leaves towards the end of the growing season, and in a mature plant 75-80% of potato dry weight comprises of tuber yield (Ivins and Bremner, 1965).

Like other crops, accumulated biomass in potato is determined by intercepted radiation, transpiration, radiation use efficiency and transpiration efficiency. Both transpiration and radiation are linearly related to potato biomass and tuber yield (Harris, 1992; Haverkort and Bicamumpaka, 1986). Photosynthetically-active radiation is intercepted by the canopy and partitioned to tubers according to limitations imposed by water, temperature and nutrients (Harris, 1992; Burton, 1989).

In temperate areas temperature can be the major limiting factor to potato growth – frost can lead to damage of early shoot growth which can delay planting and therefore harvest. In hotter conditions, heat stress can also be a problem for potato growth. High temperatures lead to reduced partitioning to tubers (Timlin et al., 2006; Wolf et al., 1990; Ewing, E. E., 1981; Ingram and McCloud, 1984), with optimal partitioning occurring at around 15°C (Ingram and McCloud, 1984) and significant decline in the tuber-to-biomass ratio occurring beyond 24°C (Timlin et al., 2006; Wolf et al., 1990; Ingram and McCloud, 1984). In these circumstances, translocation is directed more towards the stems than tubers, resulting in no net loss of weight (Wolf et al., 1990). The cause of this reduced partitioning to tubers is the inhibition of starch biosynthesis enzymes in tubers (Lafta and Lorenzen, 1995). In addition to impacts on tubers, there is some evidence for accelerated senescence at high temperatures, usually at temperatures of around 30°C (Midmore, 1990; Kooman et al., 1996).

A shallow and sparse rooting system (Opena and Porter, 1999) makes potatoes very sensitive to soil moisture stress, especially during the tuber bulking growth stages (Onder et al., 2005; Monneveux et al., 2013; Van Loon, 1981). Excess water can also be a problem for potatoes, however, with water logging leading to poor soil aeration and potentially greater risk of pest and disease attack (Benoit and Grant, 1985). Both excess and limited water can be a problem for potatoes during the same growing season (Saue and Kadaja, 2014).

Kunkel and Campbell (1987) reported a maximum potential potato yield of 124 tonnes per hectare, although yields typically range from 5 to 45 tonnes per hectare (FAO, 2016). The high fraction of dry matter going to the tubers results from potatoes not being sink limited – the soil bears the weight of sink organs, unlike major cereal crops where the plant has to divert energy to maintaining their support, imposing a sink limitation on yield (Katoh et al., 2015).

Most Potatoes have indeterminate growth – i.e. crop maturity is not driven solely by environmental and genetic factors. Management decisions are also key to when potatoes are harvested. Temperature is the most important climatic variable determining duration, but the relationship of climate variables to duration of developmental stages weakens after tuber initiation (Kooman et al., 1996). Typically potatoes are harvested when senescence has taken place for some time, allowing some canopy die back, and depending on management decisions the crop haulm is cut back using mechanical or chemical methods and left for several days. Skin hardening of tubers takes place during this time (Wilcockson et al., 1985). Management factors include the desired starch or dry matter content of tubers (Noda et al., 2004), time taken for skin hardening (Wilcockson et al., 1985), local pest and disease pressures, level of soil moisture (excessively dry or wet soils making harvest impractical) and market prices for different varieties (Harris, 1992; Burton, 1989).

### 1.4.2 Climate change and potato agriculture

Globally, potato yields are projected to decrease in future, although current modelling studies are rare and fail to simultaneously account for the impacts of rising $CO_2$ and adaptation to climate change (Raymundo et al., 2017b; Hijmans, 2003). Hijmans (2003) show that adaptations of altering planting dates and varieties help to mitigate the negative impacts of rising temperatures by mid-century. Raymundo et al. (2017b) show that $CO_2$ fertilisation results in increasing yields in parts of Europe and the tropics in 2055 compared to the present climate.

Rising temperatures and extremes of rainfall are likely to occur with climate change, and these could lead to yield reductions (Fleisher et al., 2016; Raymundo et al., 2017b; Hijmans, 2003). Potato yields could increase in future with elevated $CO_2$ due to $CO_2$ fertilisation, with water use efficiency and photosynthesis rates increasing (Fleisher et al., 2008; Finnan et al., 2005). These increases are estimated to be higher than those of other C3 crops (Magliulo et al., 2003). Raymundo et al. (2017b) projected yields to decrease globally when taking $CO_2$ fertilisation into account, however. Lobell et al. (2011) found that climate (primarily temperature) trends resulted in yield decreases for maize and wheat, with technology and $CO_2$ fertilisation gains failing to account for yield decreases.

Few studies have assessed the impact of rising $CO_2$ on potato nutrient content. Myers et al. (2014) review impacts on multiple crops, concluding that zinc, iron and protein concentrations fall in C3 crops. For potatoes specifically, protein, calcium and potassium tuber content has been found to decrease with $CO_2$ enrichment, with inconclusive impacts on tuber quality (Högy and Fangmeier, 2009; Vorne et al., 2002). Further work is needed for more general conclusions about future potato nutrient content.

Concentrations of ozone are also likely to have an impact on potato yields. Ozone can enhance leaf senescence as well as decrease photosynthesis and crop yield (Vorne et al., 2002). Feng and Kobayashi (2009) conduct a meta-analysis of the effects of ozone on multiple crops. With current ozone levels, mean potato yield losses were found to be the lowest of the crops examined at 5.3%, compared to 9.7% and 17.5% for wheat and rice for example. With projected future levels of ozone, mean potato yield losses were also the lowest compared to other crops at 11.9% in future climate. Overall, the ameliorating effects of $CO_2$ more than compensated for the losses due to ozone damage. Similar results were reported by Vorne et al. (2002) in the European CHIP (Changing climate and potential Impacts on Potato yield and quality) experimental project, with 5% yield losses due to ozone damage.

Temperature can decrease yields through mean changes by shortening crop durations (Raymundo et al., 2017a; Fleisher et al., 2016; Timlin et al., 2006). Extremes of temperature typically affect potatoes through heat stress impacts, predominately by reducing the allocation of assimilates to tubers (Lafta and Lorenzen, 1995; Rykaczewska, 2015; Timlin et al., 2006; Wolf et al., 1990; Ingram and McCloud, 1984; Kooman et al., 1996; Prange et al., 1990), although some evidence exists for increased senescence (Midmore, 1990).

With increasing drought, yields are predicted to decrease (Fleisher et al., 2016). There is substantial variation in the ability of different varieties to cope with drought stress, however, due to variable water use efficiencies (Schafleitner et al., 2011). Flooding may become more of a problem in other potato growing areas (Rosenzweig et al., 2001), and potatoes are susceptible to both excess and limited water (Saue and Kadaja, 2014). Excess water can lead to poor soil aeration, limited root growth and increased biotic stresses.

Some of the most important diseases of potato are from fungal (or the closely related oomycete) taxa and these groups are predicted to become more threatening with climate change (Bebber and Gurr, 2015; Fisher et al., 2012). Late blight is appearing earlier in the growing season in response to increasing temperatures (Roos et al., 2011; Gregory et al., 2009). In addition, there is evidence of rapid spread of new varieties of late blight that have the potential to reproduce sexually and further the evolutionary potential of the species (Cooke et al., 2012; Hwang et al., 2014; Roos et al., 2011). In the past, one clonal lineage has dominated the majority of blight populations (Goodwin et al., 1994).

Pests are expected to continue to move away from the equator in response to warming conditions (Bebber et al., 2013). For potato, examples exist that point to likely changes in pest attacks. The development rate of pests and pathogens of potato could increase through to 2050 in South Africa, meaning that pest pressures increase (Van der Waals et al., 2013). In contrast, Sparks et al. (2014) project limited increases in global late blight pressure by 2050, with an initial increase in risk followed by a decrease by mid-century.

Climate change will affect the areas that are suitable for potato agriculture in the future due to the above abiotic and biotic impacts of climate change. For example, a fall in suitability of current potato growing areas in Africa and across tropical highlands is projected by the EcoCrop model (Ramirez-Villegas et al., 2013) before mid-century due to rising temperatures (Schafleitner et al., 2011; Hijmans, 2001). Other areas are likely to be more suited to potato growth thanks to warming, such as northern Europe.

## 1.5 Objectives and thesis outline

In this chapter we have learned that potato crop modelling and the impacts of pests and diseases are neglected areas of climate impacts science. In order to support predictions of the impacts of climate change on global food security, more potato and biotic stress modelling are therefore needed. There is a lack of data available with which to model and evaluate the impacts of climate change on pests and diseases within crop models, however, especially at the global scale. Therefore, the use of alternative methods (including proxy data and empirical modelling) can be useful for building a picture of the impacts of climate on biotic stresses.

Assessing the impacts of climate change on crop yields is necessary but not sufficient in order to assess climate change impacts on food security. The impacts of climate change on agriculture are broader and more complex than simply assessing changes to yields. Understanding how yields will change remains a critical component to developing an understanding of how climate change will affect food security, however.

Global potato crop modelling is a particularly neglected field, so much so that we can have little confidence in the nature of the changes to potato yields in the future. The few studies that are currently published do not take into biotic stresses, crop management adaptations and $CO_2$ fertilisation (Raymundo et al., 2017b; Hijmans, 2003). Adaptation to climate change is important to consider in global climate change studies so that the impacts of climate change are not overestimated (Lobell, 2014). Most studies also focus on mean yield changes, rather than commenting on how the variability of crop yields could change (Challinor et al., 2018).

The lack of models currently used to assess global potato yield changes is especially important given that potatoes are an increasingly important crop for food security in the developing world. The skill of multi-model ensembles is frequently better than individual crop model skill also (Fleisher et al., 2016). There is therefore a need to develop models that simulate the potato crop globally in order to assess yield changes in the future.

Few studies assess the loss of model skill across different crop modelling domains, for example from regional to global simulations (Challinor et al., 2014a). It is important to do so in order to understand the information needed to improve global simulations to better inform policy decisions.

The ultimate objective of this thesis is to present an analysis of how climate change influences abiotic and biotic stresses in global potato cultivation. As discussed, climate change impacts on food security are complex, spanning different spatial and temporal scales and involving socio-economic as well as environmental factors. This thesis focuses on the impacts of climate on potato yields and biotic stresses, as these are current areas in particular need of analysis. In order to analyse global potato yields, several other objectives become apparent, including model development and evaluation at both regional and global scales.

More data are available at the regional scale than globally. The model is firstly evaluated using regional data, in order to know if model performance is adequate when more parameter information is available. Model skill is then assessed using the data inputs available at the global level. Differences in skill between these regional and national scale simulations are then analysed. This framework provides us with the necessary tools and confidence with which to simulate potato yields globally.

The biotic stresses of potato are assessed using the example of potato late blight, a globally important potato disease. A combined abiotic and biotic assessment is made on future potato agriculture, highlighting countries at particular risk of yield reductions and blight increases. Globally-coherent data on specific pests and diseases do not exist, and potato-specific pesticide data are also not available on the global scale. Therefore, pesticide use data is used as a proxy for data on pest pressures to evaluate broader climate change impacts on crop biotic stresses.

The objectives of this thesis are therefore as follows:

1. Develop a process-based crop model suitable for simulating large scale potato-weather relationships (Chapter 2).
2. Evaluate the process-based potato model in contrasting climates using regional data and parameter information (Chapter 3).
3. Evaluate the potato model parameter set up at the national scale for use in global simulations (Chapter 4).
4. Compare the model skill of the global and regional simulations (Chapter 5).
5. Assess the impacts of climate change on global potato yields (Chapter 6).
6. Assess the impacts of climate change on global potato biotic stress (Chapter 6).
7. Use proxy data (on pesticide use) to evaluate the links between climate and pests and predict the influence of climate change on pests globally (Chapter 7).

Chapter 8 summarises the results and conclusions of each analysis chapter in turn. This is followed by research recommendations.

# Chapter 2

# GLAM-potato model development

## 2.1 Introduction

Potato physiological and crop modelling research is rare compared to that of other major crops (see Chapter 1; Brown et al., 2011). There are, nevertheless, various potato crop models currently in use. Raymundo et al. (2014) review these models and describe their differences.

Most potato models have been derived from other crop models within the last 30 years (Raymundo et al., 2014). These use thermal time and photoperiod to control crop development, with developmental stages for emergence to tuber initiation and senescence the most commonly simulated. Growth tends to be moderated by radiation, heat and water limitations. Biomass is usually the product of intercepted radiation and a radiation use efficiency term, or transpiration and transpiration efficiency. A harvest index commonly partitions biomass to yield (Raymundo et al., 2014).

The potato model intercomparison of Fleisher et al. (2016) demonstrated that an ensemble median performed better than individual potato models, highlighting the difficulties in simulating potato – maincrop varieties have indeterminate growth and so prove challenging to simulate (Fleisher et al., 2016). Some potato models do show skill in modelling yields however. These tend to be high input models that are relatively complex (Raymundo et al., 2017a).

Of the potato crop models that do exist, most are designed for small scale simulations, such as the field-scale (Raymundo et al., 2014). GLAM is specifically designed to operate at larger spatial scales and with a relatively low input data requirement (Challinor et al., 2004). GLAM-potato was therefore developed as a potato crop modelling option that is particularly suited to large scale, low input data analyses.

This chapter describes the development of the GLAM-potato model - a tool that can be used to simulate the year-to-year variation of potato yields in response to weather variables. The processes and equations included in GLAM-potato are described, as well as the justification behind the different components of the model. Chapter 3 evaluates the model's ability to simulate weather-yield relationships in contrasting temperate and tropical environments using regional case studies in the UK and Colombia. Chapter 4 then evaluates the model using UK and Colombian national scale yield data in a parameter configuration designed for global simulations.

GLAM-potato was based on the original GLAM-groundnut set up as described in Challinor et al. (2004), simulating groundnut (*Arachis hypogaea* L.) in India. Certain components of the model are crop-generic and so unaltered (root growth, water balance and evapotranspiration routines), whereas others are crop-specific. A summary of model components that show structural differences between GLAM-groundnut and GLAM-potato can be seen in Table 2.1. Details of crop-specific parameters are in Section 2.2.11. The groundnut model was used as the basis for GLAM-potato as the code was readily available at the time of model development and there are similarities between the two crops in terms of how they are modelled, such as the biomass-to-yield partitioning and the number of developmental stages. Indeed, the majority of potato simulation models are based on already existing crop models (Raymundo et al., 2014).

Section 2.2 introduces the model and the crops that GLAM can currently simulate. Section 2.2.1 describes the input data required for GLAM. Sections 2.2.2 to 2.2.7 then detail the components of the model: a description of each component of the model is given first for GLAM-groundnut and then for GLAM-potato.

In each GLAM-potato model component section, any changes compared to GLAM-groundnut are first briefly described. The physiological background and justification for the GLAM-potato model changes are then given before changes to model structural equations and parameters are detailed.

GLAM-potato uses the same routines for transpiration (Section 2.2.7), evaporation (Section 2.2.7) and water balance (Section 2.2.6) as in Challinor et al. (2004). Crop planting, development (Section 2.2.2) and leaf area (Section 2.2.3) routines are altered. Heat stress is described in Section 2.2.8. Finally model calibration, model optimisation (both model-generic) and GLAM-potato parameters are described in Sections 2.2.9, 2.2.10 and 2.2.11 respectively.

**Table 2.1:** Summary of model structural differences between GLAM-groundnut and GLAM-potato.

| Model Component (Section) | GLAM-potato approach |
|---|---|
| Crop development (2.2.2) | Crop-specific phenology |
| Leaf growth (2.2.3) | Leaf area grows until senescing in final stage |
| Root growth (2.2.4) | Same as GLAM-groundnut |
| Biomass and yield (2.2.5) | RUE and TE approach |
| Water balance (2.2.6) | Same as GLAM-groundnut |
| Evaporation and transpiration (2.2.7) | Same as GLAM-groundnut |
| Heat stress (2.2.8) | Same as simple GLAM-groundnut routine |

## 2.2 The GLAM crop model

The General Large Area Model for annual crops (GLAM) is a process-based, one-dimensional crop model, originally designed to operate at the spatial scale of global and regional climate models. Whilst this resolution is not fixed in time, during GLAM development it was around 100 km$^2$ (Challinor et al., 2003). GLAM can simulate at any resolution, however, being mathematically one dimensional.

The model simulates crop development, growth, evapotranspiration and soil water balance at a daily time step. GLAM was originally developed for groundnut simulation (Challinor et al., 2004). Being modular, it is relatively easy to modify for other crops and has since been used to simulate spring wheat, winter wheat (Li, 2008), maize (Bergamaschi et al., 2013), soybean (Osborne et al., 2013) and sorghum (Nicklin, 2013).

The modelling philosophy of GLAM can be summarised as “appropriate model complexity”. Less complex models may omit important processes, potentially leading to poor model skill. More complex models do not necessarily result in improved model performance, however. If the quality of the input data required by complex models is poor, results could also be poor (Jamieson et al., 1998; Jagtap and Jones, 2002). Some studies have suggested that on larger spatial scales some processes become less important (Hansen and Jones, 2000; Challinor et al., 2004), allowing a less complex model to perform equally well. The relatively low number of parameters in GLAM reduces model sensitivity to poor quality input data (Challinor et al., 2004) and means that less extensive calibration is necessary, reducing the risk of ‘overtuning’ the model to data at certain sites (Cox et al., 2006).

### 2.2.1 Input data

GLAM requires daily input weather data for rainfall, surface incoming solar radiation and minimum and maximum temperatures. A sowing window is also specified. Three soil hydrological parameters are required that are constant with soil depth. These are:

- Lower limit $\theta_{\mathrm{rll}}$ - the volumetric soil moisture content at or below which no more evaporation or transpiration from the soil can occur;
- Drained upper limit $\theta_{\mathrm{dul}}$ - the volumetric soil moisture content remaining after thorough wetting and drainage;
- Saturation upper limit $\theta_{\mathrm{sat}}$ - the fully-saturated volumetric soil water content.

### 2.2.2 Crop development

#### 2.2.2.1 Crop development - GLAM-groundnut

The crop is chosen to be planted either on a specified date or when soil moisture exceeds a critical value ($C_{\mathrm{sow}}$) within a given planting window, at the end of which the crop is planted regardless (this process is called the intelligent planting routine). Subsequent crop development in GLAM is dependent on the accumulation of thermal time. The thermal time elapsed $t_{\mathrm{TT}}$ is calculated by performing the following integration over daily time, $t$:

$$t_{\mathrm{TT}} = \int_{t_i}^{\mathrm{T}} (T_{\mathrm{eff}} - T_{\mathrm{b}})\,\mathrm{d}t \tag{2.1}$$

where $T_{\mathrm{b}}$ is the base temperature, below which no thermal time is accumulated and no crop development takes place, and $T_{\mathrm{eff}}$ is the effective temperature (defined below). The time of emergence – the first day that the leaf area index (LAI) becomes non-zero – is $t_{\mathrm{em}}$. The developmental stage number is given by $i$. After a given amount of thermal time has been accumulated a new developmental stage is reached, associated with a new value of $i$. In Challinor et al. (2004) – simulating groundnut (*Arachis hypogaea* L.) in India – the developmental stage numbers are 1 between sowing and anthesis, 2 between anthesis and pod-filling, 3 between pod-filling initiation and maximum LAI and 4 for between maximum LAI and maturity.

$T_{\mathrm{eff}}$ is defined for each developmental stage using the relationship between the mean daily temperature, $\bar{T}$, and the three cardinal temperatures $T_{\mathrm{b}}$, $T_{\mathrm{o}}$ and $T_{\mathrm{m}}$, where the subscripts refer to base, optimal and maximum temperatures at which growth can occur. $\bar{T}$ is taken either directly from measurements or as the average of $T_{\mathrm{min}}$ and $T_{\mathrm{max}}$. $T_{\mathrm{eff}}$ is defined below.

$$T_{\mathrm{eff}} = \begin{cases} \bar{T} & T_{\mathrm{b}} \leq \bar{T} \leq T_{\mathrm{o}} \\ T_{\mathrm{o}} - (T_{\mathrm{o}} - T_{\mathrm{b}})(\frac{\bar{T}-T_{\mathrm{o}}}{T_{\mathrm{m}}-T_{\mathrm{o}}}) & T_{\mathrm{o}} < \bar{T} < T_{\mathrm{m}} \\ T_{\mathrm{b}} & \bar{T} \geq T_{\mathrm{m}}, \bar{T} < T_{\mathrm{b}} \end{cases} \tag{2.2}$$

As the mean temperature increases from $T_{\mathrm{b}}$ up to $T_{\mathrm{o}}$ the development rate increases linearly. A mean temperature greater than the optimum temperature and less than the maximum temperature has a reducing effect on the effective temperature, meaning that as the mean temperature increases from $T_{\mathrm{o}}$ up to $T_{\mathrm{m}}$ the development rate decreases linearly.

#### 2.2.2.2 Crop development - GLAM-potato

GLAM-potato is similar to GLAM-groundnut in that the crop develops through the accumulation of thermal time through four developmental stages. The developmental stages differ as described below, with photoperiod affecting the onset of tuber initiation.

In temperate areas temperature can be the major limiting factor for potato planting – frost can lead to damage of early shoot growth which can delay harvest (Harris, 1992). Potato development is driven mainly by temperature, but photoperiod also plays a key role in the time taken from emergence to tuber initiation – photoperiods below a critical threshold hasten tuber initiation (Gayler et al., 2002; Streck et al., 2007).

Potatoes are grown on a wide variety of soils (Harris, 1992) and as such are planted in different soil moisture conditions. However, a level of soil moisture of at least the drained upper limit of a sandy soil is desirable (Van Loon, 1981).

The physiological age of the seed tuber (i.e. the "mother tuber" from which the crop grows) influences the timing of phenological development as well as final yields (Hay and Porter, 2006). A physiologically-older seed tuber (i.e. a seed that has been kept in storage for a long period) will typically have a faster developmental cycle (quicker canopy development, tuber initiation and senescence). Dormancy of seed tubers ends when temperatures exceed 2-4°C, depending on the variety (Harris, 1992). Therefore seed tubers that experience warmer conditions lead to shorter growing seasons and lower final yields due to a reduction of overall light interception (Hay and Porter, 2006). Once planted, the emergence of the canopy depends on temperature and planting depth as well as the age of the seed tuber (Harris, 1992; MacKerron and Waister, 1985).

Potato development in models is usually based around the timing of tuber initiation (Raymundo et al., 2014). Developmental stages in other potato models include planting, emergence, tuber initiation, maximum bulking rate and tuber maturity (e.g. Sands et al., 1979; MacKerron and Waister, 1985; Streck et al., 2007). In line with GLAM model principles, a simplistic approach to potato modelling is selected when possible. As such, a relatively straightforward approach to phenology (in terms of number of developmental stages) is taken. The same number of developmental stages as GLAM-groundnut are used. This does not include a maximum bulking rate stage as this was deemed unnecessary based on the evidence available (see Section 2.2.5.2). In order, the developmental stages are from planting to emergence, followed by canopy development (at which tuber initiation – i.e. partitioning of biomass to yield – begins at a certain time) up until the onset of senescence. The developmental stage numbers $i$ are 1 between planting and emergence, 2 between emergence and tuber initiation, 3 between tuber initiation and senescence and 4 between senescence and harvest.

Whilst storage conditions do vary and have an impact on yields through the age of the seed tuber, simulating these management conditions is not practical for a regional scale model as such conditions would likely vary and average out, or are able to be tuned spatially using the yield gap parameter $C_{\mathrm{YG}}$ (see Section 2.2.3). Data on planting depth are rarely available and not simulated in GLAM-potato. A specific developmental stage for planting to emergence (the point when leaf area index becomes greater than 0) is therefore assigned to simulate the impact of temperature on plant emergence. This is in place of the GLAM-groundnut method of using the parameter $t_{\mathrm{em}}$ to govern emergence by setting a specific number of days taken from planting to emergence.

GLAM-potato uses the intelligent planting routine as used in GLAM-groundnut, with the addition of a temperature condition for planting. The crop is only planted when both minimum temperature is greater than 0°C for a set period of time and enough soil moisture is present.

The number of days that the model requires for non-frost conditions before planting was based on preliminary simulations in the temperate region where planting date information was available (Aberdeen, UK), using the preliminary parameter sets described in Chapter 3, Section 3.2.2.1. These simulations varied the number of consecutive days required to be frost-free (greater than 0°C) for planting to take place.

In GLAM, an intelligent planting window is used to control when the crop is planted. When certain conditions are met the crop is planted. The day on which the intelligent planting conditions were met (i.e. crop planted) was recorded (Figure 2.1) for the different conditions of different required consecutive days of frost free conditions. Simulations tested two different planting windows: one starting on DOY 45, the other starting on DOY 61, to test different initial conditions.

Severe frost conditions do not commonly stop until April in Aberdeen (i.e. DOY 91 onwards). As such, the number of days for frost-free conditions should be long enough to produce realistic planting dates but not so long as to commonly result in planting being delayed until the end of the planting window – the conditions are designed to produce a realistic planting date given the weather conditions, i.e. to replicate when a farmer would want to plant the crop.

Therefore it is desirable to choose a required number of days when the planting date first reaches a realistic value. As can be seen in Figure 2.1, 15 consecutive frost free days produced realistic planting dates using planting windows starting on day of year 45 and day of year 61 (the length of the intelligent planting window is kept fixed at 30 days). Therefore, this value was used in all GLAM-potato simulations in this thesis.

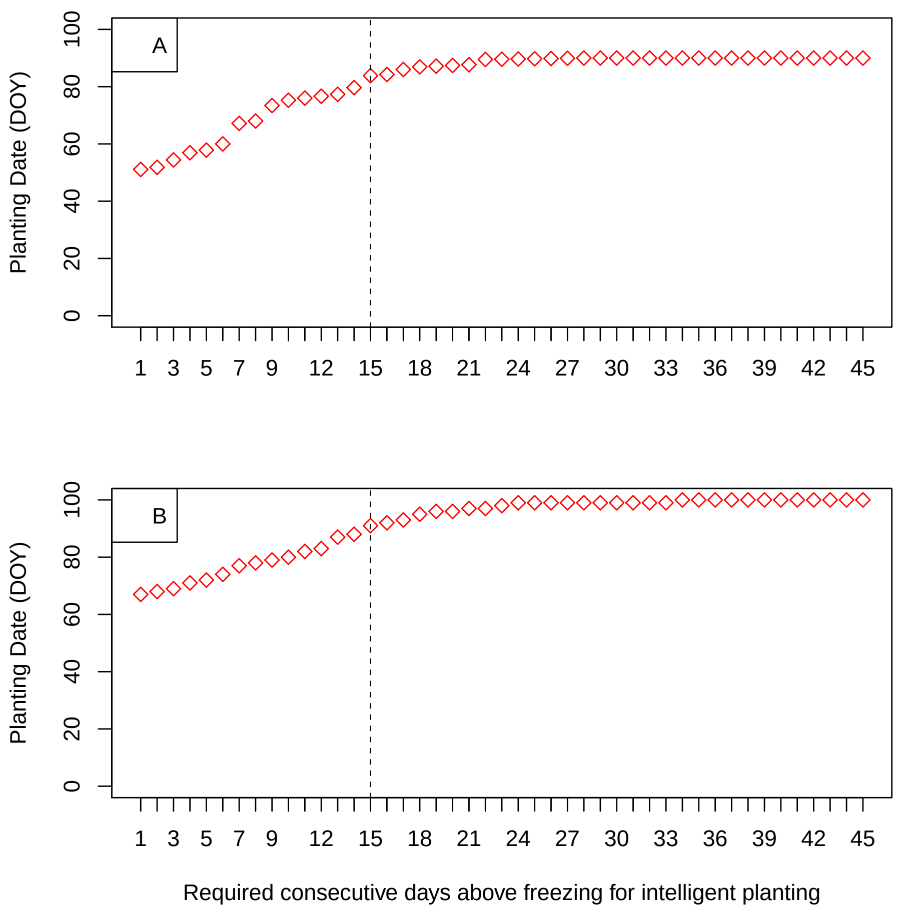



**Figure 2.1:** Day of year when the crop is planting using different required number of days of non-freezing conditions in the GLAM-potato intelligent planting window in Aberdeen, UK, using the mid-range parameter set described in Chapter 3, Section 3.2.2.1. A = start of planting window on day of year 45, B = start of planting window on day of year 61.

When the temperature condition has been met, the level of soil moisture is checked, and if sufficient moisture is present the crop is planted. The value of $C_{\text{sow}}$ was set equal to the value of the drained upper limit of a sandy soil (a volumetric soil water content of 0.1), as described by FAO soil properties (FAO, 2016).

The soil moisture routine is run for a period of 30 days before the start of the planting window in order to have a realistic level of starting soil moisture for the region. Preliminary simulations were used to test the number of days required for the soil spin-up. These tested extreme conditions of soil moisture – clay and sandy soils, no rain and excessive amounts of rain (10 mm every day) and large and small initial levels of soil moisture. In all conditions, a period of 30 days resulted in either exactly the same soil moisture or very similar levels to a 60 day spin-up, so 30 days was selected as a sufficient spin-up of the soil water routine and used for all subsequent GLAM-potato simulations (see Figure 2.2).

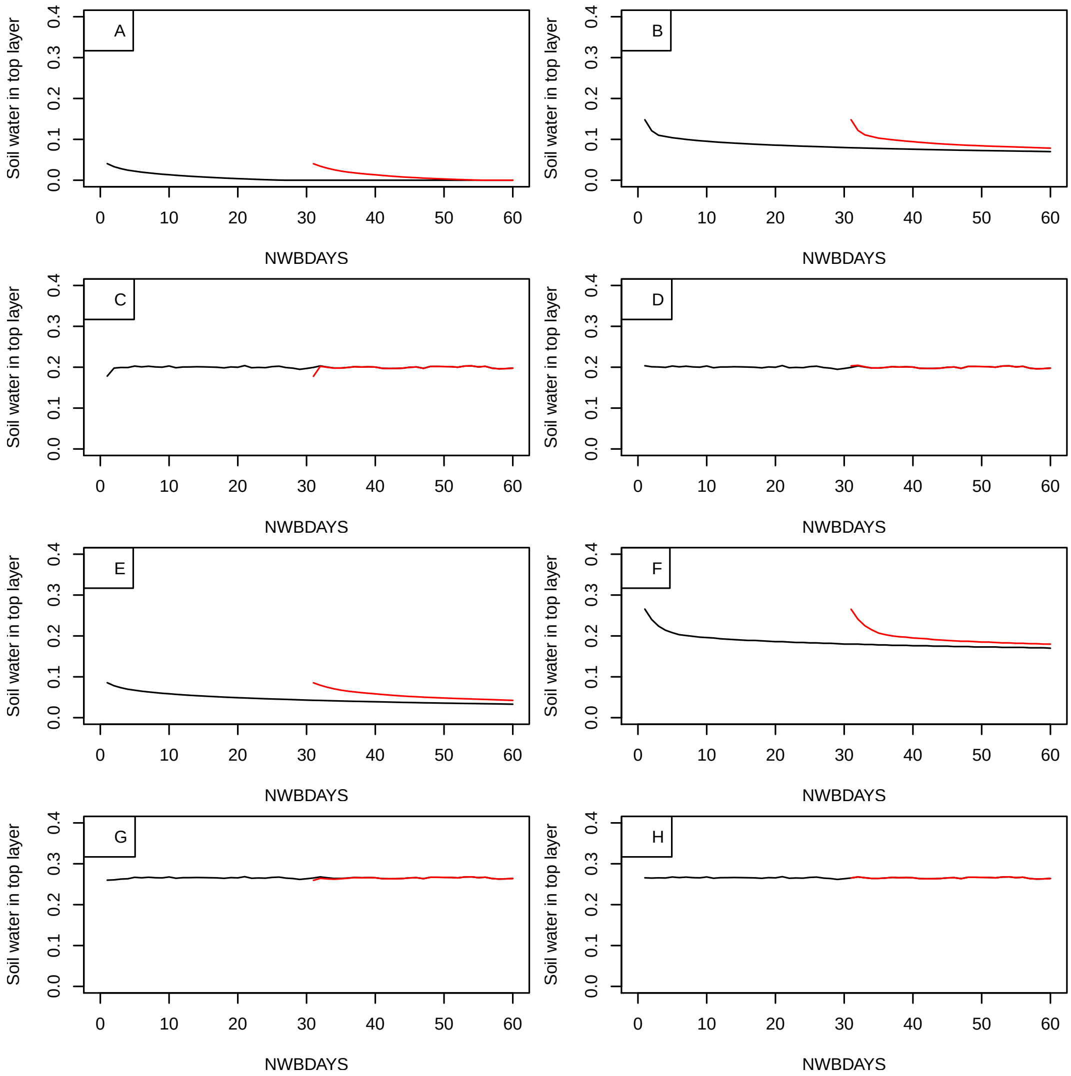



**Figure 2.2:** Soil water in the top soil layer when simulating different lengths of soil water spin-up (NWBDAYS). Red line = 30 day spin-up, black line = 60 day spin-up. The following descriptions for plots A to H describe the soil type, wet or dry rainfall time series and the initial volumetric soil water content. A = sand dry 0.5, B = sand dry 2, C = sand wet 0.5, D = sand wet 2, E = clay dry 0.5, F = clay dry 2, G = clay wet 0.5, H = clay wet 2.

Development in GLAM-potato is (as in GLAM-groundnut) driven by the accumulation of thermal time for $i$ 1, 3 and 4. Photoperiod is included in GLAM-potato to allow accurate simulation of phenological progression from emergence to tuber initiation ($i$ 2). A photoperiod response function (Streck et al., 2007) is multiplied by the thermal time calculated for each day during this developmental stage (as in the method used by Li, 2008, taken from Cao and Moss, 1997). Li (2008) use a “daily thermal sensitivity” to adjust the daily thermal time according to photoperiod and vernalisation for GLAM-winter wheat.

Vernalisation was omitted from GLAM-potato, not being relevant for potato development. A photoperiod response function $f_{(\mathrm{P})}$ is calculated as in Equation 2.3 using a critical photoperiod $P_{crit}$ and a photoperiod sensitivity $P_s$ as follows:

$$f_{(\mathrm{P})} = \mathrm{e}^{-P_s(P_h - P_{crit})} \tag{2.3}$$

with $P_h$ being the photoperiod hours, calculated as in other GLAM crops (maize and winter wheat also using photoperiod for development) using the methods used in the CERES-maize model (Jones et al., 1986):

$$D_{ec} = -23.4(\pi/180)\cos(2.0\pi(D_{\mathrm{oy}} + 10)/365) \tag{2.4}$$

$$D_l = \mathrm{acos}(-\tan(lat(\pi/180))\tan(D_{ec})) \tag{2.5}$$

$$P_h = 2/15\, D_l(180/\pi) \tag{2.6}$$

with $D_{ec}$ being sun declination, $D_{\mathrm{oy}}$ being day of year, $D_l$ being day length and $lat$ being latitude. During the 2nd crop development stage from emergence to tuber initiation, the photothermal time accumulated is calculated by multiplying $f_{(\mathrm{P})}$ by thermal time, similarly to the tuberisation rates calculated in Streck et al. (2007) and Gayler et al. (2002). The photoperiod response function of Streck et al. (2007) was preferred to that of Gayler et al. (2002). The latter function yielded very similar results but was slightly more complex and was therefore not used to limit unnecessary model complexity.

Lastly, harvest in GLAM-potato is driven by thermal time accumulation, as with other GLAM crops. Potato harvesting is a complex process, however, as maincrop potato varieties are typically indeterminate, with environmentally-driven crop maturity not the only factor involved in potato harvesting (see Chapter 1, Section 1.4.1). As a result, model simulations in this thesis typically reject parameter combinations that result in durations greater than 180 days, as this is longer than the majority of potato growing seasons (e.g. see Harris, 1992) and harvest is not solely driven by thermal time in many cases (Kooman et al., 1996).

### 2.2.3 Leaf growth

#### 2.2.3.1 Leaf growth - GLAM-groundnut

In GLAM-groundnut, crop leaf area growth is calculated as follows:

$$\frac{\partial L}{\partial t} = \begin{cases} (\frac{\partial L}{\partial t})_{\max}\ C_{\mathrm{YG}}\ \min(\frac{S}{S_{\mathrm{cr}}}, 1) & i < 3 \\ 0 & i = 3 \end{cases} \tag{2.7}$$

where $L$ is the effective LAI, $\frac{\partial L}{\partial t}_{\max}$ is a constant and $S$ is the soil water stress factor. LAI is reduced by the soil water stress factor and the yield gap parameter, $C_{\mathrm{YG}}$. $C_{\mathrm{YG}}$ is used to alter the LAI to account for the effects of pests, diseases and non-optimal management. $S$ is calculated as follows:

$$S = \frac{T_{\mathrm{T}}}{T_{\mathrm{Tpot}}} \tag{2.8}$$

where $T_{\mathrm{T}}$ and $T_{\mathrm{Tpot}}$ are the rates of transpiration and potential transpiration respectively. The potential yields as determined by the weather and crop can be calculated by setting $C_{\mathrm{YG}}$ to 1.

Specific Leaf Area (SLA) control is used to avoid an unrealistically high leaf area-to-biomass ratio that can result from very low biomass at the start of the growing season (Challinor and Wheeler, 2008). SLA is calculated as follows:

$$SLA = \frac{L}{W - Y} \tag{2.9}$$

where $L$ is the leaf area index, $W$ is the above ground biomass and $Y$ is the yield. SLA control uses two parameters, $S_{\max}$ (the maximum realistic value of SLA) and $N_D$. For the first $N_D$ days after emergence, if the SLA exceeds $S_{\max}$ the biomass is increased in order to reduce the SLA. After $N_D$, biomass changes according to Section 2.2.5 and the leaf area index is reduced if necessary.

#### 2.2.3.2 Leaf growth - GLAM-potato

Crop leaf area growth is calculated as above in Equation 2.7 for the first three developmental stages, with senescence being added for the senescence to harvest maturity stage (ISTG 3).

Senescence is the (broadly linear – Hay and Porter, 2006) reduction in canopy that takes place towards the end of the potato development cycle. The rate at which leaves senesce is shown by observations to be similar to the rate at which they grow (Gordon et al., 1997; Hay and Porter, 2006, e.g. Figure 2.3).

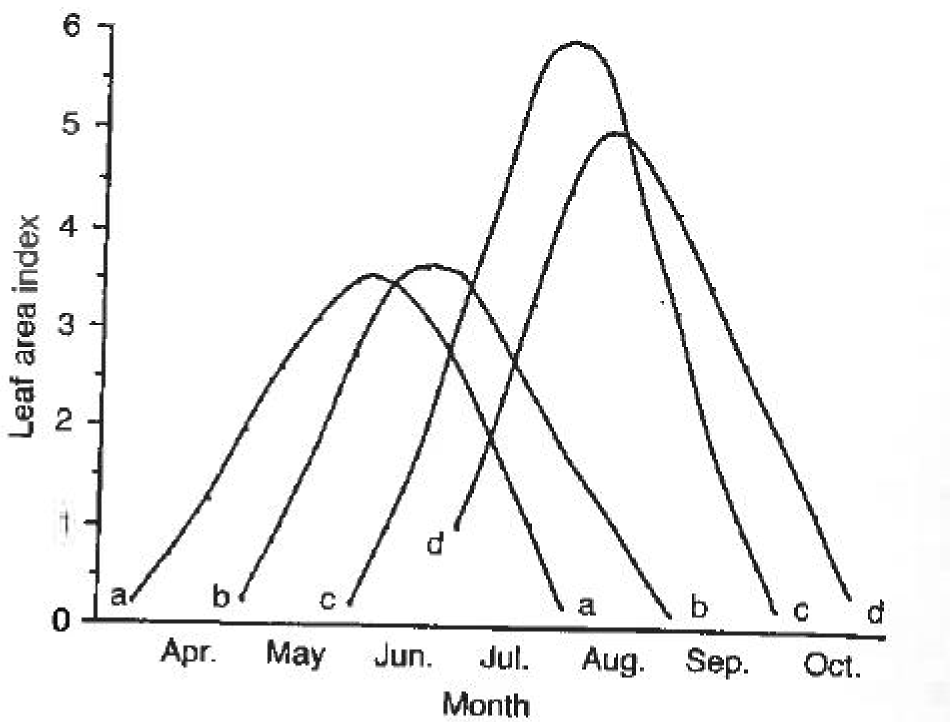



**Figure 2.3:** Figure showing observations of Leaf Area Index developing across the growing season, for both early and late maturing crops grown at Trefloyne (South Wales) and Cambridge (East Anglia). a-a, Trefloyne (early); b-b, Cambridge (early); c-c Trefloyne (late); d-d, Cambridge (late). Taken from Harris (1992).

The maximum senescence rate parameter was set equal to $\frac{\partial L}{\partial t}_{\max}$ for the final crop development stage. Senescence is then calculated as in Equation 2.10:

$$\frac{\partial L}{\partial t}_{\text{sen}} = -\left(\frac{\partial L}{\partial t}\right)_{\max} C_{\text{YG}} \left(1 + \left(1 - \min\left(\frac{S}{S_{\text{cr}}}, 1\right)\right)\right) \qquad i = 3 \qquad (2.10)$$

where $L$ is the effective LAI, $\frac{\partial L}{\partial t}_{\max}$ is a constant, $C_{\mathrm{YG}}$ is the yield gap parameter and $S$ is the soil water stress factor, as described in Section 2.2.3.1.

The process of SLA control is used in GLAM-potato to ensure a realistic relationship between leaf area index and biomass. Following Challinor and Wheeler (2008), $N_D$ is set to 5 days. $S_{\max}$ is set to 500 cm$^2$ g$^{-1}$ (Vos and Biemond, 1992).

### 2.2.4 Root growth

#### 2.2.4.1 Root growth - GLAM-groundnut

Root growth in GLAM-groundnut is dependent on LAI $L$ and described by root length density and root depth:

$$\begin{aligned}
\frac{\partial l_{\mathrm{v}}(z=0)}{\partial L} &= \textit{prescribed constant} \\
V_{\mathrm{EF}} &= \textit{prescribed constant} \\
l_{\mathrm{v}}(z=z_{\mathrm{ef}}) &= \textit{prescribed constant}
\end{aligned} \tag{2.11}$$

where $l_{\mathrm{v}}$ is the root length density by volume, $z$ is the depth into the soil, $z_{\mathrm{ef}}$ is the depth of the root extraction front and $V_{\mathrm{EF}}$ is the extraction front velocity. The value of the root length density at the surface ($z = 0$) increases linearly with leaf area index and the value at the extraction front ($z = z_{\mathrm{ef}}$) is constant. The root length density is linearly interpolated between the surface and the extraction front, which moves down into the soil with a constant velocity $V_{\mathrm{EF}}$. The extraction front descends until maturity unless it reaches the maximum obtainable rooting depth, $z_{\max}$.

#### 2.2.4.2 Root growth - GLAM-potato

GLAM-potato uses the same method as GLAM-groundnut to simulate root growth (see Section 2.2.4.1). As in GLAM-groundnut, crop yield (i.e. potato tuber) in GLAM-potato is partitioned from above-ground biomass as described below in Section 2.2.5, and GLAM-potato treats roots concerned with water uptake separately from those that store nutrients (the tubers).

Potato root length density is typically lower at the extraction front than the soil surface, with some studies suggesting more compact potato roots near the surface (Iwama, 2008; Lesczynski and Tanner, 1976; Iwama et al., 1993). Other studies suggest a more even root distribution and that distributions depend on irrigation and soil management, with irrigated crops with loosened soil having roots compacted nearer the soil surface (Stalham and Allen, 2001; Parker et al., 1989).

Initial simulations described in Sections 3.3.1.1 and 3.3.2.1 show that varying the root length density at the extraction front and root growth by LAI at the surface ($\frac{\partial l_{\mathrm{v}}(z=0)}{\partial L}$) across reported parameter ranges did not significantly affect yields. In keeping with GLAM model principles and mixed evidence from the literature, the simple linear interpolation of roots was therefore favoured over a more complex parameterisation.

These initial results did show unrealistically high mean root length densities however, increasing up to values not generally seen in the literature (e.g. see Iwama et al., 1993; Vos and Groenwold, 1986) when $\frac{\partial l_{\mathrm{v}}(z=0)}{\partial L}$ was set to a mid-point across the range found in the literature. It was therefore decided that $\frac{\partial l_{\mathrm{v}}(z=0)}{\partial L}$ should be set to the lower end of reported parameter values for subsequent simulations in order to more realistically represent root growth.

### 2.2.5 Biomass and yield

#### 2.2.5.1 Biomass and yield - GLAM-groundnut

In GLAM-groundnut, above-ground biomass ($W$) is calculated from the product of transpiration $T_{\mathrm{T}}$ and the minimum of the normalised transpiration efficiency $E_{\mathrm{T}}$ and the maximum normalised transpiration efficiency $E_{\mathrm{TN,max}}$:

$$\frac{\partial W}{\partial t} = T_{\mathrm{T}} \min(\frac{E_{\mathrm{T}}}{V}, E_{\mathrm{TN,max}}) \quad (2.12)$$

$$V = C_V(e_{\mathrm{sat}}(T_{\mathrm{max}}) - e_{\mathrm{sat}}(T_{\mathrm{min}})) \quad (2.13)$$

where $V$ is the vapour pressure deficit (the difference between the amount of moisture in the air and how much moisture the air can hold when it is saturated), calculated as shown in Equation 2.13, where $e$ is the vapour pressure. $e_{\mathrm{sat}}(T)$ is the saturation vapour pressure at temperature $T$. $E_\mathrm{T}$ can be increased in response to possible future climates to simulate increased levels of $CO_2$.

Yield ($Y$) is then determined using the harvest index $H_\mathrm{I}$, which represents the fraction of above-ground biomass that is partitioned to yield:

$$\frac{\partial H_\mathrm{I}}{\partial t} = \text{prescribed constant}, \; Y = H_\mathrm{I} W. \tag{2.14}$$

#### 2.2.5.2 Biomass and yield - GLAM-potato

GLAM-potato uses a similar method to GLAM-groundnut to simulate biomass and partitioning to yield (see Section 2.2.5.1). The only difference is the addition of a radiation use efficiency approach to simulating biomass.

Potato growth is both water and radiation limited, with significant relationships between potato dry matter and intercepted radiation and transpiration (Harris, 1992). The majority of potato crop models simulate biomass using a radiation use efficiency approach (Raymundo et al., 2014), although whether crop growth is water or radiation limited will depend on environmental conditions (Burton, 1989; Harris, 1992). Temperature primarily affects biomass through impacts on crop development, particularly on tuber initiation (Ewing and Struik, 1992).

Once tuber initiation occurs, partitioning of assimilates to tubers is fairly constant (Moriondo et al., 2005; Hay and Porter, 2006), with high temperatures potentially reducing the allocation of biomass to tubers (see Section 2.2.8). Tubers can also increase in mass during leaf senescence, as a result of assimilates being stored in stems following the die back of leaves (Moorby, 1968).

Above-ground biomass ($W$) in GLAM-potato includes biomass partitioned to yield, i.e. the tubers, as in GLAM-groundnut where above-ground biomass includes the biomass partitioned to the below-ground pods. $W$ is calculated daily from the minimum of accumulated biomass from transpiration efficiency and radiation use efficiency approaches (as for example in GLAM-Maize and the potato CropSyst model – Stöckle et al., 2003), as crop biomass is both water and radiation limited.

Transpiration-limited biomass is calculated from the product of transpiration $T_\mathrm{T}$ and the minimum of the normalised transpiration efficiency $E_\mathrm{T}$ and the maximum normalised transpiration efficiency $E_\mathrm{TN,max}$, as can be seen in Equation 2.12 in Section 2.2.5.1. Biomass from radiation use efficiency is calculated as follows:

$$\mathrm{PAR} = 0.5\, S_\mathrm{rad}(1 - e^{-k\,L}) \tag{2.15}$$

$$\frac{\partial W}{\partial t}_\mathrm{RUE} = \mathrm{RUE\ PAR} \tag{2.16}$$

where PAR is photosynthetically active radiation, RUE is radiation use efficiency, $S_\mathrm{rad}$ is solar radiation, $k$ is the extinction coefficient, $L$ is leaf area index and $\frac{\partial W}{\partial t}_\mathrm{RUE}$ is the daily increase in biomass from the radiation use efficiency approach. Biomass on any given day is then calculated as follows:

$$\frac{\partial W}{\partial t} = \min\left(\frac{\partial W}{\partial t}_\mathrm{TE}, \frac{\partial W}{\partial t}_\mathrm{RUE}\right) \tag{2.17}$$

where $\frac{\partial W}{\partial t}_\mathrm{TE}$ is the biomass calculated from the transpiration efficiency approach, as in Equation 2.12.

A linearly increasing harvest index parameter is used to partition above-ground biomass to yield, as above in Equation 2.14. Above-ground biomass here includes potato tubers – roots concerned with water uptake are considered separately. This simple method of biomass partitioning has been previously shown to be effective for potatoes (Moriondo et al., 2005). The harvest index is capped at 0.8 to avoid unrealistically-high partitioning to yield for long crop seasons (Bélanger et al., 2001; Moriondo et al., 2005; Hay and Porter, 2006).

The impacts of elevated $CO_2$ in future climates can be taken into account in GLAM-potato by altering parameters for transpiration efficiency $E_\mathrm{T}$, radiation use efficiency RUE and the physiologically limited maximum transpiration (Challinor et al., 2005b). $E_\mathrm{T}$ and RUE are increased to simulate $CO_2$ fertilisation and the physiologically limited maximum transpiration is reduced to simulate increased stomatal closure following higher $CO_2$.

### 2.2.6 Water balance

#### 2.2.6.1 Water balance - GLAM-groundnut

In GLAM-groundnut (as with other GLAM crops, the water balance routine not being crop-specific), water balance is essentially a process of filling, drainage, root extraction (according to transpiration levels) and evaporation. Rainfall runoff ($R$) is calculated as follows:

$$R = \frac{P^2}{P + S} \tag{2.18}$$

where $P$ is precipitation and $S$ is the amount of water that can soak into the soil. $S$ is set equal to $k_{\mathrm{sat}}$, which is the saturated hydraulic conductivity of the soil, representing the ease with which soil pores permit water movement. The water influx from the uppermost layer is equal to $P - R$. The soil is split into $N_{\mathrm{SL}}$ soil layers, each with a corresponding root length density and volumetric soil water content $\theta$. Drainage is calculated as follows:

$$\frac{\partial \theta}{\partial t} = -FD(\theta_{\mathrm{s}} - \theta_{\mathrm{dul}}) \tag{2.19}$$

$$D = C_{d1}{\theta^2}_{\mathrm{dul}} + C_{d2}\theta_{\mathrm{dul}} + C_{d3} \tag{2.20}$$

$$F = 1 - \frac{\ln(Q_i + 1)}{\ln(k_{\mathrm{sat}} + 1)} \tag{2.21}$$

$$k_{\mathrm{sat}} = K_{\mathrm{ks}} \left( \frac{\theta_{\mathrm{sat}} - \theta_{\mathrm{dul}}}{\theta_{\mathrm{dul}}} \right)^2 \tag{2.22}$$

where $FD$ is the drainage rate (with $F$ accounting for the inflow from the layer above $Q_i$, and $D$ for drainage into the next layer), $\theta_{\mathrm{s}}$ is the initial soil water content, $\theta_{\mathrm{dul}}$ is the soil drainage upper limit (the amount of soil moisture remaining after the soil has been thoroughly wetted and left to drain, and after this drainage has largely stopped), and $\theta_{\mathrm{sat}}$ is the saturation soil water upper limit. $C_{d1}$, $C_{d2}$, $C_{d3}$ and $K_{\mathrm{ks}}$ are empirical constants. Water is extracted over the root soil depth by roots according to transpiration and by evaporation over the evaporation soil depth $z_{\mathrm{ed}}$.

#### 2.2.6.2 Water balance - GLAM-potato

GLAM-potato uses the same method as GLAM-groundnut to simulate water balance (see Section 2.2.6.1).

The value of $N_{\mathrm{SL}}$ is not crop specific and so follows Challinor et al. (2004) to use a value of 25, as values greater than 25 were found not to change yields significantly.

Potatoes are a shallow rooted crop, with roots below a depth of 1 metre rarely exceeded even in deep, uniform soils (Harris, 1992). A value of 100 cm was therefore selected for $z_{\mathrm{max}}$. $z_{\mathrm{ed}}$ (having to be a multiple of soil layer depth) was found not to affect results and set to 20.0 cm (i.e. five soil layers).

### 2.2.7 Evaporation and transpiration

#### 2.2.7.1 Evaporation and transpiration - GLAM-groundnut

In GLAM-groundnut (as with other GLAM crops, the evapotranspiration routine not being crop-specific), transpiration $T_{\mathrm{T}}$ and evaporation $E$ rates depend on the limitations associated with plant and soil structure, energy availability and water availability. Potential rates of $T_{\mathrm{T}}$ and $E$ are defined as being limited by plant/soil structure and energy availability. The physiologically-limited transpiration $T^{\mathrm{p}}_{\mathrm{Tpot}}$ is modelled using an empirical relationship from Azam-Ali (1984):

$$T^{\mathrm{p}}_{\mathrm{Tpot}} = \begin{cases} T_{\mathrm{Tmax}}(1 - \frac{L_{\mathrm{cr}} - L}{L_{\mathrm{cr}}}) & L < L_{\mathrm{cr}} \\ T^{\mathrm{p}}_{\mathrm{Tpot}} = T_{\mathrm{Tmax}} & L \geq L_{\mathrm{cr}} \end{cases} \tag{2.23}$$

where $L_{\mathrm{cr}}$ is a threshold value of $L$ and $T_{\mathrm{Tmax}}$ is the maximum possible potential transpiration rate.

The energy-limited transpiration and evaporation rates $T^{\mathrm{e}}_{\mathrm{T}}$ and $E^{\mathrm{e}}$ are defined as in Priestley and Taylor (1972). Potential evapotranspiration is defined as follows:

$$E^{\mathrm{T}}_{\mathrm{pot}} = E^{\mathrm{e}} + T^{\mathrm{e}}_{\mathrm{T}} = \frac{\alpha}{\lambda}\frac{\Delta(R_{\mathrm{N}} - G)}{\Delta + \gamma}, \tag{2.24}$$

$$R_{\mathrm{N}} = (1 - A)S_{\mathrm{rad}}, \tag{2.25}$$

$$\alpha = 1 + (\alpha_0 - 1)\frac{V}{V_{\mathrm{ref}}} \tag{2.26}$$

$$G = C_G R_{\mathrm{N}} e^{-kL} \tag{2.27}$$

where $R_{\mathrm{N}}$ is the net all-wave radiation (calculated as in Equation 2.25 where $S_{\mathrm{rad}}$ is the short-wave radiation and $A$ is the mean albedo of the surface), $G$ is the soil heat flux, $C_G$ is a constant in Equation 2.27 (Choudhury et al., 1987), $\lambda$ is the latent heat of vapourisation of water, $\Delta = \delta e_{\mathrm{sat}}/\delta T$ (Bolton, 1980), $\gamma$ is the ratio of specific heat of air at constant pressure to the latent heat of vapourisation of water and $\alpha$ is the Priestley-Taylor coefficient. This is parameterised as a function of VPD (Jury and Tanner, 1975) as in Equation 2.26, where $V_{\mathrm{ref}}$ is a reference value of VPD (Steiner et al., 1991) and $\alpha_0$ is a pre-correction value (Priestley and Taylor, 1972). This method was chosen because it takes into account some impacts of advective effects on the exchange of water vapour from the surface, without the need for wind speed and relative humidity data that the commonly used FAO Penman-Monteith method of Allen et al. (1998) relies upon.

The energy-limited evapotranspiration is then partitioned to evaporation and transpiration considering light interception by leaves. Estimating light interception using the Beer-Bougert law (as described in Arya, 1988) – where the absorption of short-wave radiation into a plant canopy exponentially decays with depth-dependent LAI – gives

$$E^{\mathrm{e}} = E^{\mathrm{T}}_{\mathrm{pot}} \mathrm{e}^{-kL}, \tag{2.28}$$

$$T^{\mathrm{e}}_{\mathrm{T}} = E^{\mathrm{T}}_{\mathrm{pot}} (1 - \mathrm{e}^{-kL}), \tag{2.29}$$

where $k$ is the extinction coefficient. Note that Equations 2.28 and 2.29 have been altered since the publication of Challinor et al. (2004) – see Challinor et al. (2009c).

The potential evaporation (taking into account soil and energetic constraints) is modelled according to Cooper et al. (1983):

$$E_{\mathrm{pot}} = \frac{E^{\mathrm{e}}}{t_{\mathrm{R}}} \tag{2.30}$$

where $t_{\mathrm{R}}$ is the days since daily total rainfall was greater than a threshold value $P_{\mathrm{cr}}$, set to 1 mm to avoid unrealistically high potential evaporation following heavy rainfall (Challinor et al., 2004).

The potential physiological- and energy-limited transpiration rate is as follows:

$$T_{\mathrm{Tpot}} = \min(T^{\mathrm{p}}_{\mathrm{Tpot}}, T^{\mathrm{e}}_{\mathrm{T}}) \tag{2.31}$$

Structural and energetic constraints having been accounted for, water is partitioned to evaporation and transpiration according to the ratio of potential evaporation and transpiration in water-limited circumstances, or is set to potential rates, as in Equation 2.32.

$$\begin{aligned} T_{\mathrm{T}} = T_{\mathrm{Tpot}} \quad \text{and} \quad E = E_{\mathrm{pot}} \quad \text{for } \theta_{\mathrm{pe}} \geq E^{\mathrm{T}}_{\mathrm{pot}}, \\ T_{\mathrm{T}} = \theta_{\mathrm{pe}} \frac{T^{\mathrm{e}}_{\mathrm{T}}}{T^{\mathrm{e}}_{\mathrm{T}} + E^{\mathrm{e}}} \quad \text{and} \quad E = \theta_{\mathrm{pe}} \frac{E^{\mathrm{e}}}{T^{\mathrm{e}}_{\mathrm{T}} + E^{\mathrm{e}}} \quad \text{for } \theta_{\mathrm{pe}} < E^{\mathrm{T}}_{\mathrm{pot}} \end{aligned} \tag{2.32}$$

The potentially extractable soil water $\theta_{\mathrm{pe}}$ is calculated from the soil water content above the lower limit $(\theta - \theta_{\mathrm{ll}})$ and the root length density, $l_v$, in each soil layer as follows (Challinor et al., 2009c):

$$\theta_{\mathrm{pe}} = \int_0^{z_{\max}} (\theta(z) - \theta_{\mathrm{ll}})(1 - \mathrm{e}^{k_{\mathrm{DIF}} l_{\mathrm{v}}(z)})\, \mathrm{d}z, \tag{2.33}$$

where $k_{\mathrm{DIF}}$ is the uptake diffusion coefficient and $z$ is each soil layer. Note that Equation 2.33 has been altered since the publication of Challinor et al. (2004).

#### 2.2.7.2 Evaporation and transpiration - GLAM-potato

GLAM-potato uses the same method as GLAM-groundnut to simulate evapotranspiration (see Section 2.2.7.1).

### 2.2.8 Heat and water stress

#### 2.2.8.1 Heat stress - GLAM-groundnut

In GLAM-groundnut heat stress can be modelled using two parametrisations, referred to here as the "complex" and "simple" routines.

The complex heat stress routine is fully described in Challinor et al. (2005a) and can be parameterised for different sensitivities of crops to heat stress as well as different flowering distributions. High temperature stress episodes are defined as periods of time when the mean 8 a.m. - 2 p.m. temperature exceeds a critical threshold. The impact of each episode on pod-set for each day during the flowering period is then calculated. The impact on pod-set for each of these episodes depends on its temperature, timing and duration. The total reduction in pod-set due to each high temperature episode is calculated by summing the impact on each of the days during the flowering period:

$$P_{\text{tot}} = \sum_{i=1}^{i=N_{\text{f}}} P(i)F_{\text{f}}(i) \tag{2.34}$$

where $P_{\text{tot}}$ is the fractional pod-set, $N_{\text{f}}$ is the number of days during the flowering period, $P(i)$ is the fraction of pods from day $i$ that set, and $F_{\text{f}}(i)$ is the fraction of flowers opening on day $i$. The high temperature episode resulting in the lowest value of $P_{\text{tot}}$ is considered the most important and is used to calculate the reduction in the rate of change of harvest index $\frac{\partial H_{\text{I}}}{\partial t}$:

$$\frac{\partial H_{\text{I}}}{\partial t} = \left(\frac{\partial H_{\text{I}}}{\partial t}\right)_0 \left(1 - \frac{P_{\text{cr}} - P_{tot}}{P_{\text{cr}}}\right) \tag{2.35}$$

where $P_{\text{cr}}$ is the fractional pod-set below which the rate of change of harvest index begins to be reduced from its non-stressed value.

The simple heat stress routine is parameterised based on the methods of Osborne et al. (2013). For each day $t$ from anthesis to the start of pod-filling (i.e. ISTG 2 to 3) above a critical temperature $T_{\text{crit}}$, $HTS(t)$ is linearly reduced from 1 until a temperature $T_{\text{lim}}$ where $HTS(t)$ is 0. A mean value of $HTS$ across the number of days $n$ from anthesis to pod-filling is calculated, which is used to reduce $\frac{\partial H_{\text{I}}}{\partial t}$, as described below.

$$HTS(t) = 1 - \frac{\bar{T}(t) - T_{\text{crit}}}{T_{\text{lim}} - T_{\text{crit}}} \tag{2.36}$$

$$HTS = \frac{\sum_{t=1}^{n} HTS(t)}{n} \tag{2.37}$$

$$\frac{\partial H_{\text{I}}}{\partial t} = \left(\frac{\partial H_{\text{I}}}{\partial t}\right)_0 HTS \tag{2.38}$$

#### 2.2.8.2 Heat stress - GLAM-potato

Heat stress in GLAM-potato is parameterised as in the simple heat stress routine of GLAM-groundnut. In GLAM-potato, heat stress impacts yields based on the temperatures between the start of tuber initiation to the start of senescence.

Heat stress on potatoes predominately reduces partitioning to tubers (Lafta and Lorenzen, 1995; Rykaczewska, 2015; Timlin et al., 2006; Wolf et al., 1990; Ingram and McCloud, 1984; Kooman et al., 1996; Prange et al., 1990). Previous modelling studies have shown skill in simulating the impacts of high temperatures on tubers with linear reductions above a threshold temperature of 24°C until a maximum temperature of 33°C, above which tuber bulking ceases (Ingram and McCloud, 1984; Griffin et al., 1993). This process was similarly modelled using the simple GLAM heat stress routine, following the methods of Osborne et al. (2013) (Section 2.2.8.1). This method is a relatively simple parameterisation that reduces simulation time and the number of parameters needed.

#### 2.2.8.3 Water stress - GLAM-potato

The impact of water stress on $\left(\frac{\partial H_{\mathrm{I}}}{\partial t}\right)_0$ is switched off in GLAM-potato, as water stress impacts on yields are felt primarily through reductions in leaf area and photosynthesis rather than as a direct impact on the allocation of assimilates (Cabello et al., 2013; Jefferies and MacKerron, 1993; Van Loon, 1981).

### 2.2.9 Model calibration

In general, GLAM is calibrated to observed yields in order to take into account the mean effects of biotic stresses and non-optimal management using the yield gap parameter $C_{\mathrm{YG}}$. GLAM calibration using $C_{\mathrm{YG}}$ reduces leaf area index (as in Equation 2.7). $C_{\mathrm{YG}}$ is used to reduce the leaf area index from a potential value to a value that takes into account the mean effects of non-weather impacts. $C_{\mathrm{YG}}$ is varied from 0 to 1 in a set number of increments (typically 20 or 100) and $C_{\mathrm{YG}}$ associated with the lowest Root Mean Square Error (RMSE) is selected for model simulations. By reducing the leaf area index, transpiration and the absorbed photosynthetically active radiation are reduced, which in turn reduces biomass and yield.

Further details of calibration for specific analyses can be found in subsequent sections, such as Sections 3.2.3.1 and 3.2.3.2 in Chapter 3.

### 2.2.10 Model optimisation

The GLAM optimisation code used for parameter optimisation in Chapter 3 was developed by James Watson at the University of Leeds in order to select parameter values from predefined ranges. Different experimental studies often report different values for parameters, thus providing plausible ranges for parameters to be used in model simulations. The optimiser runs GLAM multiple times with different parameter sets (the parameters to be optimised are specified with ranges) and returns the parameter set of those simulated that is associated with the minimum RMSE between simulated and observed yields. For each iteration, a random new parameter value from within a predefined range is selected, and if this new value is associated with a lower RMSE it is retained.

The optimiser requires a "seed" to be chosen for a random number generator to randomly select parameter values. With different seeds, different parameters are chosen randomly and different final parameter sets result due to the ability of parameters to compensate for each other and produce the same (or at least similar) model outcomes. The optimiser is therefore typically run multiple times with different seeds, and using enough iterations per optimisation run to allow the reduction in RMSE to become relatively small with time. Further details can be found in Sections 3.2.2.1 and 3.2.2.2.

### 2.2.11 Model parameters

Table 2.2 lists all crop- and regionally-specific parameters used in GLAM-potato, together with the reported parameter values and ranges where applicable.

**Table 2.2:** Parameters used in GLAM-potato, with ranges where applicable. For the thermal time requirements, stage 1 ($i$ 1) corresponds to the planting to emergence stage, stage 2 ($i$ 2) to the emergence to tuber initiation stage, stage 3 ($i$ 3) to the tuber initiation to senescence stage and stage 4 ($i$ 4) to senescence to crop harvest.

| Parameter | Value | Source |
|---|---|---|
| Critical sowing soil moisture $C_{\mathrm{sow}}$ | 0.6 | Ejieji and Gowing, 2000 |
| | | Jefferies and Heilbronn, 1991 |
| VPD constant $C_V$ | 0.7 | Tanner and Sinclair, 1983 |
| Thermal time requirements (°days; stages 1, 2, 3, 4) | 100-400, 100-300, 200-500, 100-400 | Streck et al., 2007 |
| | | Paula et al., 2005 |
| | | Jefferies and Mackerron, 1987 |
| | | Van Keulen and Stol, 1995 |
| Cardinal temperatures (°C), base, optimum, maximum | 0-8, 15-21, 25-33 | Manrique and Hodges, 1989 |
| | | Sands et al., 1979 |
| Critical photoperiod $P_{crit}$ (hours) | 10.7-13 | Ewing and Wareing, 1978 |
| | | Streck et al., 2007 |
| Photoperiod sensitivity $P_s$ | 0.0645 | Streck et al., 2007 |
| Maximum potential transpiration (cm/day) | 3 | Campbell et al., 1976 |
| Root length density at the extraction front $l_{\mathrm{v}}(z = z_{\mathrm{ef}})$ (cm/cm$^3$) | 0.15-1 | Lesczynski and Tanner, 1976 |
| | | Parker et al., 1989 |
| | | Stalham and Allen, 2001 |
| Root length density by leaf area at surface $\frac{\partial l_{\mathrm{v}}(z=0)}{\partial L}$ (cm/cm$^3$) | 0.4-6.1 | Iwama et al., 1993 |
| Extraction front velocity $V_{\mathrm{EF}}$ (cm day$^{-1}$) | 1.5-2 | Smit and Groenwold, 2005 |
| Critical value of leaf area index | 3-6 | Bremner et al., 1967 |
| Soil water stress factor critical value $S_{\mathrm{cr}}$ | 0.6 | Ejieji and Gowing, 2000 |
| Maximum rate of change in leaf area index $\frac{\partial L}{\partial t}_{\mathrm{max}}$ | 0.14 | Hay and Porter, 2006 |
| | | Jones and Allen, 1983 |
| | | Allen and Scott, 1980 |
| Number of days of SLA control $N_D$ | 5 | see Section 2.2.3.2 |
| Max value of SLA allowed if SLA control is turned on $S_{\max}$ (cm) | 500 | Vos and Biemond, 1992 |
| | | Fasan and Haverkort, 1991 |

Table 2.2 continued.

| Parameter | Value | Source |
|---|---|---|
| Radiation Use Efficiency (g/MJ) | 1.7-3.7 | Zhou et al., 2016 |
| | | Timlin et al., 2006 |
| | | Khurana and McLaren, 1982 |
| | | Jefferies and MacKerron, 1989 |
| Transpiration efficiency (Pa) | 2-11.05 | Jefferies, 1993 |
| | | Kaminski et al., 2015 |
| | | Tanner, 1981 |
| | | Vos and Groenwold, 1989 |
| Maximum value of normalised transpiration efficiency (g/kg) | 11.31 | Vos and Groenwold, 1989 |
| Extinction coefficient | 0.3-0.8 | Haverkort et al., 1991 |
| | | Jongschaap and Booij, 2004 |
| | | Monteith and Unsworth, 2007 |
| Albedo $A$ | 0.2 | Monteith and Unsworth, 2007 |
| Soil heat flux constant $C_G$ | 0.4 | Choudhury et al., 1987 |
| Uptake diffusion coefficient $k_{\mathrm{DIF}}$ (cm$^2$/day) | 0.15 - 0.2 | Lesczynski and Tanner, 1976 |
| Reference value of VPD $V_{\mathrm{ref}}$ (kPa) | 1 | Steiner et al., 1991 |
| Maximum senescence rate | -0.14 | Hay and Porter, 2006 |
| | | Jones and Allen, 1983 |
| Priestley-Taylor constant $\alpha$ | 1.26 | Priestley and Taylor, 1972 |
| Number of soil layers $N_{\mathrm{SL}}$ | 25 | see Section 2.2.6.2 |
| Maximum root depth $z_{\max}$ (cm) | 100 | see Section 2.2.6.2 |
| Maximum value of harvest index $z_{\max}$ | 0.8 | Moriondo et al., 2005 |
| | | Hay and Porter, 2006 |
| Maximum rate of change of harvest index $\frac{\partial H_{\mathrm{I}}}{\partial t}$ | 0.008-0.012 | Moriondo et al., 2005 |
| Upper limit for heat stress $T_{\mathrm{lim}}$ (°C) | 33 | Timlin et al., 2006 |
| | | Wolf et al., 1990; Ingram and McCloud, 1984 |
| Critical temperature for heat stress $T_{\mathrm{crit}}$ (°C) | 24 | Timlin et al., 2006 |
| | | Wolf et al., 1990; Ingram and McCloud, 1984 |

# Chapter 3

# GLAM-potato regional evaluation

## 3.1 Introduction

The objective of this chapter is to evaluate the performance of GLAM-potato in simulating observed weather-yield relationships using regional yield data and regionally-optimsed parameters. The most important weather variables for determining potato development and growth are different in different regions. For example, hotter areas are often limited by excessive temperatures or insufficient rainfall. In temperate areas, the growing season is often determined by when frosts are no longer a risk (see Chapter 1, Section 1.4.1). As such, it is important to test the model in contrasting locations. The model was calibrated and tested in two contrasting environments (in Aberdeen, United Kingdom and Colombia) to see if adequate weather-yield responses can be simulated in different weather conditions. The potato agriculture in these two countries is described below in Sections 3.1.1 and 3.1.2.

See Chapter 2 for a description of GLAM-potato. See Chapter 1, Section 1.4 for a broader summary of potato agriculture.

### 3.1.1 UK potato agriculture

Potato agriculture in the UK is typically highly efficient, resulting in potato yields being comparatively high (c. 40 tonnes per hectare – FAOSTAT country average yield data, 2017). Over the latter half of the 20th century, registered potato growers in the UK decreased by 96% and the harvested area of potatoes halved at the same time as average yields nearly doubling (Daccache et al., 2011a), resulting in total production staying relatively constant (see Figure 3.1; Daccache et al., 2011a). These changes were driven by demands for higher quality and to serve large agribusinesses and supermarkets (Daccache et al., 2011a).

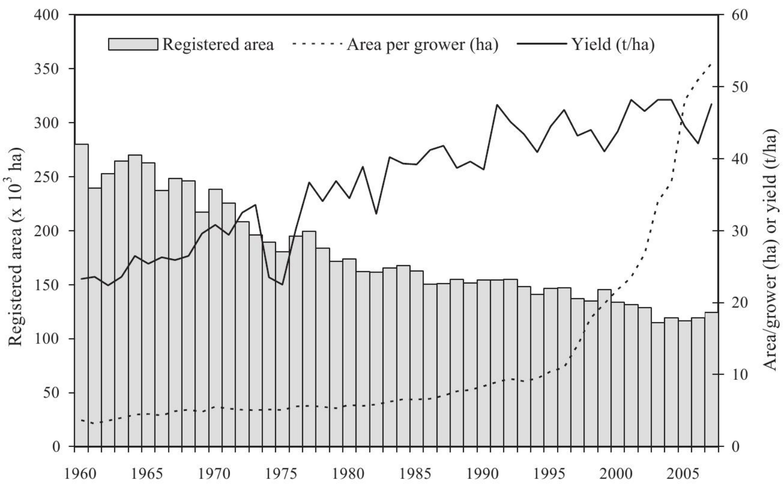



**Figure 3.1:** Potato cropped area and yield, 1960-2007. Potato production has remained relatively constant over this period due to falling growing area but increasing yields. From Daccache et al. (2011a).

The start of the UK potato growing season is primarily determined by the end of spring frosts, which can range from March to May depending on latitude (Harris, 1992). Harvesting occurs throughout the summer (depending on planting date and variety) and can be as late as October. Weather conditions are in general favourable for production, being relatively cool and moist. Maris Piper is the most common potato variety in the UK, with the majority of production made up of similar maincrop varieties (Daccache et al., 2011a). 63% of production is irrigated to some extent - there is regional variation, with most production and irrigation occurring in the drier Eastern regions (see Figure 3.2; Daccache et al., 2011b). In Scotland there is extensive potato production also, with seed potato production being especially important as the cooler conditions help prevent nematode attack (Eves-van den Akker et al., 2016).

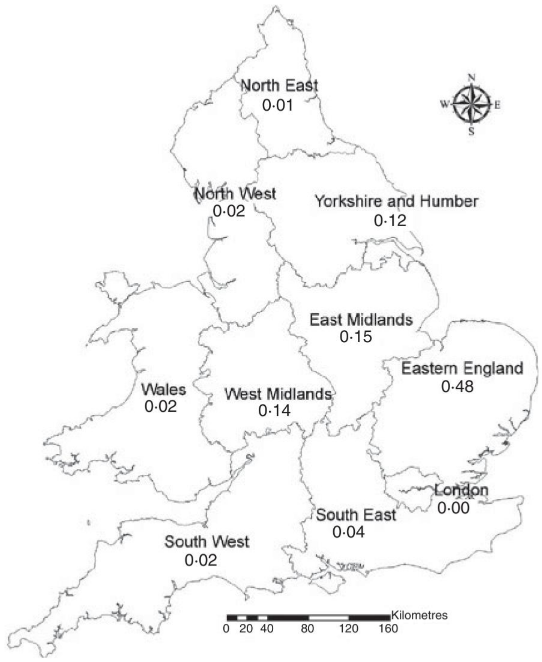



**Figure 3.2:** Proporation of total irrigated potato area in England and Wales in 2009. From Daccache et al. (2011b).

### 3.1.2 Colombia potato agriculture

Potato yields are typically modest in Colombia relative to temperate regions, where agriculture is usually more mechanised and has higher levels of irrigation. Potatoes are predominately a highland crop in Colombia, being concentrated along two mountain ranges running roughly parallel to each other from south to north in the west-centre of the country. The principle growing regions are Cundinamarca and Boyacá in central Colombia, Nariño in the south west and Antioquia to the north (Figure 3.3). Potatoes are often grown with other vegetable crops such as broad beans and green peas on steep slopes, making highly mechanised agriculture difficult. National average fresh weight yields of approximately 18 tonnes per hectare are high relative to Andean neighbours such as Ecuador (c. 7 tonnes per hectare), though still much lower than yields achieved in more mechanised agricultural systems such as the UK (FAOSTAT country average yield data, 2017).

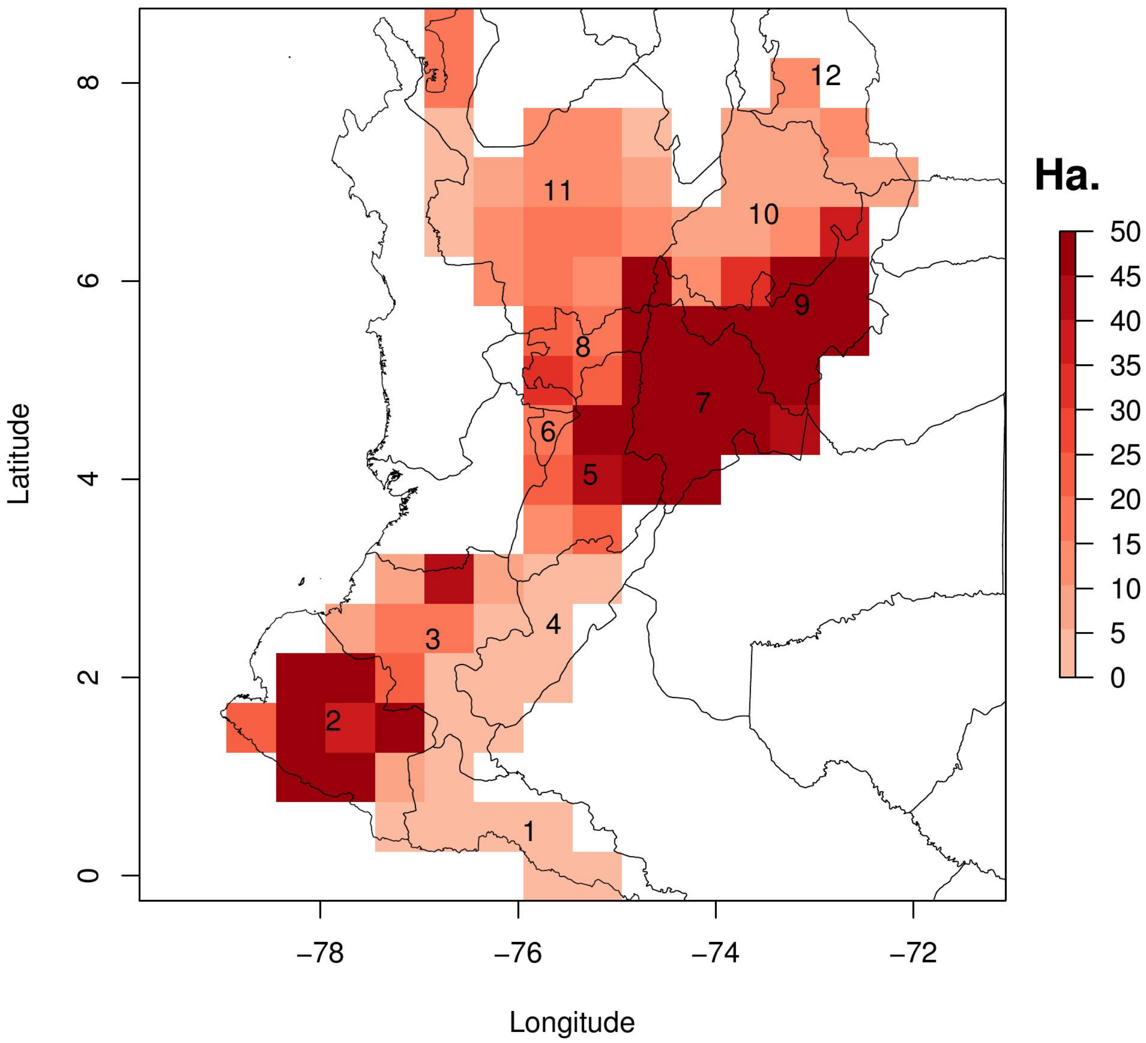



**Figure 3.3:** Potato growing area in Colombia (hectares) using data from Portmann et al. (2010) described in Section 3.2.1.4. Region 1 = Putumayo, 2 = Nariño, 3 = Cauca, 4 = Huila, 5 = Tolima, 6 = Quindío, 7 = Cundinamarca, 8 = Caldas, 9 = Boyacá, 10 = Santander, 11 = Antioquia, 12 = Norte de Santander.

Potato production is predominately rainfed in Colombia, so the main growing season coincides with the rainy season (CIP, 2009). For most of Colombia, the rainy season extends from March-May through to November (Enfield and Alfaro, 1999). The first and main growing season therefore occurs from March-May through to September-October, with a second growing season from August or September through to around February (Diana Giraldo Mendez, International Potato Council, personal communication). There is regional variation, however, as Colombia is a topographically-diverse country with large variation in climate. For example, Cundinamarca has a relatively low elevation and high mean temperature (typically around 26°C) whereas Nariño is higher, more mountainous and cooler, with mean temperatures typically around 16°C. Most commercial potato production is grown at 1800-2300 metres above sea level. Being a tropical country, there is little annual variation in temperature.

Colombian potato varieties are most often maincrop *Solanum tuberosum* ssp. *tuberosum*. There has been a decrease in area planted for native *andigena* varieties in the past few decades and the majority of production is increasingly focused on higher-yielding maincrop varieties, with 60% of production on medium-to-large scale farms. Smallholders tend to grow more of the 10 commonly used native varieties (International Potato Council, World Potato Atlas, 2009).

### 3.1.3 Objective and research question

GLAM-potato needs to be assessed across a variety of environmental conditions in order to be deemed a suitable model for potato simulations across large scales. Therefore, the aim of this chapter is to assess model performance using regional data from the UK and Colombia:

- Is GLAM-potato capable of simulating observed weather-yield relationships in the UK and Colombia?

## 3.2 Methods

This section is a summary of the methods used to evaluate GLAM-potato. In the following sections, each stage of the process is described in more detail. If applicable, differences in the methods used for the UK and Colombia are presented in subsections for each country. These differences are summarised in Table 3.1.

**Table 3.1:** Summary of differences in methods for UK and Colombia GLAM simulations.

| Difference | UK | Colombia |
|---|---|---|
| Yield data | Time series from 1985 to 2008 for an experimental site at Craibstone, Aberdeen | 11 Colombian regional yield time series from 2007 to 2010 |
| Planting date | Approximate planting window known | Planting defined by rainy season |
| Crop development | Optimised phenology parameters | Cardinal temperatures at each grid cell selected using preliminary runs |
| Optimisation | Optimise parameters on first half of yield time series | Optimise parameters on one of 11 regions (Antioquia) |
| Calibration | Calibrate $C_{YG}$ on first half of time series | Calibrate $C_{YG}$ on each of 11 regions |
| Evaluation | Assess model skill on second half of yield time series | Assess model skill on all regions apart from Antioquia |

The process used to evaluate GLAM-potato consists of parameter selection for optimisation, parameter optimisation, model calibration and finally model evaluation. Optimisation refers to the process of varying selected model parameters to ascertain those that lead to the best model skill (described in Section 3.2.2). Calibration refers to the process of setting the yield gap parameter $C_{YG}$ to account for mean observed yield levels (Section 3.2.3). Evaluation is then the test by which we judge whether or not GLAM-potato is performing adequately in simulating observed weather-yield relationships (Section 3.2.4). Figure 3.4 summarises these processes.

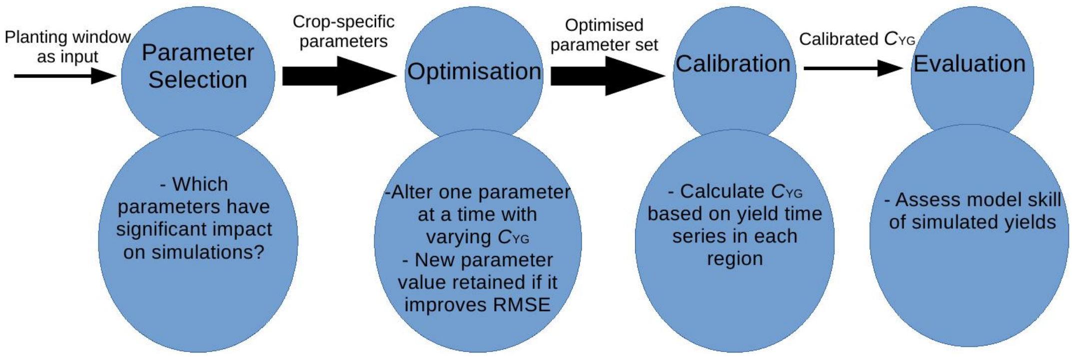



**Figure 3.4:** Flow diagram summarising methods used to evaluate GLAM-potato. Thicker arrows indicate a higher number of GLAM simulations. 9 simulations are necessary for evaluating each crop-specific parameter for optimisation (varying each parameter three times over three parameter sets). Over 20000 simulations are used for optimising parameter sets. $C_{YG}$ = Yield Gap Parameter.

### 3.2.1 Input data

The input data used in GLAM are described in this section – observed yields, soil data, weather data, growing area and irrigation information. See Chapter 2 for a full description of GLAM-potato.

#### 3.2.1.1 Yield data

As in Gregory and Marshall (2012) and Bélanger et al. (2001) (and similarly to the methods used in Müller et al., 2017 and Haverkort et al., 2013), yield data are converted from fresh weight to dry weight using an assumed proportion of tuber dry matter to fresh matter ratio of 20%. While potato tuber dry matter varies with variety and environmental conditions (Ifenkwe and Allen, 1978), this value is used as it falls midway across reported values (Harris, 1992; Gray and Hughes, 1978). Ifenkwe and Allen (1978) found that for Maris Piper (a maincrop potato cultivar), dry matter content was 20% at time of harvest. Consistency of methods is also desired across analyses in this thesis, and it is assumed that minor changes to dry matter content resulting from environmental conditions at larger scales will average out for regional scale yield data and have a negligible influence on results.

The yield time series are checked for detrending to remove any trends in the data not due to weather. This is done to remove the influence of factors not simulated explicitly by the model (e.g. technology and management). Linear and quadratic models are chosen to detrend the yield data as more complex local regression fitting is deemed undesirable due to the short time series. Linear and quadratic models are tested on each time series. Robust regression is used to fit models to the data using the R package "robust" (Wang et al., 2014), as this is superior to ordinary least squares regression when data contain outliers or otherwise break the assumptions associated with linear models (Finger, 2010). Detrended yields are not retained if they show lower mean absolute correlations between weather variables and observed yields. In this situation, observed yields are used instead. This approach assumes that any trends in yields are due to weather rather than factors not accounted for in the model.

##### 3.2.1.1.1 UK yield data

Yield data from an experimental site at Craibstone, Aberdeen, are used to test model performance in temperate latitudes. The Aberdeen data are provided by Dr. Stuart Whale, previously of the Scottish Agricultural College, via Professor Peter Gregory, as used in Gregory and Marshall (2012). Data are available from the years 1951 to 2008. The crops are fully rainfed and planted from late-March to the end of May. The potatoes are a maincrop variety (Maris Piper).

The observed yields for the years prior to 1985 were found to have a poorer relationship with the weather variables (correlation coefficient $< 0.3$ for precipitation and $< 0.1$ for minimum and maximum temperature, with associated p-values $> 0.05$ for all weather variables), so the second half of this time series (1985-2008) is used to evaluate GLAM performance, as it provides a stronger weather-yield signal for the model to pick up on.

Yield observations are available for five different sets of fertiliser treatments, as well as control observations with no fertiliser added to the crop. GLAM does not specifically account for fertiliser use in the model but does so implicitly in a mean level across a time series using a Yield Gap Parameter $C_{\mathrm{YG}}$ – see Section 3.2). No significant differences in correlations with weather variables were found across the different yield time series. Figure 3.5 shows these correlations when using weather variables averaged from late-March to the end of September. These correlations vary across different assumed starts of the growing season (looking at day of year 65, 91, 106, 121, 136 and 152), although correlations are never significantly different across fertiliser treatments and growing periods used to average weather variables. Because of this, yields with no fertiliser are chosen for model runs as GLAM does not simulate fertiliser use.

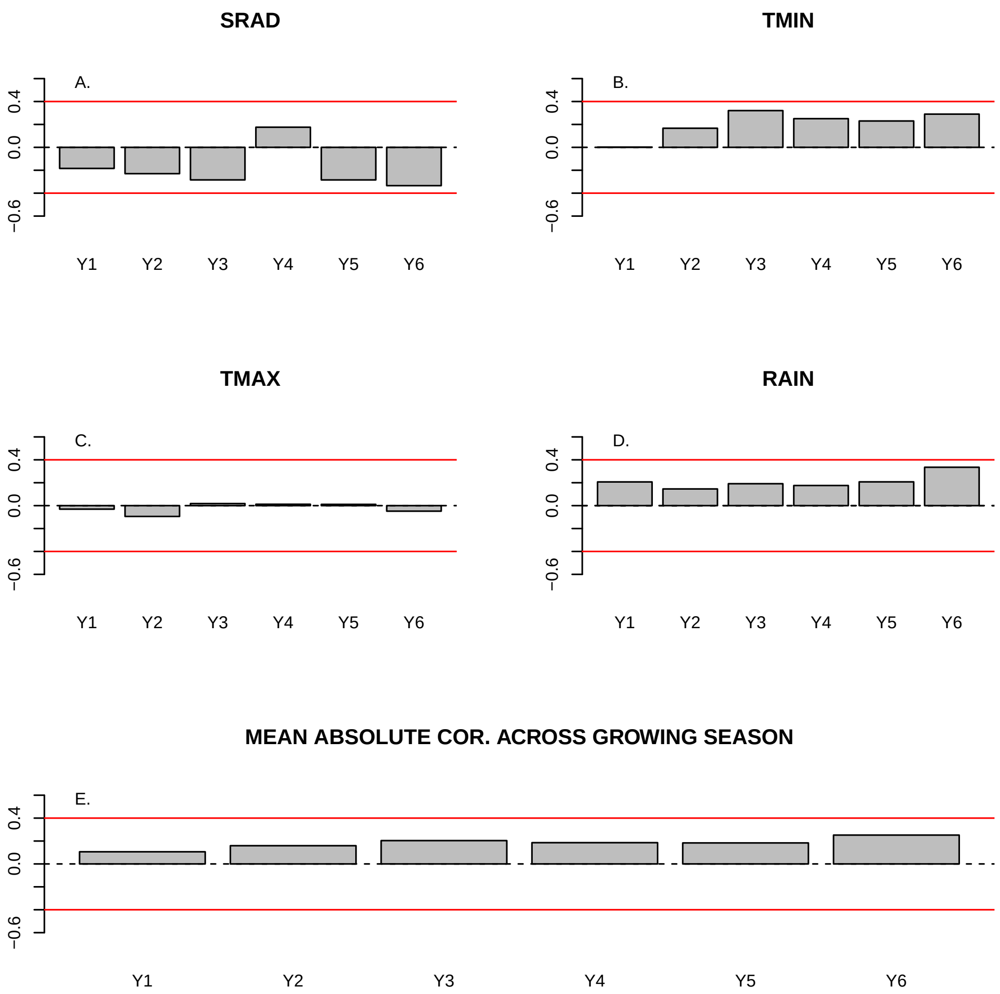



**Figure 3.5:** Correlations of yield data (1985-2008) with GLAM weather inputs (A = solar radiation, B = minimum temperature, C = maximum temperature, D = rainfall, E = mean absolute correlation) across the six fertiliser treatments across a growing season from day of year 61 to 271. Y1 = the no fertiliser data used in this study, Y2 to Y6 describe different fertiliser treatments. Horizontal lines represent the significance threshold for correlations at the 5% level.

The observed yields are not detrended as there is no significant linear or quadratic trend in the data. The first half of the UK time series is used for optimisation of parameters and calibration of $C_{\mathrm{YG}}$, and the second half used for model evaluation. This is to help ensure an independent data set with which to evaluate model performance.

The Aberdeen yield data are from experiments where crops were planted across late-March to the end of May and harvested in late September. As in Gregory and Marshall (2012), simulations assume a start of the sowing window at April 1st and allow a maximum duration of 180 days. A 45 day planting window is selected to reproduce the variation in planting dates of the experiment and to match other simulations in this thesis.

#### 3.2.1.1.2 Colombia yield data

Four-year time series for Colombian regions are used to test model performance in tropical latitudes. These represent aggregated yield data for the largest administrative areas in Colombia, known as "departments". There are 32 departments in Colombia. For the main Colombian growing season (with potatoes being planting in the first half of the calendar year), data from 12 departments are available (including the most important potato growing regions of Colombia – see Section 3.1.2), from the years 2007 to 2010. These are Santander, Nariño, Tolima, Putumayo, Antioquia, Boyacá, Quindío, Norte de Santander, Huila, Cundinamarca, Cauca and Caldas. The Colombian yield data are provided by the International Center for Tropical Agriculture (CIAT) via Julian Ramirez-Villegas. Data from Putumayo are not used as they contain very little potato growing area (see Section 3.2.1.4).

The model runs described below use yields that are not linearly detrended. No significant trend was found in all regions save for Nariño and Tolima, and when these yields were detrended the correlations between detrended yields and weather variables were lower than correlations between the raw yield data and weather variables. It was therefore decided to not detrend yields for these two regions, the assumption being that the trend in yields was due to weather variables rather than factors not accounted for by the model.

### 3.2.1.2 Weather data

The AgMERRA (Agriculture Modern-Era Restrospective analysis for Research and Applications) data set is used for baseline climate conditions, available from 1980 to 2010 (Ruane et al., 2015). This is a global baseline climate forcing data set better than many widely-available alternatives (Ruane et al., 2015). NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA; Rienecker et al., 2011) is bias-corrected using observation data and satellite data, as described in Ruane et al. (2015).

Ruane et al. (2015) showed that mean biases in maximum and minimum temperature, as well as correlations with daily data, are slightly better than other reanalysis data sets when compared to data from 2324 observational stations. There is a slight global warm bias for maximum temperature and a cool bias in minimum temperature, and results are generally better at mid-high latitudes. Correlations with precipitation are significantly better than the other reanalysis data sets. This is thought to be the result of AgMERRA's use of MERRA-Land (Reichle et al., 2011), which has improved simulation of the water cycle, as well as the incorporation of the Climate Prediction Center's precipitation data (Chen et al., 2008).

Observed weather data were available from MIDAS (Met Office Integrated Data Archive System) for the Craibstone site but were not used to make the simulations in this thesis comparable with respect to the weather inputs – see Chapter 5 for a comparison of the regional and global simulations in this thesis.

AgMERRA is compared to these observed weather data, as well as a comparable reanalysis data set (the Princeton data set – Sheffield et al., 2006) in Figure 3.6. The AgMERRA data have very similar mean daily temperature and precipitation whilst having better representation of daily variability than the Princeton data set, with correlations of AgMERRA data with observations higher on average than those of the Princeton data for both temperature and rainfall. Princeton and AgMERRA data sets are also compared in Ruane et al. (2015). They show that AgMERRA typically outperforms Princeton, although Princeton is usually very similar in its mean biases with temperature and precipitation. The correlations of temperature with daily observations are lower for Princeton, although the larger difference is in the representation of rainfall, in keeping with the greater uncertainties associated with simulating cloud formation and precipitation in climate models (see Chapter 1).

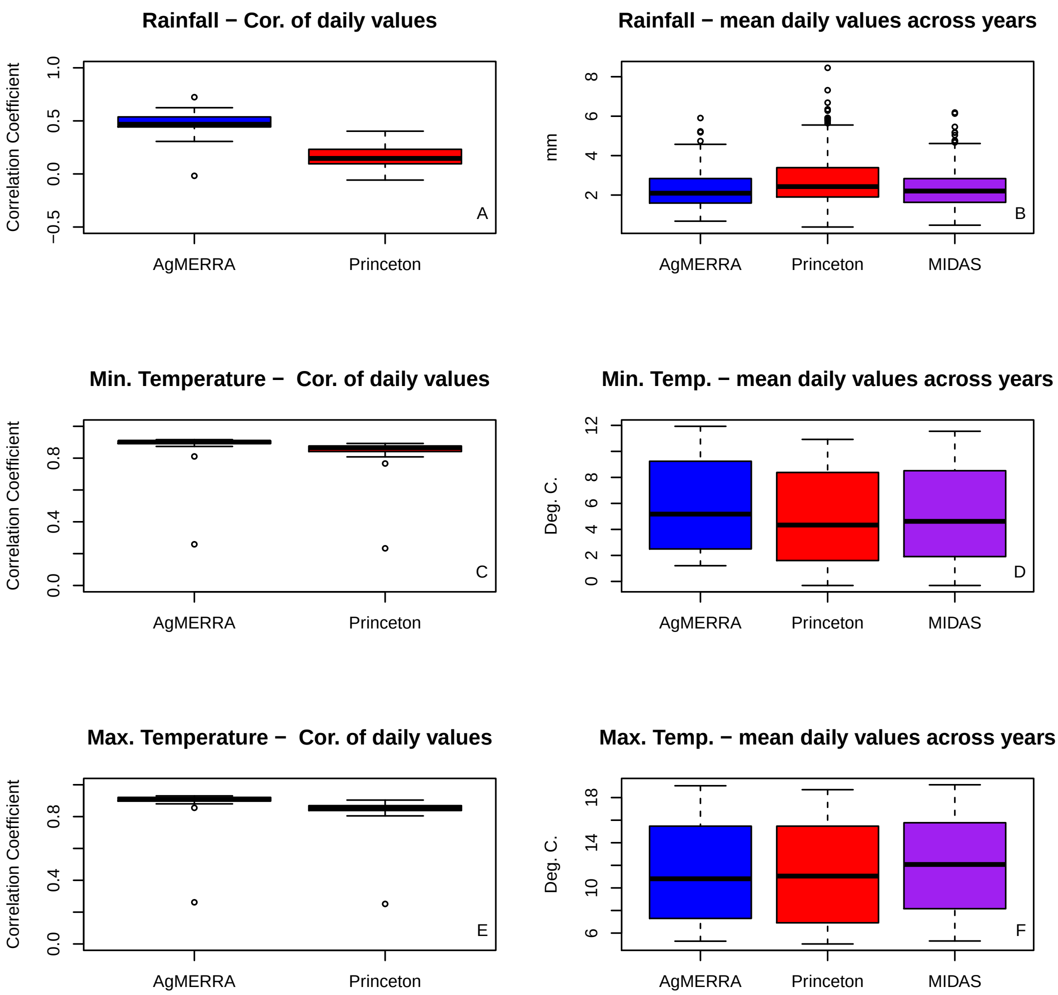



**Figure 3.6:** Comparison of AgMERRA, Princeton and MIDAS weather data. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range. A). Correlations of daily reanalysis and observed rainfall data. B). Mean daily rainfall data across 1980-2010. C). Correlations of daily reanalysis and observed minimum temperature data. D). Mean daily minimum temperature data across 1980-2010. E). Correlations of daily reanalysis and observed maximum temperature data. F). Mean daily maximum temperature data across 1980-2010.

#### 3.2.1.3 Soil data

Soil data are from the the Global Soil Dataset for Earth System Modelling (Shangguan et al., 2014). The soil inputs for GLAM are calculated using the method of Saxton et al. (1986). They use the percentage values of sand and clay to calculate values of the three soil hydrological parameters used in GLAM, drained lower limit $\theta_{\mathrm{rll}}$, drained upper limit $\theta_{\mathrm{dul}}$ and saturation limit $\theta_{\mathrm{sat}}$. These values are then averaged over the top seven soil layers (i.e. the top 1.383 m) and aggregated to a 0.5° grid using bilinear interpolation in R (R Core Team, 2017). The top seven layers are chosen to be averaged over to include the 100 cm soil depth used in GLAM-potato (see Chapter 2, Section 2.2.6.2).

#### 3.2.1.4 Potato growing area information

Grid cells are selected for simulation if they contain potato growing area, as defined by MIRCA (Monthly Irrigated and Rainfed Crop Areas – Portmann et al., 2010), representing information from the years 1998-2002. Shapefiles from the Database of Global Administrative Areas are used to define the 12 Colombian departments from which yield data are available (http://www.gadm.org/) using grid cell centres to define boundaries. Data are aggregated to a 0.5° grid using bilinear interpolation to match the available weather data using the statistical package R (R Core Team, 2017).

As shown in Chapter 4, the top 50% of grid cells by growing area contain 99% of the total potato growing area across all grid cells globally. This means that the other 50% of grid cells contain almost no potato growing area and so were excluded from analyses in this thesis as they have little influence on regional yields and production. This meant excluding the Putumayo region entirely from the Colombian simulations.

The grid cell that contains the Aberdeen site is selected to provide inputs for these simulations.

### 3.2.2 GLAM-potato parameter selection and optimisation

Parameters are selected for optimisation for the UK and Colombia when the parameters are region- and crop-specific and a significant impact on simulated yields is found across the reported parameter range from the literature. All parameters (and their ranges) tested are in Table 3.2. A few crop or regionally-specific parameters were not optimised. The maximum rate of change of leaf area index and the maximum normalised transpiration efficiency are set to the maximum of the values reported in the literature in order to potentially simulate the highest yields.

Preliminary runs are used to decide whether or not parameters are having a significant impact on simulated yields using a sequential sensitivity analysis. Three parameter sets are created, comprising of each region- and crop-specific parameter at the lower, upper and mid-point of the reported ranges from the literature. Each parameter is then varied across its range within the three parameter sets, keeping all other parameters constant. A parameter is deemed to be having a significant impact on simulated yields when across the parameter range within any of the three parameter sets there is a percentage difference in RMSE of 5% or greater. These parameters are then chosen for optimisation.

For the parameters found not to have a significant impact on yields, a mid-point of the reported parameter range is taken for use in evaluation simulations. This approach is adopted as opposed to a screening method of sensitivity analysis (e.g. see King and Perera, 2013) as it can measure the size of the effect of each parameter on model output – as opposed to simply ranking them using a screening method – and relatively few model runs are used, which is desirable for preliminary runs.

Optimisation is performed using the optimiser developed by James Watson at the University of Leeds, as used by Nicklin (2013) and described in Chapter 2, Section 2.2.10. The optimiser randomly samples the parameters selected across their specified ranges and returns the parameter set associated with the minimum RMSE after a set number of iterations. Parameter sets that result in durations across years and grid cells being greater than 180 days or maximum LAIs being less than 1 are rejected (these being unrealistic – Harris, 1992; Burton, 1989).

This process is repeated using eight different seeds to generate different parameter sets, as in Nicklin (2013) – skill across the eight seeds did not vary significantly so this was deemed sufficient following prelimary simulations that consisted of tests of the model optimsation set up. The seeds initialise the random number generator in the optimiser. Different optimised parameter sets result from different seeds, as parameters in the model can compensate for each other in differing ways. The number of iterations is chosen to be sufficient for further reductions in RMSE to be minimal, and further convergence of parameter sets (i.e. different seeds) to be insignificant in both regions. This was set to be 20000 as the preliminary results suggested no further improvement in RMSE after this point.

Each iteration of the optimisation consists of a calibration run of $C_{\mathrm{YG}}$. This varies $C_{\mathrm{YG}}$ for every GLAM simulation during the optimisation. It was decided to vary $C_{\mathrm{YG}}$, rather than fix it (as, for example, was done by Ramirez-Villegas, 2014), as this allows a full exploration of parameter space and a sensible value of $C_{\mathrm{YG}}$ to emerge from the optimisation. Fixing $C_{\mathrm{YG}}$ was considered a less viable option due to the uncertainty associated with pre-selecting a value of $C_{\mathrm{YG}}$ for each region.

**Table 3.2:** Ranges tested for the region- and crop- specific parameters varied in this study. For the thermal time requirements, stage 1 corresponds to the planting to emergence stage, stage 2 to the emergence to tuber initiation stage, stage 3 to the tuber initiation to senescence stage and stage 4 to senescence to crop harvest.

| Parameter | Range | Source |
|---|---|---|
| Thermal time requirements (°days; stages 1, 2, 3, 4) | 100-400, 100-300, 200-500, 100-400 | Streck et al., 2007 |
| | | Paula et al., 2005 |
| | | Jefferies and Mackerron, 1987 |
| | | Van Keulen and Stol, 1995 |
| Cardinal temperatures (°C), base, optimum, maximum | 0-8, 15-21, 25-33 | Manrique and Hodges, 1989 |
| | | Sands et al., 1979 |
| Critical photoperiod $P_{crit}$ (hours) | 10.7-13 | Ewing and Wareing, 1978 |
| | | Streck et al., 2007 |
| Root length density at the extraction front $l_{\mathrm{v}}(z = z_{\mathrm{ef}})$ (cm/cm$^3$) | 0.15-1 | Lesczynski and Tanner, 1976 |
| | | Parker et al., 1989 |
| | | Stalham and Allen, 2001 |
| Root length density by leaf area at surface $\frac{\partial l_{\mathrm{v}}(z=0)}{\partial L}$ (cm/cm$^3$) | 0.4-6.1 | Iwama et al., 1993 |
| Extraction front velocity $V_{\mathrm{EF}}$ (cm day$^{-1}$) | 1.5-2 | Smit and Groenwold, 2005 |
| Critical value of leaf area index | 3-6 | Bremner et al., 1967 |

Table 3.2 continued.

| Parameter | Range | Source |
|---|---|---|
| Radiation Use Efficiency (g/MJ) | 2.7 (1.7-3.7) | Zhou et al., 2016 |
| | | Timlin et al., 2006 |
| | | Khurana and McLaren, 1982 |
| | | Jefferies and MacKerron, 1989 |
| Transpiration efficiency (Pa) | 2-11.05 | Jefferies, 1993 |
| | | Kaminski et al., 2015 |
| | | Tanner, 1981 |
| | | Vos and Groenwold, 1989 |
| Extinction coefficient | 0.3-0.8 | Haverkort et al., 1991 |
| | | Jongschaap and Booij, 2004 |
| | | Monteith and Unsworth, 2007 |
| Uptake diffusion coefficient $k_{\mathrm{DIF}}$ ($\mathrm{cm}^2$/day) | 0.15 - 0.2 | Lesczynski and Tanner, 1976 |
| Maximum rate of change of harvest index $\frac{\partial H_I}{\partial t}$ | 0.008-0.012 | Moriondo et al., 2005 |

#### 3.2.2.1 UK parameter selection

The first half of the UK time series (1985 to 1996) is used for model parameter selection, optimisation and calibration. This allows the second half of the time series to be used as independent data for evaluation.

#### 3.2.2.2 Colombia parameter selection

As mentioned in Section 3.1.2, Colombia is a diverse country in terms of terrain and temperature ranges. Different potato cultivars are used across such large geographic and climatological ranges. Previous regional modelling has shown that a single parameter set can capture phenology provided the region is homogeneous in terms of climate (van Bussel, 2011) - one parameter set cannot adequately simulate potato development across the highly diverse Colombian regions, however. The planting dates and crop phenologies are therefore varied at each grid cell in order to represent this variation in potato cultivars.

This section describes the methods used to select planting date and variety parameters at each grid cell. The model parameters not involved in phenology are afterwards optimised on one region and evaluated on all other regions, as described above in Section 3.2.2. One region was chosen to optimise (as opposed to individual grid cells) as the yield data is at the regional level, and therefore the variability in yield data at the grid cell level will not always be the same as that at the regional level. The region chosen to optimise parameters on was Antioquia. This is a large region with varied climatic conditions and significant potato growing area to optimise over.

Colombia initial model runs select the date for the start of the planting window and varieties (cardinal temperatures) for each grid cell across all regions. One planting window is selected first for each grid cell based on rainfall, which primarily determines the growing season in Colombia. Planting dates use a 45 day planting window, in keeping with other GLAM simulations in this thesis. The start of this planting window is based on the level of rainfall within the usual length of growing season. Six different six month periods from January 1st to June 1st (as these yield data are associated with the main Colombian growing season, i.e. planting in the first half of the year) are tested at each grid cell to see which period had the most rainfall in each season. The start of the most common period across the four years with most rainfall was selected as the start of the planting window in GLAM for that grid cell (for example, if three years had February 1st as the start of the six month period containing the most rainfall, this start of the growing season was selected). More rainfall was associated across years on average when taking this most common maximum rainfall period rather than an average of maximum rainfall periods across years. Eight grid cells had four different six month periods selected across the four years – in these situations, a median of these four dates was selected rather than the mean, again because it resulted in more rainfall on average across years. Planting dates selected and the average total rainfall across the growing season associated with these planting dates can be seen in Figures 3.7 and 3.8 respectively. Selected planting windows tend to be nearer the end of the tested time intervals in the south and North of Colombia.

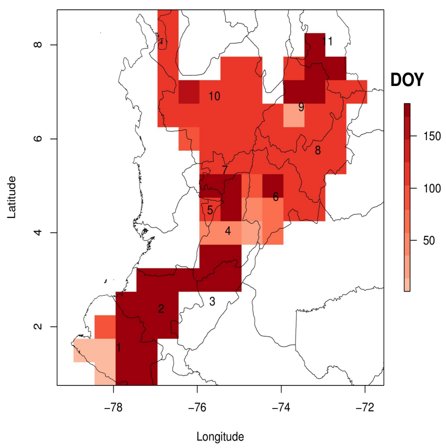



**Figure 3.7**

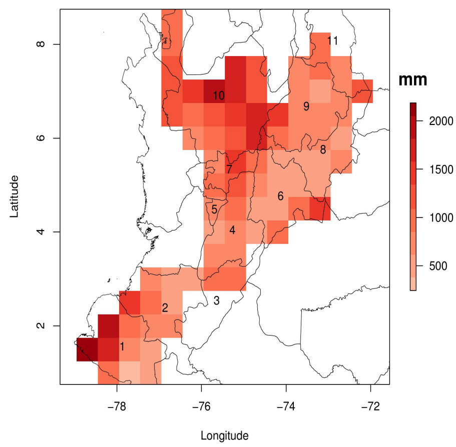



**Figure 3.8**

Left: Selected start of planting windows. Right: Sum of rainfall over the six growing season associated with selected planting dates (mm). Region 1 = Nariño, 2 = Cauca, 3 = Huila, 4 = Tolima, 5 = Quindío, 6 = Cundinamarca, 7 = Caldas, 8 = Boyacá, 9 = Santander, 10 = Antioquia, 11 = Norte de Santander.

Following planting date selection, a variety is then selected for each grid cell, based on which combination of planting date and variety has the highest mean simulated yields across the time series. This is similar to the methods used in Osborne et al. (2013) and Hijmans (2003), where varietal types are defined based on thermal time requirements. The assumption using the highest yielding combination is that the variety and planting date are optimal for the crop given the conditions and will reflect as much as possible the variety and planting date used in reality.

For defining different varieties, cardinal temperatures are varied rather than thermal time requirements as this allows the relationship between temperature and developmental time to change across varieties at each grid cell (see Table 3.3). Planting date and variety combinations that do not show emergency planting (i.e. when planting occurs at the end of the planting window at that grid cell), durations higher than 180 days or maximum LAI values of greater than 10 or less than 1 are tested to see which has the highest yields. These caps are imposed to simulate realistic crop phenology and as potato harvesting is a complex process involving climatic and non-climatic factors (see Chapter 1), with the majority of potato seasons being shorter than 180 days.

Varieties T1-T5 consist of progressively higher cardinal temperatures (Table 3.3, rows 1-5). Varieties LHT1 and LHT2 ("Low-High" temperature varieties, Table 3.3, rows 6-7) have hotter temperatures for the latter three and two developmental stages respectively (which result in longer tuber bulking periods in cooler conditions, or shortened tuber bulking in hotter conditions), and varieties HLT1 and HLT2 ("High-Low" temperature varieties, Table 3.3, rows 8-9) have hotter temperatures for the first three and two stages respectively (which result in longer tuber bulking periods in hotter conditions and shortened tuber bulking in cooler conditions). Other developmental parameters (thermal times and the critical photoperiod) are fixed across all varieties. The thermal time parameters are set to the upper end of the reported range for the senescence to harvest stage and the low end of reported ranges from emergence to senescence, in order to simulate realistic leaf area index development (i.e. allowing the leaf area index to fall near to zero, as is common in potatoes – see Section 3.3). This was decided following the Colombian simulations described in Section 3.2.2 that showed unrealistically short senescence periods – previous large scale crop modelling has shown the importance of the representation of leaf senescence for accurate model performance (van Bussel, 2011).

**Table 3.3:** Cardinal temperatures used for the different varieties for each grid cell in Colombian regions (°C). In the column names, B refers to base temperature, O refers to optimum temperature and M refers to maximum temperature and numbers 1-4 refer to the 4 developmental stages – planting to emergence (1), emergence to tuber initiation (2), tuber initiation to senescence (3) and senescence to harvest (4).

| Variety | B1 | B2 | B3 | B4 | O1 | O2 | O3 | O4 | M1 | M2 | M3 | M4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 - T1 | 0 | 0 | 0 | 0 | 15 | 15 | 15 | 15 | 25 | 25 | 25 | 25 |
| 2 - T2 | 2 | 2 | 2 | 2 | 16.5 | 16.5 | 16.5 | 16.5 | 27 | 27 | 27 | 27 |
| 3 - T3 | 4 | 4 | 4 | 4 | 18 | 18 | 18 | 18 | 29 | 29 | 29 | 29 |
| 4 - T4 | 6 | 6 | 6 | 6 | 19.5 | 19.5 | 19.5 | 19.5 | 31 | 31 | 31 | 31 |
| 5 - T5 | 8 | 8 | 8 | 8 | 21 | 21 | 21 | 21 | 33 | 33 | 33 | 33 |
| 6 -LHT1 | 0 | 4 | 4 | 4 | 15 | 18 | 18 | 18 | 25 | 29 | 29 | 29 |
| 7 -LHT2 | 0 | 0 | 4 | 4 | 15 | 15 | 18 | 18 | 25 | 25 | 29 | 29 |
| 8 - HLT1 | 8 | 8 | 8 | 6 | 21 | 21 | 21 | 19.5 | 33 | 33 | 33 | 31 |
| 9 - HLT2 | 8 | 8 | 6 | 6 | 21 | 21 | 19.5 | 19.5 | 33 | 33 | 31 | 31 |

Other parameters are set to mid-points of reported ranges for these initial simulations that select planting dates and varieties, with a few exceptions. The maximum rate of change of leaf area index, the maximum rate of change of harvest index and the maximum normalised transpiration efficiency are set to the maximum of the values reported in the literature in order to potentially simulate the highest yields. The root length density by leaf area at the soil surface is set to the low end of the reported range in order to realistically simulate root growth (see Section 2.2.4.2). The radiation use and transpiration efficiency parameters are especially important for simulating crop biomass. Transpiration efficiency was set to the low end of its reported range and radiation use efficiency fixed at the mid-point of its reported range following prelimary simulations (see Chapter 4, Section 4.2.2).

### 3.2.3 GLAM-potato calibration

GLAM is calibrated for each region to observed yields in order to take into account the mean effects of biotic stresses and non-optimal management over the time series using the yield gap parameter ($C_{\mathrm{YG}}$).

For each region, $C_{\mathrm{YG}}$ is varied from 0.05 to 1.00 in increments of 0.05 and the value of $C_{\mathrm{YG}}$ associated with the lowest RMSE is selected. The model is then evaluated using this value of $C_{\mathrm{YG}}$.

#### 3.2.3.1 UK calibration

Calibration of $C_{\mathrm{YG}}$ uses the first half of the yield time series (1985 to 1996).

#### 3.2.3.2 Colombia calibration

Calibration of $C_{\mathrm{YG}}$ uses the four year yield time series associated with each of the 11 Colombian regions (Antioquia during the optimisation process and the other 10 for evaluation).

For each Colombian region, it is necessary to calculate a regional simulated yield time series to compare to regional observed yields for calibration, optimisation and subsequent evaluation. In order to do this, regional production is calculated using the product of the area data and the simulated yields at each grid cell, which are summed for the regional production time series. A simulated yield time series is then calculated by dividing total production by total area at the regional level to compare to the regional observed yields.

### 3.2.4 Evaluation framework

Two tests are used to evaluate GLAM-potato model performance in each region:

1. Are correlations between GLAM-potato simulated yields and statistical model simulated yields not statistically different?
2. Are model output variables realistic compared to observed values?

The simulated and observed yield correlations from statistical and process-based models are compared to see if GLAM captures the seasonal weather variations comparably to a statistical model. Statistical models have previously been shown to effectively capture weather-yield relationships (e.g. Hawkins et al., 2013a), and these relationships can be used as a benchmark of model preformance (e.g Challinor et al., 2004). If GLAM-potato performs comparably to such a model (that is specifically designed to capture these relationships) as well as realistically simulating potato growth then the model is said to be getting the right answer for the right reasons. Checks to ensure that model outputs of leaf area index and harvest index are sensible (i.e. fall within the ranges of values reported in the literature) are conducted to assess the model's accuracy in simulating potato growth. Durations of developmental stages are also assessed. The leaf area index output from GLAM is reduced when calibrated using $C_{\mathrm{YG}}$, and this reduced value is compared to observations.

The focus of the evaluation is on the best performing GLAM parameter sets, as chosen from the eight parameter sets optimised as described in Section 3.2.2. The best performing parameter sets for UK and each Colombian region being evaluated are defined as those which showed the highest correlation coefficients, as the primary focus of the analysis is the accurate representation of year-to-year variability. When a correlation between observed yields and statistical model yields is found to be significant, the Williams method (Williams and Williams, 1959) is used to judge whether or not this correlation and that between GLAM yields and observed yields is significantly different. If they are not found to be significantly different and have the same sign of correlation (i.e. positive or negative) then evaluation test 1 is passed in that region. If no significant correlation is found between statistical model yields and observed yields, the sign of correlations is required to be the same only. The model output variables examined for test 2 are biomass, harvest index, maximum leaf area index and duration. If across all years and grid cells these are within the limits seen in observations from the literature then test 2 is passed.

The R function “r.test” from the package “psych” (Revelle, 2015) is used to statistically judge whether or not the correlations are significantly different. Being two modelling processes that are based on the same input weather data, the variables containing the simulated yields from the two models are not independent, and hence neither are the associated correlations. The “r.test” function is therefore used to calculate a test statistic for the difference of two dependent correlations (the correlations between the simulated yields for both modelling types and observations) using the Williams method (Williams and Williams, 1959), which has been shown to perform well relative to other methods in terms of the statistical power of the test (i.e. the probability of correctly rejecting the null hypothesis when it is false – Wilcox and Tian, 2008). The Williams method calculates a test statistic based on the correlations between the three variables concerned (both sets of simulated yields and the observed yields). The statistic is then compared to a student’s t-distribution to obtain a p-value for evidence against an equal-correlation hypothesis.

#### 3.2.4.1 UK evaluation

After optimisation and calibration of model parameters, evaluation is conducted on the second half of the UK time series (1997 to 2008). This is to ensure that the data used for optimisation and calibration are independent of those used for model evaluation.

#### 3.2.4.2 Colombia evaluation

The model is optimised on the Antioquia region, as it is a large region with varied climatic conditions and significant potato growing area to optimise over. Model evaluation then takes place on the other regions of Colombia. This is to ensure that the data used for optimisation are independent of those used for model evaluation.

Correlation coefficients evaluated are for each region. These use regional yield time series for the observed and simulated yields, calculated using regional production and area data as described in Section 3.2.3.2.

### 3.2.5 Statistical crop model

The statistical models consist of the weather variable inputs used in GLAM to allow a direct comparison between GLAM and the statistical model. A multiple linear regression model – as shown below in Equation 3.1 – consisting of mean rainfall, temperature, solar radiation and temperature-rain interactions for the growing season (defined as the weather data from the earliest possible planting date to latest harvest date) as explanatory variables and yields as the response variable over years $t$ is compared to GLAM-potato:

$$Y(t) = I + \beta_1 T_{\text{mean}}(t) + \beta_2 P(t) + \beta_3 R(t) + \beta_4 T_{\text{mean}}(t) P(t) + e \tag{3.1}$$

where $T_{\text{mean}}$ is the mean temperature during the growing season, $P$ is the mean precipitation during the growing season, $R$ is the mean solar radiation during the growing season, $T_{\text{mean}}(t)P(t)$ is the interaction between precipitation and mean temperature, $Y$ is the end-of-season yield and $e$ is a Gaussian error term. The parameters (or coefficients) associated with each variable in the model are represented by $\beta_1$ to $\beta_4$, and $I$ is the intercept. In addition to the weather inputs that GLAM uses, an interaction variable between temperature and precipitation is included as the variability between rainfall and temperature is not independent (Runge, 1968) and is therefore commonly included in statistical crop models (e.g. Hawkins et al., 2013a; Schlenker and Roberts, 2009).

#### 3.2.5.1 UK statistical model

The statistical model is calibrated on the first half of the time series and then used to simulate yields in the second half of the time series, allowing a direct comparison to GLAM model evaluation.

#### 3.2.5.2 Colombia statistical model

One statistical model is calibrated for each Colombian region. Regional observed and simulated yields are related to the average climate variables across the region, as in Hawkins et al. (2013a) - in other words, averaging the weather variables for each year across all grid cells to make regional weather time series.

To avoid model overtuning on the short four year time series, the variable of those in Equation 3.1 showing the highest correlation coefficient with observed yields in each region is selected and used as a single explanatory variable in each model.

## 3.3 Results

Results are presented separately for the UK and Colombia. An optimisation results section (Section 3.3.1.1 for the UK and Section 3.3.2.1 for Colombia) is followed by the evaluation results (Section 3.3.1.2 for the UK and Section 3.3.2.2 for Colombia).

### 3.3.1 UK

#### 3.3.1.1 Optimisation

Parameters selected for optimisation as a result of the sensitivity analysis are shown in Figure 3.9. Whilst these initial runs show that the root length density at the extraction front $l_\mathrm{v}(z = z_\mathrm{ef})$ and root growth by LAI $\frac{\partial l_\mathrm{v}(z=0)}{\partial L}$ were not significantly affecting yields (and so not optimised), the results across parameter sets used in the sensitivity analysis did show unrealistically high mean root length densities, increasing up to values not generally seen in the literature (e.g. see Iwama et al., 1993; Vos and Groenwold, 1986). It was therefore decided that $\frac{\partial l_\mathrm{v}(z=0)}{\partial L}$ should be set to the lower end of reported parameter values for subsequent simulations in order to more realistically represent root growth. This applies to all GLAM-potato simulations in this thesis, as the same was found in Colombian simulations.

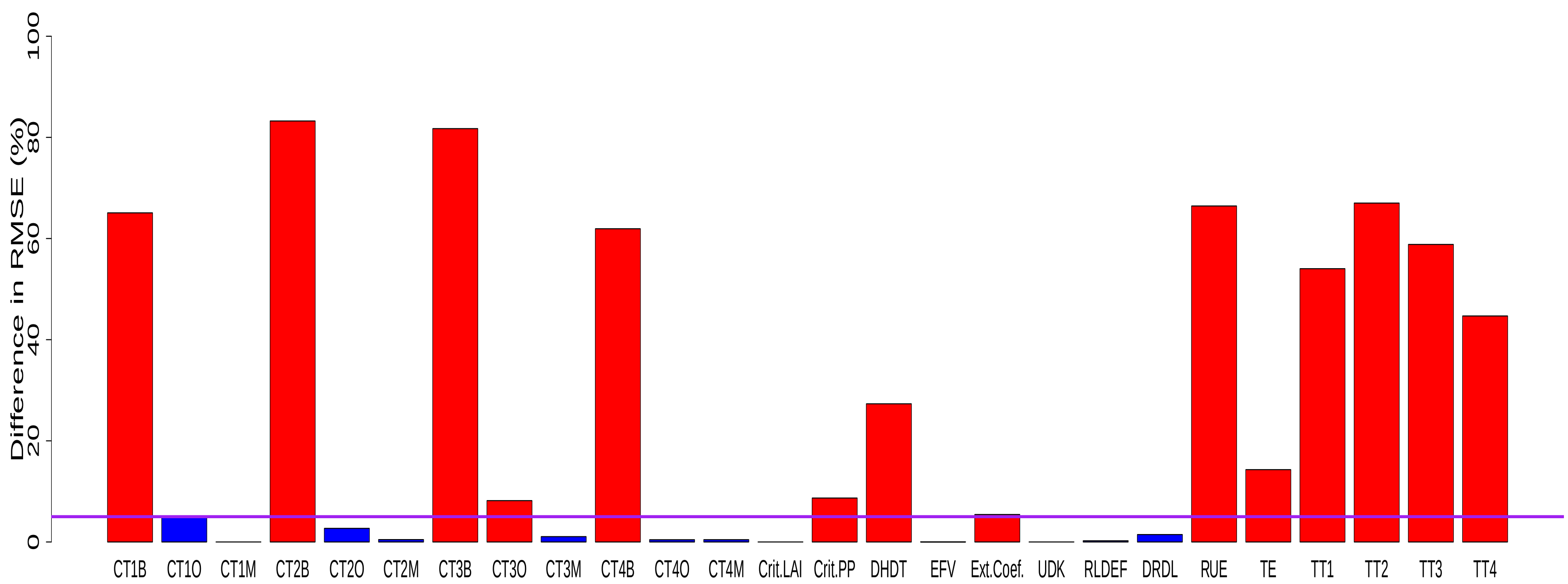



**Figure 3.9:** Maximum percentage difference in RMSE across parameter sets for each parameter varied at the Aberdeen site. The purple line represents a 5% difference in RMSE, with percentage differences greater than this meaning that the parameter is optimised, shown in red. Blue parameters are those not optimised. “CT1” to “CT4” refer to the cardinal temperatures of the 4 developmental stages, and B, O and M refer to Base, Optimum and Maximum cardinal temperatures respectively. “Crit.LAI” is the value below which transpiration is limited by LAI. “Crit.PP” is the critical photoperiod. “DHDT” is the rate of change of harvest index. “EFV” is the extraction front velocity. “Ext.Coef.” is the extinction coefficient. “UDK” is the uptake diffusion coefficient. “RLDEF” is the root length density at the extraction front. “DRDL” is the root length density by leaf area at the surface. “RUE” is radiation use efficiency. “TE” is transpiration efficiency. “TT1” to “TT4” refer to the thermal time requirements for stages 1 to 4.

The evolution of RMSE during the optimisation process on the Aberdeen time series can be seen in Figure 3.10. As can be seen, RMSE improvements take place mostly within the first 5000 iterations. Subsequent improvements to RMSE tail off and after 10000 iterations no significant improvements take place. 20000 was chosen as the final number of iterations as skill across different seeds no longer converged significantly across seeds.

Figure 3.11 shows why the RMSE is higher after optimisation in Aberdeen (around 2000 kg/ha) compared to Colombian results (which show RMSE around 200 kg/ha, see Section 3.3.2.1). The most important source in the difference in skill is the mean yield level (i.e. line 3 in Figure 3.11 shows the lowest RMSE from any single change in model setup). After this, the shorter time series is most important (line 2), with the number of parameters not having a significant effect on RMSE (line 1). Following these tests, RMSE in Aberdeen reduced to less than 1000 kg/ha, but was still not as low as seen in Colombian optimisations. The remaining difference in skill between Aberdeen and Antioquia following optimisation is due to the higher interannual variability of the Aberdeen time series compared to Antioquia. This results in higher RMSE, as while the model shows good skill in picking up the year-to-year variability in observed yields, the magnitude of the differences between observed and simulated yields are higher on average due to the higher variability in observed yields. The Antioquia time series shows less yearly variability and therefore RMSE tends to be lower.

The variation in parameters selected by the optimisation process can be seen in Figure 3.12. Model skill (both RMSE and correlation coefficient) is best for parameter sets 1, 3 and 5. All parameters show substantial variation across reported ranges, showing that compensation can occur with different parameter sets leading to similar model skill. The better performing parameter sets do show lower radiation use efficiency, transpiration use efficiency, and higher rate of change of harvest index $\frac{\partial H_{\mathrm{I}}}{\partial t}$ values, however. For the most skilful parameter sets, the $C_{\mathrm{YG}}$ is calibrated to have a maximum value of 1.

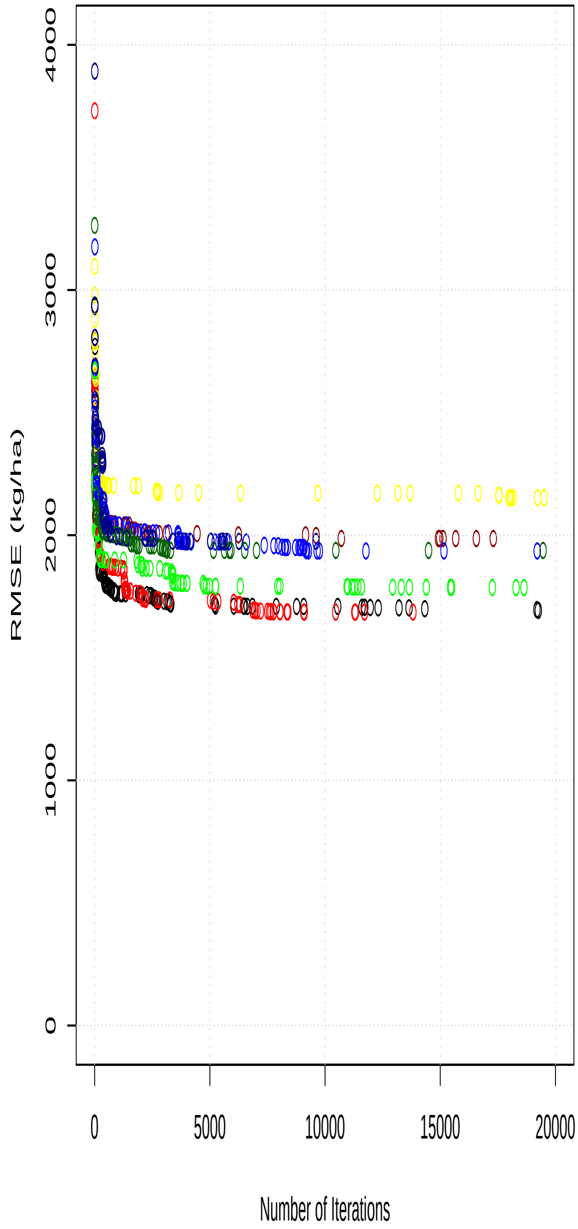



**Figure 3.10**

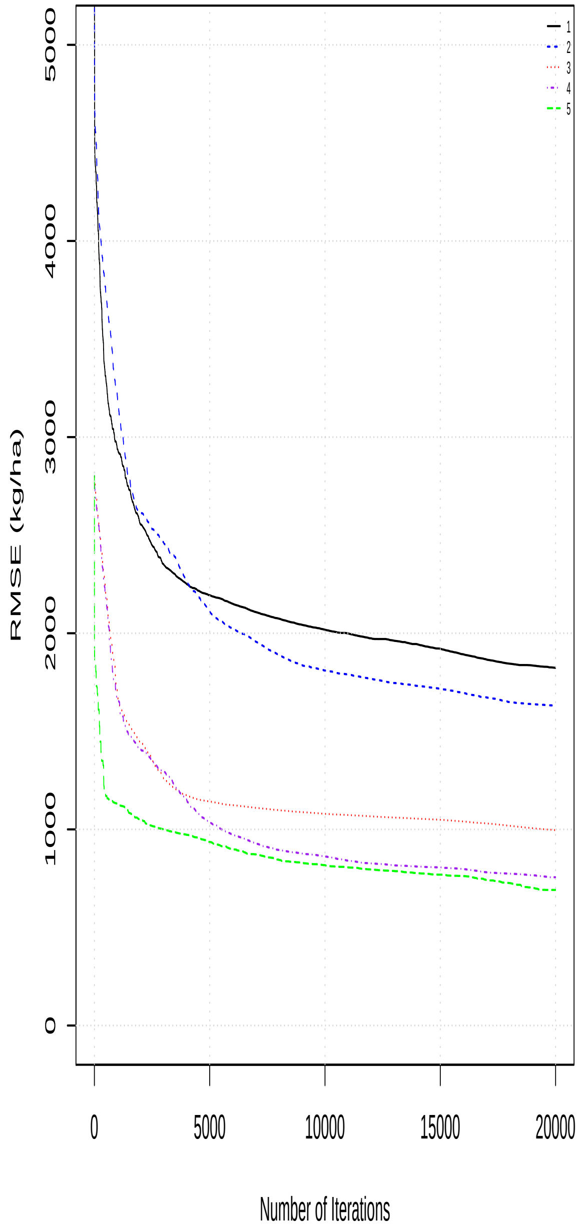



**Figure 3.11**

Left: Optimisation runs using 8 different seeds for Aberdeen, showing only the iterations that improved RMSE. Right: Optimisation runs testing the source in difference between optimised skill in Aberdeen and Colombia, showing all values of RMSE across iterations, ordered by value. 1 = All parameters optimised, 2 = four year time series optimised, 3 = yield levels half of normal Aberdeen time series, 4 = half yields and four year time series, 5 = half yields, four year time series and all parameters optimised.

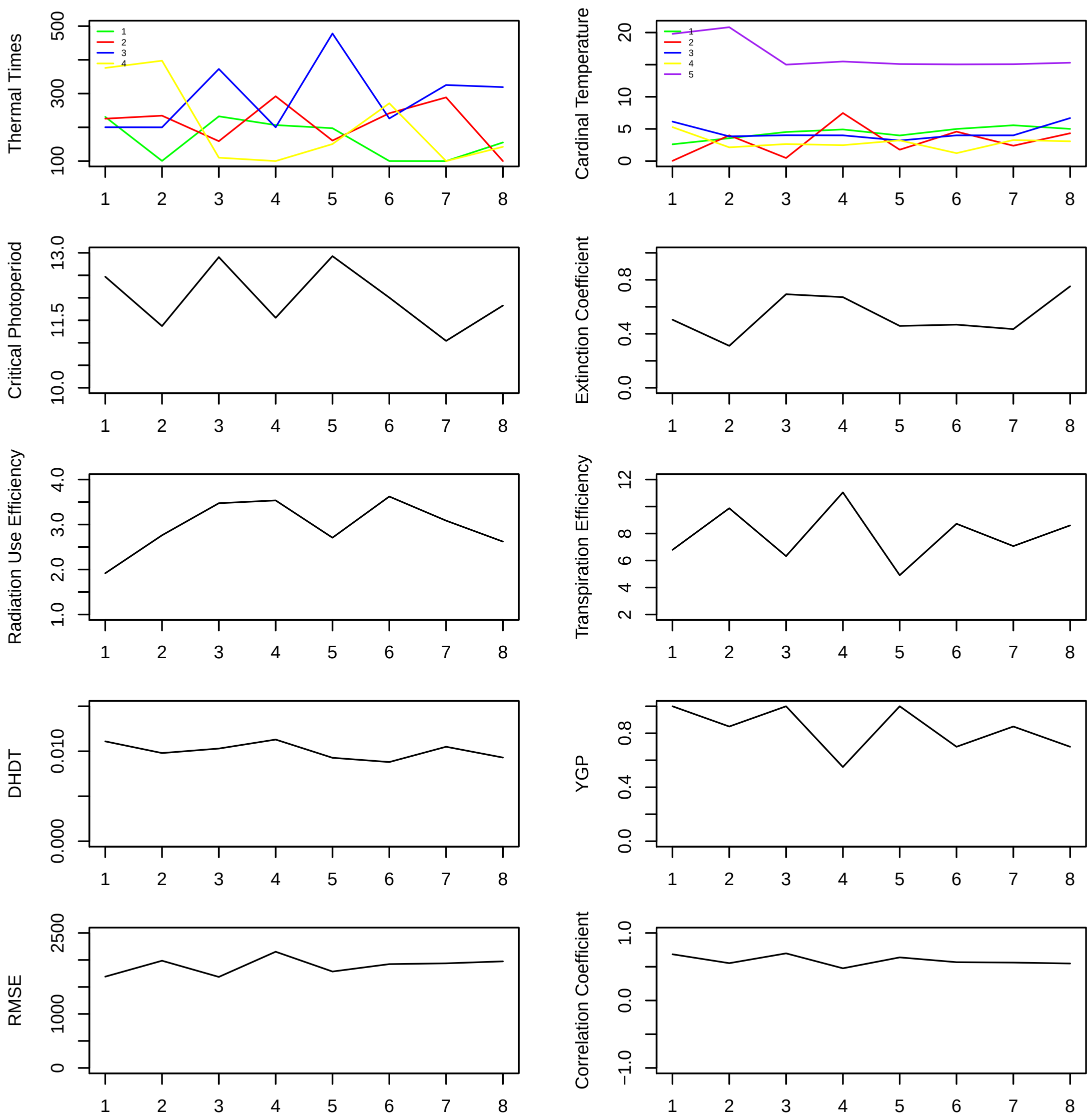



**Figure 3.12:** Parameters optimised for the Aberdeen time series. For the thermal time plot, lines 1 to 4 correspond to the 4 developmental stages. The cardinal temperature plot shows five lines: the first four correspond to developmental stages 1 to 4 for the base cardinal temperature. Line five corresponds to the optimal temperature for the 3rd developmental stage (tuber initiation to senesence - this being the only optimal temperature selected for optimisation). YGP is the Yield Gap Parameter $C_{\mathrm{YG}}$.

#### 3.3.1.2 Model Evaluation

Evaluation test 1 - that simulated GLAM yields have the same correlation with observed yields as the simulated statistical model yields - is passed, with no significant difference in the two correlations (see Figure 3.13). The correlation coefficient between observed and statistical model yields is not significantly greater than those with GLAM yields, and is in itself insignificant, suggesting that GLAM is adequately capturing weather-yield relationships. Parameter set 7 shows the highest correlation coefficient, with parameter sets 5 and 6 showing skill almost as good. There is no significant difference in correlation coefficient across parameter sets, however - whilst no correlation with observed yields is significant, most show reasonable skill in simulating the variability in year-to year yields. The significance threshold for a two-tailed Pearson correlation coefficients for this length of time series is 0.575 (n = 12). None of the GLAM or statistical model correlations are significant.

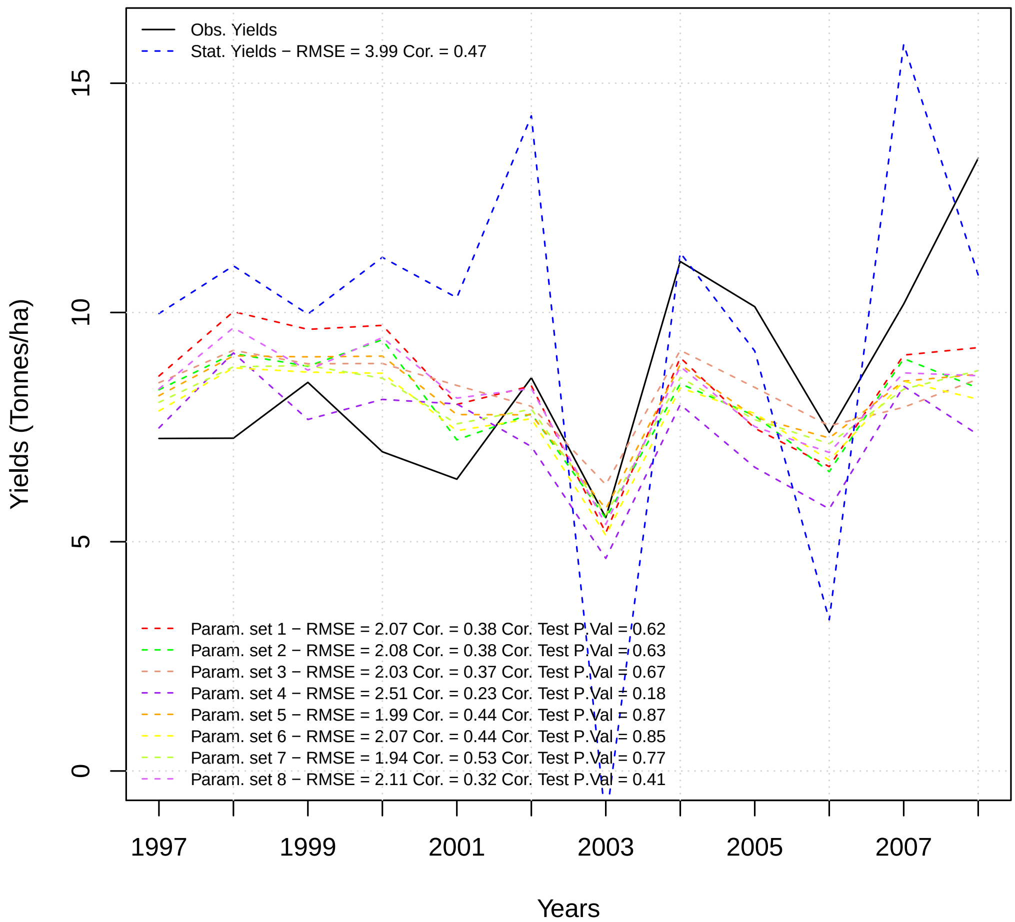



**Figure 3.13:** Observed, simulated GLAM and simulated statistical model yields, with a comparison of GLAM and statistical model skill across parameter sets.

Correlations between simulated yields and weather variables (temperature, rain and solar radiation) are the same sign as correlations between observed yields and weather variables (see Figure 3.14). The model overestimates the magnitude of the correlation between simulated yields and temperature, however - there is only a small, weak negative correlation between observed yields and temperature. The strongest correlation with observed yields is rainfall, although this is still insignificant. The interannual variability of solar radiation is larger than for temperature or rainfall, although correlations with observed yields are very low.

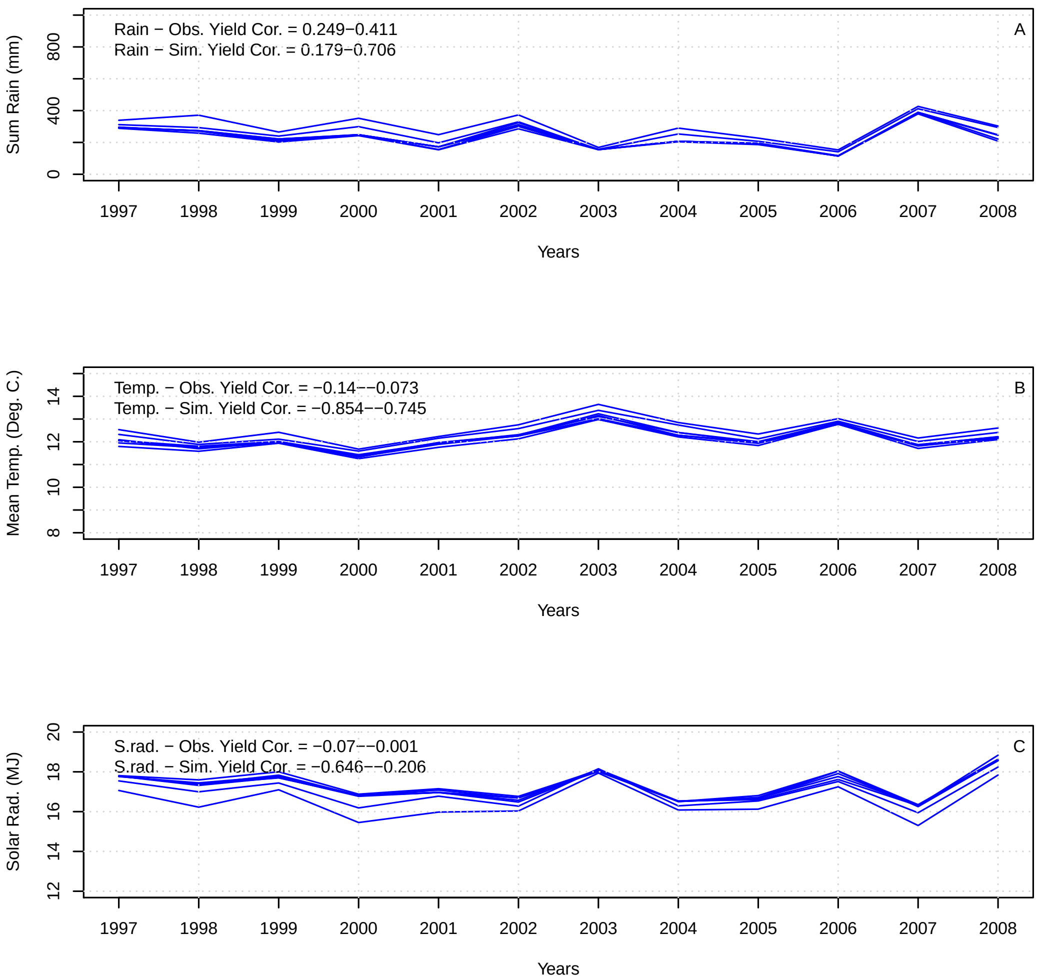



**Figure 3.14:** A). Sum of rain over the growing seasons associated with the different GLAM parameter sets. B). Mean temperature over the growing seasons associated with the different GLAM parameter sets. C). Mean solar radiation over the growing seasons associated with the different GLAM parameter sets. Correlations between weather variables and observed and simulated yields are shown, with the ranges shown for correlations associated with the different parameter sets.

**Table 3.4:** Statistical model coefficients, associated p-values and variation explained by the model variables.

| Variable | Coefficient | p-value | Variation (%) |
|---|---|---|---|
| Intercept | 221.570 | 0.069 | n/a |
| Mean Temperature | -15.489 | 0.127 | 0.003 |
| Mean Rain | -94.374 | 0.082 | 0.016 |
| Mean Solar Rad. | -2.319 | 0.263 | 0.097 |
| Mean Temperature * Mean Rain | 8.325 | 0.082 | 0.328 |

A summary of the statistical model statistics is shown in Table 3.4. No model coefficient has a significant p-value. Temperature has a weak negative correlation with observed yields as well as a very weak, negative coefficient in the statistical model. Rainfall has a positive correlation with observed yields but a negative coefficient in the statistical model. Model variation explained is dominated by the interaction variable of mean temperature multiplied by total rainfall during the growing season, which has a positive coefficient. The variability in temperature and rainfall are therefore not independent – the positive relationship between rain and observed yields is dependent on temperature also. In cooler years there tends to be more rainfall and in warmer years less rainfall. The effect of rainfall on yields therefore depends on temperature and vice versa. This is likely due to the developmental stage of the crop being important for the impacts of water on yields. Some authors suggest that both tuber initiation and bulking periods are more sensitive to drought stress than other stages (e.g. see Dalla Costa et al., 1997). Temperature affects development which will influence the timing of rainfall on the crop. There is also evidence that heat and drought stress acting together can further reduce yields (Mittler, 2006). When the interaction term is excluded from the statistical model, a positive coefficient is associated with rainfall, overall suggesting that the timing of rainfall for potato yields is key.

Years 1998 to 2000 and 2008 show observed yields that are not well simulated by GLAM (Figure 3.13), but as can be seen from the statistical model made up of the weather variable inputs in GLAM, the trend was not due to the direct influence of the weather inputs either (temperature, rainfall and solar radiation). Figure 3.14 shows weather input variables used by the models. The negative correlations with temperature and the positive correlations with rainfall dominate the inter-annual variability in simulated yields. In 1998 to 2000, rain and temperature trends cause the pattern seen by simulated yields in the statistical model and the GLAM model set-ups, i.e. less rain and higher temperatures leading to lower yields in 1999 than the surrounding years. The observed yields show the opposite trend, however. The same is happening in 2008, where less rain and average temperatures lead to lower simulated yields, but yield observations show a large increase. Solar radiation shows an increase in 1999 and 2008, but there is no positive correlation with observed yields to explain the observed yield trend. It is therefore likely that the growing season during these years is different to that being simulated. Whilst it is known from the experimental setup that planting takes place over an approximate period of March to May, there is some uncertainty over exact planting dates and hence when the timing of developmental stages take place. Because of this, the cumulative weather variables of the simulated crop may be different in some years, and this is likely taking place here, resulting in a different pattern of simulated and observed yields in those years. In both 1999 and 2008, for example, shortly after the end of the simulated growing season there are days with significant rainfall. Slight changes to phenology may therefore have significant impacts on simulated yields. In general, however, we can conclude that GLAM is picking up the relationships of yields and weather.

Evaluation test 2 - that model output variables are realistic compared to those seen in observations - is passed, although not all GLAM parameter sets show realistic values for all model output variables. Figures 3.15.A and 3.15.B show end of season biomass and harvest indices respectively across all parameter sets. The biomass shown is comparable to the ranges seen in Harris (1992) for cultivars with growing seasons simulated in this work. Harvest indices were capped at 0.8 so as to be realistic for long tuber bulking periods (Ivins and Bremner, 1965), as seen in parameter set 1.

Figure 3.15.D shows crop durations to be within observed values (Jefferies and Mackerron, 1987; Van Keulen and Stol, 1995) across all parameter sets, as expected given the limitations set on optimised parameter sets described in Section 3.2.2.1. These durations were also in agreement with those reported by Gregory and Marshall (2012) in the experimental set-up from which these data come. Figure 3.16 shows that the senescence stage in

GLAM-potato can be short compared to those seen in some observations (see Figures 3.17 and 3.18), resulting in an end of season LAI that approaches 0 but falls short of doing so. That being said, parameter set 1 shows LAI falling to at or close to 0 in many years.

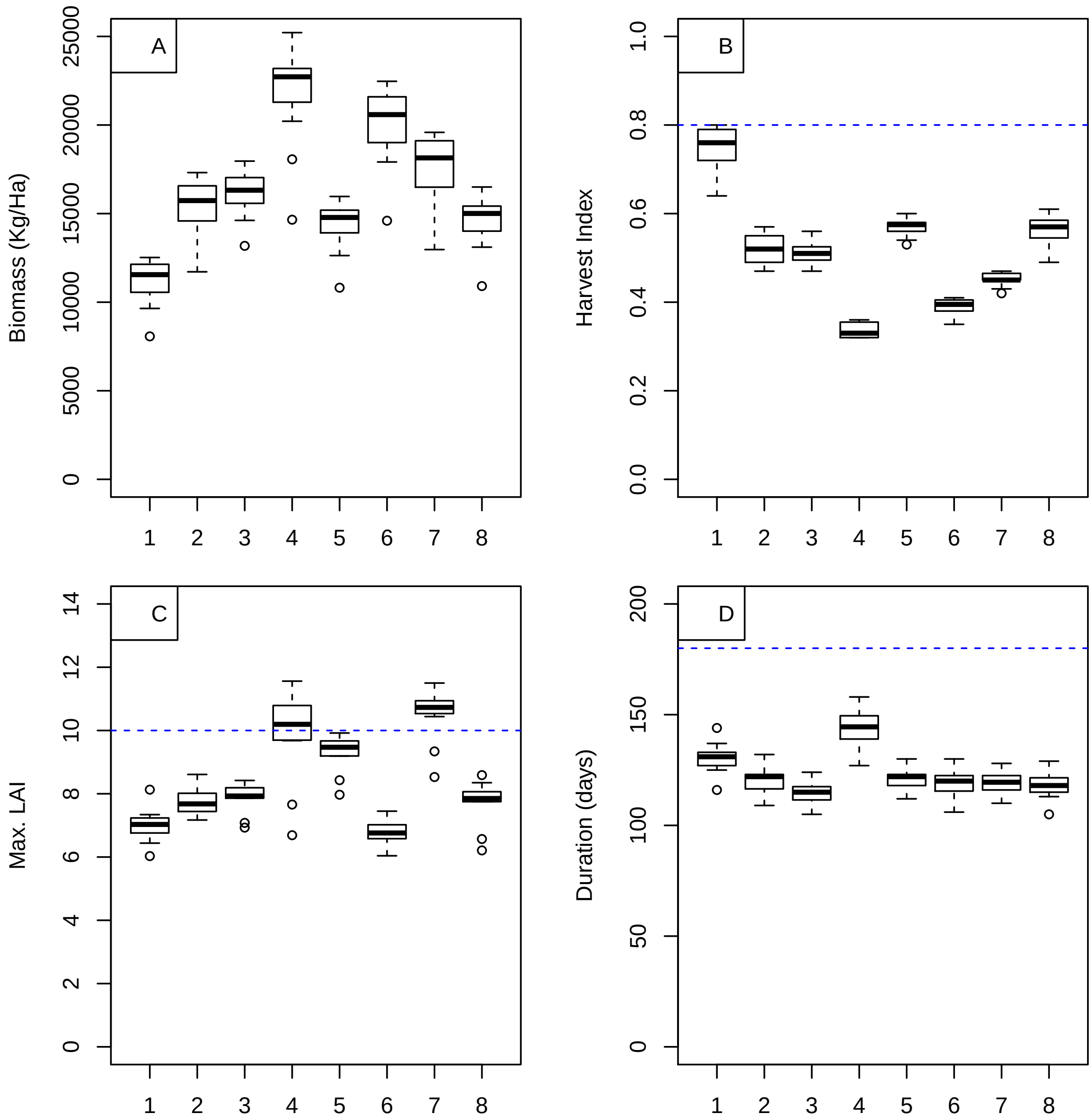



**Figure 3.15:** End of season biomass, end of season harvest index, maximum seasonal LAI and crop duration across years simulated. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range. Dashed blue lines indicate the range of realistic values for that variable. For biomass, realistic values span the range shown in the y-axis.

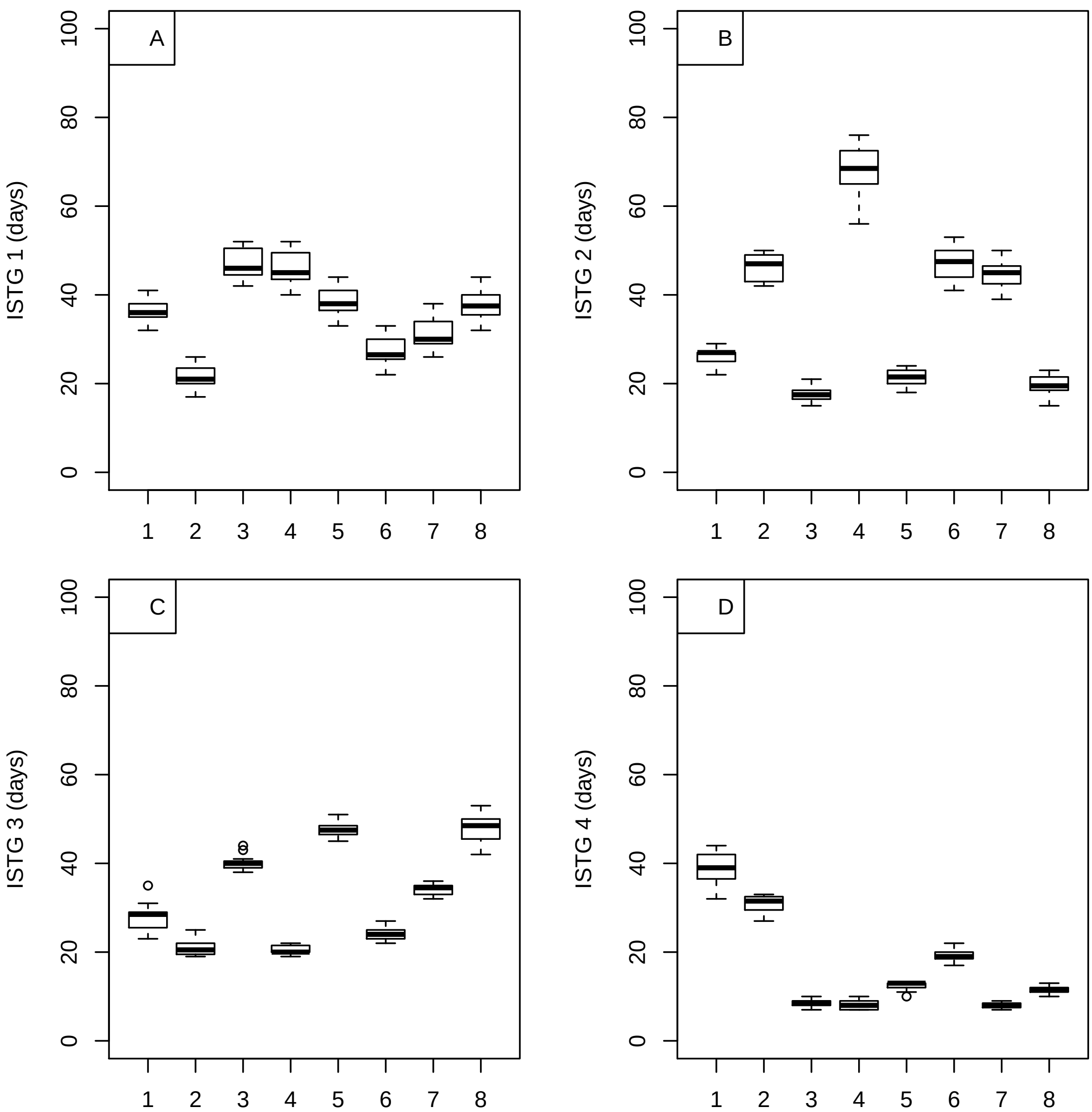



**Figure 3.16:** Durations of the developmental stages in GLAM-potato - 1 = planting to emergence, 2 = emergence to tuber initiation, 3 = tuber initiation to senescence, 4 = senescence to harvest. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

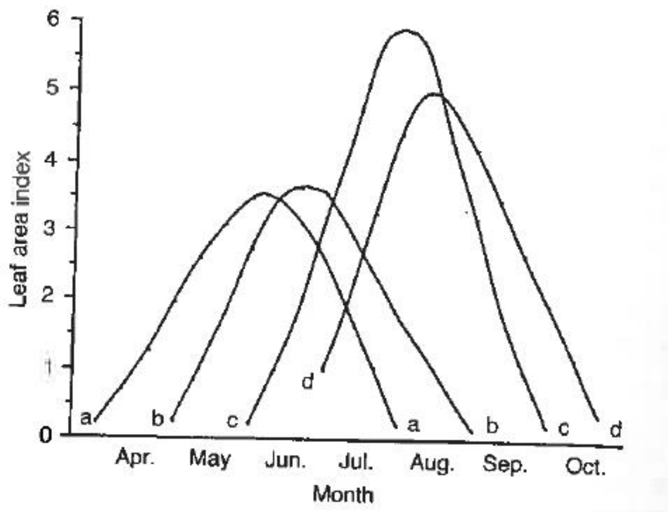



**Figure 3.17:** Observations of Leaf Area Index developing across the growing season, for both early and late maturing crops grown at Trefloyne (South Wales) and Cambridge (East Anglia). a-a, Trefloyne (early); b-b, Cambridge (early); c-c Trefloyne (late); d-d, Cambridge (late). Taken from Harris (1992). Repetition of Figure 2.3.

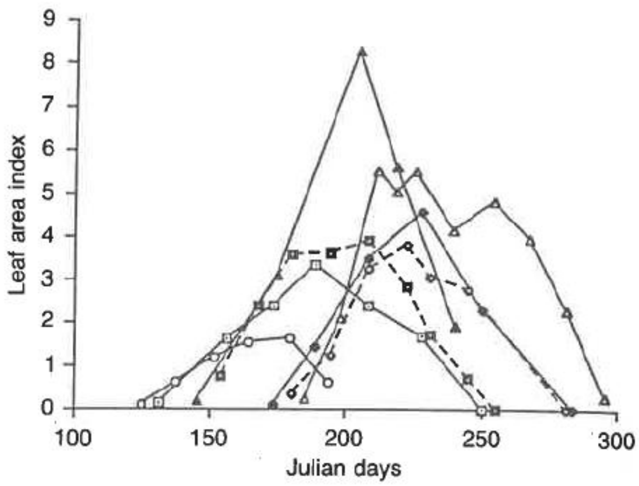



**Figure 3.18:** Range of LAI values across planting dates and varieties. Taken from Harris (1992). Clear circles = Home Guard, March 11th; clear squares = Desiree, April 1st; Black Triangles = Maris Piper, April 18th; grey diamonds = Desiree, May 28th; clear triangles = Desiree, June 10th; grey squares = Pentland Dell, April 15th; clear diamonds = Pentland Dell, May 27th.

As shown in Figure 3.15.C, parameter sets 1, 2, 3, 5, 6 and 8 show maximum LAI values that are seen in observations (see Figures 3.17 and 3.18). Other parameter sets (notably parameter set 7, which has the highest correlation coefficient between simulated and observed yields) show values higher than commonly observed. This is due to the longer leaf growing developmental stages associated with parameter sets 4 and 7 following optimisation of phenology parameters (Figure 3.16). As shown in Figure 3.12 in Section 3.3.1.1, the thermal time requirement for planting to senescence is relatively high for parameter sets 4 and 7, and that for the senescence to harvest stage is very low. Parameter set 5 is adjudged to be the best performing Aberdeen parameter set due to its high skill and realistic output variables.

An example of daily evolution of variables for parameter set 5 is shown in Figure 3.19. Yields, biomass and HI values are all realistic (Figures 3.19.A to C). Senescence is shorter than observations in some cases (Figure 3.19.D). Mean root length densities typically peak at a little over 2 $cm/cm^3$, which is in line with observations (Vos and Groenwold, 1986; Lesczynski and Tanner, 1976), and ISTGs are realistic (Figure 3.19.F).

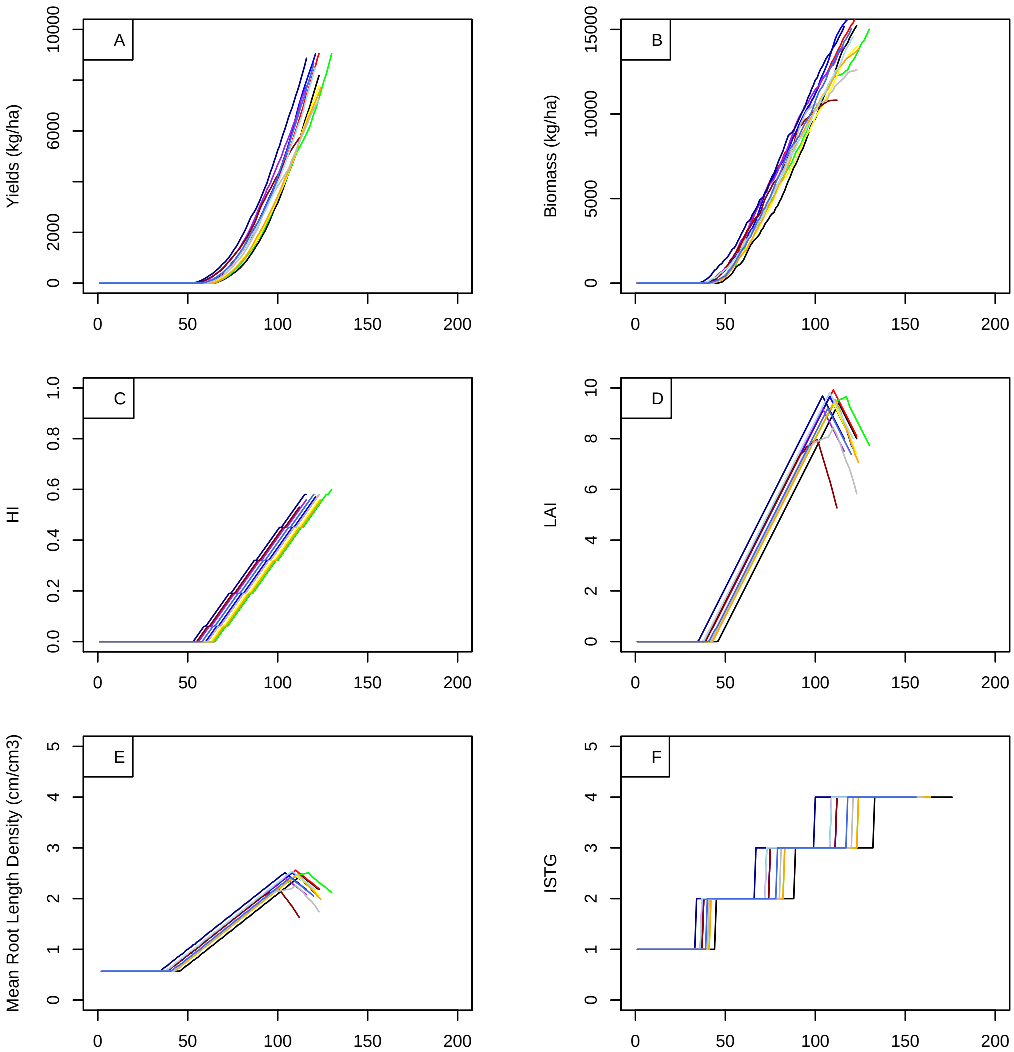



**Figure 3.19:** Daily evolution of model variables for parameter set 5 - yield, biomass, harvest index, LAI, mean root length density by volume and ISTG breakdown.

## 3.3.2 Colombia

### 3.3.2.1 Optimisation

Figure 3.20 shows the parameters selected to be optimised following the sequential sensitivity analysis (see Section 3.2.2.2 for details). Of the parameters tested (which were those not involved with simulating crop phenology) only the radiation use efficiency, transpiration use efficiency and rate of change of harvest index were found to have significant impacts on simulated yields and therefore included in the optimisation.

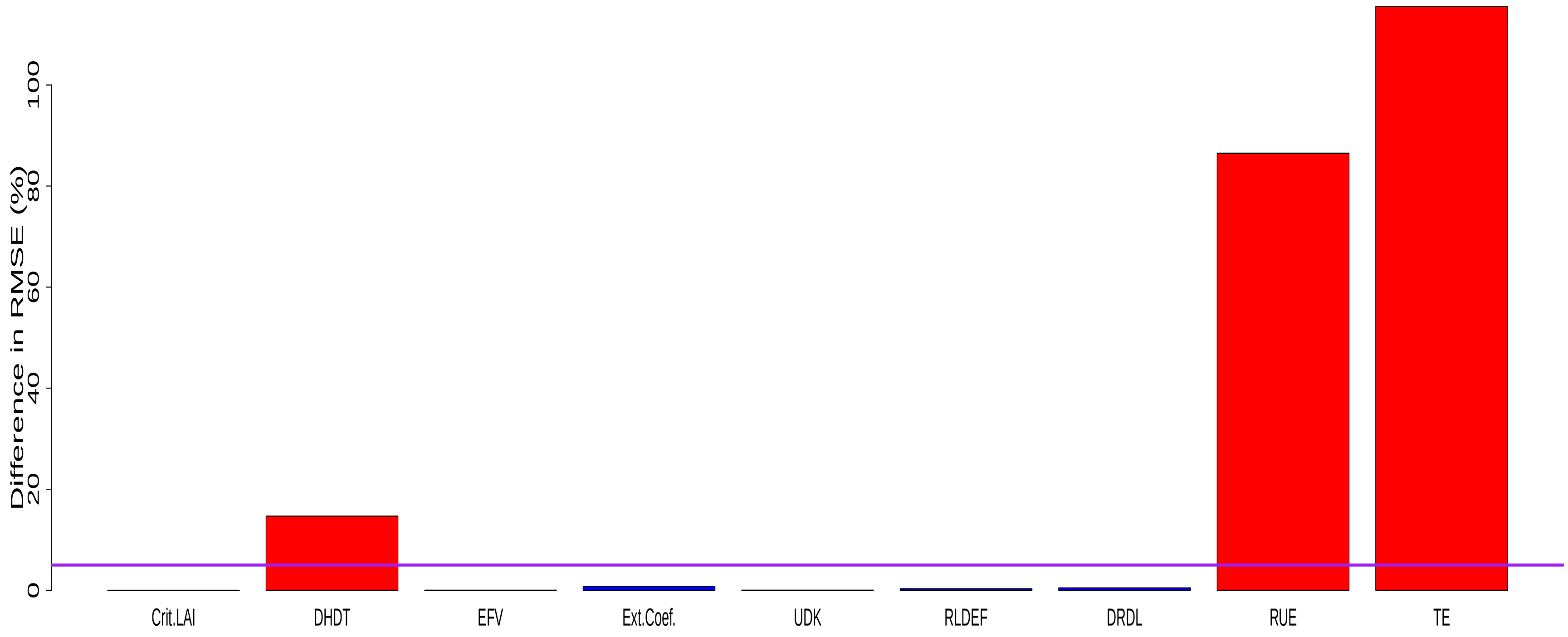



**Figure 3.20:** Maximum percentage difference in RMSE across parameter sets for each parameter varied at Antioquia. The purple line represents a 5% difference in RMSE, with percentage differences greater than this meaning that the parameter is optimised, shown in red. Blue parameters are those not optimised. "Crit.LAI" is the value below which transpiration is limited by LAI. "DHDT" is the rate of change of harvest index. "EFV" is the extraction front velocity. "Ext.Coef." is the extinction coefficient. "UDK" is the uptake diffusion coefficient. "RLDEF" is the root length density at the extraction front. "DRDL" is the root length density by leaf area at the surface. "RUE" is radiation use efficiency. "TE" is transpiration efficiency.

The evolution of RMSE during the optimisation process on the Antioquia time series can be seen in Figure 3.21. RMSE improvements take place sharply at times, with no reductions in RMSE across all seeds by 20000 iterations (this number selected as the final number of iterations to match the Aberdeen optimisation). In contrast to the Aberdeen optimisation (see Section 3.3.1.1), the improvements in RMSE are few and the vast majority of improvements come early in the optimisation process. This is the result of there being fewer parameters to optimise, with improvements in RMSE being rarer as a result.

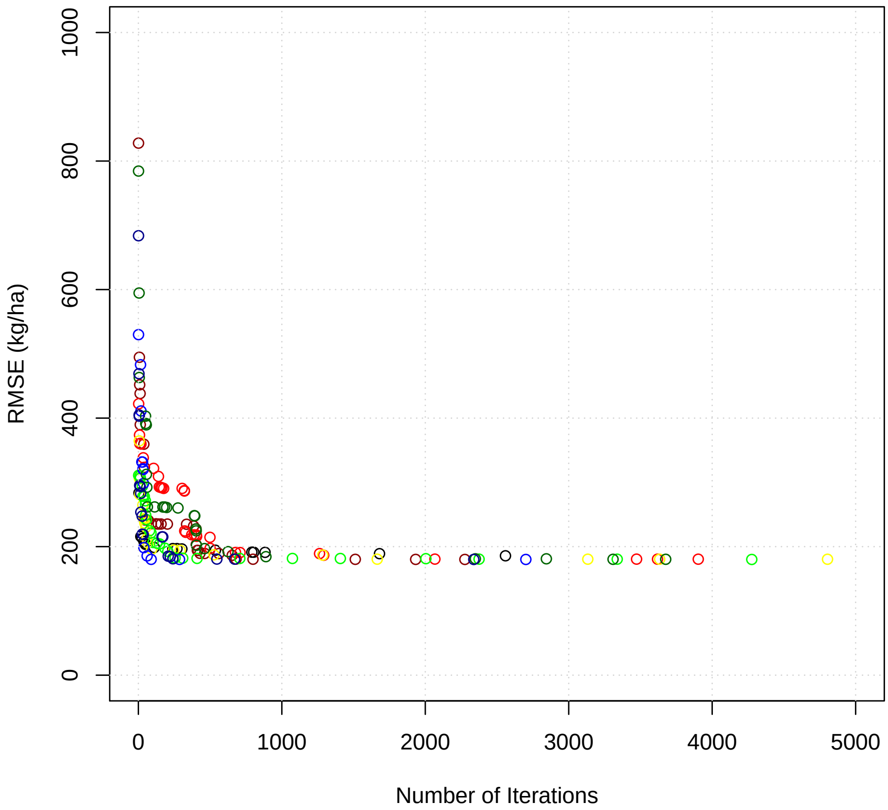



**Figure 3.21:** Optimisation runs using 8 different seeds for the Antioquia region. Only iterations that improved RMSE are shown.

All parameter sets show very similar skill, both in terms of RMSE and correlation coefficient (Figure 3.22). There is very little variation across parameter sets in any of the optimised parameters.

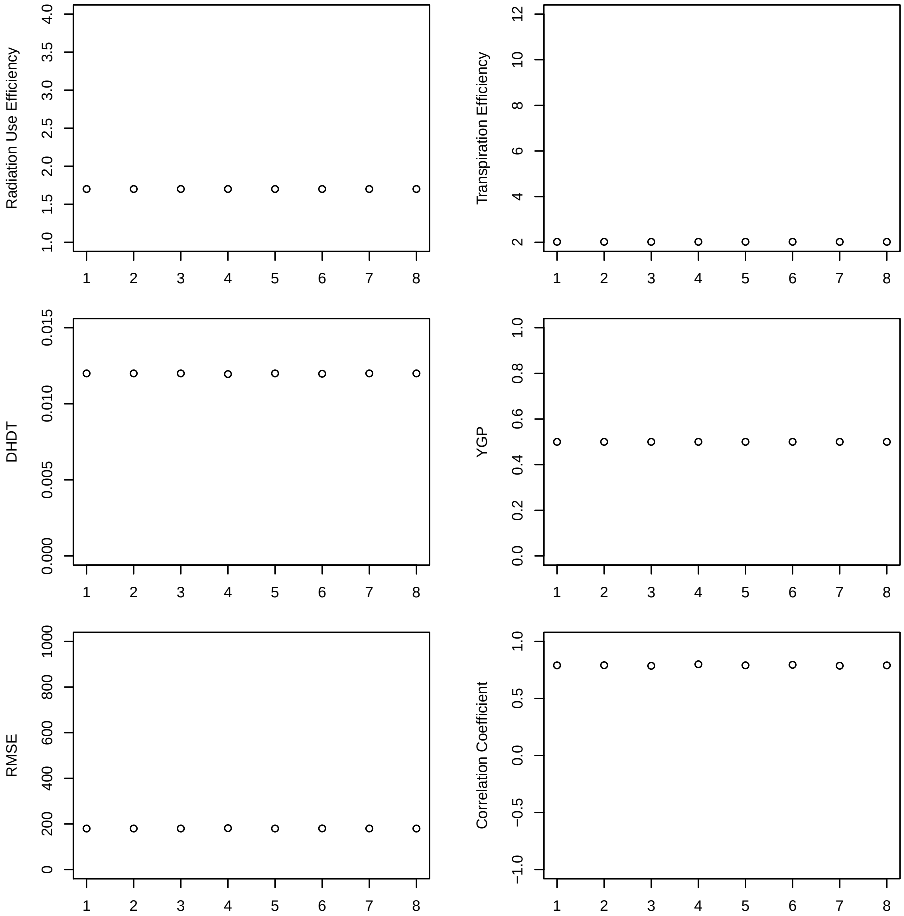



**Figure 3.22:** Parameters optimised for the Antioquia time series. YGP is the Yield Gap Parameter $C_{\mathrm{YG}}$.

#### 3.3.2.2 Model Evaluation

The tests of model performance – the statistical model comparison and the output variable assessment – are passed in six of the 10 Colombia evaluation regions (Table 3.5). Model simulations are virtually identical across all parameter sets. Spatial plots (Figures 3.23, 3.24 and 3.25) are therefore only shown for parameter set 1, which had marginally higher model skill.

**Table 3.5:** Evaluation tests summary for the 11 Colombian regions (evaluation regions and the optimised region, Antioquia). Bold regions pass evaluation tests and are therefore adjudged to adequately simulate potato yields. "Stat. Cor." refers to the test of GLAM yields and statistical model yields being the same sign and not statistically different. "Variables" refers to the test of model output variables being within observed limits. Numbers 1-11 correspond with region numbering in Figures 3.23 and 3.24. P = test passed, - = test failed.

| Region | Stat. Cor. | Variables |
|---|---|---|
| **1 - Nariño** | P | P |
| 2 - Cauca | - | P |
| 3 - Huila | - | P |
| **4 - Tolima** | P | P |
| **5 - Quindío** | P | P |
| **6 - Cundinamarca** | P | P |
| 7 - Caldas | - | P |
| **8 - Boyacá** | P | P |
| 9 - Santander | - | P |
| **10 - Antioquia** | P | P |
| **11 - Norte de Santander** | P | P |

A majority of evaluation regions show positive correlation coefficients between GLAM and observed yields (Table 3.6 and Figure 3.23.A) but none are significant (the 5% significance threshold for 4 year time series being 0.95, or for p-values of $< 0.1$, the correlation threshold value is 0.90). The statistical models are not significantly correlated with observed yields, with the exception of the Huila region. The regions where the statistical model correlation is significantly different to the GLAM correlation are Nariño, Huila and Santander. The first test of model performance is therefore not passed in these regions save for Nariño, where the statistical model correlation is not significant and the GLAM correlation is also positive. The other regions to fail this test are Cauca and Caldas due to negative correlations between GLAM and observed yields. Appendix A contains the simulated and observed yield time series and summary statistics for the 10 evaluation regions with all parameter sets shown.

In some regions, weather correlations with observed yields do not have the same sign as those with simulated yields – this is the cause of some regions showing poor skill and often the reason for test failure (see Figure 3.24). Huila and Caldas fail to represent weather relationships adequately.

**Table 3.6:** Evaluation test 1 summary for the 11 Colombian regions (evaluation regions and the optimised region, Antioquia). Bold regions pass the evaluation test. "GLAM Cor." are correlations between GLAM model and observed yields for the parameter set with the best correlation coefficient with observed yields (across all regions, no parameter set was different in terms of correlation coefficient by more than 0.01, however). "Stat. Cor." are correlations between statistical model and observed yields. "Cor. Test" refers to the p-value test of significant difference between the highest GLAM correlation with observed yields and the statistical model correlation. Numbers 1-11 correspond with region numbering in Figures 3.23 and 3.24. Asterisks denote significant correlations (** = 5% level significance, * = 10% level significance). Regions shown in bold pass evaluation test 1.

| Region | GLAM Cor. | Stat. Cor. | Cor. Test |
|---|---|---|---|
| **1 - Nariño** | 0.46 | 0.77 | 0.02** |
| 2 - Cauca | -0.50 | 0.53 | 0.64 |
| 3 - Huila | -0.84 | 0.97** | 0.07* |
| **4 - Tolima** | 0.85 | 0.86 | 0.94 |
| **5 - Quindío** | 0.72 | 0.52 | 0.71 |
| **6 - Cundinamarca** | 0.37 | 0.59 | 0.84 |
| 7 - Caldas | -0.65 | 0.72 | 0.50 |
| **8 - Boyacá** | 0.41 | 0.44 | 0.97 |
| 9 - Santander | -0.09 | 0.43 | 0.04** |
| **10 - Antioquia** | 0.79 | 0.78 | 0.98 |
| **11 - Norte de Santander** | 0.70 | 0.07 | 0.26 |

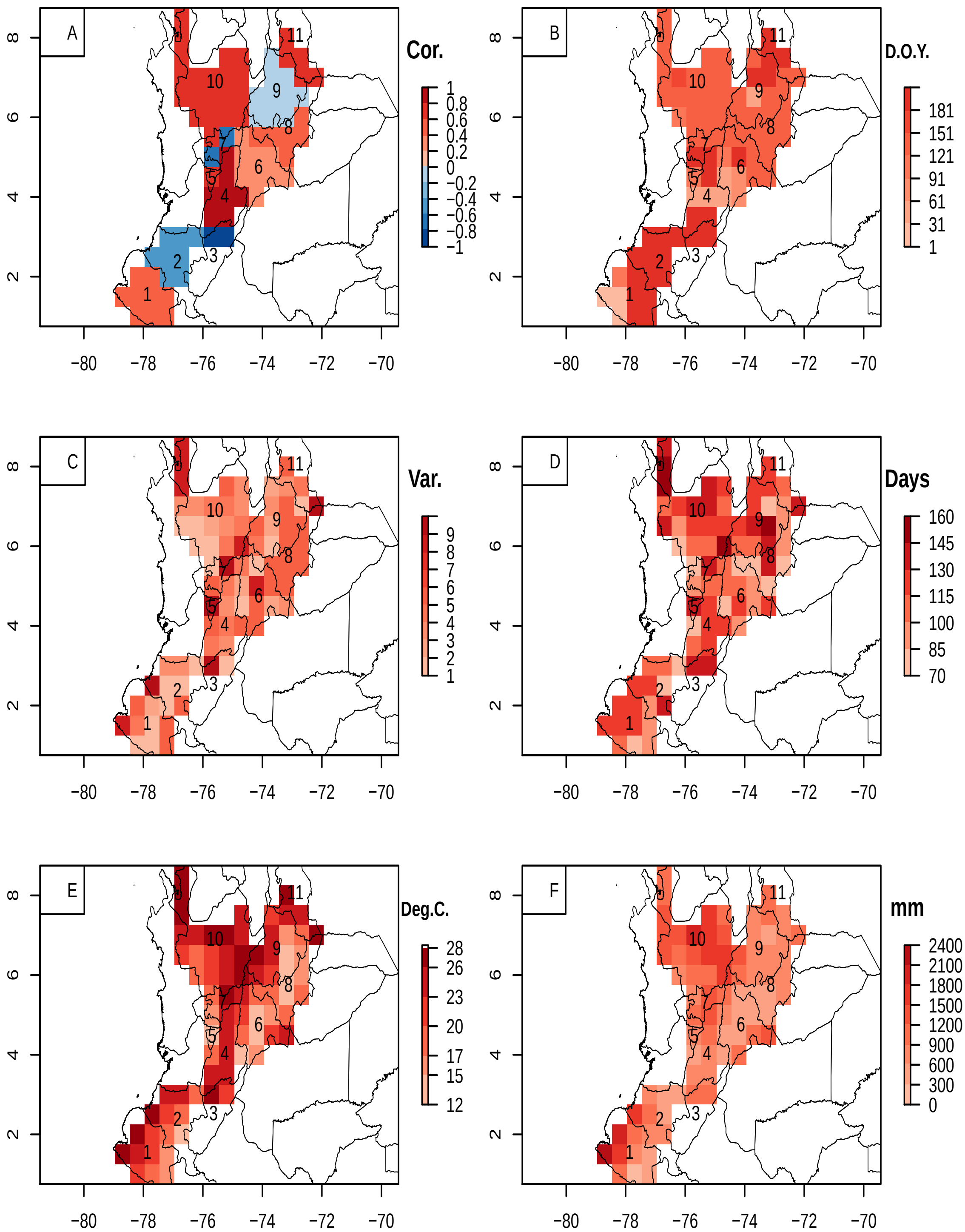



**Figure 3.23:** A = Correlations between regional simulated and observed yields for parameter set 1. B = Planting window start day of year. C = Varieties chosen. D = Mean duration for each grid cell. E = Mean daily temperature. F = Mean sum of rainfall over growing season. Region 1 = Nariño, 2 = Cauca, 3 = Huila, 4 = Tolima, 5 = Quindío, 6 = Cundinamarca, 7 = Caldas, 8 = Boyacá, 9 = Santander, 10 = Antioquia, 11 = Norte de Santander.

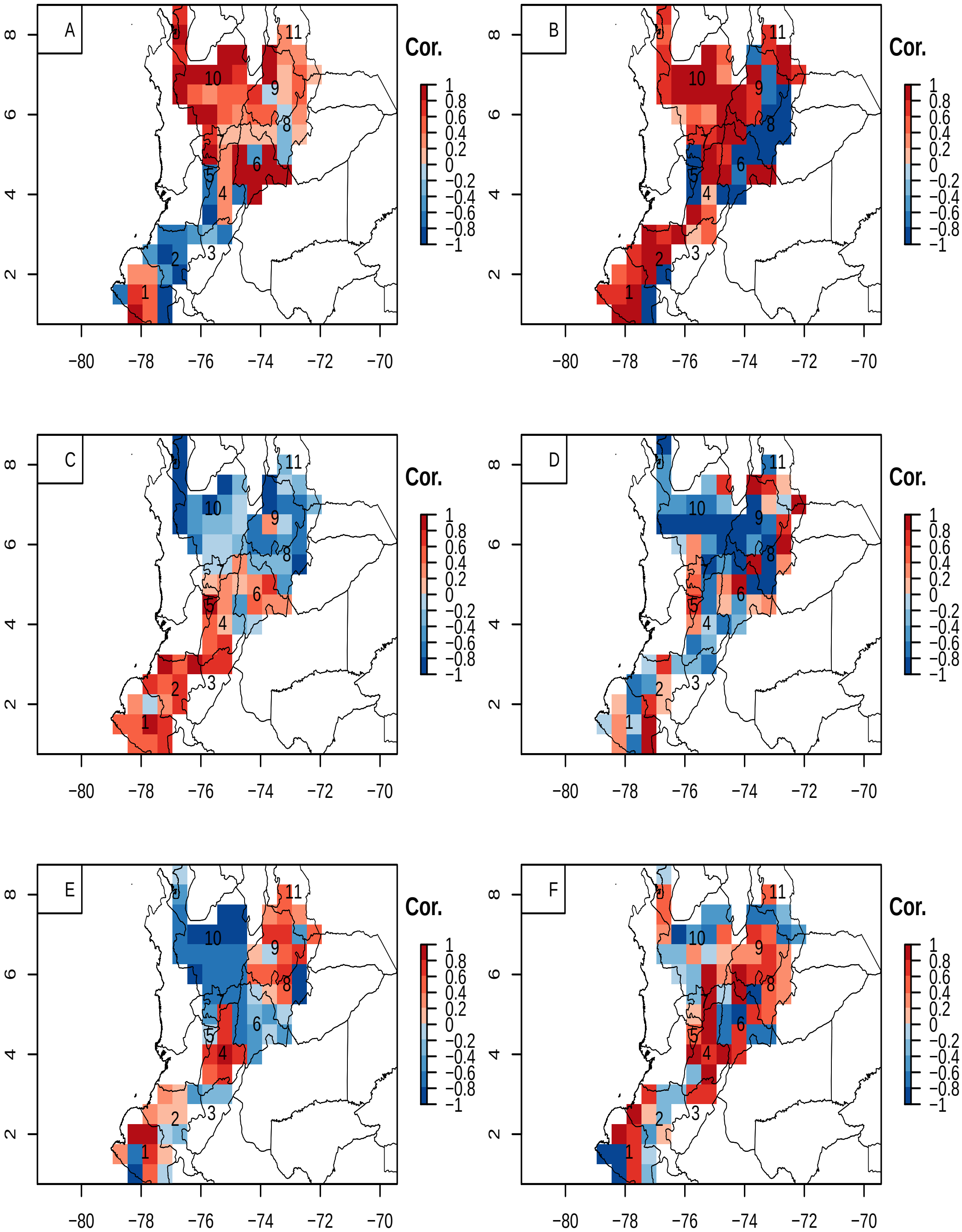



**Figure 3.24:** Correlation coefficients between growing season weather variables and simulated (parameter set 1) and observed yields. Correlations are at the grid cell level for the weather variables and yields (the same time series of observed yields were used at each grid cell in each region). A = Correlation between mean temperature and observed yields. B = Correlation between mean temperature and simulated yields. C = Correlation between sum of rainfall and observed yields. D = Correlation between sum of rainfall and simulated yields. E = Correlation between solar radiation and observed yields. F = Correlation between solar radiation and simulated yields. Region 1 = Nariño, 2 = Cauca, 3 = Huila, 4 = Tolima, 5 = Quindío, 6 = Cundinamarca, 7 = Caldas, 8 = Boyacá, 9 = Santander, 10 = Antioquia, 11 = Norte de Santander.

Model outputs other than yield are checked for evaluation test 2 (Figure 3.25). Box-plots showing variables across years and grid cells are shown in Appendix A. Phenology is set before evaluation simulations in the preliminary runs choosing planting dates and varieties at each grid cell, resulting in realistic durations across regions (e.g. Figure 3.23.D). Maximum leaf area index values for most regions are within reported ranges, typically around 1-4, with higher values occurring in some regions such as Norte de Santander.

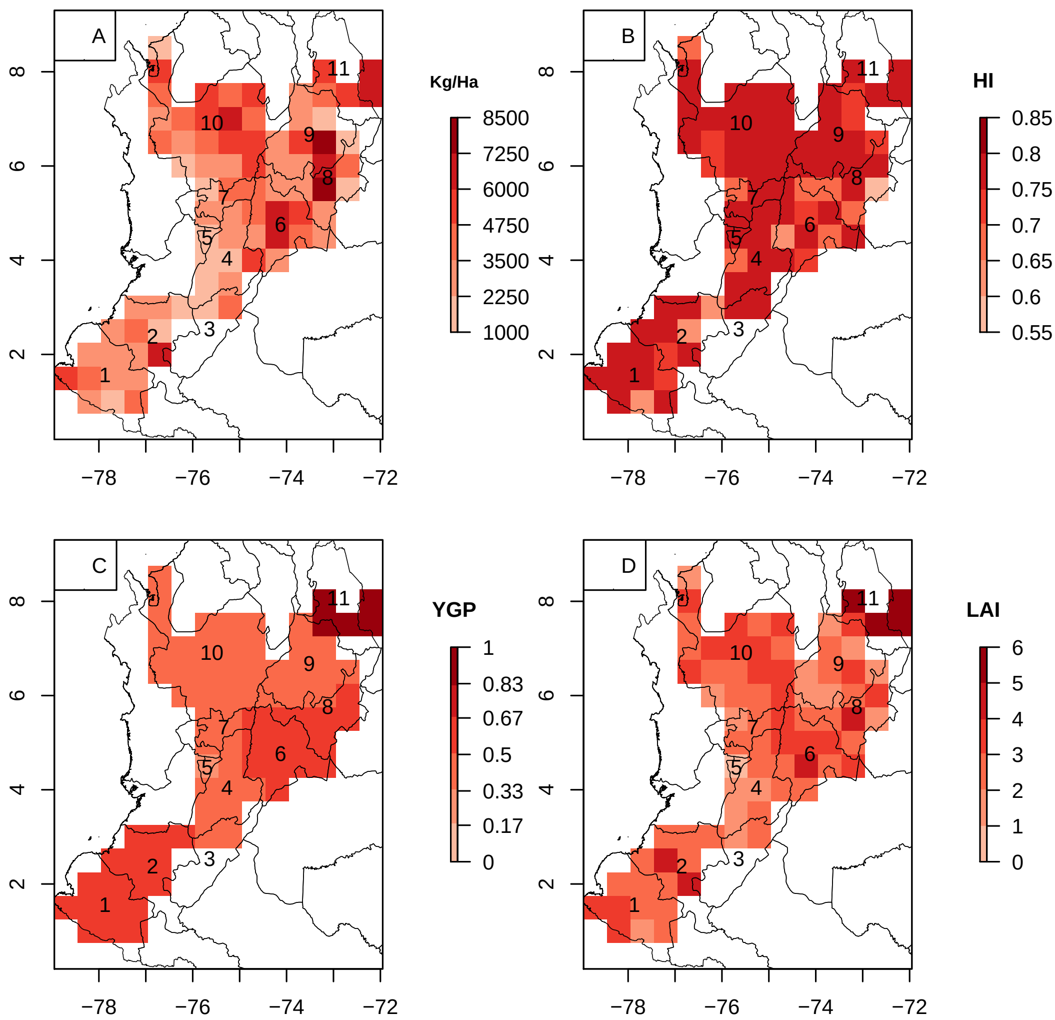



**Figure 3.25:** Mean end of season outputs for each grid cell for simulations using parameter set 1. A = Biomass. B = Harvest index. C = YGP, Yield Gap Parameter $C_{\mathrm{YG}}$. D = Maximum leaf area index from the growing season. Region 1 = Nariño, 2 = Cauca, 3 = Huila, 4 = Tolima, 5 = Quindío, 6 = Cundinamarca, 7 = Caldas, 8 = Boyacá, 9 = Santander, 10 = Antioquia, 11 = Norte de Santander.

To summarise, a majority of regions pass the evaluation tests in Colombia. The main cause of test failure and poor model skill in the other regions is the relationships with weather variables being poorly represented (Figure 3.24). In the badly performing regions of Caldas, Cauca and Huila, the correlations between observed yields and weather variables are more often a different sign (i.e. positive or negative correlation) to those with simulated yields. In the relatively well-performing regions, more often than not the relationships between observed yields and weather are the same with simulated yields. This is particularly true with respect to temperature correlations in the south of Colombia. Rainfall correlations with simulated yields are also not as positive in the south as seen with observed yields.

In both Cauca and Huila there is a strong negative correlation between observed yields and temperature, whereas simulated yields and temperature have a positive correlation (Figure 3.24). In these regions, warmer temperatures are leading to longer durations and higher yields. Correlations with rainfall are often positive with observed yields and negative with simulated yields. The correlations between solar radiation and simulated yields are usually positive and stronger than those with rainfall in these cases, causing a negative rainfall correlation with simulated yields. This means that radiation is the limiting factor for simulated yields in these regions rather than rainfall – i.e. in conditions with higher solar radiation, there is less rainfall as there is likely less cloud cover.

Planting dates tend to be at the end of tested values in the badly performing regions. Mean temperatures in the region suggest that higher temperatures lead to longer durations and higher yields, causing the positive correlation between temperature and simulated yields. The relationship between observed yields and temperature has a negative correlation, however, suggesting that the planting date and variety combinations selected that produced the highest simulated yields are not producing realistic responses to temperature. Further evidence that unrealistic planting dates are being selected comes from the rainfall correlations being positive with simulated yields and negative with observed yields – i.e. rainfall should be a limiting factor but is often not in poorly performing regions.

There tends to be more rainfall towards the end of the year than in the first rainy season in southern Colombian regions. As a result, late planting dates and long duration varieties are being selected that result in the simulated growing season including some of this second rainy season. There is indeed more than sufficient rainfall for a typical potato growing season in many grid cells in these simulations (Figure 3.23.F). These planting date and variety combinations are probably not realistic, however, as they are resulting in harvest being too late in the calendar year in southern regions.

## 3.4 Discussion and conclusions

This chapter aims to see if GLAM-potato can simulate the observed relationship between yields and weather variables in UK and Colombian regions. GLAM is satisfactorily simulating the relationship between yield and weather at the Aberdeen location, corroborating the results seen in Gregory and Marshall (2012), who demonstrate some skill in simulating yields at this location (but do not show statistics comparing simulated and observed yields). The good model performance here can be attributed to the correlations between observed yields and weather variables being the same sign as those with simulated yields, albeit with correlations with simulated yields often being stronger than those seen with observed yields. Given that GLAM simulates yields as a function of weather inputs, it is not surprising that correlations are stronger than those seen with observed yields as non-climatic factors not included in the model will be influencing observed yields. These factors could include pests, diseases and changes in management or technology over time. The potato disease late blight *Phytophthora infestans* has been shown to have changed its timing of emergence in the last 30 years, for example (Gregory et al., 2009). These factors could be influencing certain years in the observed yield time series, and given that they are not included in the model explicitly this could lead to poor representation of yields in some cases. Given the experimental set-up used for the observed yield data in this study, however, any changes in management should be minimal. It is also not surprising that some years fail to show accurate simulation of yields given the relatively weak relationship between observed yields and weather.

The model shows some skill in simulating observed yields in Colombia. When poor model performance does occur, it is usually due to the relationship between temperature and simulated yields being different to the relationship between temperature and observed yields. In some southern regions in particular, the positive relationships between simulated yields and temperature are not realistic. The combination of planting date and variety selected for these simulations produces this unrealistic relationship with temperature. In this case, a lack of detailed information on planting dates and crop varieties is hampering simulations.

van Bussel (2011) found that the assumption to use one phenological parameter set to capture the mean response of different German winter wheat cultivars was justified across a region. This was for a homogenous region though, and the different climatic conditions and different potato varieties grown across Colombia prompted the use of different phenological parameters across grid cells.

For both Aberdeen and Colombia, GLAM-potato has been shown to satisfactorily simulate potato development, growth and yield in a majority of cases. There are exceptions to the general good performance of the model in both regions, however - certain years in Aberdeen and certain regions of Colombia show poor skill in simulating yields. The common problem for these simulations is uncertainty in the choice of planting dates and phenology. The short time series in Colombia make parameter selection and model evaluation difficult. For either region, small changes to planting dates can lead to different weather inputs and simulated yields. In Colombia, for example, planting dates are based on rainfall over various tested six month periods. The data used are not perfectly representative of observed rainfall and therefore chosen planting dates may not reflect those used in the field in some cases. There is also uncertainty over the method used to select the onset of rainfall and therefore the growing season (Bombardi et al., 2017; Coelho et al., 2017). The highest yielding variety selected in Colombia may not necessarily be the best for capturing interannual variability. See Chapter 4 for more on the selection of planting date and variety combinations in Colombia and the UK in relation to the simulation of weather-yield relationships and model skill.

With more parameters optimised and a longer time series with which to optimise and calibrate on, it is not surprising that model performance in simulating inter-annual variability is stronger in Aberdeen than the majority of the Colombian regions. Importantly, however, the model has shown the ability to capture inter-annual variability in observed yields in both tropical and temperate latitudes. It is therefore concluded that GLAM-potato is an adequate tool for regional scale potato simulations. Improvements in model skill would doubtless be seen with observed weather data, more accurate information on planting dates and (for Colombia in particular) longer time series on which to optimise, calibrate and evaluate the model.

# Chapter 4

# Variety and management parameterisation for global simulations

## 4.1 Introduction

Very few modelling studies have assessed the impacts of climate change on potatoes globally, and there is therefore a need to develop models capable of simulating potatoes at large scales (see Chapter 1, Section 1.1). This chapter tests the suitability of a method that selects planting date and variety parameters for global simulations. This method will be used in simulations that aim to assess the impacts of climate change on potatoes (Chapter 6).

GLAM requires only minimal management data inputs, in contrast to other more complex crop models (e.g. Tan and Shibasaki, 2003; Jones et al., 2003), and was originally designed to work at the resolution of global climate models (Challinor et al., 2003, 2004). Previous work has shown that high model complexity can be associated with higher sensitivity to aggregation of input data (van Bussel, 2011). As such, a relatively simple process based crop model such as GLAM is potentially better suited to large scale modelling studies that require some form of data aggregation. Osborne et al. (2013) demonstrate a previous global crop modelling study using GLAM that showed good skill in simulating wheat and soybean yields for some of the highest production countries.

In terms of management inputs into GLAM, planting date and soil information needs to be specified, along with choices regarding irrigation (see Chapter 2). Global crop modelling studies commonly use sources of planting date information such as data sets like that described in Sacks et al. (2010) or use a climate suitability algorithm as outlined in Osborne et al. (2013) to define realistic crop growing seasons based on climate inputs.

Parameters that govern crop growth and development can be variety-specific. At regional or smaller scales, studies make use of optimisation or specific information to select these parameters (e.g. Nicklin, 2013). In Chapter 3, simulations used prior knowledge about planting dates and computationally intensive optimisation to obtain parameters for the simulation of crop growth and phenology at regional scales.

For global simulations there is a lack of detailed parameter information. There is little evidence for different parameter values across different regions for potatoes in particular, due to there being relatively few potato crop modelling studies (see Chapter 1). It is also not computationally feasible to calibrate the model using detailed optimisation techniques. As a result, crop growth parameters are often fixed and simulations used to select realistic crop developmental parameters across large scales, representing hypothetical varieties of the crop (Osborne et al., 2013; Hijmans, 2003).

This chapter will use simulations in the UK and Colombia to test a method that selects planting date and variety parameters for global potato simulations, not using regionally-specific planting date or parameter inputs.

### 4.1.1 Research Questions

The objective of this chapter is to test the performance of a method for selecting planting date and variety parameters (referred to as the global parameter method). The two research questions test performance. Firstly, whether realistic planting dates and model outputs are being simulated (research question 1) and secondly, if any significant inter-annual relationships between observed yields and weather variables are identified, is the model capturing these at the national level (research question 2):

1. Are realistic planting dates, durations and Leaf Area Index (LAI) being simulated using the global parameter method?
2. Are observed national scale yield-weather relationships simulated using the global parameter method?

## 4.2 Methods overview

How global simulations are conducted using national scale yield data is summarised in Figure 4.1. The global parameter method is used to select planting date and variety parameters that are used at each grid cell for the subsequent calibration and evaluation of model performance, without using computationally-expensive parameter optimisation and in the absence of regionally-specific information on planting dates or crop developmental (i.e. variety) parameters. Different varieties are defined using different developmental parameters. Crop growth parameters are fixed across varieties. This is both because there is a lack of evidence for how growth parameters vary at large scales and because GLAM calibrates mean yield levels to match observations using the yield gap parameter $C_{\mathrm{YG}}$ (see Chapter 2), meaning that realistic crop growth at the mean level is accounted for spatially to some extent.

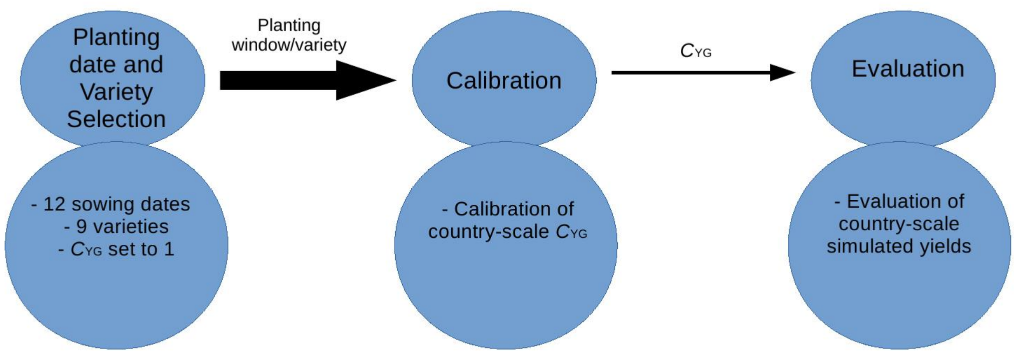



**Figure 4.1:** Flow diagram summarising the global parameter method used for global GLAM-potato simulations. The thicker arrow indicates a higher number of GLAM simulations. For each time period and climate model, 108 simulations (i.e. 12 sowing dates multiplied by 9 varieties) are necessary for the planting date/variety selection simulations. $C_{\mathrm{YG}}$ = Yield Gap Parameter.

The highest yielding combination of planting date and variety parameters at each grid cell is selected, providing these show realistic crop durations and LAI. Unrealistic simulations are defined as those that have maximum LAI values above 10 or growing season durations over 180 days (both limits are based on the observations and information shown in Chapter 3). The planting dates of the realistic combinations are assessed for realism based on the qualitative information available on the two countries studied, the UK and Colombia (see Chapter 3). In both countries, the main potato growing season starts from approximately March to May. In Colombia, a second growing season starts from August to September, although potatoes are planted all year round in important growing regions.

The focus of the global analysis in Chapter 6 is on analysing the impacts of climate change. It is important to have confidence in the predictability of the model in order to reliably assess the impacts of future climate on potato yields. Because of this, the focus on the skill of the model in the global simulations is on the weather-driven year-to-year variability in potato yields (as in Müller et al., 2017). Unlike in Chapter 3, statistical models of simulated yields are not compared to the GLAM-model simulations as an assessment of this year-to-year variability, as at national scales it is increasingly likely that factors other than weather will determine yields and lead to poor statistical model results. Correlation coefficients between weather variables are used instead as a simple assessment of relationships between weather, observed yields and simulated yields.

Following the identification of realistic combinations of planting dates and varieties, any significant correlations between weather variables and observed yields are identified. In these cases the correlations between weather variables and simulated yields are tested to see if they are significantly different using the Williams method (Williams and Williams, 1959). If insignificant correlations are observed then the model results are tested to see if the signs of correlations are the same, as in Chapter 3.

### 4.2.1 Input data

#### 4.2.1.1 Climate data

The AgMERRA (Agriculture Modern-Era Restrospective analysis for Research and Applications) data set is used for base climate conditions, available from 1980 to 2010 (Ruane et al., 2015). See Chapter 3 for a description of why this data set is selected rather than other reanalysis data sets.

#### 4.2.1.2 Potato growing area

Grid cells are selected for simulation if they contain potato growing area, as defined by MIRCA (Monthly Irrigated and Rainfed Crop Areas – Portmann et al., 2010), representing information from the years 1998-2002. Irrigation is determined by a majority grid cell approach. If a grid cell contains greater than 50% of growing area irrigated, fully irrigated simulations are used for that grid cell. Otherwise simulations for the grid cell are rainfed. No grid cells in Colombia had greater than 50% of growing area irrigated, whereas some in the UK did (see Figure 4.8 in the results section for map of UK irrigated areas).

Shapefiles from the Database of Global Administrative Areas are used to define national boundaries used in this analysis using grid cell centres to define boundaries (http://www.gadm.org/). Data are gridded onto a 0.5° grid to match the available weather data using the statistical package R (R Core Team, 2017).

After aggregation to the model grid, grid cells are ranked globally in terms of the amount of potato growing area they contain. As shown below in Figure 4.2, the top 50% of grid cells by growing area contain 99% of the total potato growing area across all the grid cells. This means that the other 50% of grid cells contain almost no potato growing area and so are excluded from the analysis. Excluding a higher fraction of grid cells results in important potato growing grid cells being excluded.

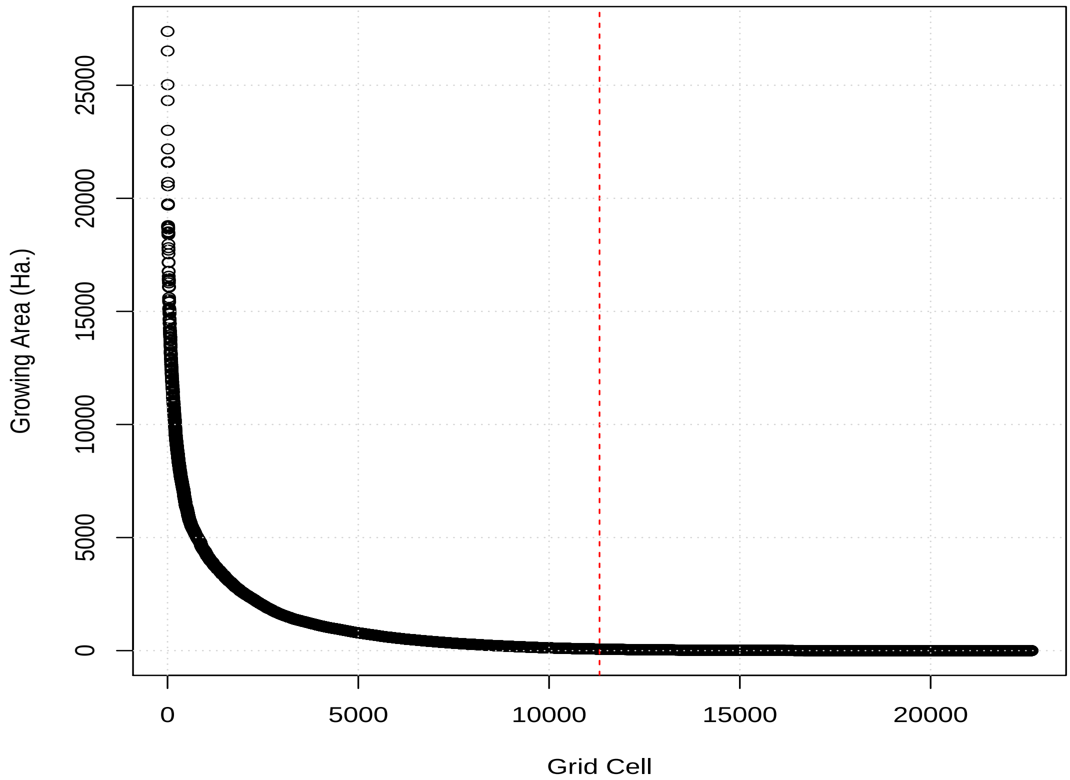



**Figure 4.2:** Global potato growing area grid cells ranked by area in each grid cell. The vertical dashed red line is half way along the X axis, i.e. representing 50% of the grid cells left and right of the line. Over 99% of cumulative potato growing area is represented by the cells to the left of this line.

#### 4.2.1.3 Yield data

FAOSTAT country-level data (FAO, 2016) are used to simulate the main growing season for each country in this study. See Chapter 6 for a description of the preparation of this data for all countries.

Data examined are from the years 1980 to 2009 to coincide with available weather data. Checks are performed on these time series of data prior to detrending and modelling which are outlined in Chapter 6. To summarise for the UK and Colombia, no years were dropped due to unrealistic yield data, and detrending of yields was not conducted as this was found to weaken weather-yield observed relationships.

#### 4.2.1.4 Soil data

Soil data are from the the Global Soil Dataset for Earth System Modelling (Shangguan et al., 2014). See Chapter 3 for a description of data preparation.

### 4.2.2 Parameterisation

GLAM-potato is used to simulate the potato crop, as described in Chapter 2. Model runs take into account irrigation levels and potato growing areas (see Section 4.2.1). GLAM's intelligent planting window is turned on (accounting for seasonal differences in temperature and soil moisture in planting – see Section 2.2.2).

A simple approach is taken regarding GLAM management and variety parameters, similar to the methods of previous global GLAM modelling studies on wheat, soybean and maize (Osborne et al., 2013; Dawson et al., 2016; Rose et al., 2016) and previous global potato simulations (Hijmans, 2003). In the previous GLAM studies, existing GLAM crop models were used and parameterised by varying phenological parameters and selecting planting dates for each grid cell, as is done in this chapter. In Osborne et al. (2013), each grid cell is analysed for a suitable growing period, defined as a period of time during which the crop reaches maturity within a realistic duration and there is sufficient rainfall. If suitable growing periods were not found for every year then that grid cell was not simulated. For suitable grid cells, the median starting date over the 30 years was then used for the planting date in GLAM.

For the global potato parameter configuration, nine hypothetical varieties of potato are tested in simulations that are representative of crops that mature optimally in different environments. Specific information on crop growth parameters is not available across different regions of the globe, so these are kept constant across grid cells.

Maturity classes are defined using phenological requirements, simulated using different cardinal temperatures. Thermal times are fixed at mid-points across reported ranges for all varieties. Harvest is defined as when the required thermal time for the growing season has been accumulated. There is evidence from the literature that both cardinal temperatures and thermal times vary across potato cultivars (see papers listed in Table 4.3). Cardinal

**Table 4.1:** Cardinal temperatures used for the different varieties in the global study (°C). B refers to base temperature, O refers to optimum temperature and M refers to maximum temperature. Numbers 1-4 refer to the 4 developmental stages – planting to emergence (1), emergence to tuber initiation (2), tuber initiation to senescence (3) and senescence to harvest (4).

| Variety | B1 | B2 | B3 | B4 | O1 | O2 | O3 | O4 | M1 | M2 | M3 | M4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 - T1 | 0 | 0 | 0 | 0 | 15 | 15 | 15 | 15 | 25 | 25 | 25 | 25 |
| 2 - T2 | 2 | 2 | 2 | 2 | 16.5 | 16.5 | 16.5 | 16.5 | 27 | 27 | 27 | 27 |
| 3 - T3 | 4 | 4 | 4 | 4 | 18 | 18 | 18 | 18 | 29 | 29 | 29 | 29 |
| 4 - T4 | 6 | 6 | 6 | 6 | 19.5 | 19.5 | 19.5 | 19.5 | 31 | 31 | 31 | 31 |
| 5 - T5 | 8 | 8 | 8 | 8 | 21 | 21 | 21 | 21 | 33 | 33 | 33 | 33 |
| 6 -LHT1 | 0 | 4 | 4 | 4 | 15 | 18 | 18 | 18 | 25 | 29 | 29 | 29 |
| 7 -LHT2 | 0 | 0 | 4 | 4 | 15 | 15 | 18 | 18 | 25 | 25 | 29 | 29 |
| 8 - HLT1 | 8 | 8 | 8 | 6 | 21 | 21 | 21 | 19.5 | 33 | 33 | 33 | 31 |
| 9 - HLT2 | 8 | 8 | 6 | 6 | 21 | 21 | 19.5 | 19.5 | 33 | 33 | 31 | 31 |

temperatures are varied rather than thermal time requirements as this allows realistic relationships with temperature to be simulated. For example, in a warm country, warmer temperatures might typically lead to shorter growing seasons. With fixed cardinal temperatures at a central point, however, this warming might lead to a lengthening of the growing season instead and an unrealistic response of duration to temperature.

Varieties T1-T5 consist of progressively higher cardinal temperatures. Varieties LHT1 and LHT2 have hotter temperatures for the latter three and two developmental stages respectively (which result in longer tuber bulking periods in cooler conditions, or shortened tuber bulking in hotter conditions), and varieties HLT1 and HLT2 have hotter temperatures for the first three and two stages respectively (which result in longer tuber bulking periods in hotter conditions and shortened tuber bulking in cooler conditions). Other developmental parameters (thermal times and the critical photoperiod) were fixed across all varieties. The thermal time parameters were set towards the upper end of the reported range for the senescence to harvest stage and the low end of reported ranges from emergence to senescence, in order to simulate realistic leaf area index development (i.e. allowing the leaf area index to fall near to zero, as is common in potatoes – see Section 3.3). This was decided following preliminary simulations in the UK and Colombia that showed unrealistically short senescence periods (described in Chapter 3, Section 3.2.2). The cardinal temperatures used for the different varieties are listed in Table 4.1. Note that these are identical to those described in Chapter 3, Section 3.2.2.2.

The start of the GLAM simulation is varied from the beginning of each month. These are referred to throughout as planting dates for simplicity, but include a 30 day soil water spin-up followed by a 45 day sowing window (for example, planting date 1 starts the 30 day soil water spin-up on January 1st, with the crop being planted from day of year 31 to 76). During the sowing window, the crop is planted when temperature and soil moisture conditions are met within this window, with the crop being planted on the last day of the window if conditions are not met (see Section 2.2.2.2). This method of allowing the model simulations to choose the planting date is preferred to using a data set such as that described in Sacks et al. (2010) as planting windows were found to be slightly early and late for important potato growing regions in the UK and Colombia respectively. In the UK, Sacks planting windows start exclusively in mid-February for the whole country, which is too early for northern areas in particular. In Colombia the start of the Sacks planting window varies but mostly is at the beginning of June. This is later than the start of the main growing season for Colombian potatoes (see Chapter 3, Section 3.1.2).

Other parameters are set to a mid-point of reported ranges. Exceptions were the maximum rate of change of leaf area index, the maximum rate of change of harvest index and the maximum normalised transpiration efficiency, which are set to the maximum of the values reported in the literature in order to potentially simulate the highest yields, and the root length density by leaf area at the soil surface, which is set to the low end of the reported range in order to realistically simulate root growth (see Chapter 2, Section 2.2.4.2).

Preliminary simulations showed that the radiation use and transpiration efficiency (RUE and TE) are particularly important for the simulation of yields (see Chapter 3, Section 3.2.2). Therefore, in preliminary runs using national scale yield data for the UK and Colombia and the parameter set up described in Chapter 3, Section 3.2.2, four combinations of transpiration efficiency and radiation use efficiency parameters were tested, varying both from a low to medium value from the ranges reported in the literature. High values of these parameters were not tested, as it was recognised from preliminary simulations that these lead to unrealistically low values of LAI. The combinations tested are summarised in Table 4.2. These simulations fixed planting dates and varieties across all grid cells and tested all possible combinations of plating dates and varieties in order to see a broad range of model responses.

**Table 4.2:** Parameter set-up for the transpiration and radiation use efficiency parameters tested in preliminary simulations. TE = Transpiration Efficiency value. RUE = Radiation Use Efficiency value.

| Parameter set-up | TE (Pa) | RUE (g/MJ) |
|---|---|---|
| TLRL | 2 | 1.7 |
| TLRM | 2 | 2.7 |
| TMRL | 6.525 | 1.7 |
| TMRM | 6.525 | 2.7 |

Different combinations of TE and RUE produced different mean yield levels which in turn affected model calibration and hence LAI. When both parameters were at the low end of reported ranges the model typically struggled to simulate yields high enough in the UK compared to observations. When both parameters were set to the middle of reported ranges, calibration resulted in unrealistic LAI values for the lower yielding regions of Colombia, with maximum LAI values for the growing season often falling below 1. Therefore a combination of parameters that is intermediate between these two is desirable. This allowed simulations to have realistic outputs of mean yield and LAI. Out of the TLRM and TMRL combinations, the TLRM simulations showed more realistic simulation of the correlations between temperature and rainfall and observed yields for Colombia (Figures 4.3 and 4.4). UK results were very similar using both TLRM and TMRL parameters. Therefore the TLRM combination was preferred for subsequent simulations.

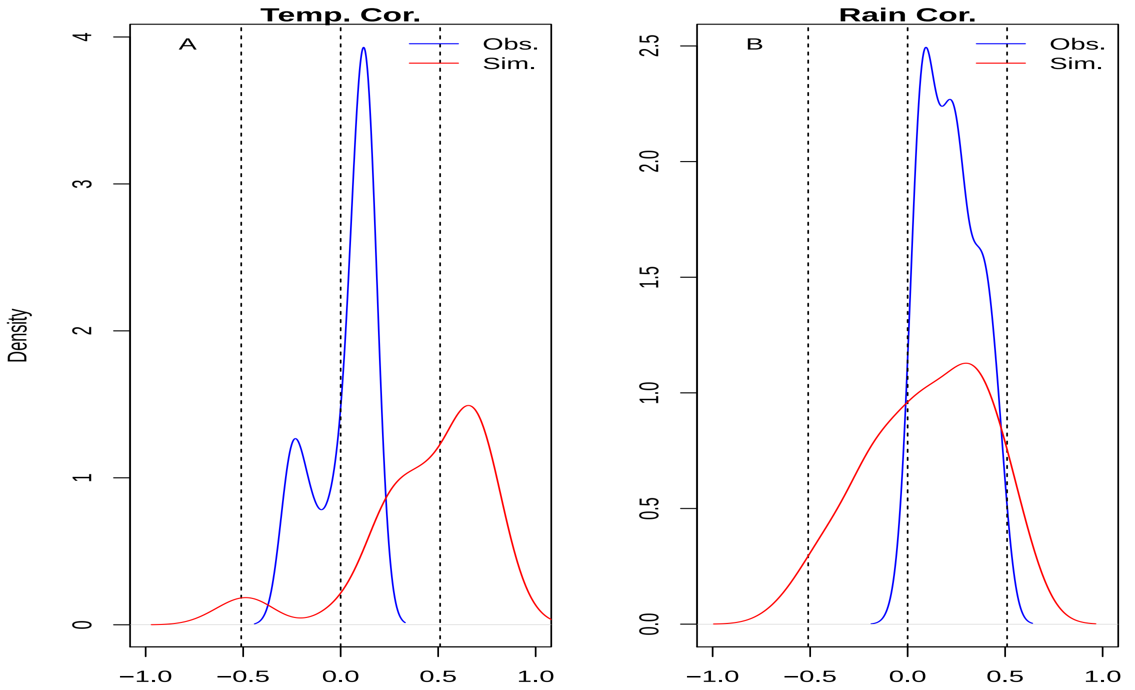



**Figure 4.3:** Correlation coefficients for Colombia yields and weather variables using TMRL parameters (A = Temp., B = Rain). "Density" is the kernel smoothed distribution of correlations.

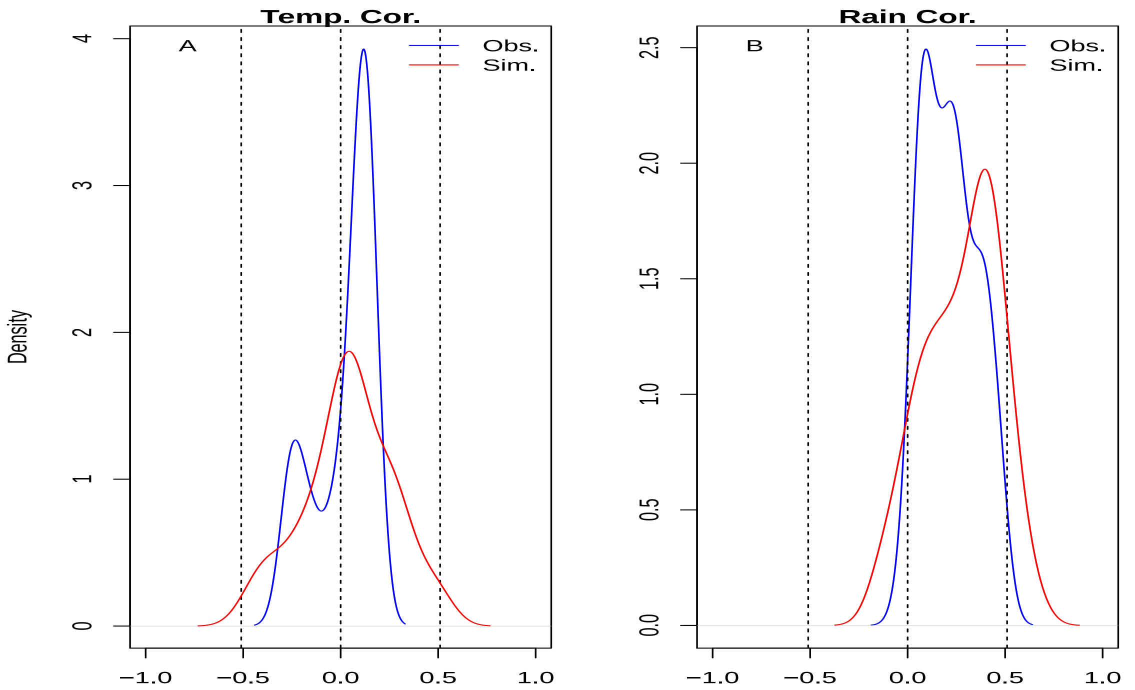



**Figure 4.4:** Correlation coefficients for Colombia yields and weather variables using TLRM parameters (A = Temp., B = Rain). "Density" is the kernel smoothed distribution of correlations.

The yield gap parameter $C_{\text{YG}}$ is used to reduce yields to account for spatial differences in crop management that are not explicitly included in GLAM (see Chapter 2). One value of $C_{\mathrm{YG}}$ is calibrated for each country. The first half of each time series is used for calibration and the other for model evaluation. A simulated yield time series is calculated for each country for calibrating $C_{\mathrm{YG}}$ by dividing total country production (calculated using the simulated yields in each grid cell and the potato growing area for that grid cell) by total area. This provides a simulated yield time series for calibration, weighted by the growing area of each grid cell (Equation 4.1). Weather variables are similarly weighted by growing area for the national scale correlation coefficients between yields and weather – all correlation coefficients in this chapter are nationally-weighted in this way, save for those shown in the spatial Figures 4.7 and 4.11, which use grid cell scale weather variables and simulated yields. The weather variables associated with each grid cell are multiplied by the growing area for that grid cell. All grid cell values are then summed and divided by the sum of the national growing area to calculate area-weighted weather variables. See Table 4.3 for all parameter values.

$$Y = \frac{Pr_{\mathrm{sum}}}{A_{\mathrm{sum}}} \tag{4.1}$$

The combination of variety and start of planting window that results in the highest mean simulated yield and has realistic crop durations (less than 180 days, with LAI values not smaller than 1 or greater than 10 and without emergency planting) across the time series is chosen for each grid cell. These caps are imposed to simulate realistic crop phenology and as potato harvesting is a complex process involving climatic and non-climatic factors (see Chapter 1), with the majority of potato seasons not being longer than 180 days.

The combination of planting date and variety that results in the best correlation coefficient between observed and simulated yields is not chosen as only national scale yield data are available for potato, and the variability of year-to-year yields at the grid cell level may not match with the national scale variability. In order to compute the best correlating combination of planting date and variety using all grid cells nationally, every combination of variety and planting date varying across all grid cells would need to be tested, which is not computationally feasible. The assumption using the highest yielding combination is that the variety and planting date are optimal for the crop given the conditions and will reflect as much as possible the variety and planting date used in reality.

**Table 4.3:** GLAM parameters used in this analysis, with ranges where applicable. For the thermal time requirements, stage 1 corresponds to the planting to emergence stage, stage 2 to the emergence to tuber initiation stage, stage 3 to the tuber initiation to senescence stage and stage 4 to senescence to crop harvest.

| Parameter | Range | Source |
|---|---|---|
| Thermal time requirements (°days; stages 1, 2, 3, 4) | 100, 100, 200,300 | Streck et al., 2007 |
| | | Paula et al., 2005 |
| | | Jefferies and Mackerron, 1987 |
| | | Van Keulen and Stol, 1995 |
| Cardinal temperatures (°C), base, optimum, maximum | 0-8, 15-21, 25-33 | Manrique and Hodges, 1989 |
| | | Sands et al., 1979 |
| Critical photoperiod $P_{crit}$ (hours) | 11.85 | Ewing and Wareing, 1978 |
| | | Streck et al., 2007 |
| Root length density at the extraction front $l_{\mathrm{v}}(z = z_{\mathrm{ef}})$ (cm/cm$^3$) | 0.575 | Lesczynski and Tanner, 1976 |
| | | Parker et al., 1989 |
| | | Stalham and Allen, 2001 |
| Root length density by leaf area at surface $\frac{\partial l_{\mathrm{v}}(z=0)}{\partial L}$ (cm/cm$^3$) | 0.4 | Iwama et al., 1993 |
| Extraction front velocity $V_{\mathrm{EF}}$ (cm day$^{-1}$) | 1.75 | Smit and Groenwold, 2005 |
| Critical value of leaf area index | 4.5 | Bremner et al., 1967 |

Table 4.3 continued.

| Parameter | Range | Source |
|---|---|---|
| Radiation Use Efficiency (g/MJ) | 2.7 | Zhou et al., 2016 |
| | | Timlin et al., 2006 |
| | | Khurana and McLaren, 1982 |
| | | Jefferies and MacKerron, 1989 |
| Transpiration efficiency (Pa) | 2 | Jefferies, 1993 |
| | | Kaminski et al., 2015 |
| | | Tanner, 1981 |
| | | Vos and Groenwold, 1989 |
| Extinction coefficient | 0.55 | Haverkort et al., 1991 |
| | | Jongschaap and Booij, 2004 |
| | | Monteith and Unsworth, 2007 |
| Uptake diffusion coefficient $k_{\mathrm{DIF}}$ ($\mathrm{cm}^2$/day) | 0.175 | Lesczynski and Tanner, 1976 |
| Maximum rate of change of harvest index $\frac{\partial H_{\mathrm{I}}}{\partial t}$ | 0.012 | Moriondo et al., 2005 |

## 4.3 Results

The following results are the test of the global parameter method for the simulation of national scale potatoes, allowing planting dates and varieties to vary across grid cells.

Model results in the UK show realistic planting dates (with the start of the planting window ranging from the beginning of March to May - see Figure 4.8.C), durations (averaging 112 days) and maximum LAI (averaging 6.96). The inter-annual variability of observed yields is poorly represented, however (Figure 4.5). Mean yield levels are also lower than observed yields. Low mean yields result from model calibration of $C_{\mathrm{YG}}$ on the first half of the time series where mean yield levels are lower. Detrending of observed yields was not performed as this was found to weaken relationships between yields and weather variables. TE and RUE parameters strongly influence simulated biomass also, and these were not put to higher values as preliminary simulations (described in Section 4.2.2) showed this to result in poorer representation of inter-annual yield variability.

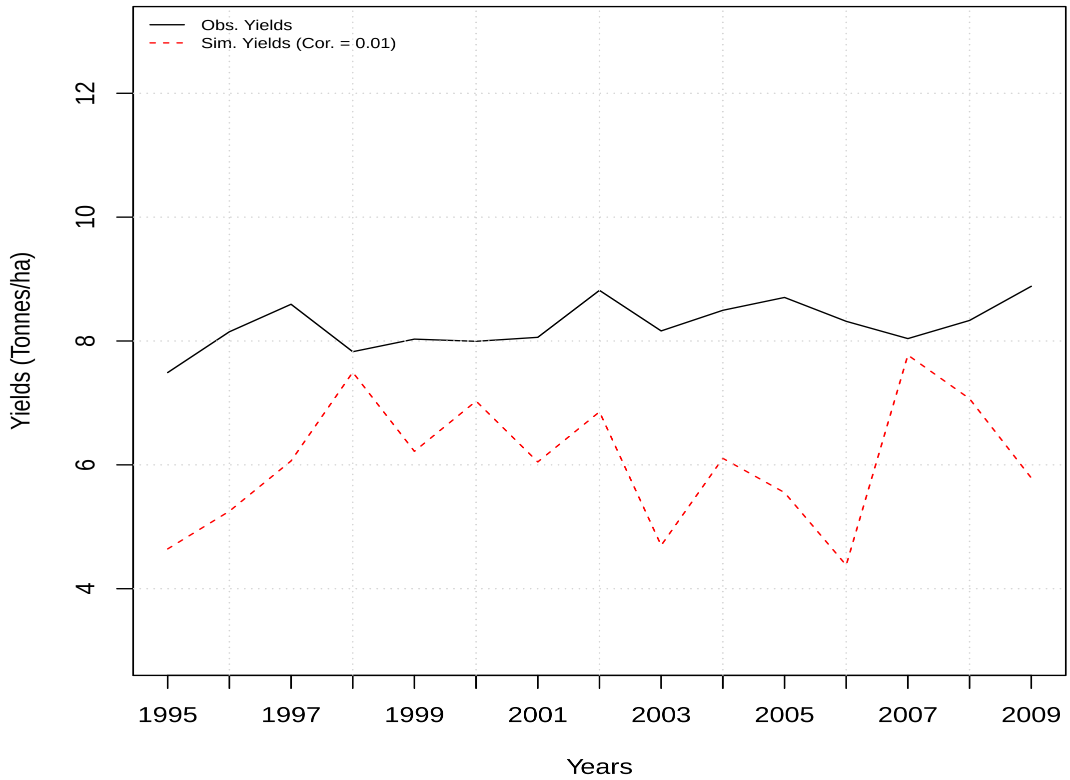



**Figure 4.5:** Observed and simulated national area-weighted yields for the UK with national scale correlation coefficients. The dashed red line is the simulated yields. The solid black line is the observed yields.

The correlations between observed yields and weather variables are low, in particular that with temperature (Figures 4.6 and 4.7). The two weather variables that have some relationship with observed yields are rainfall and solar radiation, and these relationships are well-represented by the model. Years when the model fails to predict observed yields well result from there being no relationship between temperature and observed yields and a negative correlation with simulated yields. In 1997 to 1999, for example, the inter-annual variability of yields is poorly represented. Rainfall increased in 1998 relative to the surrounding two years, and solar radiation decreased relative to the surrounding two years. The temperature is slightly lower in 1998 relative to the surrounding years, causing simulated yields to increase. The same response is not seen in observed yields. The same pattern is occurring in years 2006 to 2009. There is very little inter-annual variability in temperature, so other years capture the yield trend when other weather variables are more important drivers of observed yields (e.g. 2001 to 2004).

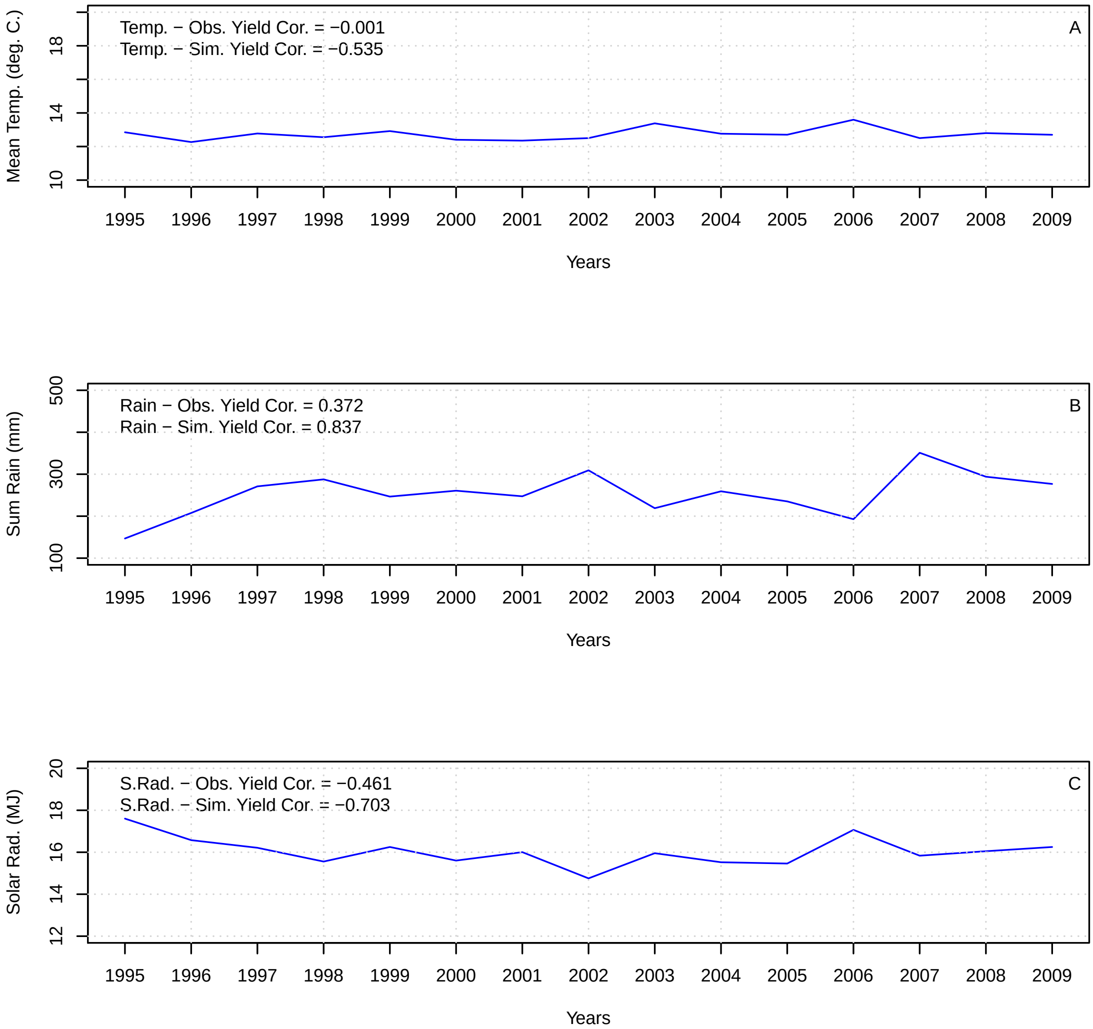



**Figure 4.6:** Area-weighted weather variables for the UK with correlation coefficients with observed yields. A = mean temperature, B = mean rainfall, C = mean solar radiation.

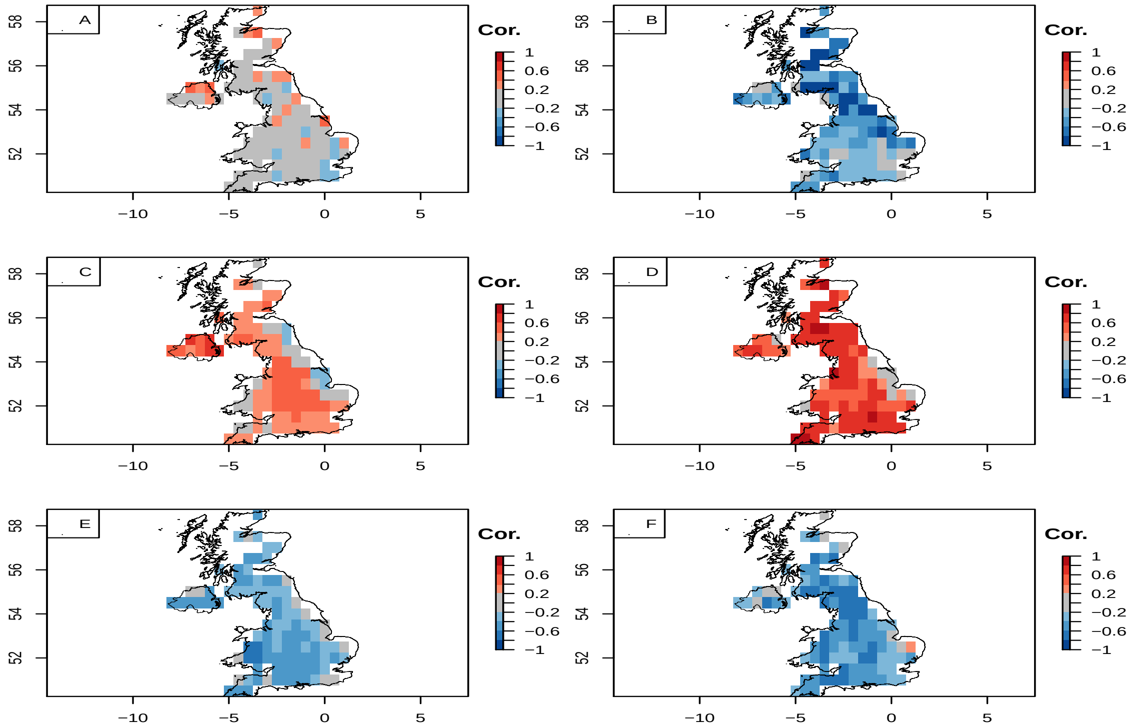



**Figure 4.7:** UK correlations between weather variables across the growing season and yields. Correlations are at the grid cell level for the weather variables and yields (the same time series of observed yields were used at each grid cell). A. Mean temperature and observed yields. B. Mean temperature and simulated yields. C. Sum of rainfall and observed yields. D. Sum of rainfall and simulated yields. E. Mean solar radiation and observed yields. F. Mean solar radiation and simulated yields.

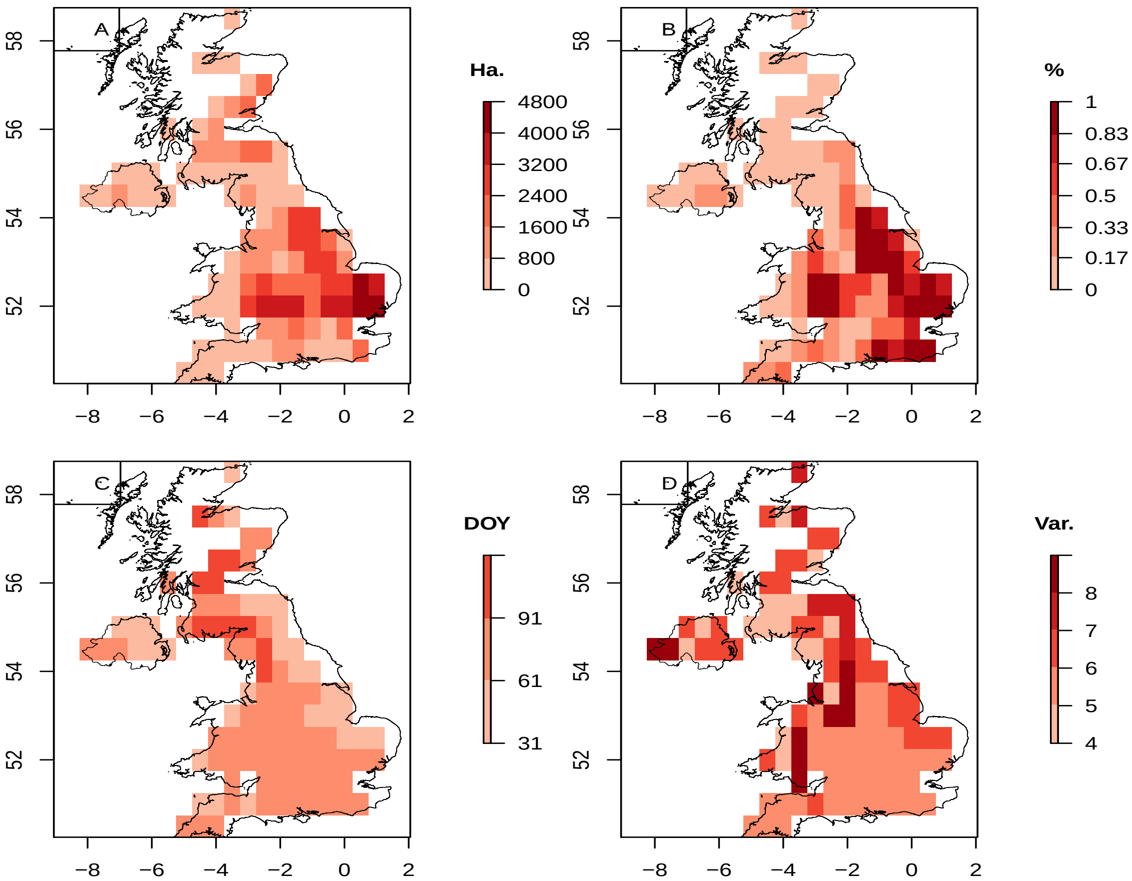



**Figure 4.8:** UK A. Potato growing area. B. Irrigation percentage per grid cell. C. Start of planting window. D. Variety selected.

Model results in Colombia show a wider variety of planting dates selected (Figure 4.12), which is in line with potato agriculture in the region where potatoes are grown all year round. There is a slight tendency for planting dates to be nearer the start of the year in these important growing areas, in keeping with when they are planted in Colombia to coincide with the first rainy season (see Chapter 3). Realistic durations (averaging 128 days) and maximum LAI (averaging 2.53) are also within observed values (see Chapter 3). The inter-annual variability of observed yields is poorly represented, however (Figure 4.9). Mean yield levels are accurately represented.

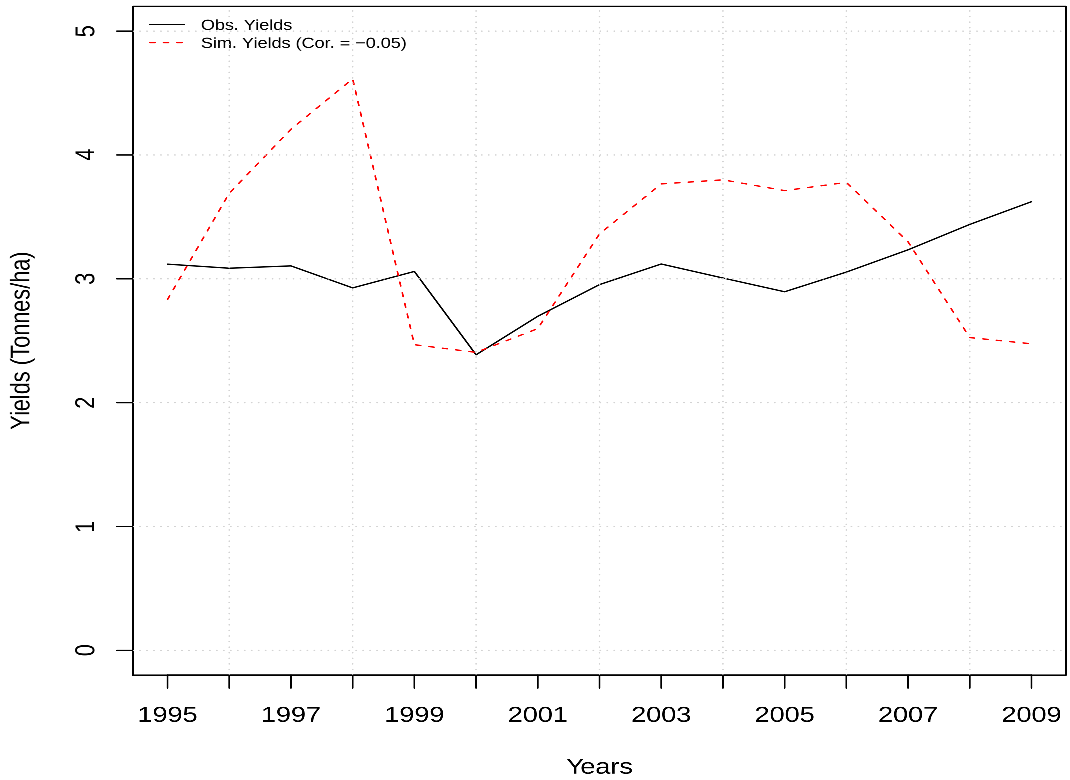



**Figure 4.9:** Observed and simulated area-weighted national yields for Colombia with national scale correlation coefficients. The dashed red line is the simulated yields. The solid black line is the observed yields.

Again there are low correlations between observed yields and weather variables, in particular those with temperature and rainfall (Figures 4.10 and 4.11). The model fails to represent the relationship between solar radiation and observed yields. Inter-annual variability of this variable is very low, however. In 1999 to 2006, the inter-annual variability in observed yields is better captured by the model. In the surrounding years, the lack of a relationship between temperature and rainfall with observed yields means that the relatively high variability in weather results in unrealistic simulated yields.

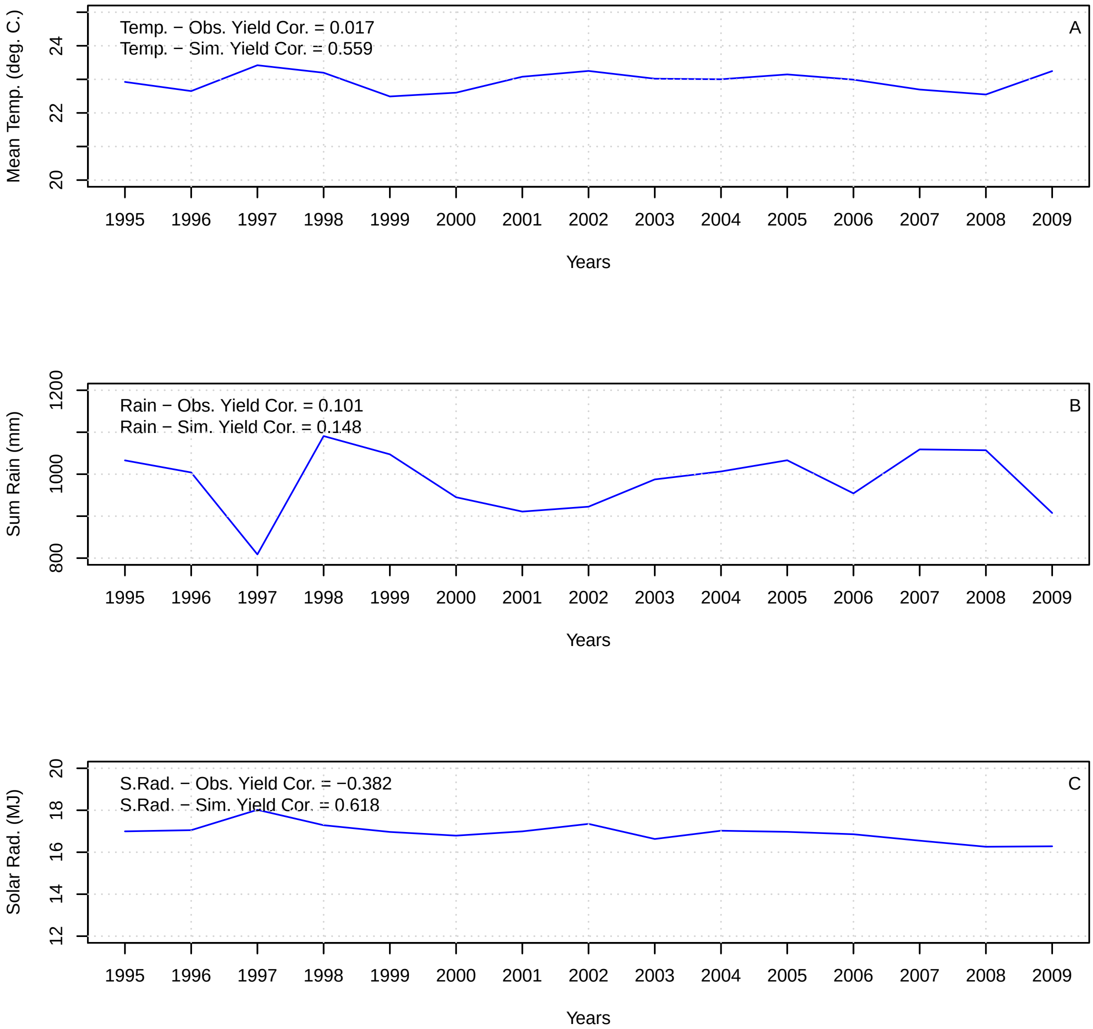



**Figure 4.10:** Area-weighted weather variables for Colombia with correlation coefficients with observed yields. A = mean temperature, B = mean rainfall, C = mean solar radiation.

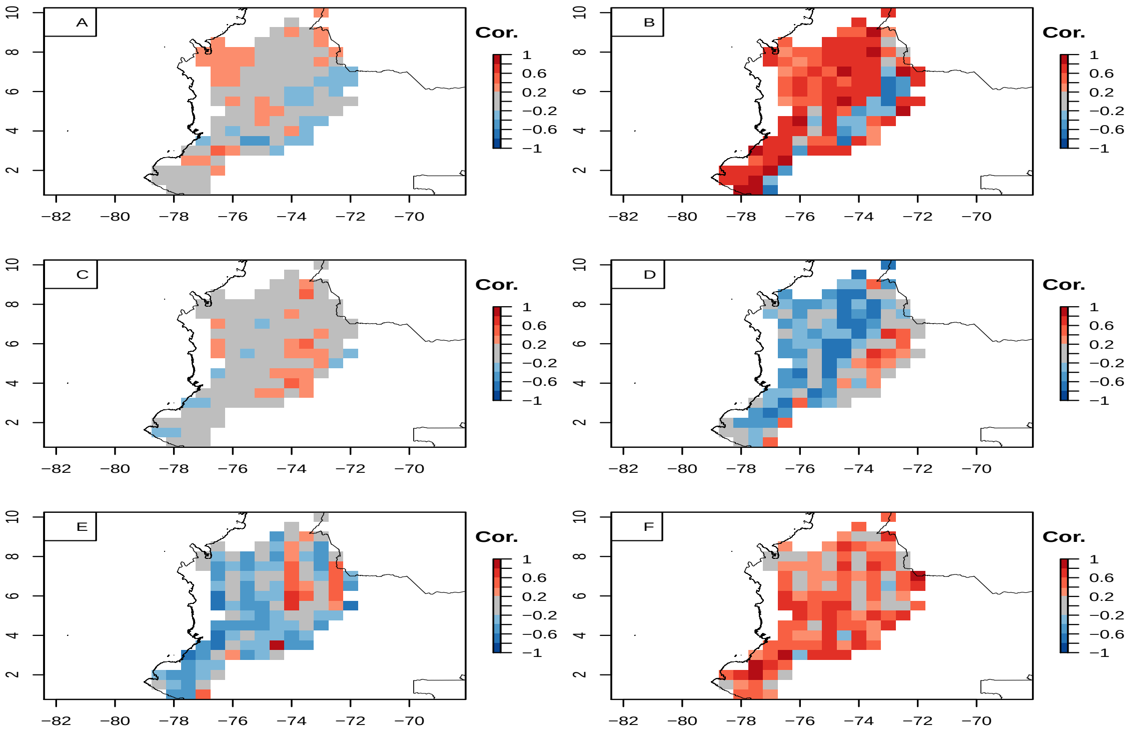



**Figure 4.11:** Colombia correlations between weather variables across the growing season and yields. Correlations are at the grid cell level for the weather variables and yields (the same time series of observed yields were used at each grid cell). A. Mean temperature and observed yields. B. Mean temperature and simulated yields. C. Sum of rainfall and observed yields. D. Sum of rainfall and simulated yields. E. Mean solar radiation and observed yields. F. Mean solar radiation and simulated yields.

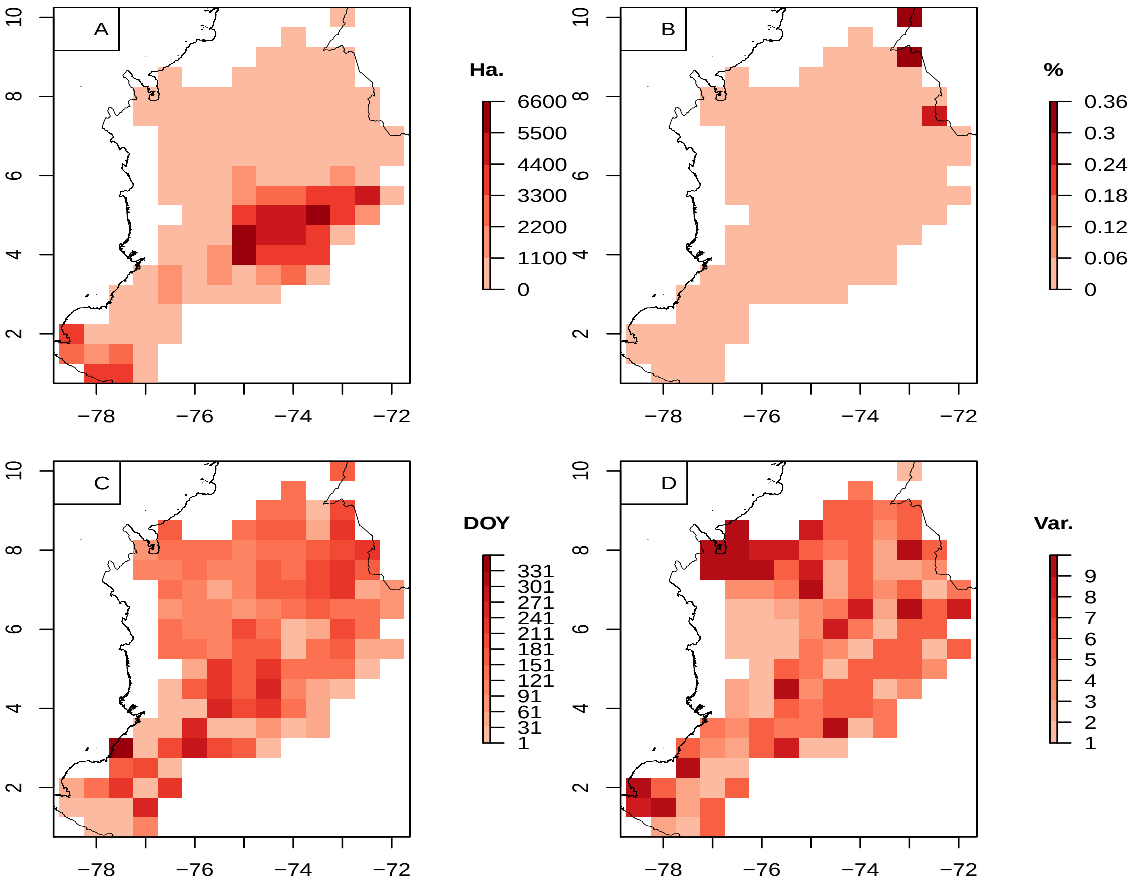



**Figure 4.12:** Colombia A. Potato growing area. B. Irrigation percentage per grid cell. C. Start of planting window. D. Variety selected.

A broader look at how GLAM is simulating the relationship between yields and weather in the UK and Colombia is shown in Figures 4.13 and 4.14. Here, the range of correlations is across planting date and variety combinations, fixing these across all grid cells in each country. These tell us whether other planting date and variety combinations show more significant relationships with weather variables and help us to see if the global parameter method is not capturing observed weather-yield relationships. Simulations that had unrealistic durations and LAI values were not included in these figures. As is shown across planting dates and varieties, correlations with observed yields and temperature are never significant and with rainfall very rarely significant. Simulations mostly capture these relationships. The correlations between simulated yields and temperature are mostly negative in the UK, however. The relationship between temperature and crop duration is responsible for this - higher temperatures lead to shorter growing seasons and lower yields.

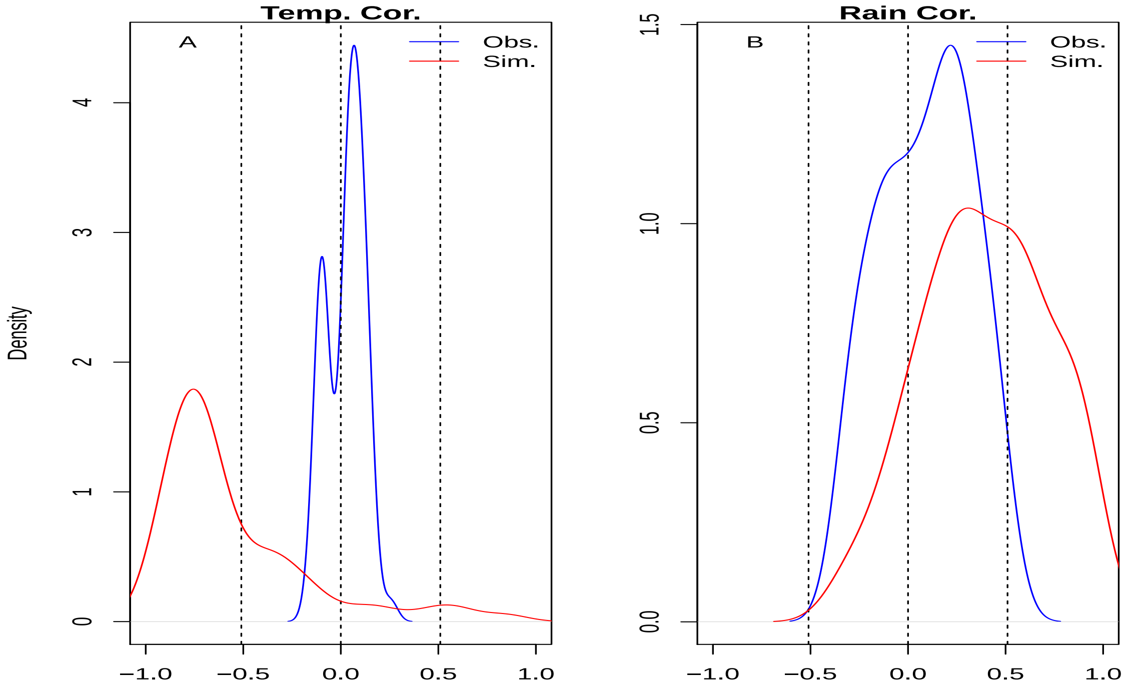



**Figure 4.13:** National scale correlation coefficients for UK yields and area-weighted weather variables (A = Temp., B = Rain). "Density" is the kernel smoothed distribution of correlations.

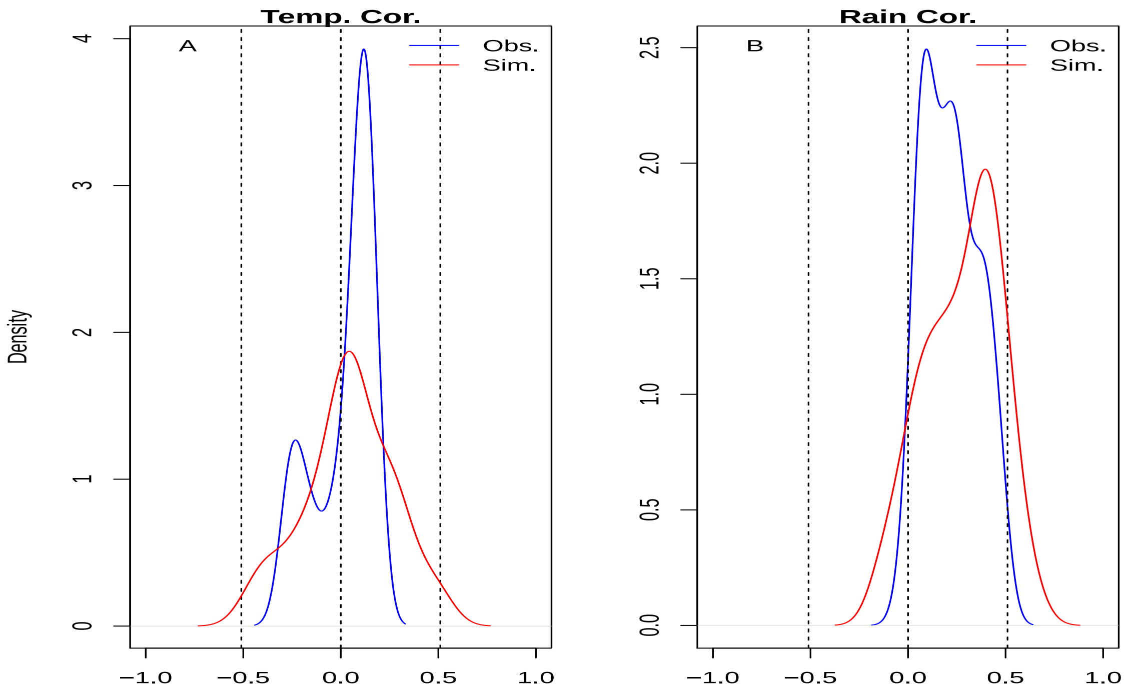



**Figure 4.14:** National scale correlation coefficients for Colombia yields and area-weighted weather variables (A = Temp., B = Rain). "Density" is the kernel smoothed distribution of correlations.

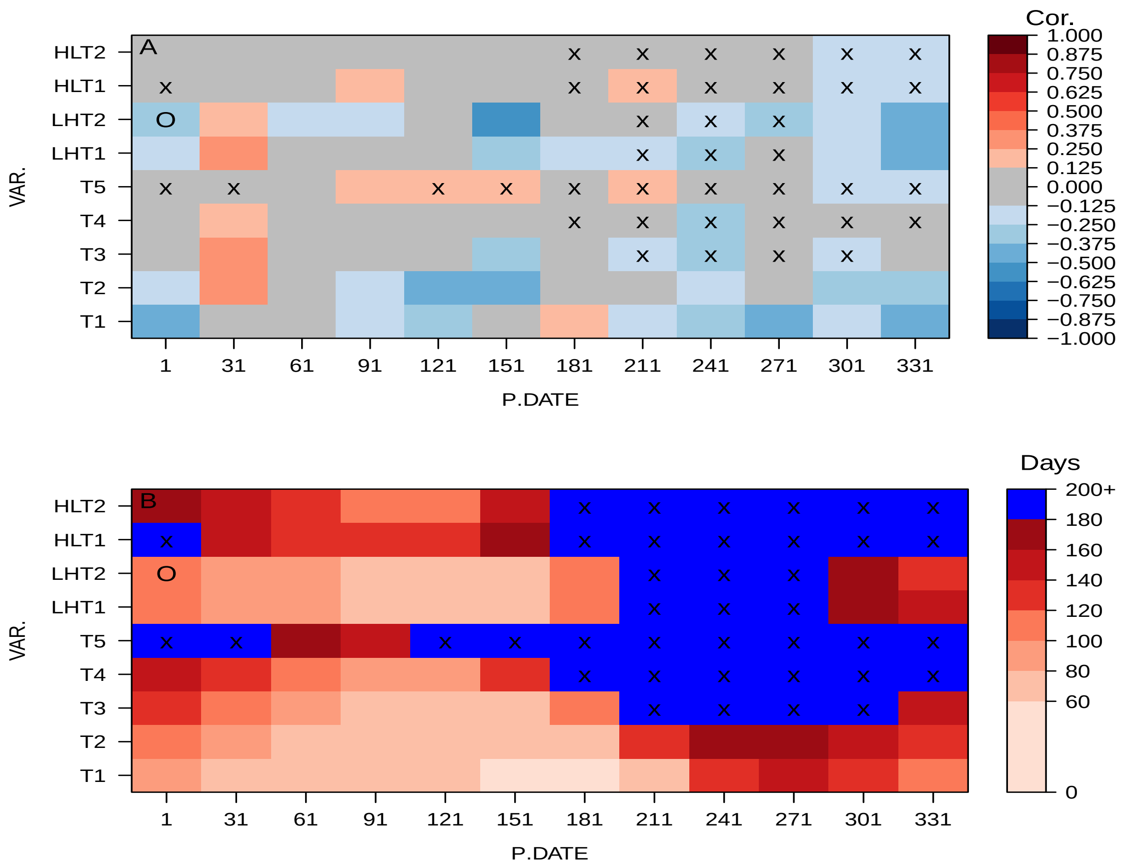



**Figure 4.15:** UK national scale correlation coefficients between observed and simulated yields (A) and crop durations (B) across planting date and variety combinations. 'X' indicates a combination ruled out as unrealistic due to high crop duration, high LAI or emergency planting. 'O' indicates the highest yielding realistic combination. Blue cells in the duration plot indicate unrealistic durations.

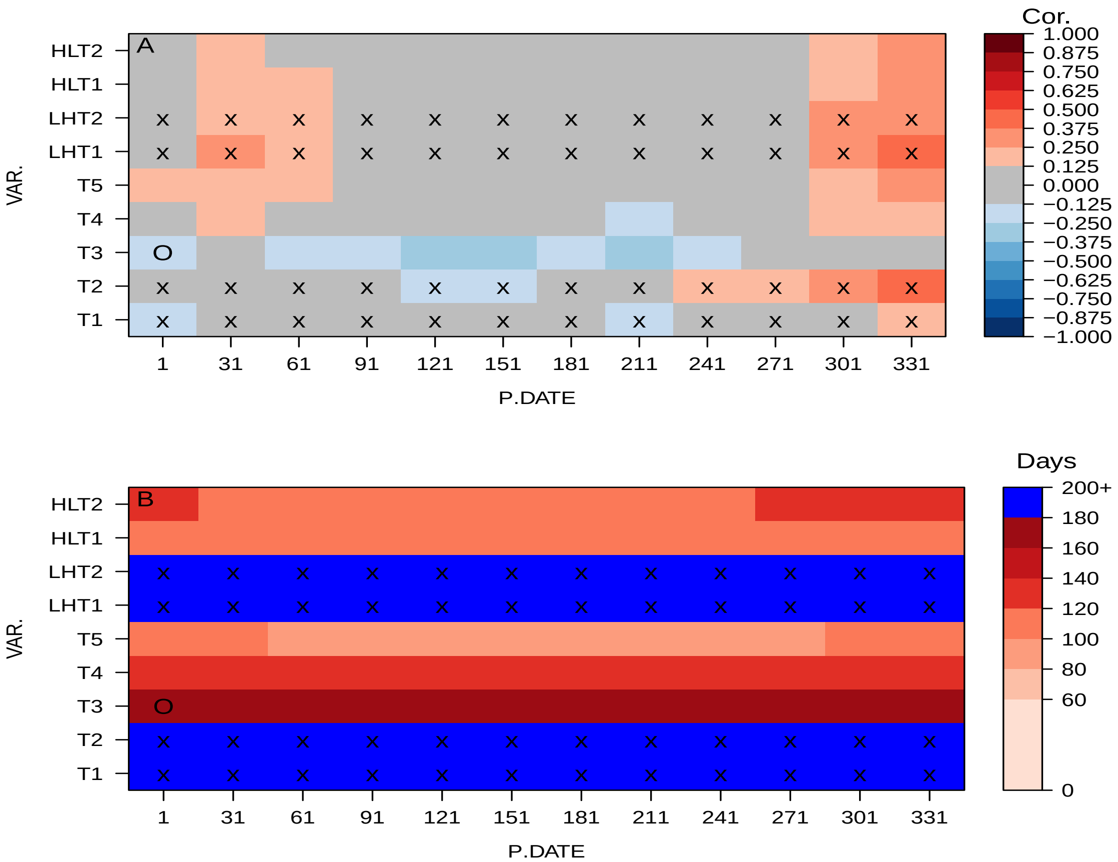



**Figure 4.16:** Colombia national scale correlation coefficients between observed and simulated yields (A) and crop durations (B) across planting date and variety combinations. 'X' indicates a combination ruled out as unrealistic due to high crop duration, high LAI or emergency planting. 'O' indicates the highest yielding realistic combination. Blue cells in the duration plot indicate unrealistic durations

Figures 4.15 and 4.16 show differences in model skill (A) and durations (B) across different planting date and variety combinations for the UK and Colombia respectively, with planting dates and varieties fixed across all grid cells. As can be seen, correlations are rarely significant in these countries across any combinations. In these countries there are some differences in skill for different planting dates and varieties, however, although these differences are also not statistically significant.

To summarise, although both countries show poor representation of inter-annual yield variability, when weak relationships with weather variables are present they are mostly captured. This is shown by certain years of the simulations showing similar variability to those observed. At the same time, sensible planting dates are chosen, realistic phenologies are being simulated and LAI values are within observed limits.

## 4.4 Discussion and conclusions

This chapter has two research questions:

1. Are realistic planting dates, durations and LAI being simulated using the global parameter method?
2. Are observed national scale yield-weather relationships simulated using the global parameter method?

Results showed that planting dates, durations and LAI were within observed ranges and therefore realistically simulated, therefore research question one was satisfactorily passed. There were no significant correlations between observed yields and weather variables at the national level. Of the weak correlations between weather relationships and observed yields, rainfall relationships were well represented in both countries. Both countries showed very weak relationships between national observed yields and temperature, with the model exaggerating these relationships. However, the majority of relationships between weather variables and observed yields were simulated with the correct sign, therefore research question two was also satisfactorily passed.

The model usually picked up the limited relationships between weather variables and observed yields and did so with realistic planting dates. In the UK, relationships with rainfall and solar radiation were well represented by the model. The correlation with rainfall was still low, however, which is not surprising in a country with substantial irrigation of potatoes, particularly in drier areas – there is more irrigation in the UK than the average European country.

The negative relationship with temperature in the UK comes from temperature impacts on growing season length - as is often the case for annual crops, faster temperatures lead to shorter growing seasons and lower yields (Hatfield and Prueger, 2015). In this case there was no such relationship seen in observations which is surprising, and possibly indicates that early season temperatures that determine planting in the UK have an impact on yields, as well as temperature-duration effects - i.e. the temperature at the start of the year may be a limiting factor to the length of the growing season and therefore yield (Harris, 1992). There were no significant correlations between early season temperatures and observed yields, however, and as GLAM takes into account early season frost impacts on planting (see Chapter 2, Section 2.2.2.2), the model is deemed capable of simulating significant relationships with temperature should they occur in other regions. Simulations in this chapter and those in Chapter 3 indicate that effects of temperature on yields come mainly through impacts of temperature on crop duration, as is commonly reported (Haverkort, 1990; Hijmans, 2003; MacKerron and Waister, 1985). The climate is milder in winter in the UK compared to nearby mainland European countries. Management factors could therefore be relatively important for determining accurate potato planting dates, such as when other crops are planted in the region (e.g. winter wheat). Flooding could also have an influence on planting and harvest in wetter areas.

In Colombia, the only correlation with simulated yields that was unrealistic compared to observations was that with solar radiation. This showed a negative relationship with observations and a positive relationship with simulated yields. The negative correlation between solar radiation and observed yields is to be expected when rainfall is a limiting factor to yields, given that cloudy conditions and more rainfall will correlate with less solar radiation. However, the lack of a clear signal with rain made simulating year-to-year variability challenging in this country.

GLAM often exaggerated relationships between weather variables and yields but correctly captured the sign of these relationships in the important potato growing areas. GLAM simulates yields as a function of weather inputs. It is therefore not surprising that correlations with simulated yields are often stronger than those seen with observed yields, as non-climatic factors not included in the model will influence observed yields. Model calibration of the yield gap parameter $C_{\mathrm{YG}}$ will account for these non-climatic factors to some extent, but this only varies at the country-scale spatially and does not influence the simulated inter-annual variability. These factors could include pests, diseases and management that could change over time (e.g. potato late blight emerging earlier in the growing season in the UK – Gregory et al., 2009). Weather variables can also average out across large scales, weakening national yield relationships with weather.

Transpiration and radiation use efficiency parameters were selected to better simulate weather-yield relationships across different climates and produce more realistic LAI. Yields were also not detrended in these countries as this was found to weaken the observed weather-yield relationships. This, along with the parameters chosen that influence biomass, resulted in calibrated mean simulated yields being lower than observations in the relatively high-yielding UK. Both the detrending and parameter choices are consistent with trying to maximise the ability of the model set-up to simulate year-to-year variability of yields. As shown here this can come at the expense of simulating correct mean yield levels.

It is not surprising that some years fail to show accurate simulation of yields given the relatively weak relationship between observed yields and weather seen in these countries. However, given that these results were for countries with only limited relationships with weather variables, and that simulations showed realism with respect to phenology and other model outputs, it can be concluded that this model set-up is adequate for national scale potato yield simulations.

With yield data only available at the national scale, modelling weather-yield relationships remains a challenge, as weather-yield relationships can average out across large scales. We necessarily have less confidence in climate change predictions in such countries as the UK and Colombia that show poor model skill due to low weather-yield relationships (e.g. see Chapter 6). Global studies assessing the impacts of climate change on potato remain very rare, however. This study and its methods therefore represent useful additions to the potato canon.

# Chapter 5

# Model skill in regional and global studies

## 5.1 Introduction

Agricultural systems are complex and require an understanding of many processes that operate at different spatial scales (Ewert et al., 2011). Crop models can be deployed to assess various aspects of these systems at varying spatial scales. Most often this is at the local or field scale (Ruane et al., 2017), although many studies use models at a different spatial scale than that at which they were designed and calibrated on (Ramirez-Villegas et al., 2015).

Global and regional climate impacts studies have different strengths and weaknesses and are used for different purposes. Global studies are defined here as those with full global coverage, and regional studies as those with limited geographic extent, such as at the province or field scale (Challinor et al., 2014a).

Global studies typically use globally-consistent input data and assumptions concerning parameter configurations in order to provide assessments of uncertainty and model comparisons (e.g. Müller et al., 2017) – i.e. data are of the same resolution and detail across the world. They usually do not involve detailed model parameter optimisation across specific regions. Significant calibration of parameters for global studies is computationally limited, the data are often lacking that enable calibration across regions and confident evaluation (Ruane et al., 2017; Therond et al., 2011; van Bussel, 2011), and this kind of optimisation may be undesirable when trying to achieve a consistent model set up to evaluate models across a broad range of environments.

Regional studies use more detailed simulations, with more data and specific knowledge to improve model accuracy and inform policy decisions (e.g. Lv et al., 2013). Whilst regional parameter information is often limited, parameters can be optimised to best represent the crop in certain environments, tuning parameters that are important for yield simulation to provide accurate regional results (Ruane et al., 2017). An example of this could be optimising parameters that adjust mean yield levels across a region (Challinor et al., 2004) or optimising phenology parameters to provide realistic durations given certain temperature conditions (Nicklin, 2013). The purpose of such regional impacts modelling is often to provide an assessment of the impacts of climate change using a regional impacts model, or an assessment of model skill to see if an impacts model can accurately represent the regional inter-annual variability in observed yields. In order to optimise and test parameters, sufficient data have to be available with which to optimise and independently evaluate the model.

It is common to use national level yield data (Müller et al., 2017) in global climate impacts studies, especially for crops not as frequently modelled such as potato (Brown et al., 2011). However, it is difficult to effectively evaluate model performance using national scale yield data alone due to aggregation issues (Porwollik et al., 2017; van Bussel, 2011). There are sometimes regions within countries where more spatially detailed data are available, which can aid in model evaluation.

Variability in year-to-year observed yield data can average out at larger scales (van Bussel, 2011), leading to lower correlations with weather variables and hence poorer model results. It can be difficult to identify the cause of poor model skill in global studies (Challinor et al., 2018). Certain areas can show that there are other drivers of yield than the direct impacts of weather variables, resulting in an improved knowledge of why models perform well in these regions. Alternative drivers of yields can include technology and management changes and biotic stresses (Lobell et al., 2011).

To summarise, global studies produce consistent evaluation world-wide, but the data are often lacking to see if there are losses of information at large scales. Such losses potentially include parameter and management information as well as input data detail. There is therefore a danger that seemingly robust global simulations will in fact lack regional skill. This potentially leads to misinformation at the policy level. Although there is currently no evidence of such misinformation, in-depth analyses have rarely been performed (Challinor et al., 2014a). Zampieri et al. (2017) offer an example of a regional and global comparison for wheat, but focus on yield similarities rather than assessing model skill.

Therefore there is a need to assess whether or not global studies are different to regional studies in terms of skill. The two main ways regional studies differ from global studies are in parameter configuration detail and the spatial scale of the input data. The data at regional scales are often more detailed spatially, but few studies have shown whether they are more representative of yield-weather relationships and can therefore provide better model evaluations (e.g. see van Bussel, 2011). This chapter will compare regional and national scale studies (that are used as part of a global analysis) in order to assess whether or not regional information is being lost in a global impacts study. Furthermore, this work provides an analysis of the source of any difference in skill between crop modelling studies at different scales.

### 5.1.1 Objectives and Research Questions

Previous chapters in this thesis have shown simulations at the regional and national scale in the UK and Colombia (Chapters 3 and 4). The regional simulations in Chapter 3 used parameter optimisation and any crop management information available in order to assess the best possible model skill in these regions. In all cases, model skill is measured using correlation coefficients, as the primary interest of this work is on the year-to-year variability of yields in relation to weather (rather than, for example, mean yield levels). Results in Chapter 3 showed some model skill in simulating the impacts of weather on regional yields, although in some cases there was poor representation of weather-yield relationships, likely due to a lack of planting date and phenology information.

In Chapter 4, the global model configuration was evaluated using national scale yield data in the UK and Colombia. Results here showed some clear representation of weather-yield relationships, but often these relationships were weak and therefore model results showed low correlation coefficients. In summary, these results often indicated better model skill at the regional scale for these two case study countries.

As mentioned in Section 5.1, studies that explicitly measure differences in model skill in regional and global simulations are lacking. This chapter therefore aims to use these case study simulations to quantify any differences in skill. Figure 5.1 summarises the research aims and hypotheses for this chapter. A typical regional simulation would sit at the top left of the diagram, whilst global simulations would sit at the bottom right, showing coarser spatial scale and lower parameter detail.

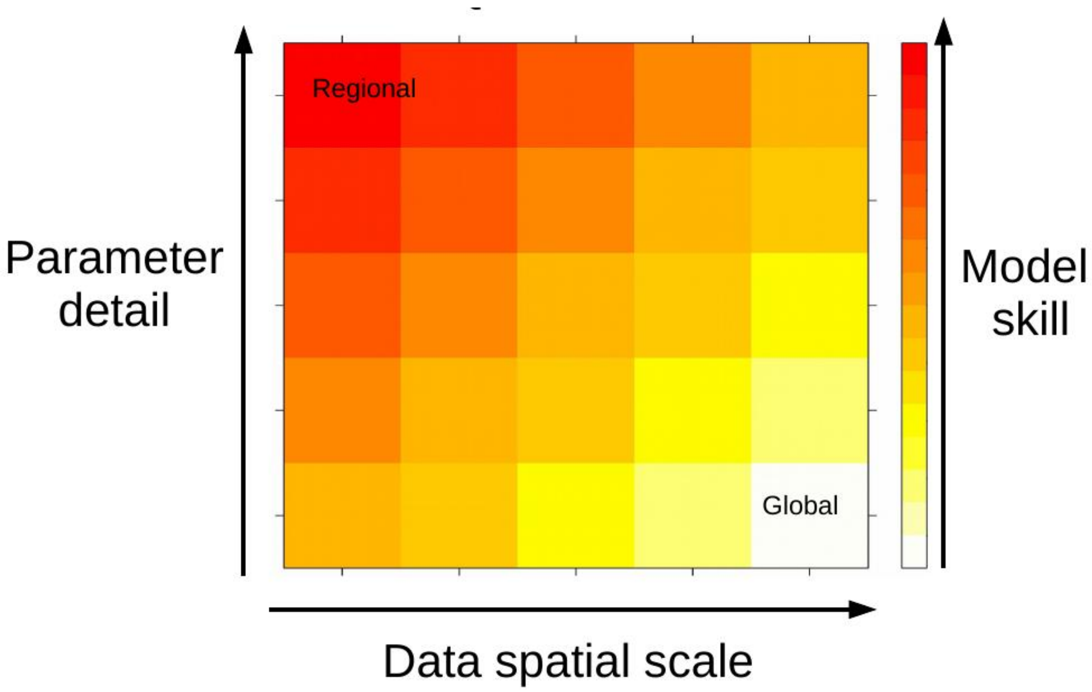



**Figure 5.1:** Predicted relationships between model skill, input data scale and parameter detail. Increasing parameter detail is on the Y axis and increasing spatial scale is on the X axis. Global studies are typically found in the bottom right corner (i.e. large spatial scale and low parameter detail) and regional studies more towards the top left (high parameter detail and smaller spatial scale).

It is expected that regional data and specific parameter configurations lead to better model skill. Using regional yield data, relationships between yields and weather variables may be stronger in some cases compared to national scale data, which would lead to better model skill. This is because yields in certain regions will be driven primarily by weather as opposed to other factors (e.g. management and technology) and weather-yield relationships may average out at larger scales.

A greater level of parameter detail is hypothesised to lead to better model skill as parameters more associated with a given region and crop should be able to best capture weather-yield relationships. It is also hypothesised that parameter detail will lead to larger improvements in simulations compared to the scale of the input yield data. This is because the improvements due to finer resolution input data are often associated with data quality improving, as well as the relationships with weather variables being stronger at smaller scales, and both of these factors are not necessarily the case at finer scales and across different regions.

The research questions are therefore as follows:

1. Is there a significant difference in model skill in regional and global case studies in the UK and Colombia?
2. Is there a significant difference in model skill using regionally-optimised parameters compared with global parameter configurations in the UK and Colombia?
3. Is there a significant difference in model skill when simulating regional and national yields in the UK and Colombia?
4. Which difference in skill is larger – data scale or parameter detail?

## 5.2 Methods

### 5.2.1 Methods Overview

The simulations, data and research questions used in this chapter are summarised in Table 5.1. The regional simulations (RY-RP) of Chapter 3 and the global simulations (GY-

GP) of Chapter 4 are firstly compared to identify any significant difference in model skill. Another set of regional simulations using the global parameter configuration (RY-GP) is then added in this chapter. These are used to assess what causes any difference in model skill - the spatial scale of the yield data or the level of parameter detail. The methods for the RY-GP simulations are outlined in Section 5.2.3.

**Table 5.1:** Naming conventions for parameter configurations, yield data, model results used and research questions in this chapter.

| Yield Data | Description |
|---|---|
| RY (Regional Yield) | Aberdeen and Colombian regional yields used in Chapter 3 |
| GY (Global Yield) | FAOSTAT national yields used in Chapters 4 and 6 |
| Parameter Set | Description |
| RP (Regional Parameters) | Parameter sets optimised for UK and Colombia regions in Chapters 3 |
| GP (Global Parameters) | Fixed parameters used for global simulations in Chapters 4 and 6. |
| Simulation Name | Description |
| RY-RP | Chapter 3 GLAM regional baseline climate evaluation results in UK and Colombia using regionally-optimised parameter configuration |
| RY-GP | Chapter 5 GLAM regional baseline climate results in UK and Colombia using global parameter configuration |
| GY-GP | Chapter 4 and 6 GLAM global baseline climate results using global parameter configuration |
| Research Questions | Description |
| 1). R-skill (regional study value) | RY-RP vs. GY-GP – Is there a difference in model skill when comparing regional and global studies? |
| 2). RP-skill (regional parameter value) | RY-RP vs. RY-GP – What improvement in model skill is associated with using regionally-optimised parameter sets compared with parameter sets used in global simulations? |
| 3). RY-skill (regional yield data value) | RY-GP vs. GY-GP – Do regional scale yield simulations show more skill than national scale yield simulations? |
| 4). R-diff (source of skill difference) | RP-skill vs. RY-skill – What is the source of the difference in skill between global and regional simulations? |

The value of regional over global studies can first be assessed using RY-RP and GY-GP simulations. It is hypothesised that there is better model skill associated with regional simulations. The model skill of the regional optimisation study (RY-RP) results are compared with the global country-scale (GY-GP) results. The correlation coefficients across regions (RY-RP) are compared to the national-scale (GY-GP) correlation coefficient. Correlations are tested for significant differences across analyses.

Different levels of parameter detail are then assessed. It is hypothesised that more parameter detail leads to better model skill. The model skill of the regional optimisation study (RY-RP) results are compared with the regional-scale simulations using the global parameter configuration (RY-GP) results. The correlation coefficients across regions (RY-RP) are compared in both parameter configurations. Correlations are tested for significant differences across analyses.

The value of regional-scale yield data is assessed. It is hypothesised that regional (rather than national scale) yield data leads to better model skill. The model skill of the regional study using the global parameter configuration (RY-GP) is compared with the global country-scale (GY-GP) study. The correlation coefficients across regions (RY-RP) are compared to the national-scale (GY-GP) correlation coefficient. Correlations are tested for significant differences across analyses.

Lastly, of parameter detail and data scale, which is most important for improving regional over global simulations is assessed. It is hypothesised that parameter detail is the more important difference in terms of model skill of regional and global studies. The results from the simulations comparing parameter detail and yield data across regional and global simulations are compared to see which is the larger source of difference in model skill between regional and global simulations. The number of regions showing significant differences in model skill are used to judge which is the larger contributor.

The R function "r.test" from the package "psych" (Revelle, 2015) is used to statistically judge if correlations are significantly different in research tests 1 to 3. The "r.test" function is used to calculate a test statistic for the difference between correlations (the correlations between the simulated yields and observations for both modelling types) using the Williams method (Williams and Williams, 1959), which has been shown to perform well relative to other methods in terms of the statistical power of the test (i.e. the probability of correctly rejecting the null hypothesis when it is false – Wilcox and Tian, 2008). The Williams method calculates a test statistic based on the correlations between the three variables concerned (both sets of simulated yields and the observed yields). The statistic is then compared to a student's t-distribution to obtain a p-value for evidence against an equal-correlation hypothesis.

Confidence intervals are included as a measure of uncertainty in correlations - these represent the interval where, if the experiment were repeated a large number of times, the true value of the statistic would lie within 95% of such intervals.

For research questions 1 to 3, if the regional study shows significantly higher correlations than the global study across more regions than show a fall in skill – i.e. if there is a net increase in the number of regions showing a positive significant difference in correlation coefficient – then the regional study is judged to show an improvement in model skill.

### 5.2.2 Input data

All data for all simulations are described in Chapters 3 and 4 and so this information is not repeated here. Chapter 3 details the data used for Aberdeen and Colombian regions. Chapter 4 details the data used for the national scale simulations.

### 5.2.3 Model set-up

Model results from Chapters 3 and 4 (RY-RP and GY-GP) were obtained using the methods set out in those chapters. Those results are compared to the simulations described here (RY-GP) to answer the research questions outlined in Section 5.1.1. RY-RP results presented here are from the best performing optimised GLAM parameter sets from the eight optimised in those analyses. These were parameter set 1 in the Colombian regions and parameter set 5 in the UK (Aberdeen site) optimisation.

GLAM-potato (see Chapter 2) is used to simulate potato yields for the RY-GP simulations. These use the regional yield data described in Chapter 3 in conjunction with the global parameter configuration described in Chapter 4. Parameters used for these simulations are identical to those shown in Table 4.3 in Chapter 4.

## 5.3 Results

Results are presented by research question below. Research questions 1 to 3 show simulation results across analyses. In Section 5.3.4, the sources of differences in model skill are discussed (research question 4).

Confidence intervals are included in all subsequent figures. These all span zero and are large, which result from the short time series (four years) in Colombian regions and a lack of significant model skill in the UK simulations (as described in Chapters 3 and 4).

### 5.3.1 Results - regional vs. global: RY-RP vs. GY-GP

Research question 1 assesses whether there is a significant difference in model skill in regional and global case studies in the UK and Colombia.

Figure 5.2 shows the correlation coefficients between simulated and observed yields for the RY-RP and GY-GP analyses for the UK and Colombia.

Correlation coefficients are higher in both the UK and Colombia on average for the RY-RP study. There were no significant correlations across countries and analyses, however. The correlations were not significantly different for the two analyses in the UK, although higher for the RY-RP study. Colombia regions 1, 8, 9 and 11 had significantly higher correlations for the RY-RP simulations and region 6 had a significantly lower correlation. The GY-GP simulations show low correlations between weather variables and observed yields, therefore limiting model skill. Certain regions are able to successfully simulate stronger observed weather-yield relationships in the RY-RP simulations.

It can be concluded therefore that regional scale studies lead to higher model skill in both the UK and Colombia case studies in some cases. Certain regions in Colombia show significant improvements and both UK and Colombian simulations show higher correlations in the RY-RP study.

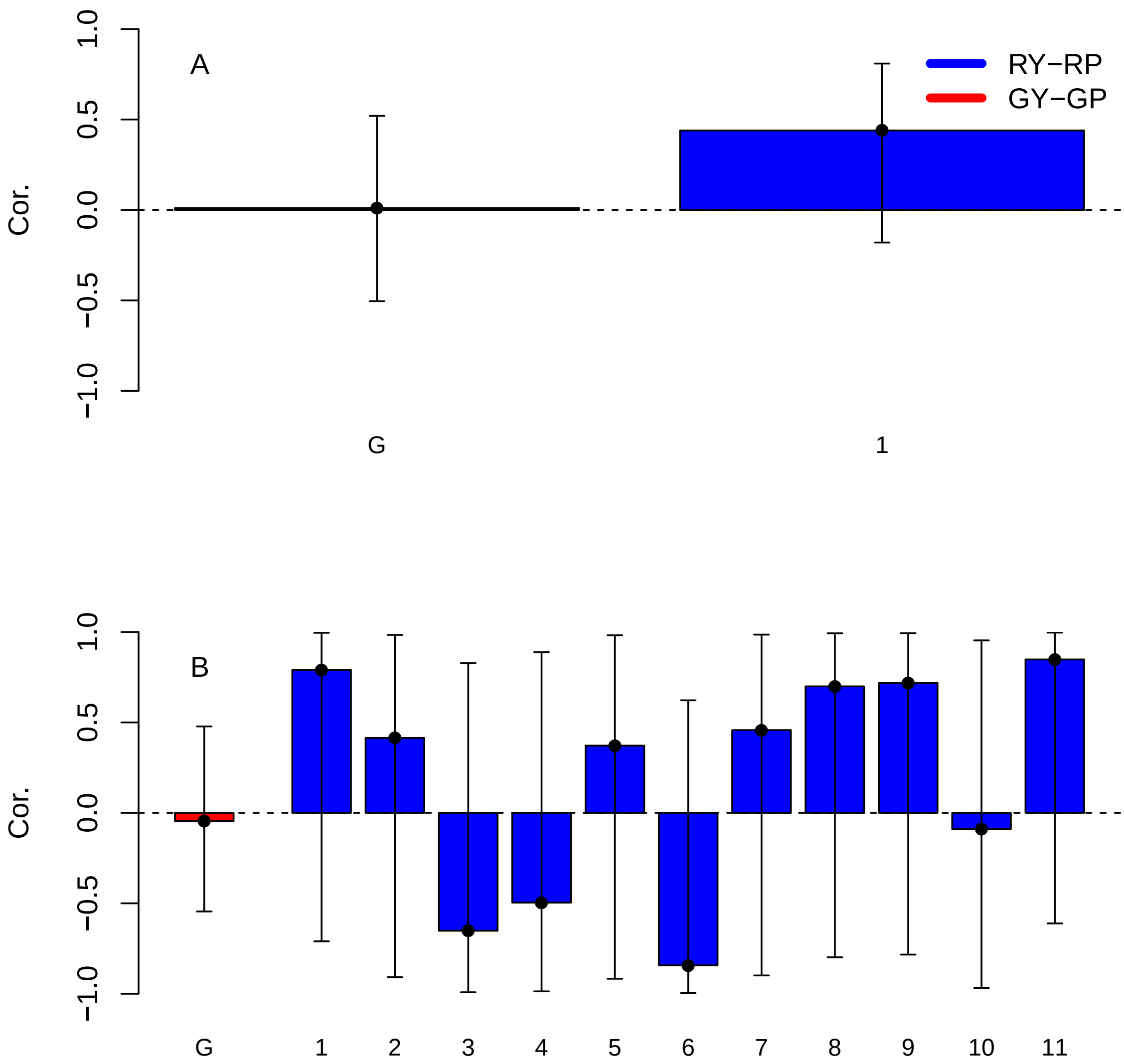



**Figure 5.2:** Correlation coefficients between simulated and observed yields for the RY-RP and GY-GP (G) simulations. A). UK. 1 = Aberdeen site. B). Colombia. Regions are numbered 1 = Antioquia, 2 = Boyacá, 3 = Caldas', 4 = Cauca, 5 = Cundinamarca, 6 = Huila, 7 = Nariño, 8 = Norte de Santander, 9 = Quindío, 10 = Santander, 11 = Tolima. Bars show 95% confidence intervals.

### 5.3.2 Results - parameter detail comparison: RY-RP vs. RY-GP

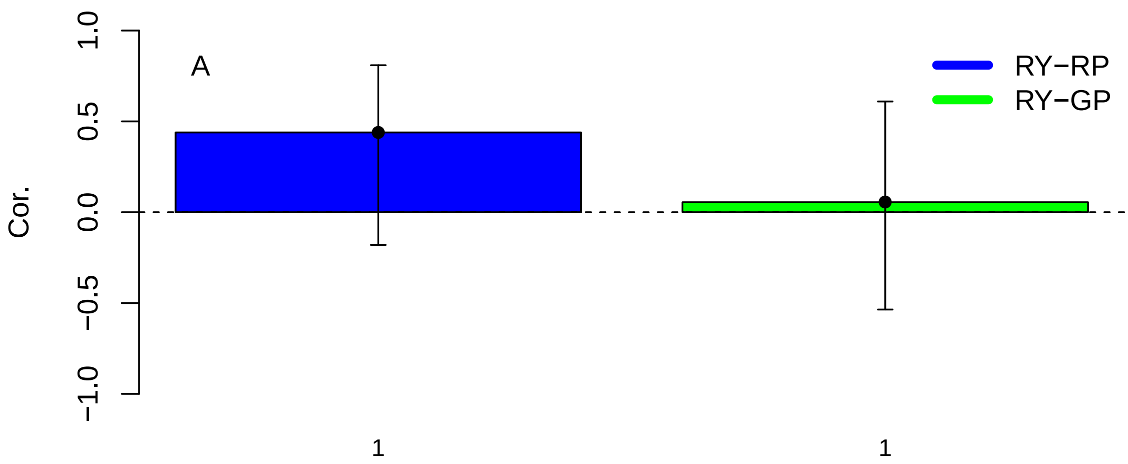
Research question 2 assesses whether there is a significant difference in model skill using regionally-optimised parameters compared with global parameter configurations in the UK and Colombia.

Figure 5.3 shows the correlation coefficients between simulated and observed yields for the RY-RP and RY-GP analyses for the UK and Colombia. As can be seen here, correlation coefficients are higher in both the UK and Colombia on average for the RY-RP study. There were no significant correlations across countries and analyses.

The correlations were not significantly different for the UK, although there were significant differences between the correlations associated with the two analyses across Colombian regions. Regions 1, 7, 8, 9 and 10 had higher correlations associated with the RY-RP study, whereas regions 2, 4 and 6 showed significantly lower correlations. Improvements in skill in the RY-RP study result from optimised parameters better representing weather-yield observed relationships. In the southern Colombian regions where skill is lower in RY-RP studies, planting dates are not as accurately represented using the regional method. They tend to be late in the season, whereas the RY-GP study selects them to be nearer the start of the calendar year (as they should be). This leads to poor skill in the RY-RP study in Cauca and Huila (regions 4 and 6). Region 2 (Boyaca) also shows poorer planting dates in the RY-RP study. Here, planting dates are sometimes earlier and sometimes later in the RY-GP study, but the general affect of the planting date and variety combinations associated with the global parameter set is for more realistic relationships with temperature in those grid cells and longer durations than those simulated in the RY-RP study.

In Colombian regions, planting dates were sometimes selected at the end of the calendar year with the RY-GP simulations when these should be in the first half of the calendar year, as in the RY-RP simulations. This leads to the better representation of weather-yield relationships in RY-RP simulations. For the UK RY-GP simulations, the simulated planting date was slightly earlier in the season than observed. It can be concluded therefore that the RY-RP analysis - and therefore greater parameter detail - is associated with higher model skill in certain regions.

Colombian regions 3, 4, 6 and 10 show particularly low skill in both the RY-RP and RY-GP simulations. The combination of planting date and variety selected for these simulations produces unrealistic relationships with temperature, causing poor model skill. Regions 7, 8 and 9 show good skill in simulating yields in the RY-RP study but poor skill in the RY-GP study. The biggest difference in these simulations comes from the representation of the relationship between yields and temperature, which is worse in the RY-GP simulations but well captured in the RY-RP simulations.



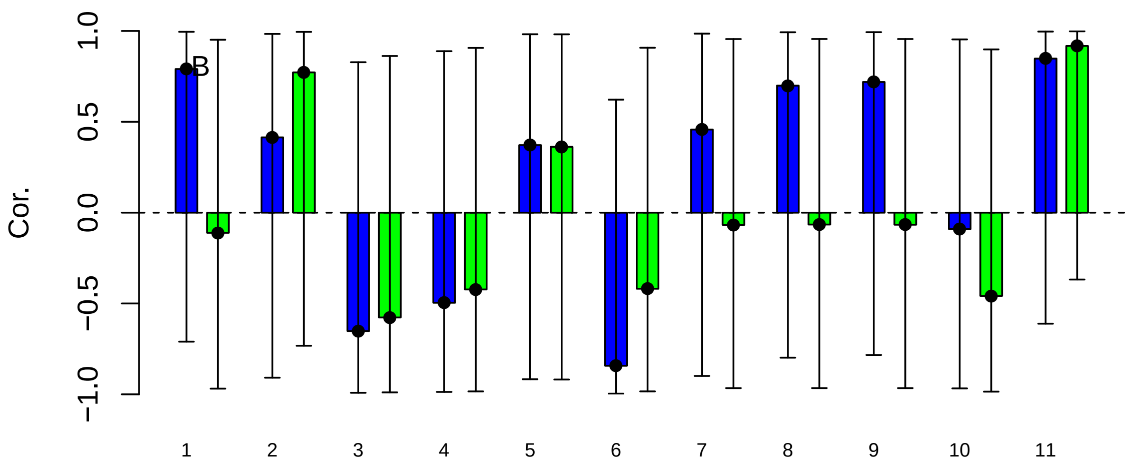




**Figure 5.3:** Correlation coefficients between simulated and observed yields for the RY-RP and RY-GP simulations. A). 1 = UK, Aberdeen site, UK. B). Colombia. Regions are numbered 1 = Antioquia, 2 = Boyacá, 3 = Caldas', 4 = Cauca, 5 = Cundinamarca, 6 = Huila, 7 = Nariño, 8 = Norte de Santander, 9 = Quindío, 10 = Santander, 11 = Tolima. Bars show 95% confidence intervals.

### 5.3.3 Results - yield data scale comparison: RY-GP vs. GY-GP

Research question 3 assesses whether there is there a significant difference in model skill when simulating regional and national yields in the UK and Colombia.

Figure 5.4 shows the correlation coefficients between simulated and observed yields for the RY-GP and GY-GP analyses. As can be seen here, the RY-GP and GY-GP correlations are both very low and are statistically not different in the UK and most Colombian regions. No correlations were significant for either country and analysis.

Colombian regions 2 and 11 (Boyacá and Tolima) had significantly higher correlations associated with the RY-GP study compared to the GY-GP study. It can therefore be concluded that finer scale yield data leads to higher model skill in two regions, although there is not evidence for significant differences in the other regions. In these two regions, some relationships between observed yields and weather variables are captured, whereas at the national scale only very weak relationships are present, leading to lower model skill.

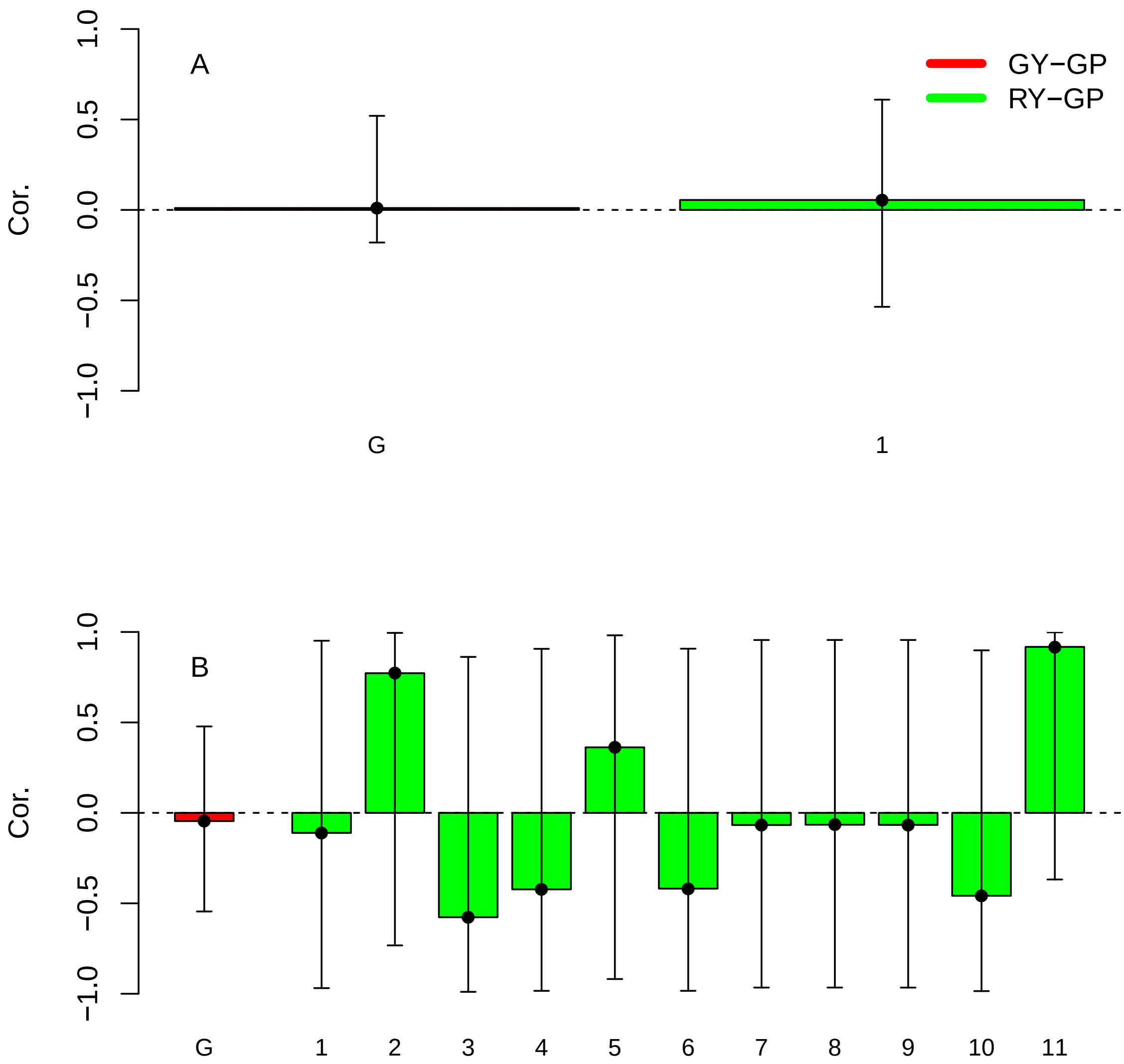



**Figure 5.4:** Correlation coefficients between simulated and observed yields for the RY-GP (C, 1-11) and GY-GP (G) simulations. A). 1 = UK, Aberdeen site. B). Colombia. Regions are numbered 1 = Antioquia, 2 = Boyacá, 3 = Caldas', 4 = Cauca, 5 = Cundinamarca, 6 = Huila, 7 = Nariño, 8 = Norte de Santander, 9 = Quindío, 10 = Santander, 11 = Tolima. Bars show 95% confidence intervals.

### 5.3.4 Results - yield scale and parameter detail comparison

Research questions 4 assesses which difference in skill is larger – data scale or parameter detail.

Results in Section 5.3.1 showed an improvement in model skill for some regional simulations compared to global simulations. Results in Sections 5.3.2 and 5.3.3 (Figures 5.3 and 5.4) can tell us something about what is causing this difference in skill.

There is a difference in model skill when comparing parameter detail in the RY-RP and RY-GP simulations. In Colombia, five regions show significantly higher skill in RY-RP simulations. There is a smaller difference when comparing yield data in studies RY-GP and GY-GP, with only two regions showing significantly higher skill in the RY-GP simulations. In the UK, the differences in correlations are never significant, although the highest skill is associated with the RY-RP simulations. Therefore, parameter detail is more often the cause of higher model skill than the spatial scale of the yield data.

In most regions where we see an improvement in skill between regional and global simulations, the relationships with weather variables, and in particular temperature, are better represented by the regional simulations. In well performing Colombian regions, for example, temperature relationships are well captured, whereas for the global simulations, relationships are weak between observed yields and temperature and sometimes poorly represented. The UK GY-GP simulations show no relationship between observed yields and temperature, whereas the RY-RP UK simulations capture a weak relationship with temperature. The parameters that are chiefly responsible for these differences are planting dates and crop phenology parameters. For the UK RY-RP simulations, known planting dates and optimised phenology parameters lead to improvements in skill. For the Colombia RY-RP simulations, planting dates are selected from a pre-defined range of dates known from the literature. These improvements are leading to more realistic crop growing seasons and consequently better representations of observed weather-yield relationships.

## 5.4 Discussion

This study has four research questions:

1. Is there a significant difference in model skill in regional and global case studies in the UK and Colombia?

2. Is there a significant difference in model skill using regionally-optimised parameters

compared with global parameter configurations in the UK and Colombia?

3. Is there a significant difference in model skill when simulating regional and national yields in the UK and Colombia?

4. Which difference in skill is larger – data scale or parameter detail?

Results for research question 1 were in line with the hypothesis of higher skill being associated with regional simulations. There were some significant differences in regional simulations in Colombia. UK simulations showed (insignificantly) higher skill in the regional simulations. The reasons for the higher skill sometimes associated with the regional studies are discussed below.

Results for research question 2 were in agreement with the hypothesis of higher skill being associated with greater parameter detail. Regionally-optimised parameters led to better skill than the global parameter configurations, although this positive significant difference was only significant in five Colombian regions. More realistic planting dates were the primary cause of better results in these regions, although optimised phenology parameters also resulted in more realistic weather-yield relationships. As was shown in Chapter 4, different planting date and variety combinations can lead to differences in model skill.

Management inputs such as accurate data on planting dates are often lacking in crop modelling studies, especially at larger scales (e.g. Ewert et al., 2011). Unsurprisingly, when phenological parameter calibration is performed skill has been shown to improve in previous studies (Therond et al., 2011; Angulo et al., 2013). Parameter optimisation is important for the accurate simulation of crop growth processes (Ramirez-Villegas et al., 2017), and results in this chapter provide further evidence of this. Few studies have looked into the appropriate level of model complexity and parameter detail for a given spatial scale of analysis (Ewert et al., 2011). This work highlights the need to simulate crop phenology in more detail, in agreement with (Adam et al., 2011; van Bussel, 2011).

Most crop modelling studies are site-based, at the local or field scale (Ruane et al., 2017; Challinor et al., 2014b). These tend to rely on more detailed experimental data for crop phenology parameters, as well as planting and harvest dates. Coordinated studies (e.g. Ruane et al., 2017) can begin to make use of this information at large (e.g. global) scales, although site-based studies cannot currently provide the comprehensive coverage that global modelling requires. Therefore more data collection for important crop phenology and management dates is desirable, perhaps using new technologies such as remote sensing to allow accurate simulation of planting dates and crop phenology across large regions (Gao et al., 2017). Such techniques could be "bias-corrected" using observations from experimental sites to verify and improve accuracy. These approaches could be highly beneficial to global crop modelling studies that currently rely on either model algorithms (e.g. Osborne et al., 2013) or interpolated data from coarse resolution (e.g. Sacks et al., 2010) for planting date information.

Results for research question 3 were in agreement with the hypothesis of higher skill being associated with regional yield data, although evidence for this was limited. Whilst there was some evidence that having regional yield data improves model skill, few regions showed significant improvements. This is in keeping with literature on the effects of data aggregation on simulation results, which generally show small impacts (Kuhnert et al., 2016; Hoffmann et al., 2015; van Bussel, 2011).

Data are usually associated with a particular spatial scale, and aggregation is necessary to model on larger scales (Ewert et al., 2011). In this case, yield data require aggregation to the national scale for globally comprehensive modelling, with a resultant loss of information compared to regional data. Aggregation of other data inputs, such as weather and sowing dates, may have a limited impact on results (van Bussel et al., 2011), although soil aggregation uncertainty can be significant (Folberth et al., 2016). Porwollik et al. (2017) show that different crop growing area data sets can lead to uncertainty in different simulated regional yield time series, which is another potential source of model error at larger scales.

One reason why smaller scale simulations could show improvements in skill is that certain regions may have stronger weather-yield relationships (Watson and Challinor, 2013), and these relationships may average out when looking at larger scales. It is therefore not surprising that these results do not show clear skill improvements across all regions, as this hypothesis implies some regions having weaker relationships with weather than others (and some regions having weaker relationships than those at the national scale). National scale correlations with weather variables are indeed low in the UK and Colombia (see Chapter 4).

More regions showed significant improvements in model skill due to more parameter information. Research question 4 therefore is answered in agreement with the stated hypothesis that parameter information is of most importance. More realistic simulated weather-yield relationships resulted more often from improvements in simulated crop phenology rather than the regional yield data.

### 5.4.1 Limitations

It is important to note that the analyses in this chapter are limited by the data available, and to a single crop and crop model. Studies and data are limited for potato in contrast to other important global crops (see Chapter 1). Only two countries were simulated regionally for comparison with global simulations. Time series in Colombia were also short. Our conclusions here are based on the fact that the significant differences in model skill identified are more often than not in agreement with stated hypotheses. The majority of regions do not show significant differences in skill, however, and model skill is in general low. It is in this context that conclusions about the global and regional comparison are made - whilst some patterns emerge concerning the differences in skill and the sources of this difference, further work is needed in order to corroborate these findings. This would ideally consist of regional data of longer time series, across more countries with further contrasting climates, at different spatial scales and with different levels of parameter detail. The uncertainty in input data sources (growing area, soils, irrigation, weather) and crop model structure are also not accounted for in this work and are important to take into consideration.

### 5.4.2 Conclusions

This work has shown that there are some differences in model skill between regional and global simulations in the UK and Colombia. For these studies, the source of improvement in model skill is largely the higher level of parameter detail associated with regional studies. In particular, planting dates and crop phenology are better represented in the RY-RP simulations. This leads to more realistic representations of weather-yield relationships. van Bussel et al. (2011) highlight the need for better information on crop phenology in global studies and results in this chapter agree. More data and analyses are needed to make more general conclusions, however.

For most global crop modelling analyses, globally-coherent data sets and parameter configurations are needed. High levels of parameter detail are usually unavailable, either because of a lack of regionally-specific information or due to computational limitations when needing to optimise parameters. This work highlights the need to have more detailed parameter information for global studies in order to improve climate impacts modelling. Particular emphasis should be placed on better planting date information and realistic simulation of crop phenology.

# Chapter 6

# The impacts of climate change on potato agriculture: global analysis

## 6.1 Introduction

This chapter presents work highlighting the impacts of climate change on global potato agriculture. It uses the process-based crop model GLAM-potato (see Chapter 2) alongside the late blight risk forecasting model SimCastMeta (Sparks et al., 2011) to assess both the abiotic and biotic impacts of climate change on potato agriculture.

There has been a lack of previous potato modelling studies compared to other crops, especially at the global level. Hijmans (2003) is one of very few examples, but this study only examined the impacts of temperature changes on potential yields, not including changes to $CO_2$ and precipitation. Being a C3 crop, potato yields are likely to increase with elevated $CO_2$ due to $CO_2$ fertilisation (Fleisher et al., 2008; Finnan et al., 2005). Including these impacts is especially important as some studies suggest rising $CO_2$ to be more important than other mean climatic changes (Haverkort et al., 2013) and that $CO_2$ fertilisation for potatoes could be higher than for other C3 crops (Magliulo et al., 2003). Raymundo et al. (2017b) include a detailed $CO_2$ parameterisation but do not consider adaptations of cultivar and planting date changes in the future. Raymundo et al. (2017b) project global yield decreases by the mid 21st century of 2-6% and Hijmans (2003) 9-18% when considering adaptation but no $CO_2$ fertilisation.

Studies that examine yield changes that allow planting dates and varieties to vary in future climate for other major crops are becoming increasingly common, rather than using so-called "dumb farmer" planting dates and varieties that do not vary in future climate (Deryng et al., 2014; Rosenzweig et al., 2014). Previous global gridded modelling studies have featured simulations that allow planting dates and crop phenologies to vary as well as simulations that keep these fixed in the baseline climate (Müller et al., 2017; Deryng et al., 2014) – in other words, adaptation to climate change is or is not considered in previous global crop simulations.

Of 91 published analyses on climate change impacts included in The Intergovernmental Panel on Climate Change 5th Assessment report, 33 included adaptation measures. These measures were limited to changes in planting date, irrigation, crop variety and fertiliser (Challinor et al., 2014b). Risk assessments risk losing accuracy if they do not include at least some autonomous adaptations measures (Challinor et al., 2018).

A technology change should only be considered an adaptation to climate change if it is measured in the baseline as well as future climate (Lobell, 2014). Changing planting dates and varieties in future may not be straightforward, however, due to factors not typically taken into account in modelling studies, including market pressures, pests and diseases, other crops and water availability (Hijmans, 2003). Many adaptation scenarios can be envisaged, ranging from the so-called "dumb farmer" who does not react at all to climate change to the "clairvoyant farmer" who reacts with no restrictions to resources for adaptation (Füssel, 2007; Schneider et al., 2000). The most realistic adaptation scenario will be context specific, depending on regional constraints such as cultivar availability. For this reason, global studies necessarily have to make assumptions that will not apply to all regions – an example of global studies losing regional skill (Challinor et al., 2014a). Some studies preferentially avoid a dumb farmer scenario, assuming that farmers will adapt in some ways to climate change and if not including adaptation the impacts of climate change will be overestimated (e.g. Mendelsohn et al., 2000). Others assess the potential benefits of clairvoyant adaptation strategies (Hijmans, 2003).

The simulations in this chapter include $CO_2$ fertilisation and precipitation changes alongside adaptation to climate change (varying planting dates and varieties), unlike previous global potato climate change modelling studies (Hijmans, 2003; Raymundo et al., 2017b).

As discussed in Chapter 1, the explicit incorporation of pest impacts into global crop modelling remains impractical due to reasons of appropriate model complexity and a lack of global data. Therefore, biotic stress work is included alongside the crop modelling, focusing on the oomycete pathogen of potato, late blight *Phytophthora infestans*, a widespread and destructive potato disease responsible for yield losses that can be as high as 30% (Dowley et al., 2008; Oerke, 2006). Late blight causes such substantial yield losses by damaging most parts of the plant – the leaves, stems and tubers (Hwang et al., 2014).

Late blight has shown rapid evolution in the past (Gregory et al., 2009; Goodwin et al., 1995), despite historically one clonal lineage dominating the majority of blight populations (Goodwin et al., 1994). Blight is a heterothallic oomycete, meaning that two compatible partners (known as mating types) are necessary in order to sexually reproduce. Evolutionary potential (i.e. the potential of a species to adapt to environmental conditions) could increase in the future thanks to the increasing prevalence of a second blight mating type (Chowdappa et al., 2015; McDonald and Linde, 2002). This increases the opportunity for genetic recombination, contributing to greater genetic diversity (Hwang et al., 2014). As pointed out by Bale et al. (2002), flexible species that have wide geographic ranges and diverse diets - such as late blight - usually show high evolutionary potential.

For blight, there are increasing numbers of lineages and sexual reproduction is likely to become more common, resulting in more genetic variation being available within and across populations. Whilst it is uncertain how much novel genetic mutations can lead to adaptive responses to climate change (Parmesan, 2006), Hof et al. (2011) theorise that pre-existing genetic variation within species may have allowed them to cope with climatic change in the past and could do some in future. There is evidence that blight varieties respond differently to environmental conditions, particularly that different varieties show different levels of virulence in response to changing temperatures (see Chapter 1).

It is therefore important to take evolution into account when predicting future biotic stresses - something not incorporated in the majority of studies concerning food security (Scherm, 2004; Davis et al., 2005; Forbes et al., 2003). Sparks et al. (2014) studied the impacts of climate change on global late blight but did not consider any changes to the pathogen over the course of the 21st century. They predicted that under the A2 SRES climate scenario, late blight risk would globally on average increase up to 2050 and then fall slightly towards the latter part of the century.

Often range shifts and changes to phenology are the only adaptive responses taken into account in climate change studies, and these typically result from phenotypic plasticity rather than genetic changes (Scherm, 2004). This analysis goes a step further, allowing the response of blight to temperature to vary by including the emergence of new blight varieties that are adapted to different temperature conditions. Without including this response, our efforts to quantify the likely impacts of climate change on biotic stresses may at best be uncertain, and at worst dangerously inaccurate.

The changing impacts of one of the most important biotic stresses of potato, late blight *Phytophthora infestans*, are considered alongside crop model simulations to give a fuller picture of global potato agriculture and climate change.

### 6.1.1 Research questions

As described in Section 6.1, this chapter uses model simulations to assess the impacts of climate change on global potato agriculture. Three specific research questions are addressed that look at the abiotic and biotic impacts of climate change:

1. How will climate change affect potato yields globally?
2. How will climate change affect late blight globally?
3. Which countries will be associated with the largest changes to yields and late blight risk with climate change?

## 6.2 Methods

### 6.2.1 Methods Overview

The GLAM-potato model is used to simulate potato yields globally in the baseline and the future (see Section 6.2.3.1). This model has been shown to adequately simulate weather-yield relationships in the UK and Colombia at regional (Chapter 3) and national scales (Chapter 4).

Simulations in this chapter firstly test the model's ability to simulate potatoes globally in a baseline (1980-2010) climate. Subsequent simulations are then used to assess the impacts of climate change on yields, simulating yields both in the baseline period and in the future with and without adaptations to climate change (2041-2050). "Adaptation" in the GLAM simulations refers to the adaptation of potato agriculture to climate change by allowing planting dates and varieties to vary in the future.

The same baseline and future periods are simulated using the SimCastMeta model to investigate the impacts of changing climate on risk of late blight attack, with and without adaptation (see Section 6.2.3.2). Blight "adaptation" to climate change refers to the simulation of new blight varieties that better suit different temperature conditions. In all blight future climate simulations, the phenologies of host crop and blight are matched (i.e. the growing seasons for blight and potato are defined using the same planting dates as those selected in future climate GLAM simulations).

The countries associated with the largest changes in yields and blight risk are identified for both the adaptation and non-adaptation simulations. The GLAM dumb-farmer simulations are included as a point of reference to agricultural adaptation simulations, which are seen as more realistic as they avoid the "dumb farmer" bias (Füssel, 2007; Schneider et al., 2000). Assumptions have to be made regarding resource availability in the agricultural adaptation simulations but these are seen as more realistic than assuming constant planting dates and varieties between now and 2050 (Mendelsohn et al., 2000). Similarly, the blight adaptation simulations allow for pathogen response to climate change and are therefore seen as more realistic (Bale et al., 2002), with the non-adaptation simulations providing a point of reference.

### 6.2.2 Input data

#### 6.2.2.1 Climate data

The AgMERRA (Agriculture Modern-Era Restrospective analysis for Research and Applications) data set is used for historical climate conditions, available from 1980 to 2010 (Ruane et al., 2015). See Chapter 3, Section 3.2.1.2 for further description.

ISI-MIP (Inter-Sectoral Impact Model Intercomparison Project) bias-corrected input data are used for future climate data (Hempel et al., 2013). Statistical bias-correction is used on these data, as described in Hempel et al. (2013). This approach bias-corrects the monthly mean and daily variability of the data, preserving trends of absolute temperature change and relative precipitation change.

Five GCMs are used (HadGEM2-ES, GFDL-ESM2, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M). ISI-MIP data are selected for use as they represent a globally-coherent data set that is a reasonable subset of the CMIP5 ensemble, as demonstrated by McSweeney and Jones (2016), and are therefore a climate ensemble suitable for use in climate impacts studies (see Chapter 1, Section 1.3 for details of climate models, bias correction and ensembles). McSweeney and Jones (2016) found that significantly more models would have to be included in an ensemble to offer significant improvement on the five models of the ISI-MIP ensemble. The period 2041-2050 is chosen for future climate simulations as this period is important from a policy perspective (for example, the deadline for the Paris Agreement). The RCP 8.5 scenario is used, representing a severe climate change scenario, although different socio-economic scenarios show relatively little difference until this period (Moss et al., 2010).

ISI-MIP historical data do not represent actual years of climate data but the climatology of the historical periods. As such, the ISI-MIP data were compared to the AgMERRA data in order to see if the central tendencies and variabilities of the data were similar. As can be seen in Figure 6.1, there are no significant differences in these aspects of the data, with the median values of each typically overlapping to a large extent. The largest difference is in

European precipitation, where the median AgMERRA value is lower than all the median ISIMIP values. Ruane et al. (2015) report a slight dry bias in AgMERRA in some areas of the world, however, including Europe. The ISI-MIP data were therefore adjudged to be fit for use in the climate change analysis.

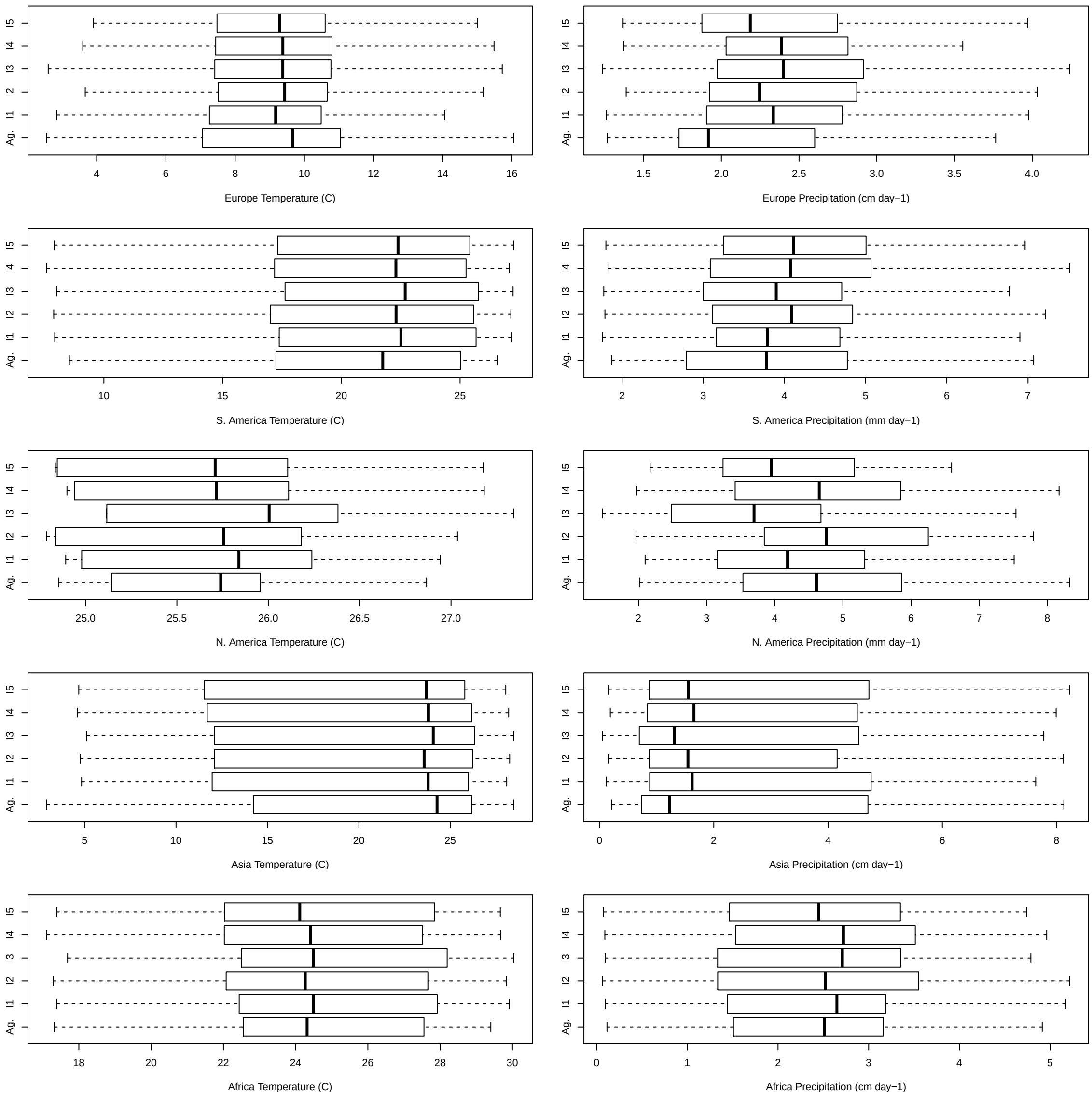



**Figure 6.1:** Comparison of ISI-MIP and AgMERRA daily temperature and precipitation data for the baseline climate (1990-2010). Data plotted are the mean climate variables for each country in each continent across years. "Ag." refers to the AgMERRA data. "I1" to "I5" refer to the 5 models of the ISI-MIP data. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

#### 6.2.2.2 Potato growing area, irrigation and soil data

See Chapter 3, Section 3.2.1.3 for details of soil data information and Chapter 4, Section 4.2.1.2 for growing area, shapefile and irrigation data information.

Soil data are from the the Global Soil Dataset for Earth System Modelling (Shangguan et al., 2014).

Global growing areas and irrigation are shown in Figure 6.2 and are from the MIRCA data set (Monthly Irrigated and Rainfed Crop Areas – Portmann et al., 2010), representing information from the years 1998-2002. Only grid cells using the top 50% of potato growing area are used in this analysis, as described in Chapter 4. Irrigation is taken into account using a majority grid cell approach - this assumes full irrigation in grid cells with over 50% irrigated potato growing area, and rainfed conditions in all other grid cells.

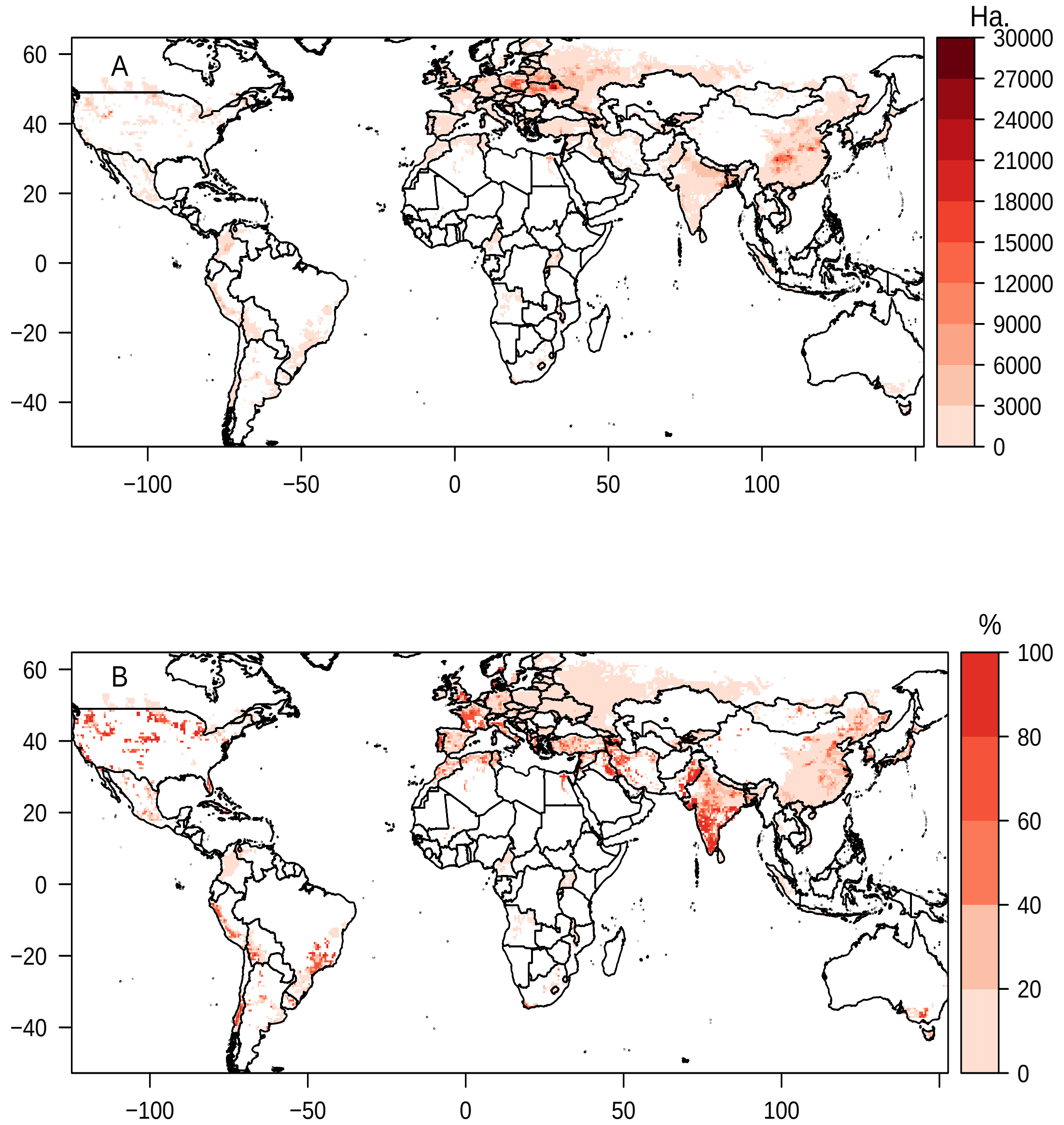



**Figure 6.2:** A. Potato growing area per grid cell (Ha) and B. percentage of irrigation per grid cell for the baseline climate based on MIRCA data (Portmann et al., 2010). Note this figure is a repetition of Figure 1.3.

#### 6.2.2.3 Yield data

FAOSTAT country-level yield data (FAO, 2016) are used to simulate the main growing season for each country in this study. Data examined are from the years 1980 to 2009 to coincide with available weather data (some growing seasons going into a second calendar year). Checks are performed on these time series of data prior to detrending and modelling which are outlined here.

Data were dropped from each time series if consecutive years with identical yields were reported, these being deemed unrealistic. As another check, yield data were manually calculated using area and production data from FAOSTAT. If the manually-calculated yield data were correlated significantly with the observed yield data and if these data had approximately the same mean yield level, time series were deemed acceptable for modelling. Years with yield values more than two standard deviations away from the mean were examined alongside the area and production, in an effort to see if any outliers could be deemed unrealistic and dropped due to FAOSTAT data inconsistencies (none were found).

FAOSTAT define the year associated with the yield data as that when the majority of the harvest took place. The year associated with the yield data in GLAM is the year associated with planting. As such, countries with the bulk of harvest taking place in a different year to planting need to be identified so GLAM associates the correct year with the yield data. These countries (Angola, Argentina, Lesotho, Malawi, Mauritania, Mali, Morocco, Mozambique, Namibia, Papua New Guinea, Rwanda, South Africa, Swaziland, Zimbabwe, Bolivia, Brazil, Cuba, Peru, Venezuela, Australia, Timor-Leste, Bangladesh, India, Pakistan, Fiji, Indonesia, Sri Lanka, UAE and Vietnam) are predominately in the southern hemisphere, with a few exceptions. Information on the main growing seasons (planting and harvest date information) was taken from the World Potato Atlas provided by the International Potato Centre, Colombia (CIP, 2009) and using the FAO crop calendar (FAO, 2016). When this information provided no clear main growing season, the median harvest dates from Sacks et al. (2010) where used to determine the main growing season for the country.

The detrending process detailed below aims to remove trends in the data not due to weather. Before this process, each time series was examined to identify any sudden large changes in mean yield levels across the time series that would not be well explained by the simple linear or quadratic relationships used for detrending. These were deemed to be such “multi-state” time series if upon visual inspection they exhibited large changes in mean yields that were sustained for three or more years. Such time series were excluded from the analysis. Countries excluded for exhibiting such multi-state time series are in Table B1 in Appendix B. An exception was made for China – which shows some multi-state yield data – as it produces the most potatoes globally.

The resulting time series were then detrended to remove any trends in the data. This is done to remove the influence of factors not simulated by the model (technology and management). Linear and quadratic models were chosen to detrend the yield data as more complex local regression fitting was deemed undesirable due to the frequent short time series available from FAOSTAT. Linear and quadratic models were tested on each time series. Robust regression was used to fit models to the data using the R package “robust” (Wang et al., 2014), as this is superior to ordinary least squares regression when data contain outliers or otherwise break the assumptions associated with linear models (Finger, 2010).

In order to avoid taking away trends in the time series due to weather (rather than factors not simulated by the model), and to not weaken observed weather-yield relationships, detrended yields were not retained if they showed lower mean absolute correlations between weather variables (temperature, rainfall and solar radiation) and observed yields. In this situation, observed yields were used instead. This approach assumes that any trends in yields in these countries are due to weather rather than factors not accounted for in the model. This approach was preferred due to the difficulties associated with accounting for the relative contribution of different factors to observed trends across many different countries - using this method, the model should be able to capture the maximum possible weather-yield relationship seen in observed yields. The majority of countries were not detrended as a result of weaker relationships between weather variables and detrended yields. This was mostly due to temperature - significant positive correlations of temperature with observed yields often became insignificant after detrending. See Table B1 in Appendix B for the countries affected. 27 countries were detrended, 21 quadratically, 6 linearly, out of a total of 102 simulated.

Robust stepwise model selection using the "step.lmRob" function in the robust R package was used to determine whether a quadratic or linear model should be fitted to the data for detrending. This is based on assessing model error changes that result from deleting variables from the maximal model using backward elimination. Backward elimination involves starting with all candidate variables, testing the deletion of each variable using a chosen model fit criterion, deleting the variable (if any) whose loss gives the most statistically insignificant deterioration of the model fit, and repeating this process until no further variables can be deleted without a statistically significant loss of fit.

Following detrending, checks were conducted for values beyond a potential potato yield value of 20000 kg/ha (a figure larger than agricultural yields even in the highest potato yielding countries - FAO, 2016) and for values that had been detrended to below 0; none were present. Lastly, any countries were removed from the analysis if they had fewer than 6 years of data following the other checks. The majority of countries had over 16 years of data. Full details of the yield data selection and detrending process for each country can be seen in Table B1 in Appendix B.

### 6.2.3 Model set-up

#### 6.2.3.1 GLAM model

GLAM-potato (described in Chapter 2) is used to simulate the abiotic impacts of climate change. Model runs for the current climate take into account irrigation levels and current potato growing areas. Future runs also account for $CO_2$ fertilisation and allow planting dates and varieties to change. See Chapter 4 for a description of the global GLAM parameter configuration.

GLAM is used to select the highest yielding planting date and variety combination in the baseline climate, using the first half of the baseline time series. The Yield Gap Parameter $C_{\mathrm{YG}}$ is then calibrated and run on the first half of the time series in the baseline climate before the model is evaluated using the second half of the time series. Planting date and variety selection as well as model calibration use firstly the evaluation climate data (AgMERRA) before the baseline data in the climate change analysis are used (ISI-MIP).

Future climate runs using GLAM look at the difference between baseline and future yields between the baseline period (1980-2010) and a future climate period (2041-2050). The impacts of elevated $CO_2$ are taken into account by altering GLAM parameters concerned with biomass production (Radiation Use Efficiency RUE and Transpiration Efficiency TE), as well as limiting the physiologically-limited potential transpiration of the crop, ensuring that reductions in transpiration are driven by physiology (stomatal closure) rather than energy limitations (Challinor and Wheeler, 2008; Challinor et al., 2005b).

Previous potato modelling studies parameterise the impacts of $CO_2$ increases in future climate using experimental data (Free Air $CO_2$ and chamber experiments that assess the impacts of controlled $CO_2$ increases in on biomass and yields), with increases to biomass and yields between 20-28.5% reported (Wolf, 2002; Haverkort et al., 2013). A mid-point of this range (24.25%) is used for the increase to both TE and RUE for this future climate analysis and the decrease in the physiologically-limited potential transpiration is set to 5% (Wolf, 2002). These changes to TE and RUE are slightly larger than the increases used in a previous global climate change analysis using GLAM (Osborne et al., 2013), which used increases in TE and RUE of 21 and 18% for soybean and spring wheat respectively. This larger increase is consistent with the larger increases in yield due to $CO_2$ fertilisation expected for potato compared to other C3 crops. An additional sensitivity analysis is conducted that explores the sensitivity of projected yield changes to the range of parameters cited here – see Section 6.21 for details and results (methods outlined in the results section as the countries chosen for this analysis depend upon country-level model skill which is featured in the results, as well as having large levels of potato production).

Agricultural adaptations are tested for future climate simulations relative to the baseline climate. These consist of allowing the start of the sowing window and the variety to vary. The methods described in Chapter 4 are used to select planting date and variety combinations - i.e. the highest yielding combination that does not have unrealistically long durations, emergency planting or unrealistic maximum LAI.

Non-adapted future climate simulations (i.e. a dumb farmer approach) are also included as a point of reference to adaptation simulations, showing the benefits of allowing planting dates and varieties to change in the future. Non-adapted future simulations use the same planting dates and varieties as those selected in the baseline climate. Those grid cells with future planting dates and varieties that have been ruled out as unrealistic are not simulated for the dumb farmer simulations. If these grid cells are included, unrealistic planting date and variety combinations are simulated in the future. A direct comparison between the adapted and non-adapted simulations is then not possible.

Global mean yield changes are calculated for each climate model using the simulated national area-weighted yield time series averaged for each grid cell. These are then summed for a global mean yield value for both baseline and future climates.

#### 6.2.3.2 SimCastMeta model

Used alongside GLAM-potato, the SimCastMeta model provides an assessment of likely future changes of biotic stresses. It does so by assessing changes to risk of late blight attack. This model is fully described in Sparks et al. (2011).

The SimCastMeta model is used to quantify how outbreaks of the most significant global disease of potato, late blight *Phytophthora infestans*, will change in future. These simulations are conducted over the same grid cells as GLAM-potato simulations. SimCastMeta uses monthly mean temperature and relative humidity data to assess the risk of blight attack. It is a rescaled version of the SimCast model (Fry et al., 1983), designed to work at coarser spatial and temporal resolutions for ease of use at larger scales. SimCast calculates "blight units" based on the temperature of consecutive hours in a day where relative humidity is above 90% (see Figure 6.3). SimCast has been previously shown to have significant skill in predicting fungicide applications for blight outbreaks across many countries (Grünwald et al., 2000; Hijmans et al., 2000). It is also a relatively simple model, suitable for large scale analyses, with the metamodel calibrated using monthly climate data showing no significant loss of skill compared to the original model calibrated using daily time step data (Sparks et al., 2011; Hijmans et al., 2000).

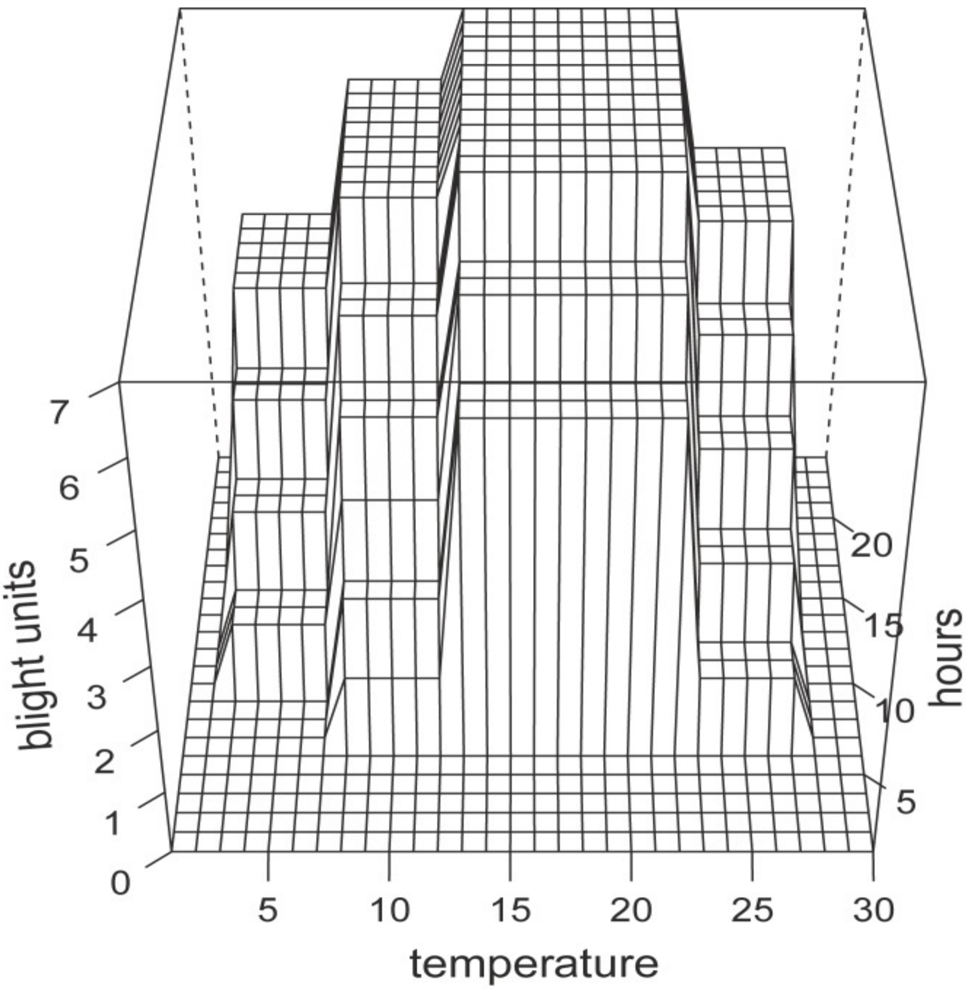



**Figure 6.3:** Graphical representation of late blight unit relationship with temperature and hours when relative humidity is greater than 90%. Taken from Lehsten et al. (2017).

SimCastMeta uses monthly data for both "susceptible" and "resistant" potato cultivars (the cultivars differing in terms of blight unit accumulation for given weather conditions). The "susceptible" cultivar is used for this study, as most widely-cultivated potato varieties are susceptible to late blight (Forbes, 2012) and it is assumed that they will continue to be so in the future (Goodwin et al., 1995) – there have been several incidences of blight evolving to overcome resistant cultivars in the past (Forbes, 2012).

The blight units calculated by SimCastMeta represent a relative measure of risk of blight outbreak. In SimCastMeta, blight unit accumulation decreasing by one is equivalent to one pesticide application fewer per month for a susceptible cultivar. A value of one therefore indicates a relatively small risk of significant outbreak, with significant protective measures (e.g. pesticide application) unlikely to be needed to maintain yields. Values as high as four indicate substantial losses from blight are likely in the absence of protective measures.

The model is first calibrated as described in Sparks et al. (2011) before being used for simulations using baseline and future climate data as described in Section 6.2.2.1. The blight units calculated are the mean daily blight unit accumulation for the optimal six month potato growing seasons in baseline and future climates, which are defined using the planting dates used in the GLAM analysis for those periods. Six month growing seasons are chosen as these cover the longest likely potato growing seasons for any variety.

In order to account for genetic adaptation to climate change, different blight varieties are simulated in the future. In previous work using SimCastMeta, resistant and susceptible potato cultivars were modelled, with the same blight variety used in all cases (Sparks et al., 2011, 2014). Blight varieties are simulated in this analysis, varying in their response of blight risk to temperature. Blight unit accumulation values from the base model set-up are assumed to represent a mid-range blight variety, as the model was developed to represent blight across a wide geographic range (Sparks et al., 2011), and therefore represents the variety of blight found to be most common in past studies (Goodwin et al., 1994). Five models in total are constructed, using modified temperature data to reflect different responses of blight to temperature. Models are constructed with temperature data reduced by 2.5 and 5°C and increased by 2.5 and 5°C, as well as with unmodified temperature data, using the same blight units for each model. These temperature changes were chosen to reflect both projected average global temperature increases by 2050 using the RCP 8.5 scenario (c. 2.5°C) as well as larger increases in temperature (5°C) that will likely be found in some areas with this severe climate change scenario (Schurer et al., 2017). Varieties adapted to cooler conditions are included to see if blight can become better adapted to cooler areas. The varieties simulated assume that blight has the ability to adapt to temperature changes of this magnitude. This assumption is based on the high evolutionary potential of pathogens, differing observed blight responses to temperature (see Chapter 1, Section 1.2.2) as well as predicted temperature changes.

The most virulent blight variety for each grid cell is chosen for the future climate, representing the evolution of new varieties in the future climate. As such, blight varieties are allowed to change through time (i.e. matching growing seasons of the host crop and pest) and space (allowing different blight varieties to be present across the globe), reflecting adaptation to the warming associated with climate change. This approach assumes that all blight varieties have access to all regions, which is an assumption in keeping with future predictions of pests and diseases increasingly saturating the host crops on which they are found (Bebber et al., 2014a). Blight-potato interactions are assumed to stay constant with climate change, represented through the matching of phenology (i.e. keeping blight and potato growing seasons linked) and growing areas, which remain constant in the baseline and future periods.

## 6.3 Results

Results sections are presented below for global GLAM evaluation (Section 6.3.1.1), the impacts of climate change on potatoes (Section 6.3.1.2), the impacts of climate change on late blight (Section 6.3.2) and the combined impacts of abiotic and blight changes on potatoes (Section 6.3.3).

Variables used in maps in the results sections of this chapter represent averages over the years of simulation, with data taken from across the simulated growing seasons (i.e. simulated planting to maturity). Weather variables are the mean daily values over the growing season, unless otherwise stated.

### 6.3.1 Global GLAM results

#### 6.3.1.1 Global model evaluation

Correlations between observed and simulated yields for the baseline period are typically positive but low (Figure 6.4). The bulk of significant yield correlations are in Europe, although the majority of correlations are insignificant. The countries with positive correlations with p-values $< 0.1$ are Albania, Austria, Bangladesh, Croatia, Denmark, Egypt, France, Germany, Latvia, Lithuania, Netherlands, Poland, Russia, Slovenia, Switzerland, Thailand and Uganda. The $C_{\mathrm{YG}}$ is most often calibrated to be near 1 in the higher yielding countries of the northern hemisphere (Figure 6.5), with simulated yields often lower than those observed (Figure 6.6). In some countries (such as China) a $C_{\mathrm{YG}}$ of lower than 1 results in observed yields being higher than simulated yields. This is due to such time series not being detrended, with higher observed yields often in the second half of the times series and the model calibrated on the first half of the time series. Globally, there is a mean country-level RRMSE of 32%. The mean observed yield standard deviation across countries was 0.39 T/Ha. The simulated mean standard deviation was slightly higher at 0.53 T/Ha.

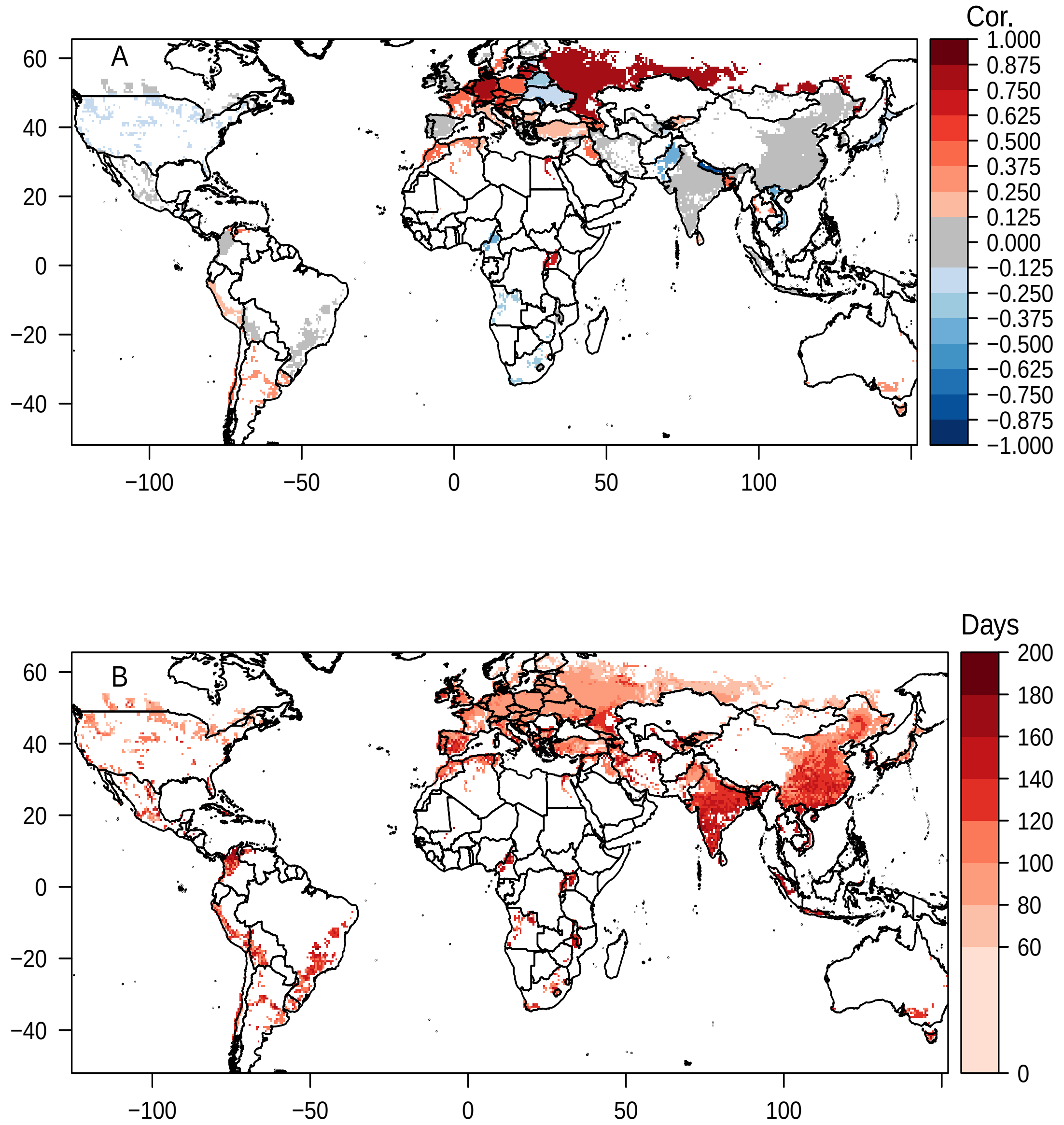



**Figure 6.4:** A. Correlation coefficient between simulated and observed national yields. B. Mean simulated duration of growing season.

Simulated growing season durations are shown in Figure 6.4.B. These are around 120 days in the northern hemisphere and higher in subtropical and tropical regions, in line with observed duration lengths (see Chapter 3, Sections 3.1.1 and 3.1.2 for examples). There is a significant but weak negative correlation (-0.25, p-value $< 0.05$) between duration and model skill. This is due to the higher durations and lower skill of tropical regions (expanded upon later). Harvest indices typically peak near 0.8, which is again in line with observed values (Figure 6.7).

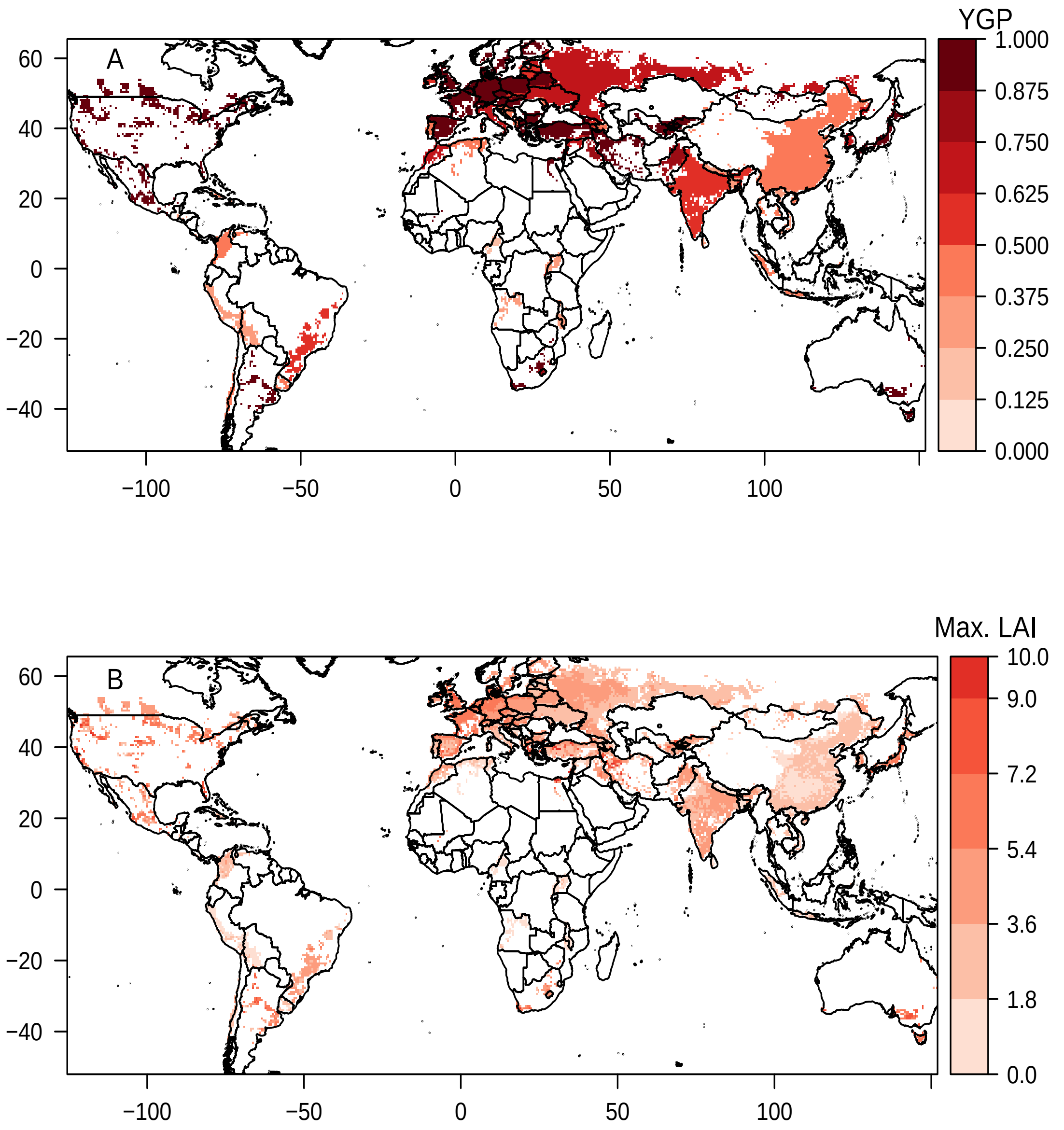



**Figure 6.5:** A. National scale Yield Gap Parameter $C_{\mathrm{YG}}$. B. Simulated mean maximum LAI over growing season (maximum LAI before senescence takes place).

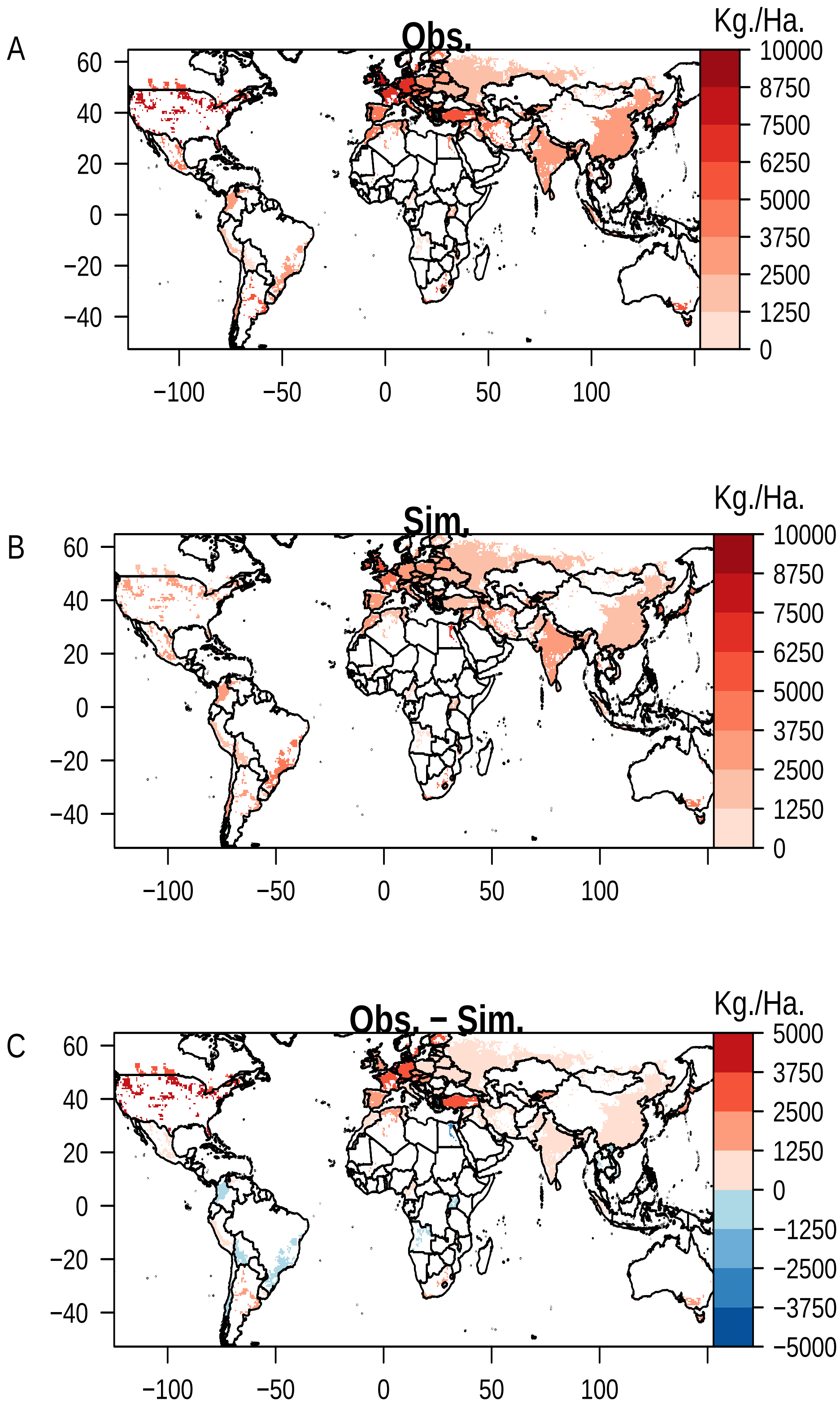



**Figure 6.6:** A. Observed mean national yields across years. B. Simulated mean national yields across years. C. Difference between observed and simulated yields.

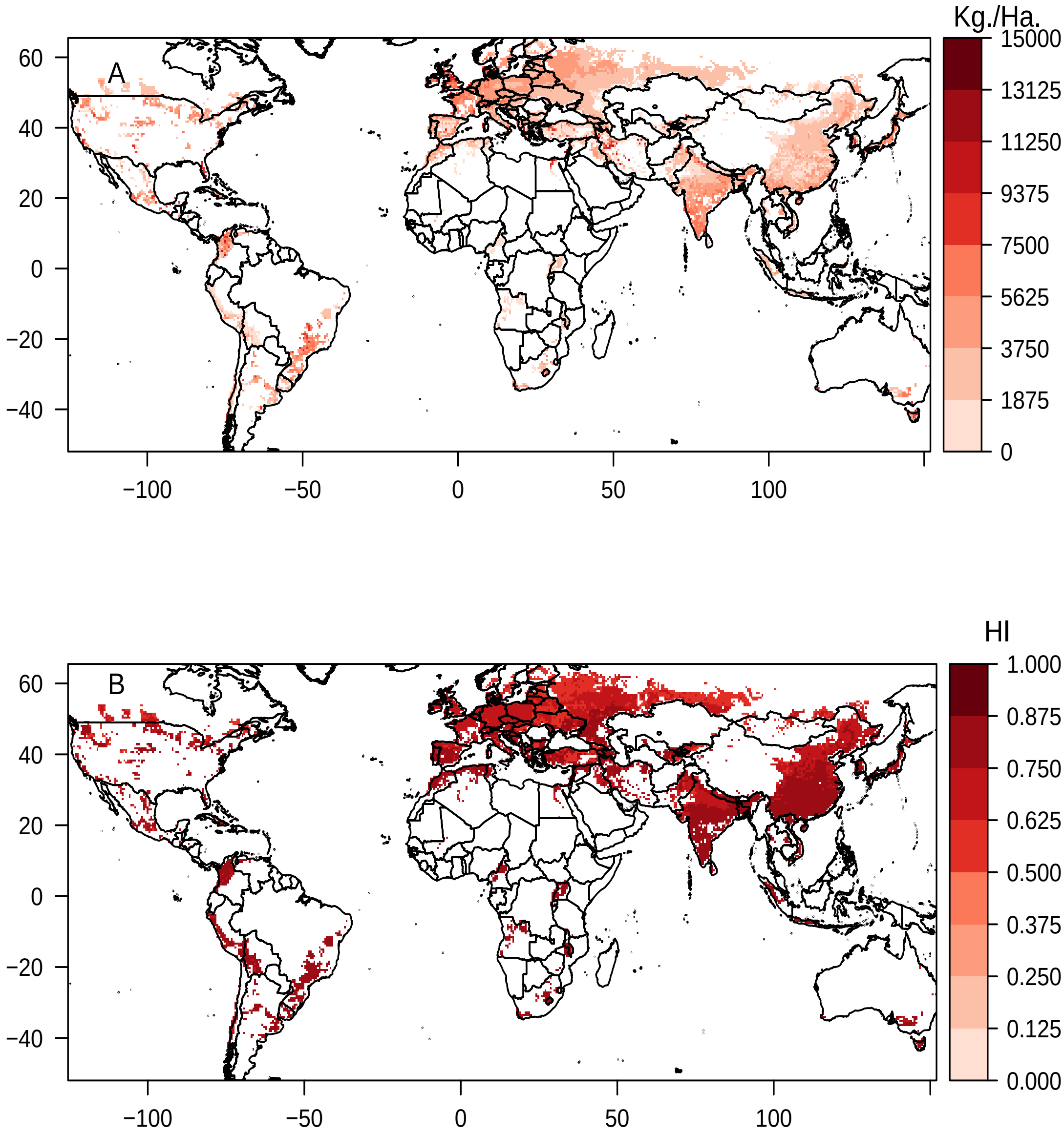



**Figure 6.7:** A. Simulated mean biomass at the end of the growing season. B. Mean Harvest Index at the end of the growing season.

The start of the sowing window and varieties chosen for the baseline evaluation are shown in Figure 6.8. Sowing windows typically begin in the first half of the year in Europe and northern America. In subtropical and tropical regions planting tends towards the latter half of the year, although there is variation, as expected given the varied potato growing seasons in these regions. These are broadly similar to the planting dates of the

Sacks et al. (2010) data set, as well as those used by Raymundo et al. (2017b).

Observed planting dates from experimental sites across 17 countries in Raymundo et al. (2017a) are significantly correlated with mean sowing dates in GLAM (correlation of 0.75, p-value $< 0.001$). The mean planting dates for each country for Sacks and in GLAM are also correlated (0.40, p-value $< 0.001$). The countries that showed the largest differences in planting dates between GLAM and Sacks sowing dates did not necessarily show poor model skill; some countries perform well despite large differences in average planting date. For example, Algeria and Bangladesh show correlations between observed and simulated yields above 0.42, despite having mean planting dates over 150 days different to Sacks. It is important to note that good model skill does not necessarily mean that realistic growing seasons are being simulated, however.

Some countries typically have potato planting towards the end of the year and harvesting in the next calendar year in the important potato growing areas. Of these, 10 show GLAM planting dates in the first half of the year, contrary to expectations (Australia, Bangladesh, Cuba, India, Indonesia, Mali, Rwanda, Sri Lanka, Venezuela and Vietnam). 14 countries have GLAM planting dates in the second half of the year as expected (Angola, Argentina, Bolivia, Brazil, Lesotho, Malawi, Mauritania, Morocco, Mozambique, Pakistan, Peru, South Africa, Swaziland and Zimbabwe). Model skill is mixed for both of these groups; uncertainty over planting dates is likely having a negative impact on model skill in some of these countries.

The level of irrigation has no overall effect on model skill, with the mean irrigation percentage in each country not being correlated with model skill (i.e. correlation coefficient between observed and simulated yields). The length of yield time series only had a weak, insignificant negative correlation (-0.17, p-value 0.11) with model skill, so there is little no evidence for shorter time series leading to poorer model skill.

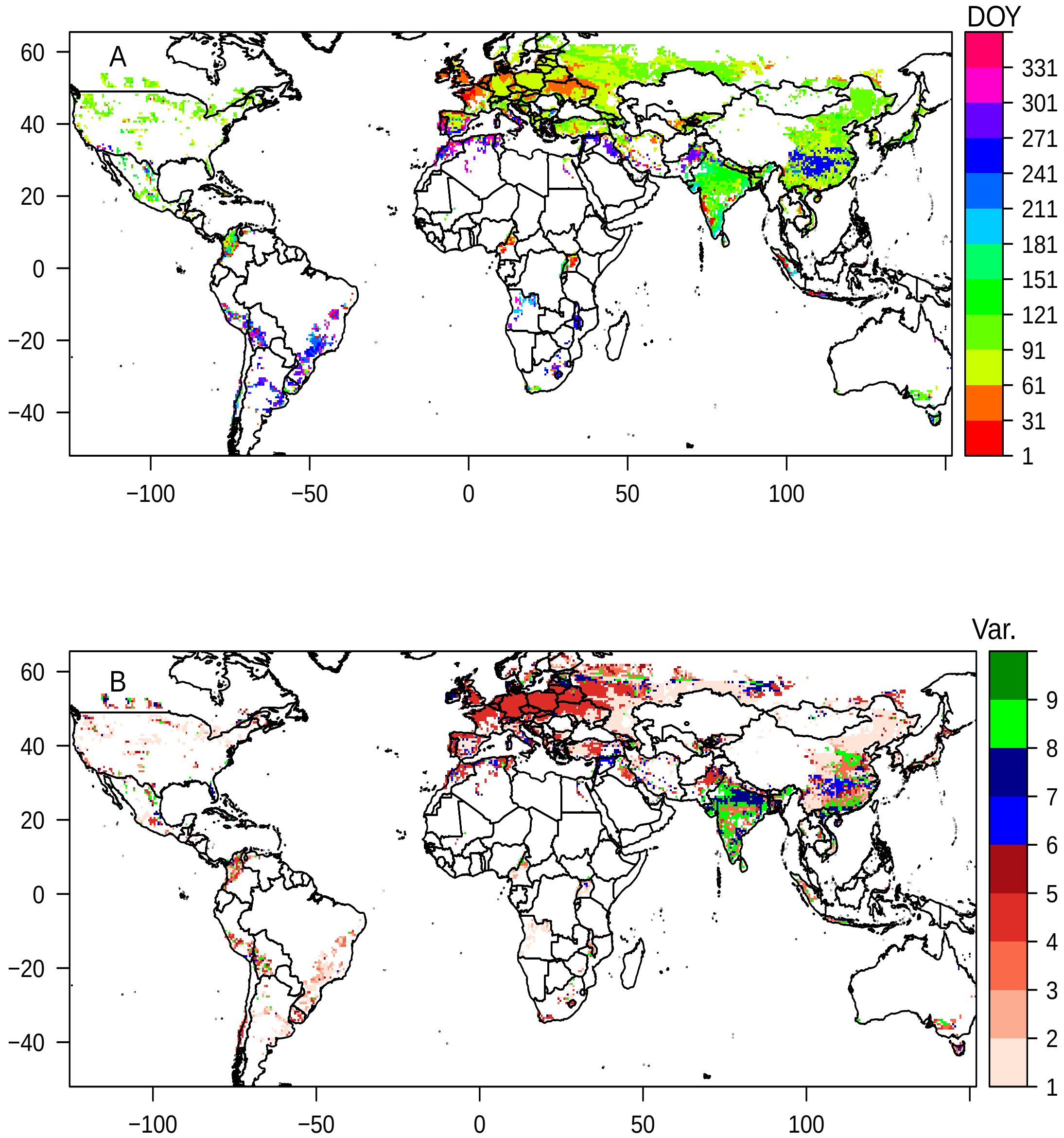



**Figure 6.8:** A. Start of selected planting window and B. Variety chosen for each grid cell in the baseline climate. These are selected using the global parameter method described in Chapter 4.

Low model skill is associated with grid cells that fail to simulate observed weather-yield relationships or where these relationships are prohibitively low (Figures 6.10 to 6.12). How well the model simulates the relationship between observed yields and temperature is a good indication of model performance. In most of Europe, there is a negative correlation between observed yields and temperature and this is well simulated. The areas that are not well simulated in Europe are those that have weak relationships between weather variables and yields (such as the UK) or those that poorly simulate these relationships. This is most often a poor representation of negative correlations between rainfall and observed yields in parts of eastern Europe, which is likely due to there not being a flooding parameterisation in GLAM.

Correlations between observed yields and solar radiation are weak in many parts of the world (Figure 6.12.A). Negative relationships are seen where model skill is higher in Europe, however. In these regions, rainfall has a positive correlation with observed yields, acting as an important limiting factor to potato yields. Cloudy conditions lead to more rainfall and higher yields, but also less solar radiation, resulting in this negative correlation.

In the important potato growing countries of India, China and the USA, weather-yield relationships are not well simulated and model skill is poor. Relationships between observed yields and rainfall are not usually as strong as those with temperature, in part due to the irrigation of potatoes in many important production areas. Results in these countries are examined in turn to point towards possible model limitations and improvements.

In India, planting is most often simulated to be in June and July in the most important areas for potato across the Indo-Gangetic plain. This is earlier than typically reported planting dates for the region, where potato is a winter crop, sown from October to November (CIP, 2009). The varieties chosen for this region are those with hotter optimal temperatures for the latter two developmental stages – these varieties typically result in shorter durations for hotter countries for the tuber bulking stages. The correlations with rainfall and observed yields show a very weak relationship, which is in line with the high levels of irrigation used for potatoes in the Indo-Gangetic plain. The percentage of irrigation in this region is lower than the average for the country, however, with a majority of grid cells using rainfed simulations. The simulated yields and rainfall show a positive correlation here, indicating a water-limitation on simulated yields that is not present in observations (Figure 6.11). It is likely therefore that irrigation levels in this data set and the majority grid cell approach are not sufficient to prevent significant water limitation on yields. There is heat stress simulated in the region during the summer months, with the harvest index reduced by around 50% as a result of high temperatures during the tuber bulking stage (Figure 6.9). The soil water stress factor is also striking in this region though – the water limitation is imposing a bigger limitation on yields than heat stress. This results in planting dates in the first half of the year when more rainfall is present, although these planting dates are not in line with observations in the Indo-Gangetic plain, leading to poor model skill.

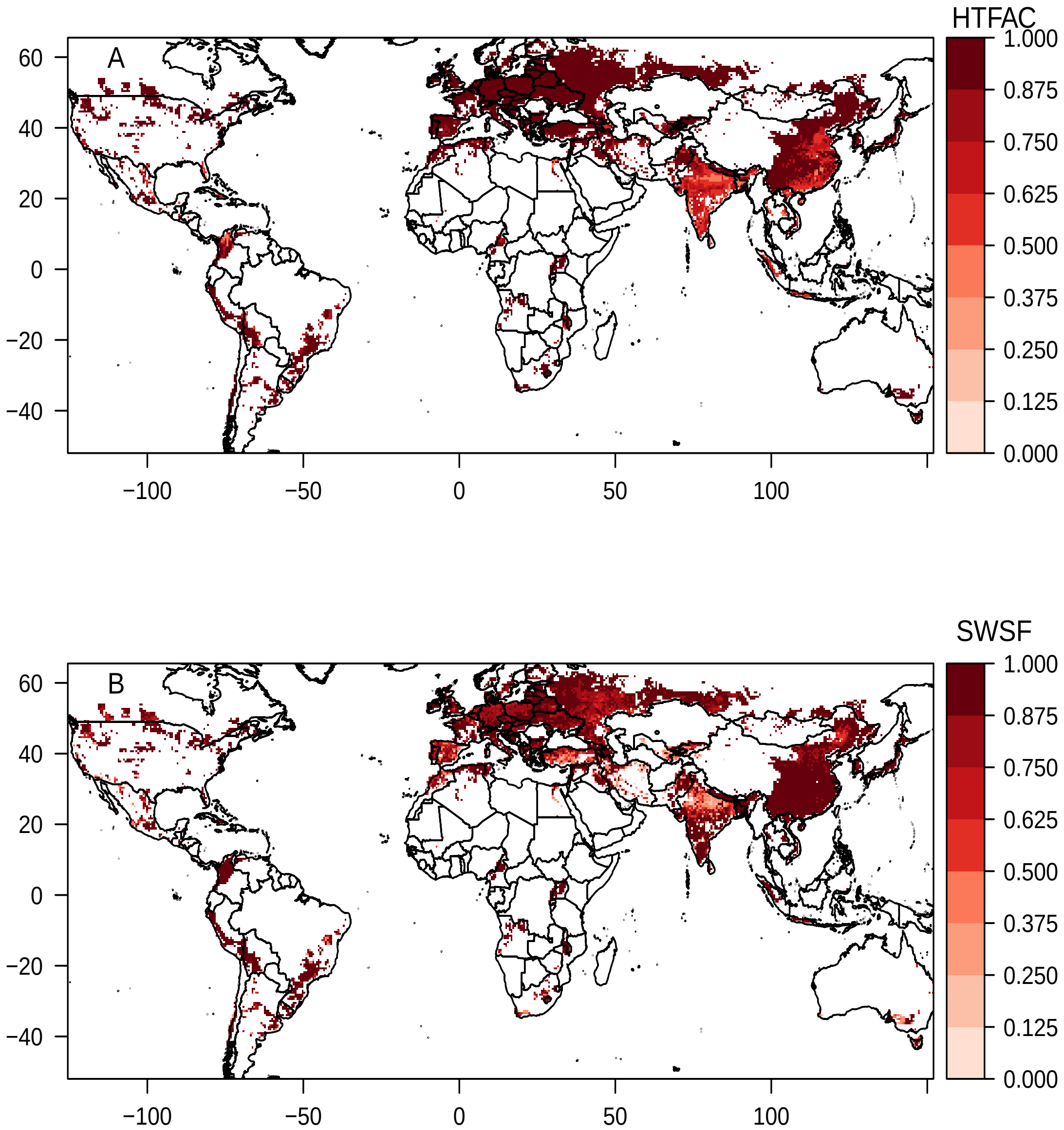



**Figure 6.9:** A. Mean Heat Stress Factor (HTFAC, factor harvest index reduced by). B. Mean soil water stress factor.

In China, two agri-ecological zones dominate the potato landscape: the northern region and the south western region (CIP, 2009). Potato cultivation in these regions is varied, with planting dates depending on topography, variety and climate. Potato planting takes place in both spring and winter in all but the higher latitudes. GLAM simulations show planting windows often selected to be in the second half of the year in most important growing areas. The varieties being selected and cool conditions lead to long tuber bulking periods in the key growing areas. Spring planting dates are also important in most growing areas, however. This vast country highlights problems associating one national yield time series with highly contrasting growing areas. Potato growth is theoretically possible in many important areas all year round. The correct selection of planting dates and varieties for these regions can therefore depend on having detailed local yield and management information, for example regarding when other crops are grown as well as potato. Another factor in poor skill may be the observed yield time series itself, which has a sharp increase in mean yield levels in the year 1992.

Planting dates in the USA are mostly realistic, with the starts of the sowing window in the first half of the year. In some areas the varieties selected are those with lower optimal cardinal temperatures, resulting in warming leading to temperatures further away from the optimal developmental temperature, longer durations and higher yields. This results in tuber bulking stages being longer in particular. The relationship between observed yields and temperature is negative in this region however, meaning that warming should lead to yield decreases. Relationships with rainfall are usually weak due to high levels of irrigation, however in the areas with poorly represented temperature relationships there is a stronger positive relationship between rainfall and observed yields. This relationship is also not well simulated by the model. Given the high levels of irrigation, the majority grid cell approach is often resulting in irrigated model simulations being used in these grid cells. As a result, varieties are being selected that maximise yields in the absence of any water limitations. In reality, it is likely that although irrigation is widespread, full irrigation is not realistic. When choosing planting dates and varieties based on rainfed model runs only, some of these grid cells show varieties that have higher cardinal temperatures, meaning that they show a more realistic temperature-simulated yield relationship.

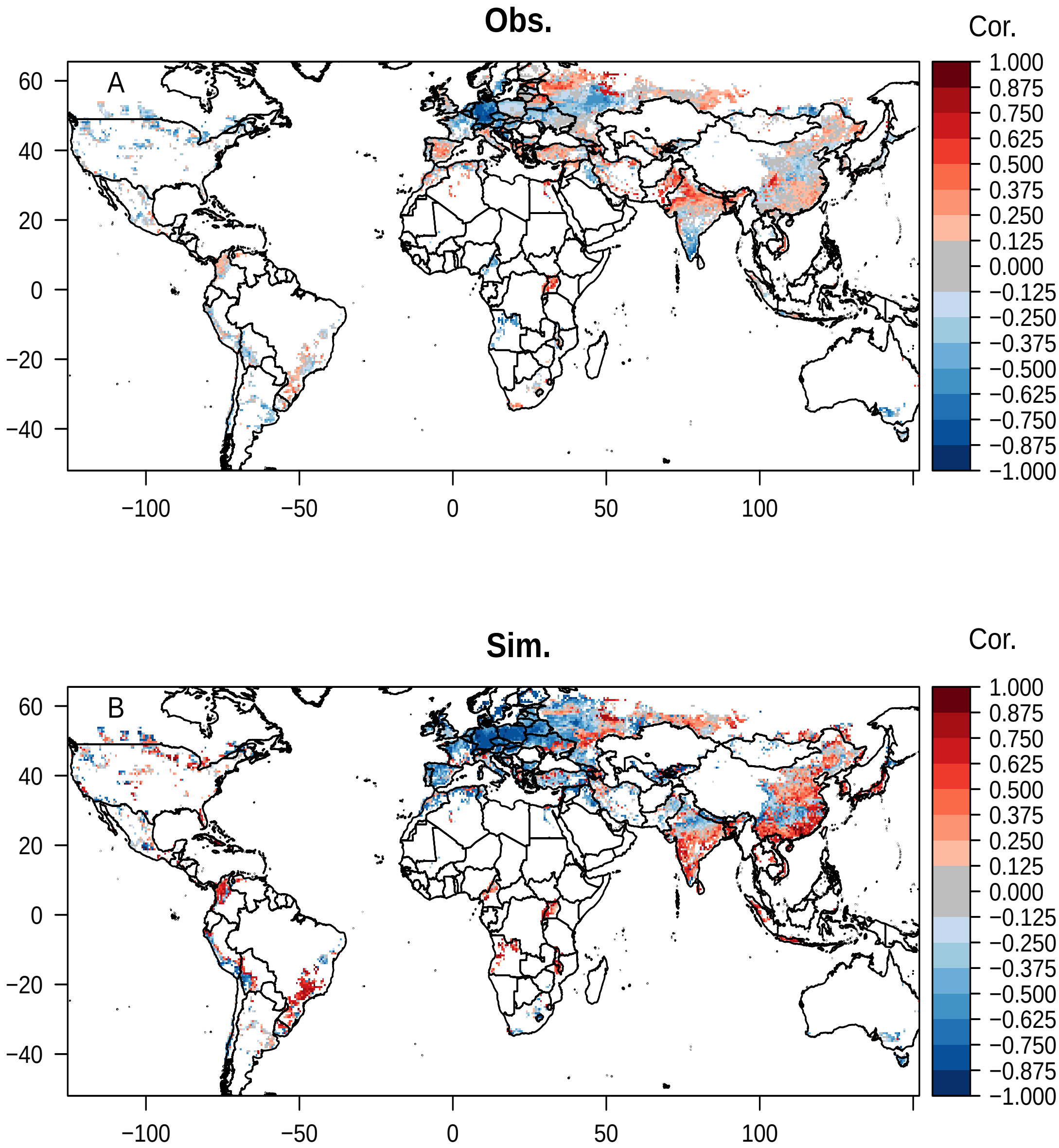



**Figure 6.10:** A. Correlation coefficient between observed national yields and temperature. B. Correlation coefficient between simulated national yields and temperature.

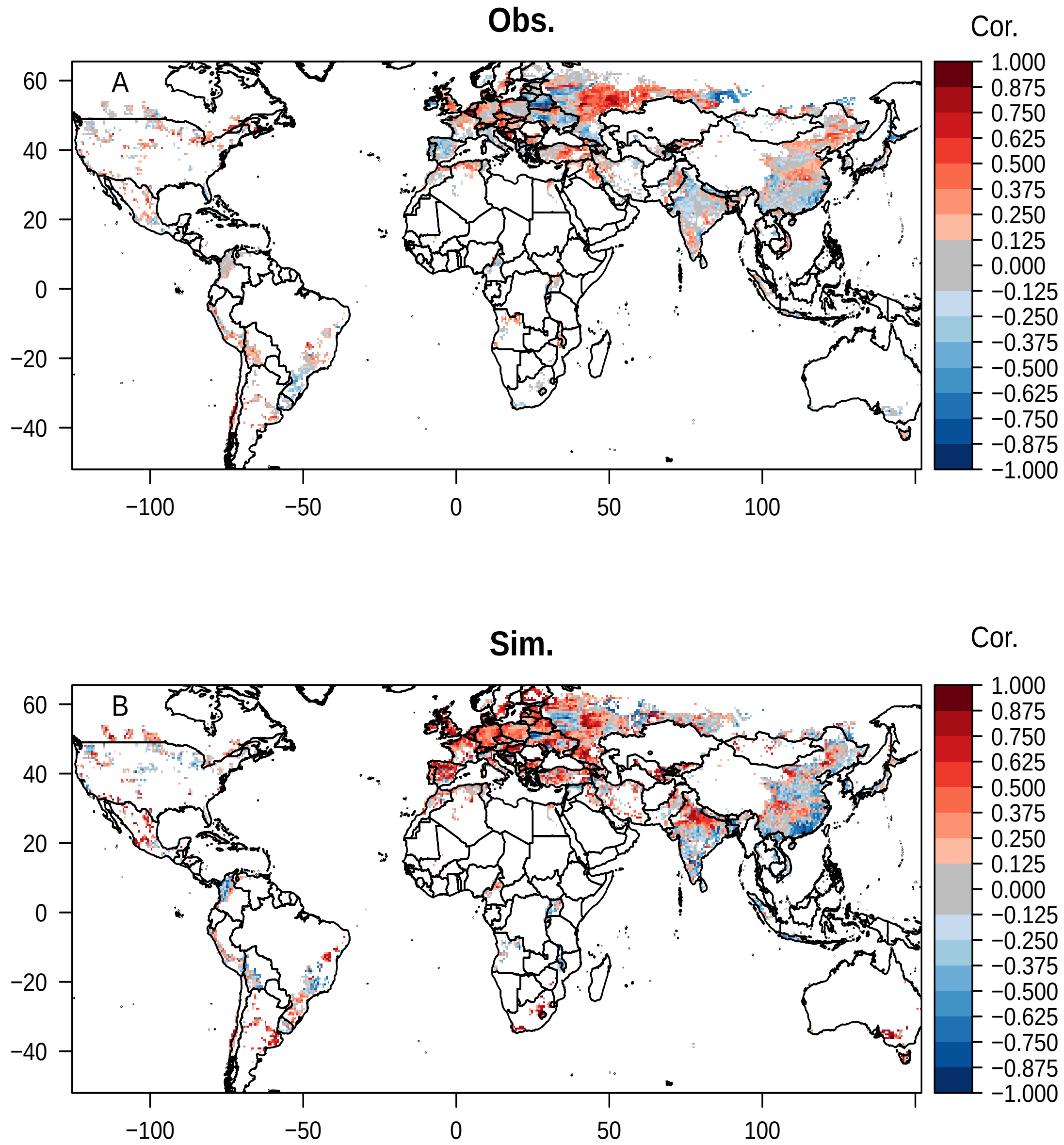



**Figure 6.11:** A. Correlation coefficient between observed national yields and rainfall. B. Correlation coefficient between simulated national yields and rainfall.

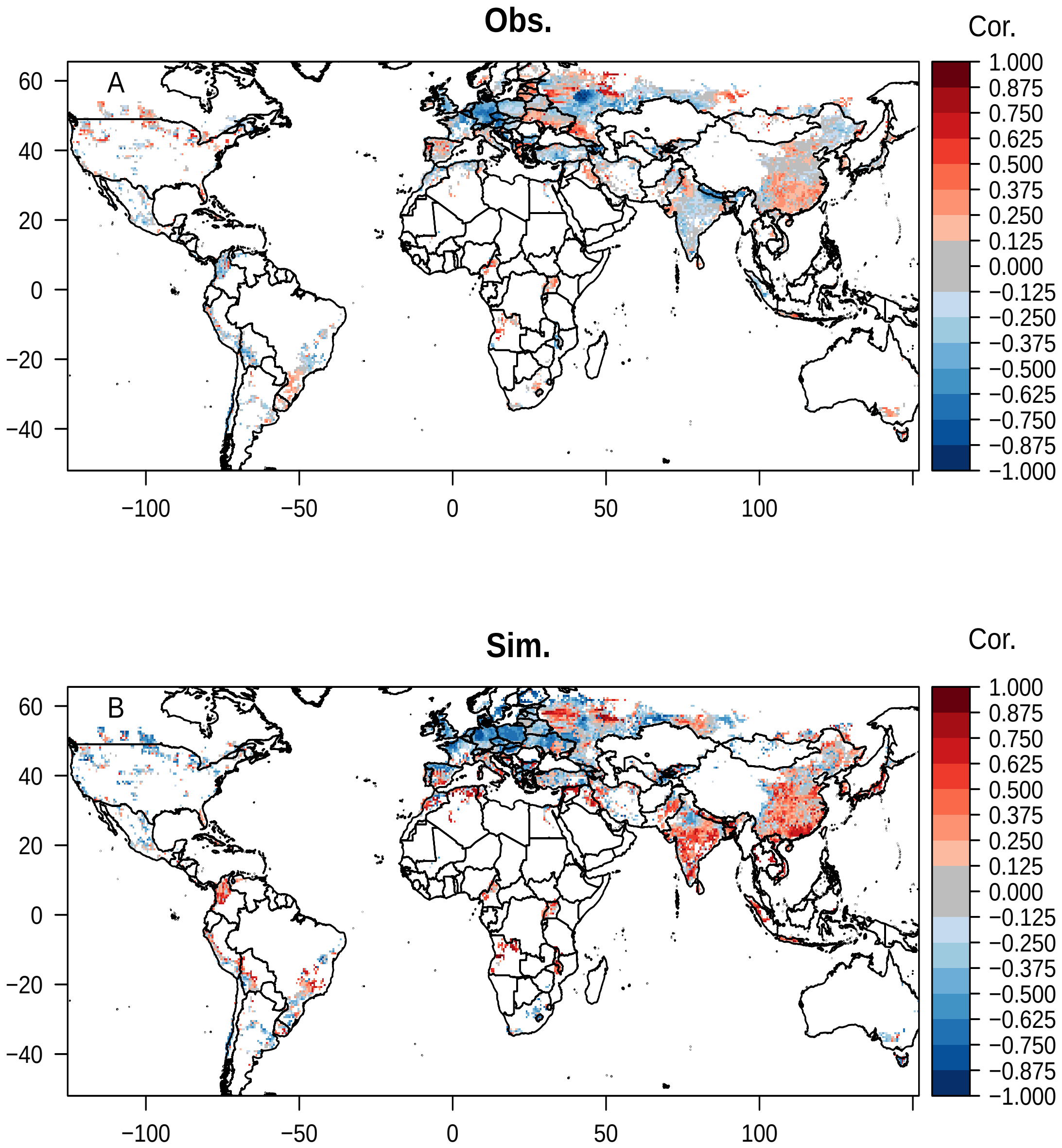



**Figure 6.12:** A. Correlation coefficient between observed national yields and solar radiation. B. Correlation coefficient between simulated national yields and solar radiation.

#### 6.3.1.2 Global future yield changes

Global average yield changes show predicted yield changes from -6 to 16% without adaptation and increases from 33 to 47% with adaptation to climate change (see Appendix B for yield changes associated with each climate model). This large difference reflects the potential that adaptation of changing planting dates and varieties has for yield increases in the future.

Figures in this section show fewer grid cells simulated in the non-adaptation simulations - this is the result of grid cells not being included in non-adaptation future climate simulations if planting date and variety combinations become unrealistic in the future climate. The number of grid cells dropped is significant, with the number remaining for these simulations 5906 for model 1, 5719 for model 2, 5255 for model 3, 5845 for model 4 and 5709 for model 5 out of a total of approximately 11000 grid cells simulated for each model in the baseline climate (representing the top 50% of potato growing area grid cells). The grid cells used for the non-adaptation simulations account for approximately 56% of total potato growing area, as opposed to 96% of growing area for the adaptation simulations.

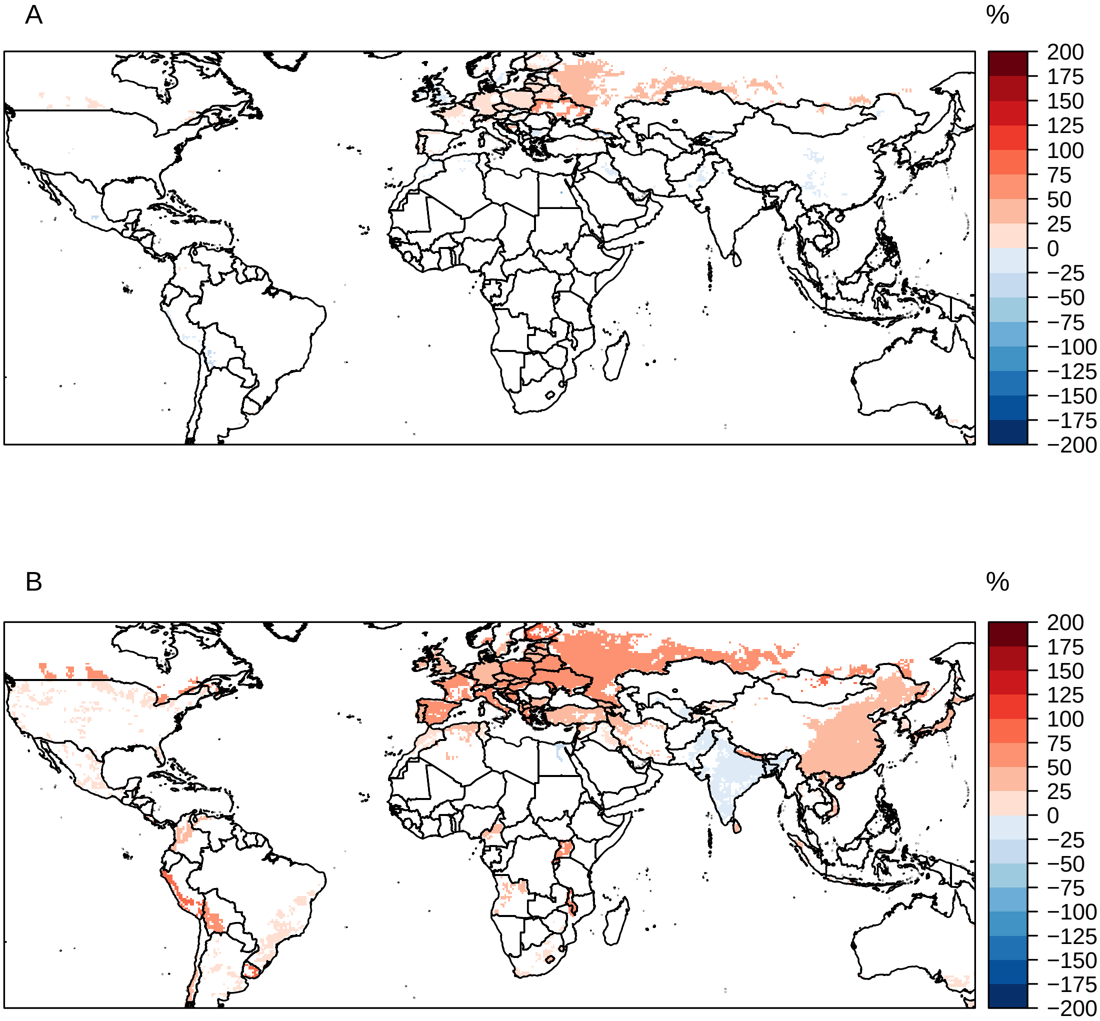



**Figure 6.13:** Yield percentage change from baseline climate to 2041-2050. Values shown are mean values across climate models. A = non-adaptation simulations. B = adaptation to future climate.

Yield changes are most often positive in the northern hemisphere (Figure 6.13) and especially so in the adaptation simulations. Figures 6.14 and 6.15 show positive and negative yield changes respectively by country for both the non-adaptation and adaptation simulations. Only 5 countries show yield decreases when adaptation to climate change is considered – Egypt, Cuba, India, Bangladesh and Pakistan. Many more countries show yield decreases when not allowing planting dates and varieties to vary, however. Yield decreases usually a result from potato growing season durations decreasing in a warming climate, with soil water and heat stress also increasing in some areas.

Climate projections show that temperatures over the non-adaptation growing season will increase in Europe by approximately 2°C by 2045. Rainfall is also projected to decrease by approximately 50 mm in many growing areas in Europe, although it increases in parts of Eastern Europe. Consequently, yields fall as a result of decreased durations and precipitation in European non-adaptation simulations in most cases.

Adaptation simulations alter growing seasons in future climate - GCM projections then show similar warming in Central and Eastern Europe but a mild cooling of 1-2°C in parts of Western and Southern Europe due to planting dates shifting to later in the year. Rainfall in general increases in the adaptation simulations – in some cases in Europe by over 100 mm. Durations usually increase slightly thanks to shifting planting dates and varieties to adapt to the moderate temperature changes.

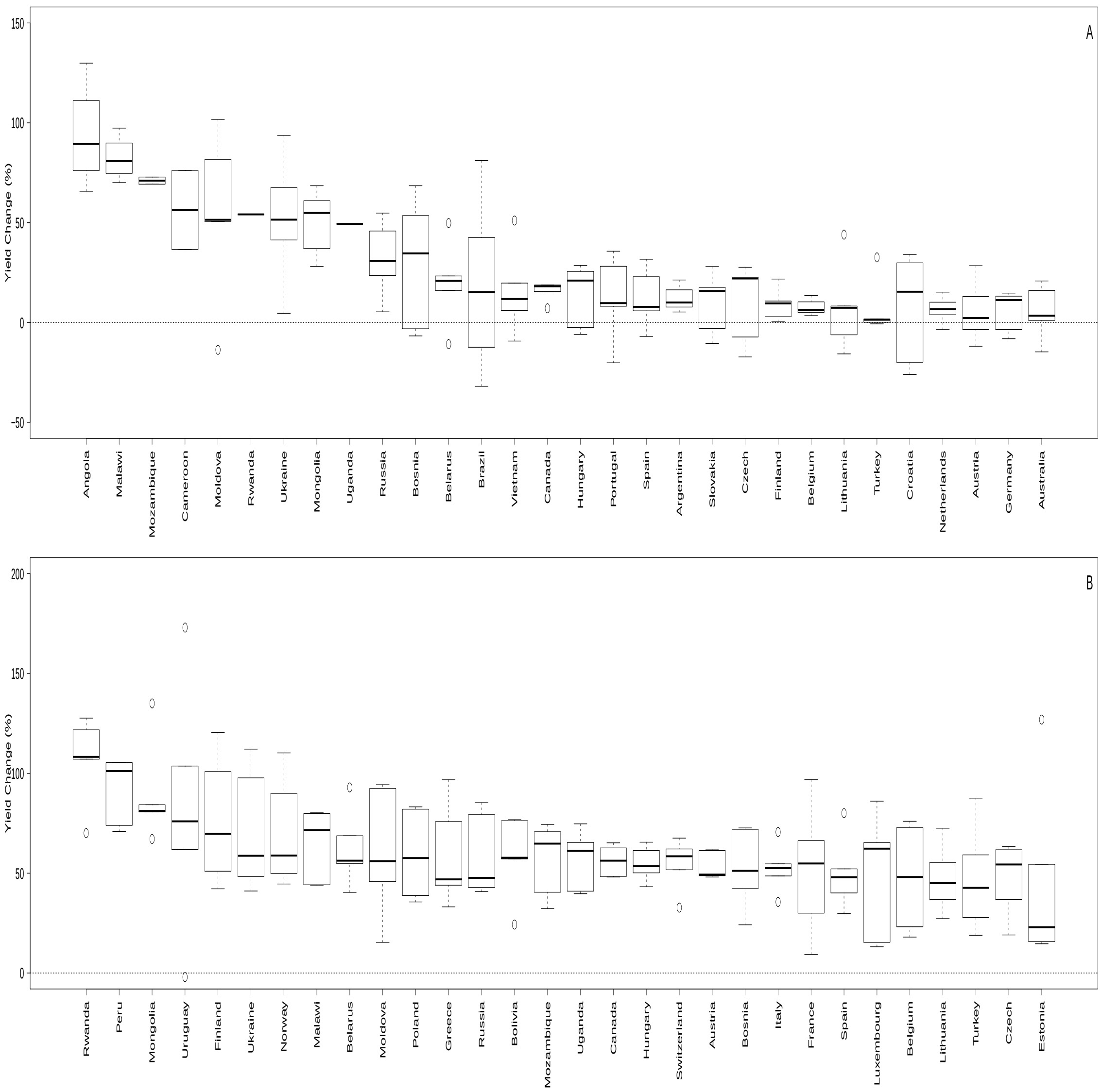



**Figure 6.14:** Countries associated with the largest increase in yields from a baseline to 2041-2050, with ranges across climate models. A. Non-adaptation. B. Adaptation. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

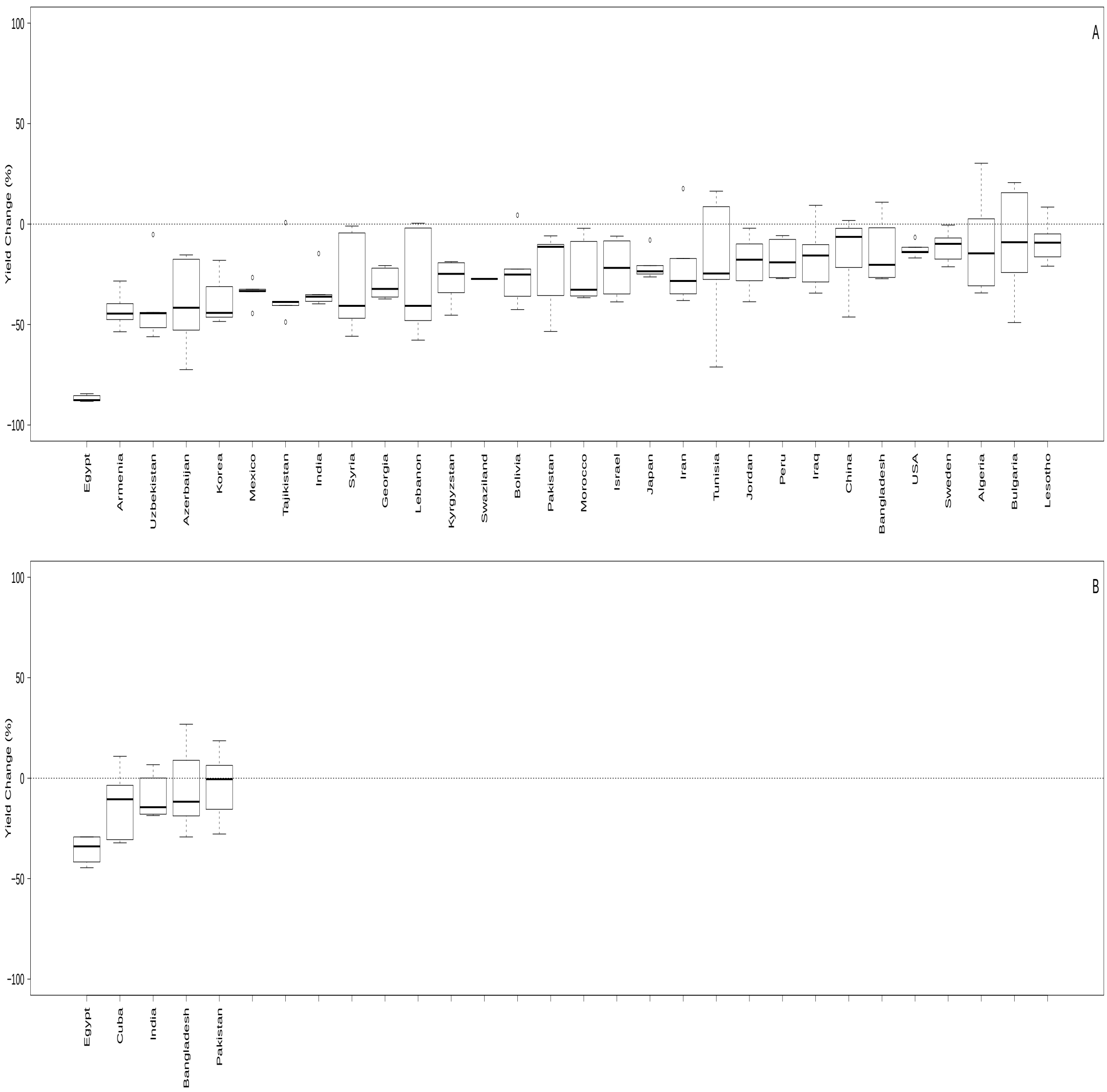



**Figure 6.15:** Countries associated with the largest decrease in yields from a baseline to 2041-2050, with ranges across climate models. A. Non-adaptation. B. Adaptation. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

Yield increases are largely due to the impact of $CO_2$ fertilisation. Warming often leads to reduced durations in the non-adaptation simulations (Figure 6.17) and duration increases in the adaptation simulations. Biomass and yields typically increase in both sets of simulations due to the higher transpiration and radiation use efficiencies used in the future climate simulations.

Standard deviations increase from 0.42 to 0.51 T/Ha in the baseline to 0.51 to 0.71 T/Ha in future climate non-adaptation and 0.54 to 0.69 T/Ha in adaptation simulations (ranges across climate models). This means that extreme yields are projected to be more likely in the future – i.e. crop failures could become more common.

Planting dates and varieties selected in the future climate are shown for one of the 5 climate models in Figure 6.16 (other model planting dates and varieties are similar and are shown in Appendix B). The adaptation simulations that allow planting dates and varieties to shift in future climate show that in general in the northern hemisphere, planting takes place later in the season with harvest often occurring as late as December. Warmer conditions later in the year allow potatoes to take advantage of some of the months that were previously too cold for growth and contain more rainfall (Figure 6.18). Rainfall over the growing season therefore increases in some cases (Figure 6.19). Solar radiation falls in these areas in the adaptation simulations as a result of the months potatoes are projected to be grown in being cloudier and wetter (Figure 6.20).

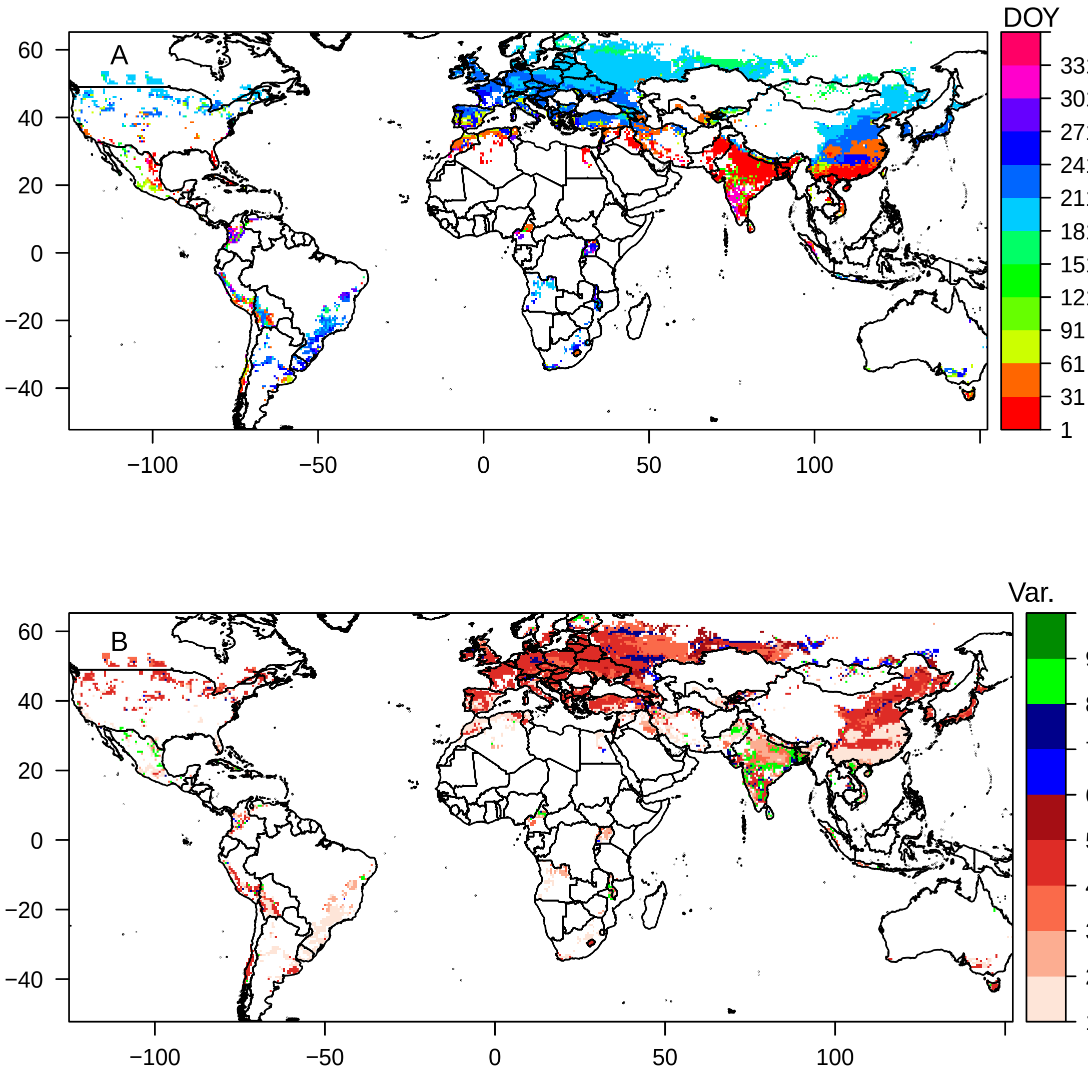



**Figure 6.16:** A. Start of the sowing window and B. varieties chosen for 2041-2050 using the hadgem2-es model.

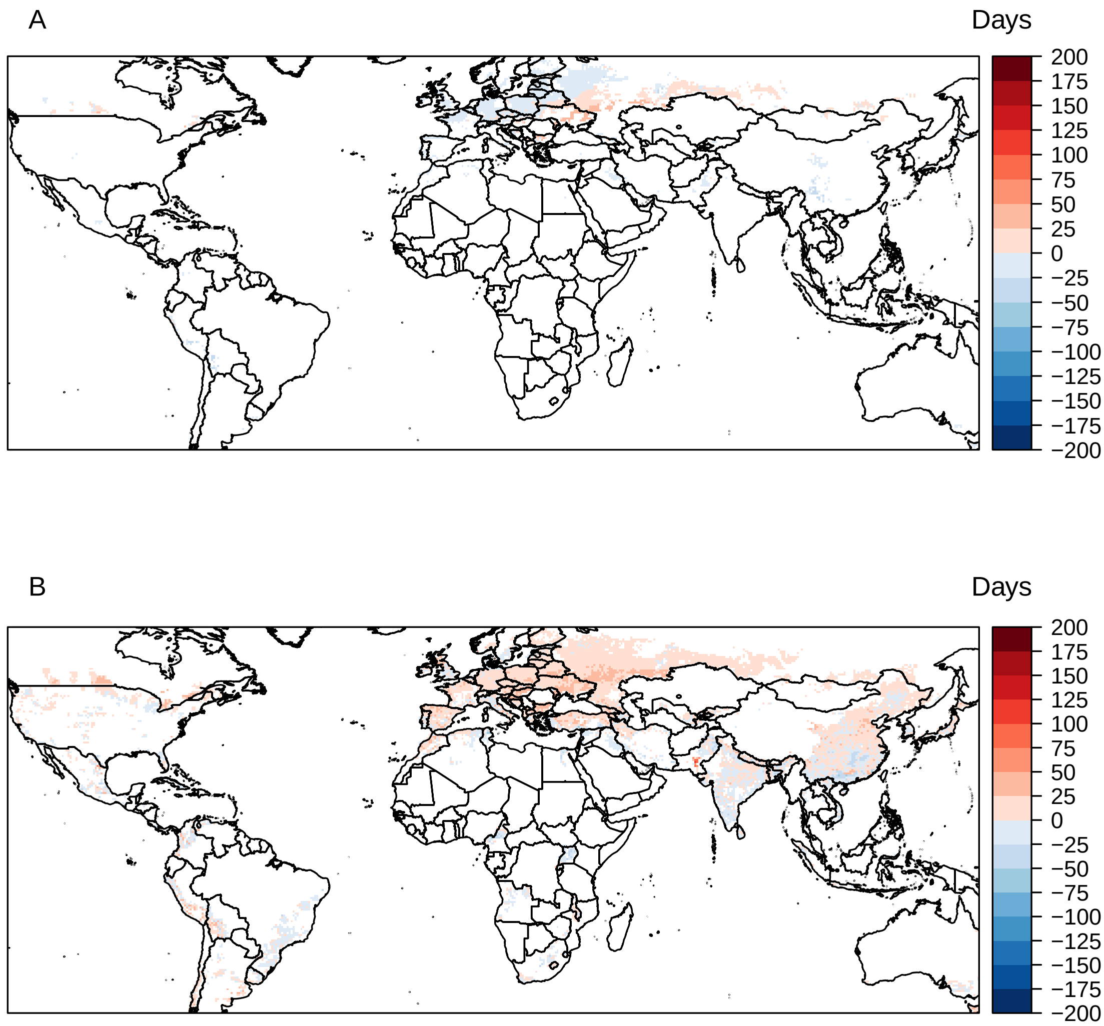



**Figure 6.17:** Mean simulated duration change from baseline climate to 2041-2050. Values shown are mean values across climate models. A = non-adaptation simulations. B = adaptation to future climate.

Tropical regions have more varied future planting dates and varieties across the 5 climate models. Planting often takes place earlier in the growing season and there tends to be a trend towards varieties with lower temperatures in the tuber bulking developmental stages. This results in a lengthening of the tuber bulking stages, although durations often still fall as a result of increasing temperatures. In spite of this, yields often increase in the adaptation simulations thanks to increased biomass from $CO_2$ fertilisation, although some countries (such as India) show yield decreases.

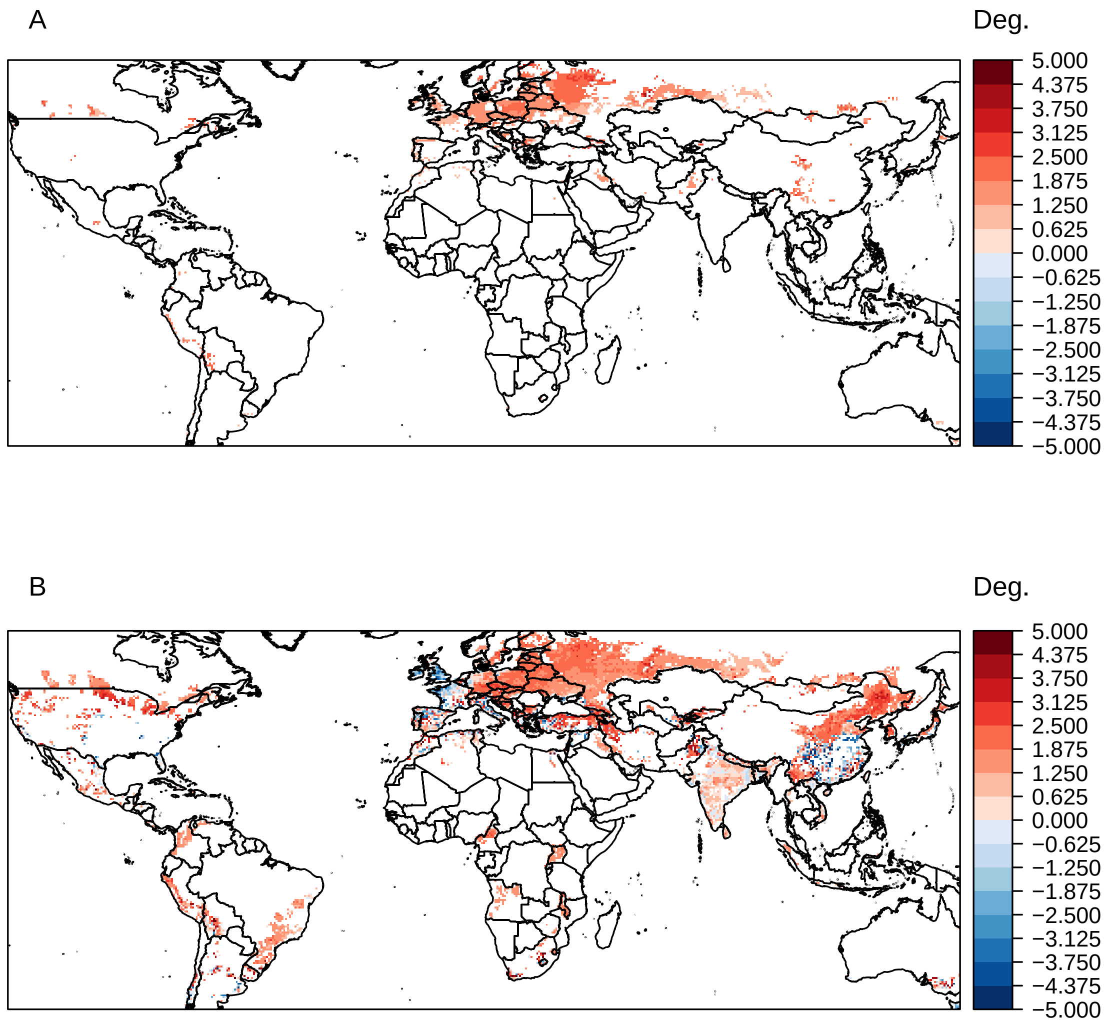



**Figure 6.18:** Mean temperature change from baseline climate to 2041-2050. Values shown are mean values across climate models. A = non-adaptation simulations. B = adaptation to future climate.

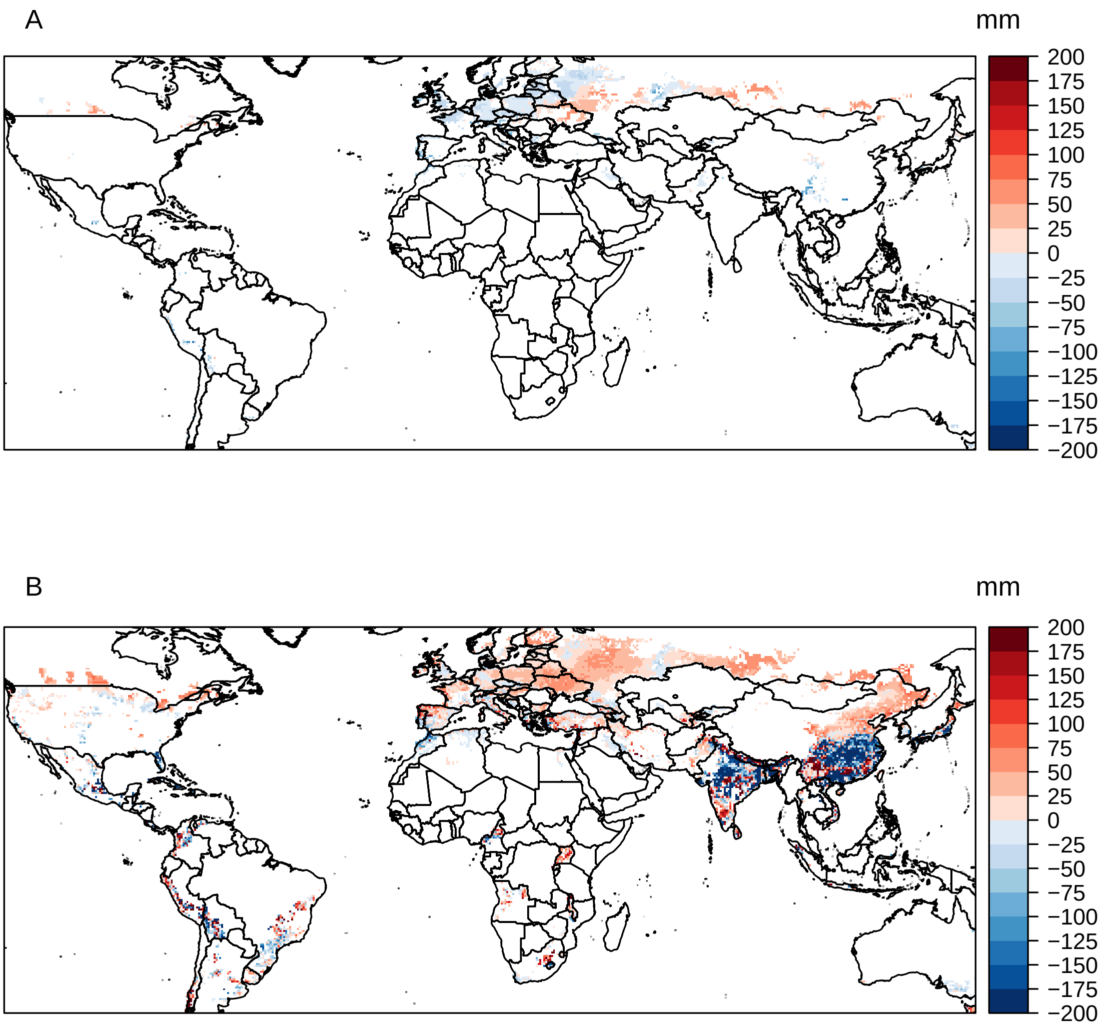



**Figure 6.19:** Change in total rainfall over the growing season from baseline climate to 2041-2050. Values shown are mean values across climate models. A = non-adaptation simulations. B = adaptation to future climate.

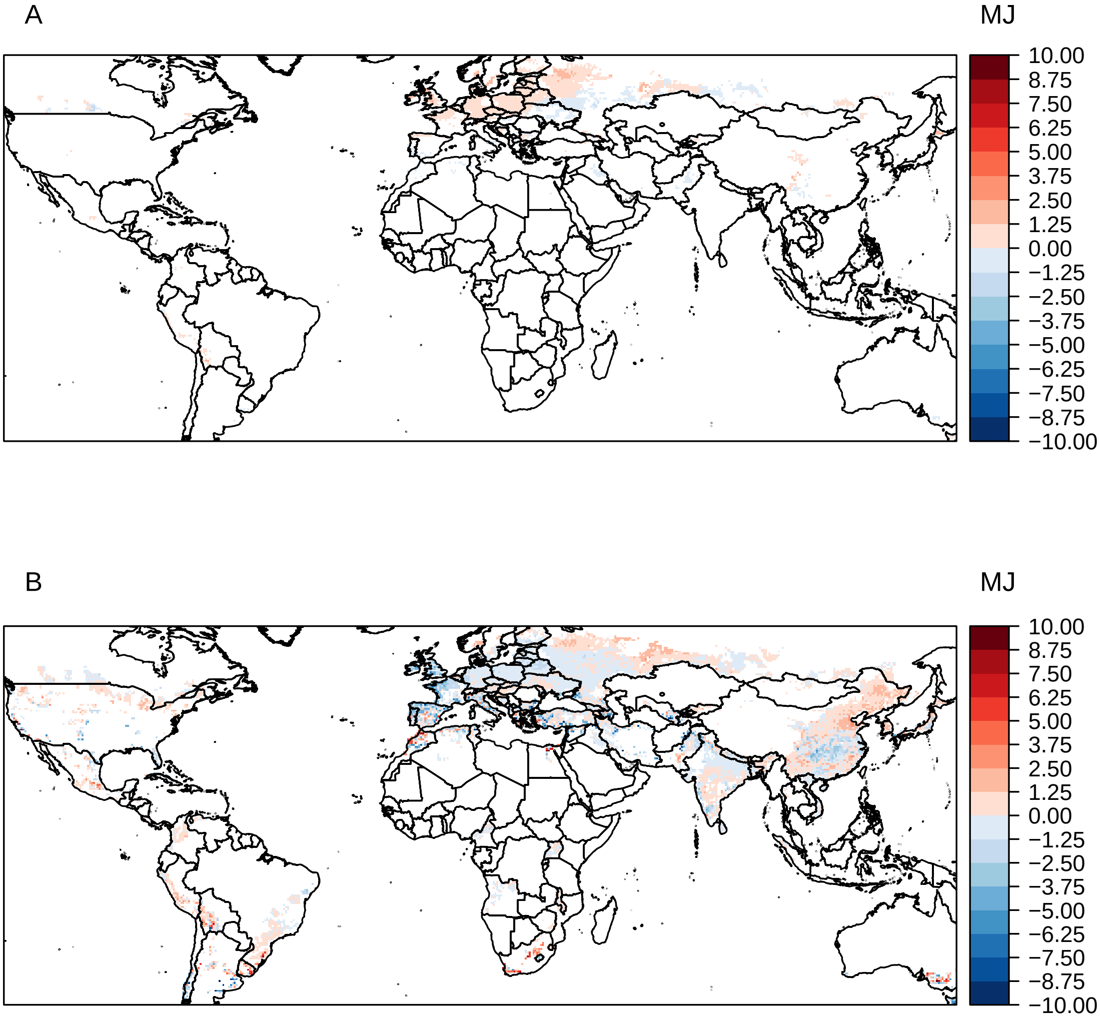



**Figure 6.20:** Mean solar radiation change from baseline climate to 2041-2050. Values shown are mean values across climate models. A = non-adaptation simulations. B = adaptation to future climate.

#### 6.3.1.3 $CO_2$ sensitivity analysis

##### 6.3.1.3.1 Methods

Four countries are used to assess the sensitivity of projected potato yield changes to $CO_2$ fertilisation. These are Germany, Egypt, Bangladesh and Peru. These four countries are all in the top 20 of global potato production and represent a wide environmental and geographic range. Germany, Bangladesh and Egypt have good model skill (correlations between observed and simulated yields are highly significant in Germany and Egypt, with a p-value of 0.07 in Bangladesh). Peru model skill is insignificant but is the top South American potato producer (and no country has significant skill in South America). A global sensitivity analysis was not conducted as model skill was often poor in large potato production countries such as the USA, India and China, making projected yield changes uncertain.

Future climate change simulations for these four countries are conducted that vary the TE and RUE parameters across reported ranges cited in Section 6.2.3.1. Simulations with no $CO_2$ fertilisation are also included for comparison. Simulations will therefore be conducted with the following percentage increases in TE and RUE in future climate: 0, 20, 22.125, 24.25 (matching the other future climate simulations in thesis), 26.375, 28.5.

These simulations use the same model configuration as the adaptation simulations, with planting dates and varieties varying for each climate model. The simulations use the adaptation configuration only as these simulations are considered more realistic than dumb farmer future simulations.

#### 6.3.1.3.2 Results

Projected changes in yields vary according to the parameterisation of $CO_2$ fertilisation (Figure 6.21). Mean yield changes vary across $CO_2$ parameterisations from -11% to 3% in Bangladesh, from -38% to -33% in Egypt, from 40% to 51% in Germany and from 83% to 107% in Peru.

In Egypt, Germany and Peru the mean sign of yield change (i.e. whether there is a projected increase or decrease in yields in the future) across climate models is the same whether $CO_2$ fertilisation is turned on or not. In Bangladesh, a mean decrease in projected yields becomes a modest increase with the highest level of $CO_2$ fertilisation (although note that the median value across climate models for parameterisation 5 still shows a yield decrease).

In all four countries there is a steady increase in yields across the $CO_2$ parameterisations, reflecting the incremental increase in TE and RUE parameters that result in incremental increases in biomass and yields.

There is a smaller difference in yield changes across $CO_2$ parameterisations in Egypt as the LAI is relatively high, resulting in higher biomass than the other three countries in this analysis. Therefore for a given increase in TE and RUE the percentage increase in biomass (and hence yields) is lower. There is a larger difference in yield changes across $CO_2$ parameterisations in Peru as the LAI and biomass are comparatively small, with the changes in TE and RUE therefore contributing to larger percentage increases in biomass and yields.

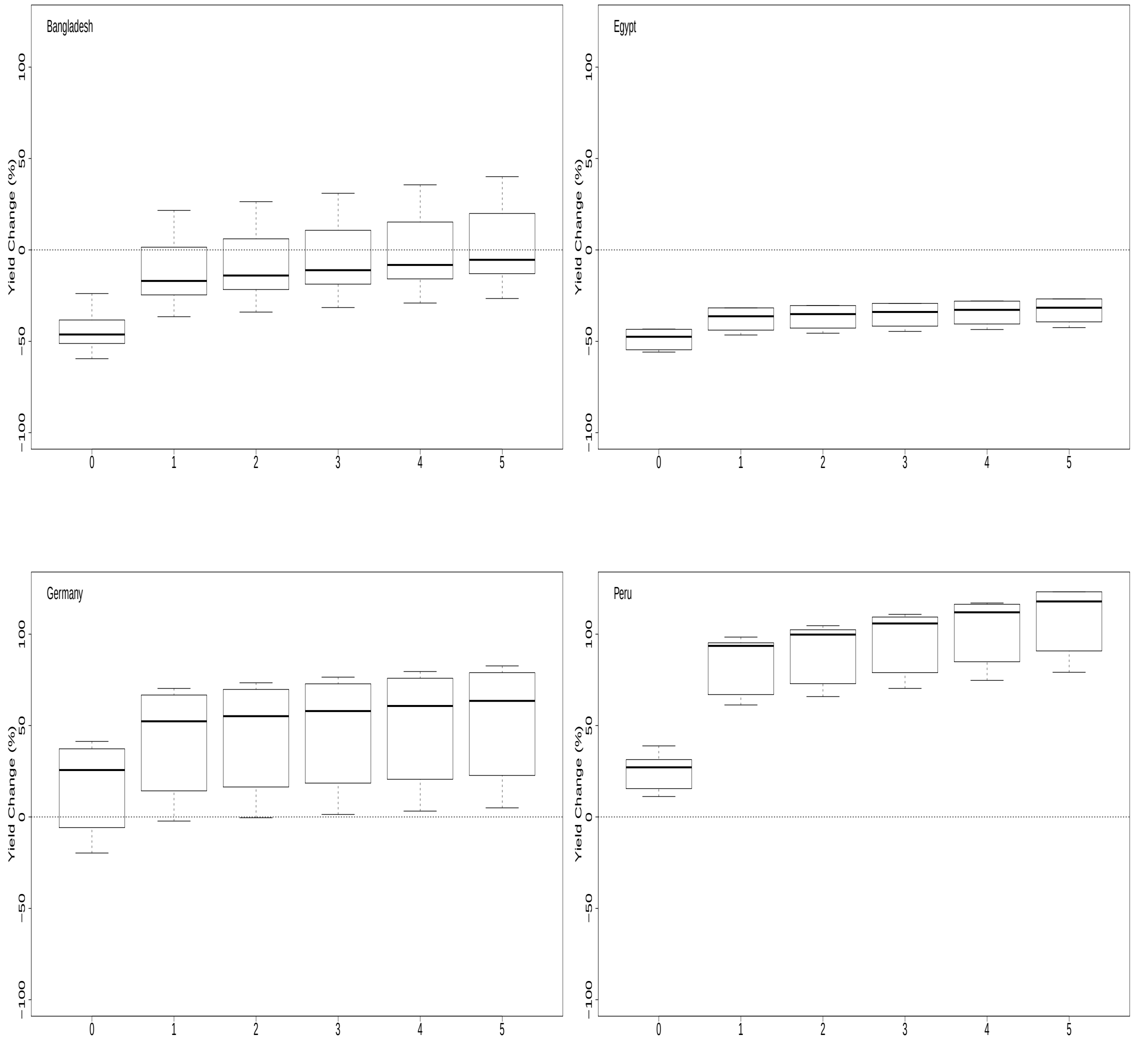



**Figure 6.21:** Projected changes in yields in Bangladesh, Egypt, Germany and Peru using different levels of $CO_2$ fertilisation. $CO_2$ parameterisation 0 = no $CO_2$ fertilisation, 1 = 20%, 2 = 22.125%, 3 = 24.25%, 4 = 26.375%, 5 = 28.5% increase in TE and RUE. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

### 6.3.2 Global blight changes

Changes to blight units are shown in Figure 6.22. The largest increases and decreases in blight units are shown by country in Figures 6.24 and 6.25 respectively.

For the blight simulations not allowing adaptation of new varieties to warming, risk of disease attack is usually reduced as a result of warming and falling relative humidity (Figures 6.22 and 6.23). When allowing adaptation of blight to warming the severity of blight attack in future climate is considerably higher, especially in the northern hemisphere.

Unsurprisingly given the expected warming, the two blight varieties that are adapted to warming climates contribute most to the increase in blight units expected when allowing adaptation. The blight variety associated with the largest increase in blight units is the variety adapted to temperatures of 5°C higher than the baseline climate. The 2.5°C warming variety shows similar results, with slightly less virulence in a future climate.

For the growing seasons simulated in the blight analysis, projected temperature increases of c. 3°C and relatively small rainfall changes mean that relative humidity usually falls slightly by less than 15% in most grid cells. For the adaptation simulations, blight unit changes are largely driven by the increases in temperature projected rather than the changes in relative humidity, as temperature optima of blight can shift to match warmer temperatures and maximise blight units. Intuitively, blight units often fall in the non-adaptation simulations, as falling relative humidity and warming leads to fewer blight units accumulated during the growing season.

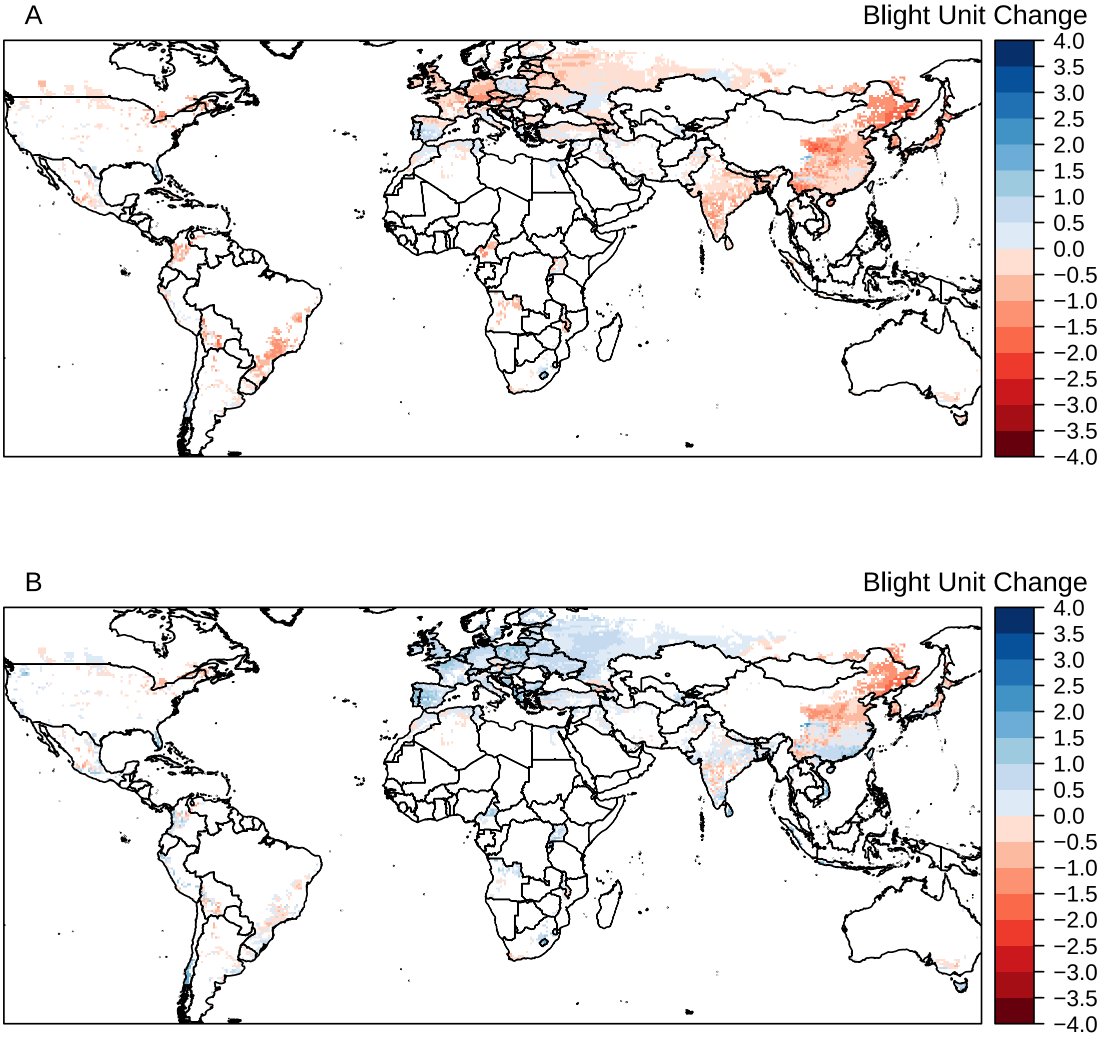



**Figure 6.22:** Global late blight unit change from baseline climate to 2041-2050. Values shown are mean values across climate models. A = the same variety as baseline. B = the most virulent blight variety in future climate. Note that positive changes are coloured blue for these plots, unlike in yield change plots where positive changes are red. This is for a visual comparison of adversely affected regions when looking at both biotic and abiotic impacts.

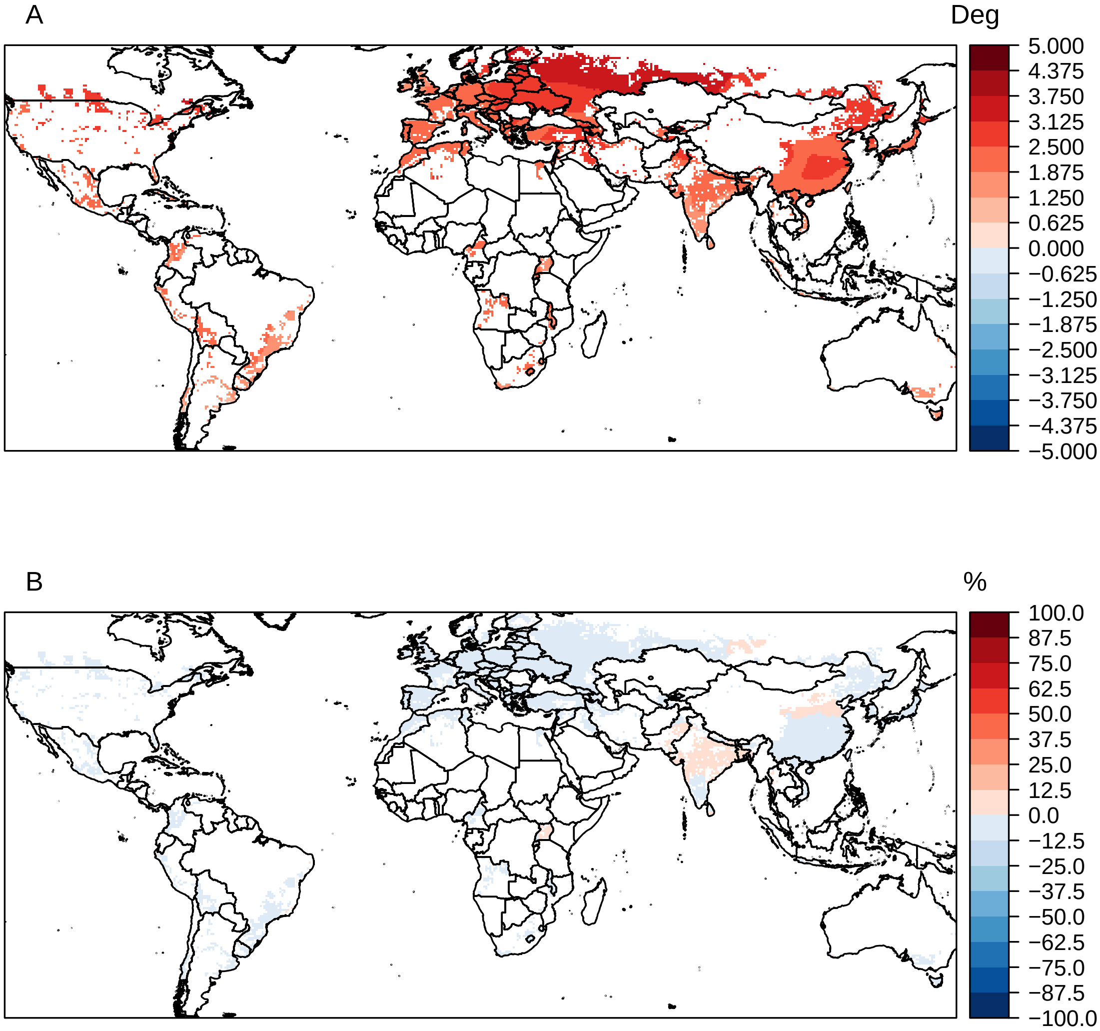



**Figure 6.23:** Changes in temperature (A) and relative humidity (B) from baseline climate to 2041-2050. Values shown are mean values across climate models.

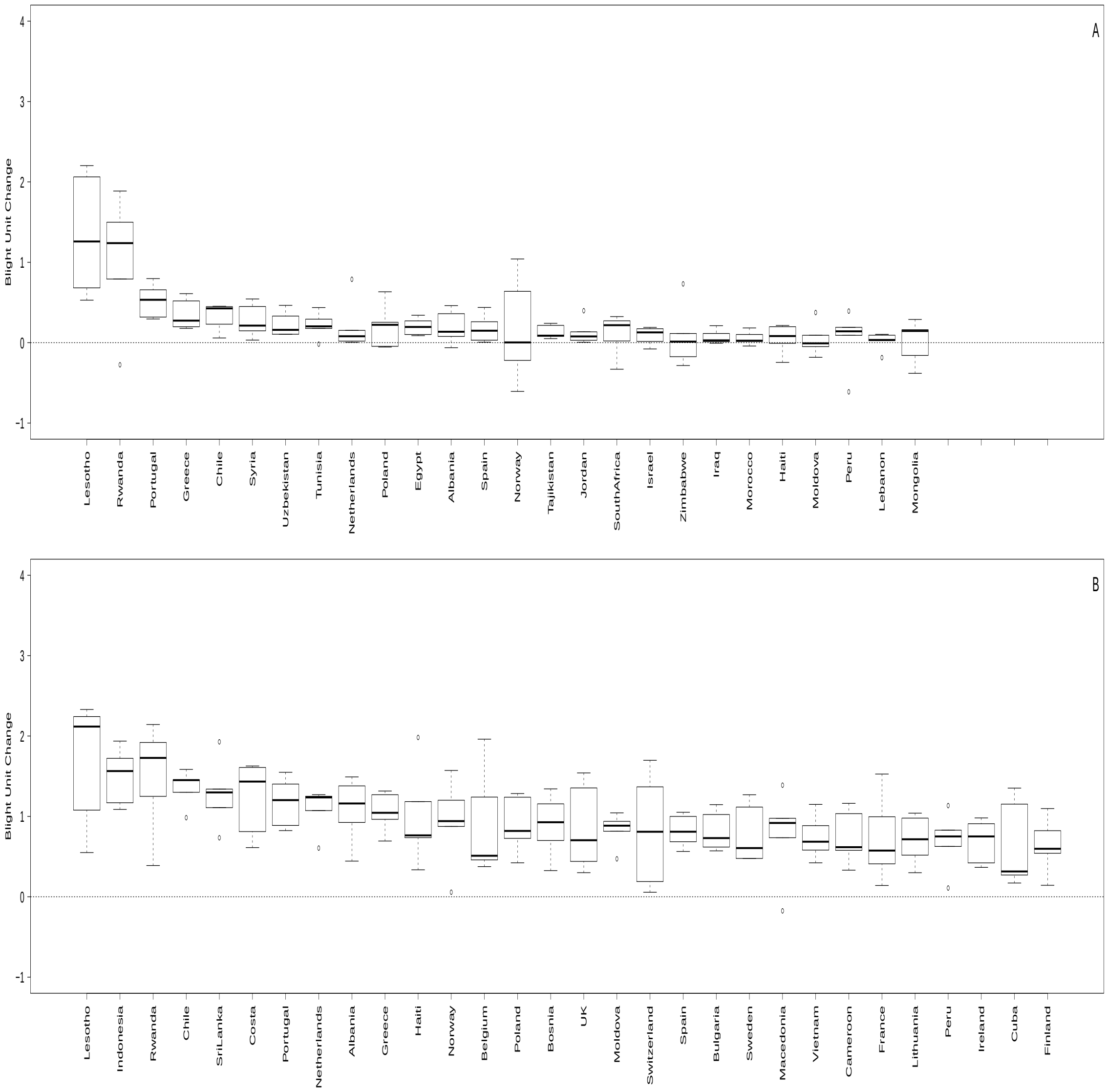



**Figure 6.24:** Countries associated with the largest increase in mean blight units with variation across climate models. Changes from baseline to 2041-2050. A = the same variety as baseline. B = the most virulent blight variety in future climate. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

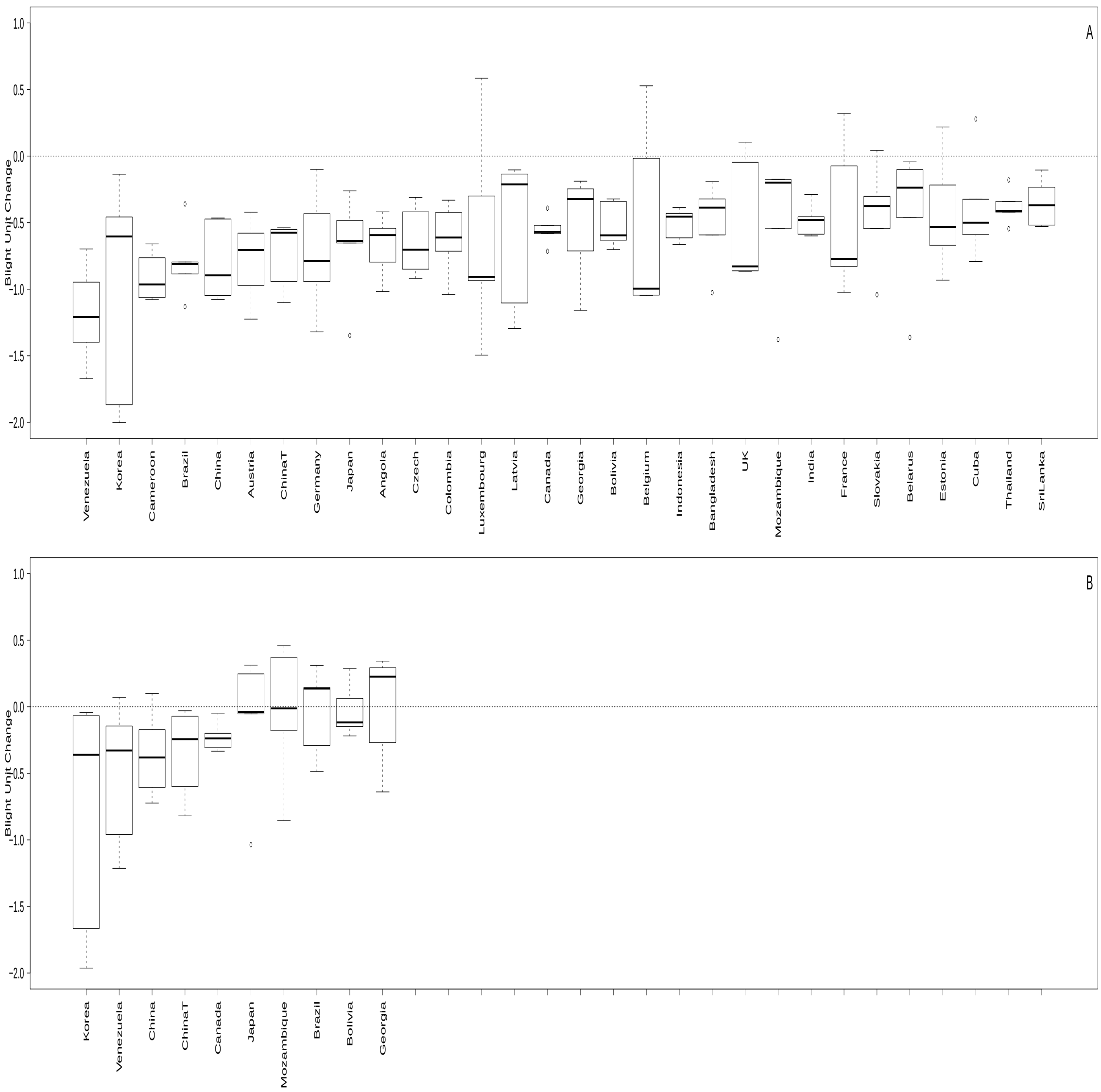



**Figure 6.25:** Countries associated with the largest decrease in mean blight units with variation across climate models. Changes from baseline to 2041-2050. A = the same variety as baseline. B = the most virulent blight variety in future climate. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

### 6.3.3 Global abiotic and biotic changes

The mean results for the adaptation to climate change for potato yields and late blight are shown in Figure 6.26. As discussed in Sections 6.3.1.2 and 6.3.2, potato yields and blight units are projected to increase, particularly in the northern hemisphere.

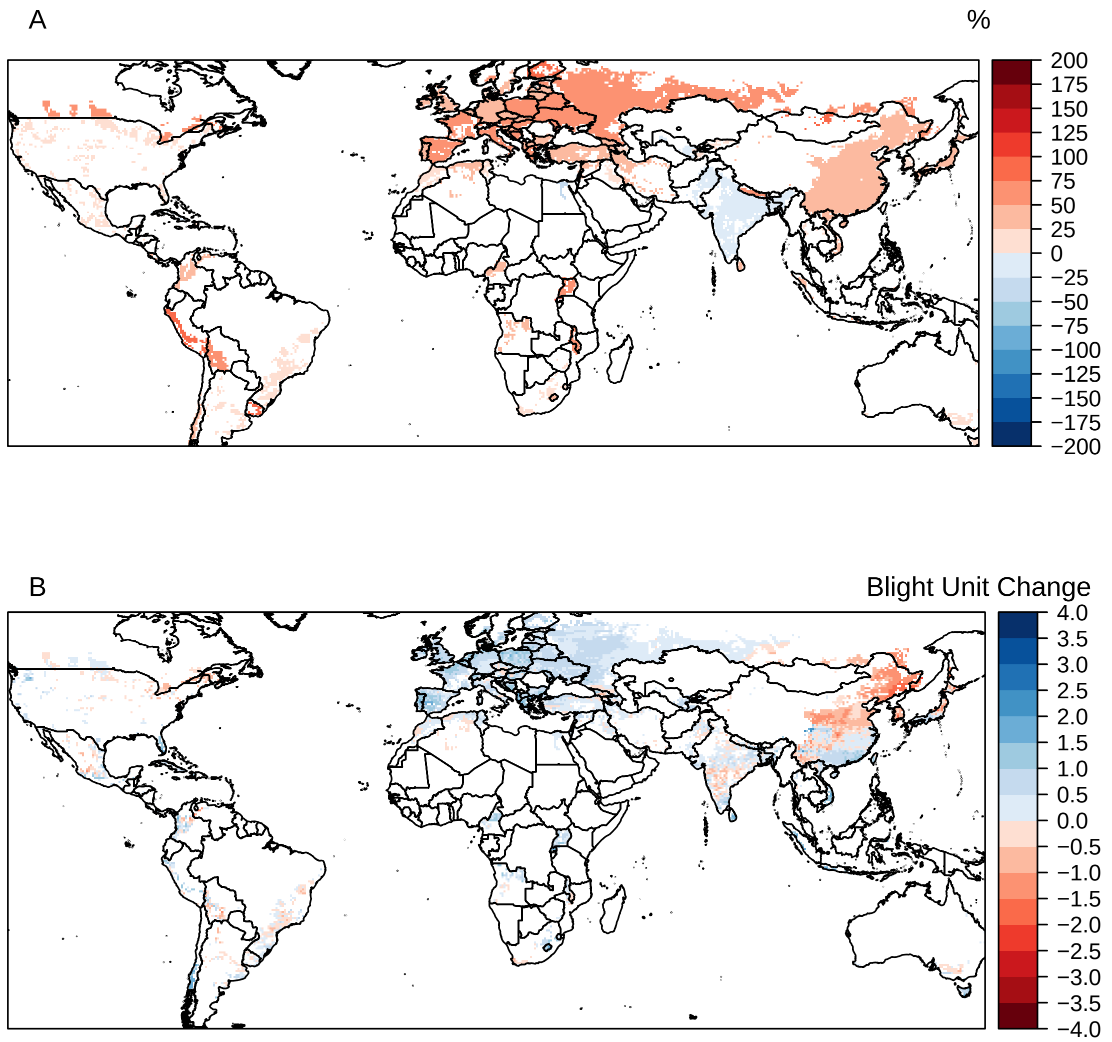



**Figure 6.26:** Changes in mean yields (A) and blight units (B) from baseline climate to 2041-2050. Values shown are mean values across climate models. Both A. and B. use future climate adaptation simulations. Note that positive changes are coloured red in A and blue in B. This is for a visual comparison of adversely affected regions when looking at both biotic and abiotic impacts.

China and Brazil are amongst the few countries projected to see yield increases and blight reductions (Figure 6.26). Yield increases are modest in Brazil, largely due to $CO_2$ fertilisation. In China, earlier sowing dates in key growing areas lead to falling temperatures, resulting in projected duration and therefore yield increases. These countries show insignificant GLAM model skill, however, so little confidence can be placed in the yield change predictions. Projected European yield gains could be offset by increases in blight attack, as shown in Figure 6.26.

Few countries are projected to see a reduction in yields by 2041-2050 (Egypt, Cuba, India, Bangladesh and Pakistan). Of these countries, only Cuba has all five climate models predicting a blight unit increase of greater than 1, with the other countries showing negligible increases.

Many countries are predicted to suffer an increase in blight risk, however, with 79 countries showing mean increases in blight units across climate models when considering blight adaptation. Across Europe, adapted blight varieties are typically showing increases of 1-4 blight units relative to historical levels. The projected yield increases in Europe are high in many cases, with median increases across climate models of over 50% common (as shown in Figure 6.14 in Section 6.3.1.2).

## 6.4 Discussion

This analysis aimed to project yield and blight changes towards the mid-21st century and highlight areas where potatoes will be most at risk from climate change.

Late blight is projected to increase in much of Europe when allowing blight adaptation to warming conditions (i.e. the emergence of new blight varieties with different temperature optima). Without this adaptation, blight is projected to subside in most areas due to temperatures and relative humidity going beyond blight optima – i.e. shifting the blight optimal temperature allows the disease to react favourably to warming conditions. Without adaptation, temperatures in Europe increase such that the optimum temperatures of c. 20°C are surpassed more often and fewer blight units accrue.

Sparks et al. (2014) projected blight decreases as the century passes, largely through cooling temperatures when allowing growing seasons to shift. They assume a constant pathogen response to temperature, however. This important inclusion in this analysis highlights the differences in responses of biotic stresses when taking into account not only the host response to climate change (i.e. the crop) but that of the disease also. Fungal diseases are predicted to become more threatening to global food security with climate change (Bebber and Gurr, 2015; Fisher et al., 2012). Results in this chapter agree that the fungal-like oomycete late blight is likely to become more problematic in key growing areas in the future.

The blight variety associated with the largest increase in blight units compared to the baseline is the variety adapted to temperatures of 5°C warming. The 2.5°C warming variety also has higher virulence in a future climate. Given that warming is usually not projected to be as high as 5°C, this implies that blight is currently not optimally suited to temperature conditions. This is perhaps not surprising given that potatoes and blight originated in warmer tropical regions; even though both can grow across a wide temperature range, optimal temperatures are often higher than those experienced in colder latitudes. That being said, results for the 2.5°C variety are almost as virulent, meaning that adapting to less warming also produces significantly more blight in the future climate.

Given that pesticide legislation in important potato growing areas like the European Union is already highly restrictive (Handford et al., 2015), it is unlikely that increasing pesticide use to control pathogens such as light blight will be viable in the future in many regions. More nuanced Integrated Pest Management techniques will require investigation (Alyokhin et al., 2015; Guedes et al., 2016). Chapter 7 looks into pesticide use and climate change in more detail in an analysis that looks at broader pest-climate change projections.

The areas with the highest confidence associated with baseline yield simulations are mostly in the northern hemisphere. Yields are generally predicted to increase in these areas. When considering both adaptation (i.e. allowing planting dates and varieties to vary in the future) and $CO_2$ fertilisation, projected yield changes are large. The range of global mean yield changes shown across climate models is -6 to 16% without adaptation and 33 to 47% increases with adaptation. These increases are larger than those reported in previous global potato crop modelling studies (Raymundo et al., 2017b; Hijmans, 2003). Previous studies do not include the simultaneous impacts of adaptation to climate change and $CO_2$ fertilisation, however, which cause the increases in yields projected here. Past studies also do not comment on model skill in simulating the inter-annual variability of national scale yields and do not report crop model outputs such as LAI and duration.

Previous studies of global crop model using GLAM have simulated wheat, maize and soybean rather than potato (Osborne et al., 2013; Rose et al., 2016; Dawson et al., 2016). Of these studies, model skill is only commented on in Osborne et al. (2013). Here, correlations between observed and simulated national scale yields were significant in only four of the top 15 soybean production countries and in only three of the top 15 wheat producing countries. Mean simulated yields were often underestimated also. In short, model skill of global GLAM-potato is comparable to that shown in previous global GLAM analysis.

$CO_2$ fertilisation mitigates many of the negative influences of changing climate such as rising heat stress, water stress and shortened durations. The $CO_2$ fertilisation sensitivity analysis shows the range of yield changes across different parameterisations of $CO_2$ fertilisation. The range of yield changes across parameterisations in the four countries analysed in this analysis were 14% in Bangladesh, 5% in Egypt, 11% in Germany and 24% in Peru. For some of the lower biomass countries such as Peru, the difference across parametersiations is higher due to lower biomass, resulting in the altered TE and RUE parameters having a relatively large impact on biomass and yields. Conversely, higher biomass countries such as Egypt and Germany showed a smaller range of yield percentage changes across parameterisations. Given that the higher biomass countries in the northern hemisphere typically show better model skill, it is reasonable to conclude that the yield changes that we have most confidence in are reasonably robust across the range of $CO_2$ fertilisations cited in this study. However, the uncertainty surrounding the yield change projections for some important countries with both high and low biomass levels is large, both given poor model skill and significant parameter uncertainty for $CO_2$ fertilisation.

Projected future yield losses for potato from ozone damage are estimated to be around 12% on average across studies (with a range across studies of c. 6-18%) (Feng and Kobayashi, 2009). For potatoes, $CO_2$ fertilisation is predicted to more than compensate for ozone-induced losses, although both the size of the effect of $CO_2$ fertilisation and ozone damage are uncertain (Raymundo et al., 2017b; Feng and Kobayashi, 2009). Similarly, $CO_2$ and ozone impacts on potato tuber quality and nutrition are complex – studies have reported losses in protein, calcium and potassium tuber content but impacts on tuber quality are uncertain (Högy and Fangmeier, 2009; Vorne et al., 2002). More studies are needed to make robust statements about the implications of nutrient loss in key potato growing areas in food insecure regions such as India and China.

This study primarily focuses on the impacts of climate change on yields, with changes to climate variables (temperature, precipitation and solar radiation) and $CO_2$ accounted for. At the time of the analysis ozone damage was not included in GLAM so this was not accounted for. However, it is possible to use current ozone yield damage projections to put results into context. Global mean yield changes are projected in this study across climate models to be -6 to 16% without adaptation and 33 to 47% increases with adaptation. Decreasing these ranges by the mean projected ozone damage leads to global mean yield changes of -18 to 4% without adaptation, and 21 to 35% with adaptation.

It is important to note that ozone damage is variable across regions, dependent on local pollution, and therefore more work is needed to identify particular areas of risk to ozone damage in key growing areas (Feng and Kobayashi, 2009). Europe, for example, have substantial potato production with some projected ozone-induced yield losses (Vorne et al., 2002) but are not an area predicted to be at great risk from food insecurity. Other regions of the world that are more vulnerable, such as India and China, need further study.

Including the uncertainty range over the parameterisation of $CO_2$ fertilisation is also important when examining confidence in both global and country-level projections of yield changes. Based on the results of the sensitivity analysis, the uncertainty range around the size of the $CO_2$ fertilisation effect can be large but will rarely change the sign of yield change at the country scale or globally. In European countries, for example, using Germany as a case study, the parameterisation of $CO_2$ fertilisation is associated with yield changes 5% lower or higher than the mean $CO_2$ fertilisation level that is used in the main results section. Combined with ozone damage of around 5% shown in the European CHIP analysis (Vorne et al., 2002), yield changes would then be around the same or as much as 5% higher, depending on the choice of $CO_2$ parameterisation.

The potential for adaptation to increase yields is large, with yield increases of 30% common compared to yields using dumb farmer planting dates and varieties. It is important to note that a large fraction of potato growing area was omitted from potato non-adaptation simulations due to these grid cells not having realistic planting date-variety combinations in the future climate. This provides further support to considering the adaptation simulations as the most realistic in future climate in this model set up, alongside the need to avoid the dumb farmer bias (Füssel, 2007; Schneider et al., 2000).

Previous global crop modelling studies do show skill in some cases at representing mean yield levels and interannual variability (e.g. Müller et al., 2017), with ensembles typically performing better than individual models (Fleisher et al., 2016). For potato such studies are rare, however. Regional studies show better results than the global GLAM-potato configuration in some cases, as shown in this thesis in Chapter 5. Singh et al. (2005) use the INFOCROP-POTATO model to study potato in India. INFOCROP-POTATO does not allow potato growth above 30°C and has significant correlations for crop development and growth, which is likely due to high input data detail. Raymundo et al. (2017b) show mixed results in representing the variability and mean of FAO national yields across the globe, and do not show correlation coefficients with which to compare to the results presented here. Their results showed higher simulated than observed yield variability and high RRMSE (56% on average globally). Mean yields are calibrated in GLAM, although in some cases mean simulated yields are lower than observed mean yields due to parameterisation and data preparation choices, as discussed in Chapter 4. The focus of the GLAM analysis is on capturing interannual variability in observed yields. Whilst mean yields are poorly represented in some cases, confidence in percentage changes to yields is associated most with interannual variability - i.e. how well the model can simulated the relationship between yields and climate (Müller et al., 2017).

These other studies do include more complex parameterisations of processes in some cases but model performance is mixed at the global scale. There are reductions in RUE and increases in senescence at higher temperatures in Raymundo et al. (2017b). China and India in particular still showed overestimation of country-level production. Müller et al. (2017) also found poor model skill for Chinese wheat and soybean, illustrating the difficulties in simulating crops in these important potato growing regions using national scale yield data. In this chapter, the mean yield levels of the Chinese yield time series fluctuate substantially mid-time series, making model calibration and skill difficult.

The larger countries simulated in this analysis usually have poor model skill (Russia being the exception to this) and this is probably not a coincidence. The use of national scale yield data is likely a part of the reason for poor skill as the variability of the national scale yield data may not apply to that at the level of the grid cell. The FAOSTAT yield data are associated with the year when the majority of the harvest takes place. Large and climatically-variable countries such as China and India have planting dates in different times of the year, and therefore the yield data for a given year may not be representative of all grid cells.

In Raymundo et al. (2017b), yields were projected to decrease for the temperate regions of north America, eastern Europe and Asia, whilst increasing in western Europe in the climate change analysis using RCP 8.5 from 1979-2009 to 2040-2070. For subtropical and tropical regions yields were generally predicted to increase. Whilst results in this chapter show more yield increases in much of the northern hemisphere than Raymundo et al. (2017b), these differences are likely due to their treatment of $CO_2$ fertilisation leading to less of an increase in yields and the inclusion in this study of adaptation of farmers to climate change. Raymundo et al. (2017b) acknowledge that the response of yields to $CO_2$ fertilisation is highly uncertain. Whilst their representation of this process is more detailed than the one used in this chapter, their results show an under-estimation of the increase in yields due to rises in $CO_2$ concentration. Haverkort et al. (2013) found that increasing $CO_2$ more than compensated for yield losses due to rising temperatures and reduced water availability for South African potatoes by 2050. Whilst the size of the $CO_2$ fertilisation effect on biomass is uncertain, current experimental evidence does indicate substantial biomass gains in potato (Fleisher et al., 2008; Finnan et al., 2005; Magliulo et al., 2003). Potato uses the C3 photosynthetic pathway, which is predicted to lead to more $CO_2$ fertilisation as $CO_2$ is less saturating in baseline conditions (Leakey et al., 2009). This effect is also predicted to be larger than for other crops (McGrath and Lobell, 2013; Magliulo et al., 2003), making it especially important to account for.

### 6.4.1 Study limitations

Study limitations will be discussed for the GLAM simulations firstly, followed by the late blight simulations. This study explores the biophysical impacts of climate change on potatoes, but little is known of the evolution of food systems and farming practises, and these factors are not addressed in this study.

The only region to perform consistently well in terms of model skill in the baseline climate was Europe. Whilst other countries sometimes showed significant correlations, most did not, which limits the confidence one can place in the analysis of global yield changes.

Only one crop model was used in this study, meaning that the structural uncertainty associated with different crop models is not accounted for. A range of input data sets (apart from climate inputs) are also not a part of this analysis - Folberth et al. (2016) highlight how the uncertainty due to soil data inputs can be important, so this in particular should be investigated in future work.

Only using a single crop area data set can lead to a lack of quantification of aggregation uncertainty in simulated yield time series (Challinor et al., 2018; Porwollik et al., 2017). However, previous work has shown that regions with more potato growing area are associated with better model skill (Watson et al., 2015). Only the top 50% of potato growing area grid cells are included in this analysis. It is assumed that these grid cells are more often the same across growing area data sets than the low area grid cells in more marginal potato growing regions. Uncertainty due to growing area data sets is therefore assumed to be small, as was most often the case in Porwollik et al. (2017).

Technology impacts on yields are also beyond the scope of the current study; these can have major impacts on yields, as demonstrated by Lobell et al. (2011), who found that for global maize, wheat, rice and soybean, one year of gains from technology trends can compensate for 10 years of negative impacts from climate trends.

This study did not examine multiple cropping seasons for potato which could impact annual mean yields. Ozone damage and nitrogen limitations were not taken into account explicitly for baseline or future simulations, although the $C_{\mathrm{YG}}$ captures some of these impacts implicitly in a mean level across the time series for the baseline climate. Irrigating the crop fully was not seen as a viable adaptation strategy so was not simulated, given water limitations already apparent in important growing regions (Kumar et al., 2005). Land use changes were also not considered. Such an adaptation option would potentially allow more suitable grid cells to be simulated for potatoes in future, which could lead to more potato yield increases. This was beyond the scope of the current study due to uncertainties around future land use patterns and time constraints.

For future climate simulations, changing planting dates and varieties may not be straightforward due to market pressures, pests and diseases, other crops and water availability (Hijmans, 2003). There is a large diversity of potato cultivars that could be exploited by breeders to help improve tolerance to climate change impacts (Schafleitner et al., 2011), but the access of new varieties to farmers will likely remain problematic in poorer countries. The realism of altering planting dates will likely depend on factors not accounted for in this study, namely other crops, market pressures and broader pest and disease impacts. Moore and Lobell (2014) found that the rate at which farmers adapt to warming is an important source of uncertainty in climate impact projections. Although the representation of adaptation in terms of changing planting dates and varieties is arguably optimistic, other adaptations are not included in this study which could help in adapting to climate change. The lack of representation of a more diverse array of adaptation options is common in crop modelling studies (Challinor et al., 2018).

An important point regarding the choice of planting dates in this analysis is that GLAM selects the best performing planting date and variety combination in the absence of any limitations imposed by the growing seasons of other crops. The selected planting dates could be theoretically realistic – based on environmental inputs – but not actually observed due to other crops being planted at that time. Both potato planting and harvest are affected by management decisions as well as environmental factors, making model selection of these difficult. van Bussel (2011) had some difficulty choosing the correct planting dates for cassava, for example, which is a crop with similarities to potato in terms of phenology and growth (Singh et al., 1998).

The heat stress parameterisation used in this chapter could be overly-simplistic, both in terms of model structure and parametrisation - the percentage decrease in yields resulting from heat stress may be too low in some hotter countries such as India. High temperatures did not affect transpiration or radiation use efficiency in this analysis, but recent evidence and modelling studies suggest this to be of some importance (Raymundo et al., 2017b; Zhou et al., 2017). Results in India may indicate this, with long durations resulting from high temperatures that might be insufficiently reducing yields. Whilst some heat stress was apparent in simulations it was possibly not severe enough. There was no correlation between heat stress severity and model skill, however.

Studies such as Raymundo et al. (2017b) and Singh et al. (2005) use more complex models with higher input data requirements, suggesting potential improvements to the parameterisations of heat stress and $CO_2$ fertilisation used in GLAM-potato. There is evidence that different varieties of potato show different responses to heat stress (Wolf et al., 1990). As stated in Chapter 4, a simple parameterisation for global simulations was chosen due to a lack of data and regional information. Therefore, different varieties of potato did not include different heat stress parameterisations.

Müller et al. (2017) correlate simulated yields with FAO national yield time series and test correlations when the observed yields are allowed to shift by one year. The one year shift is selected if it improves the correlation by greater than 0.3. This approach improved correlations in Müller et al. (2017), particularly in tropical countries. This has the advantage of allowing the model to choose the best performing time series, however in some cases the “wrong” years are bound to be associated with the data, so the more knowledge-based approach of prior selection was preferred here. Neither approach is perfect however - in Vietnam, for example, there was a significant negative correlation coefficient between observed and simulated yields and it is possible that the observed yield time series should be shifted.

Regarding the impacts of climate change on the biotic stress of potatoes – only one species is simulated in this study. This is the obvious limitation as to how much can be concluded from this work about the biotic impacts of climate change on potato agriculture. Whilst it is a globally important disease, other species are likely to show different responses to climate change, and other species will be particularly important in some areas. The study highlights important regions of potential risk as a result of this important potato disease, however. As ever, data limitations on pests and diseases limit the possibility for evaluating the large scale biotic stress modelling in this chapter (Donatelli et al., 2017; Bale et al., 2002), although the model in use has shown skill in the past (e.g. Sparks et al., 2011).

Interactions between the pest and host crop are accounted for only in some basic ways, such as assuming growing seasons between pest and host continue to match and assuming that potatoes will be equally susceptible to blight attack in the future. These assumptions are based upon work that highlights the continued vulnerability of crops to pests and their continued matching phenologies (Oerke, 2006; Bebber et al., 2014a).

### 6.4.2 Conclusions and future work

Improved crop model simulations would allow us to have more confidence in yield change predictions across the globe. Multiple crop models and input data sets (such as soil, growing area and irrigation data sets) could be used to better estimate the uncertainty associated with projected yields. Better crop management and phenology information (planting and harvesting dates) would in particular improve results (van Bussel, 2011), although more accurate global data are not currently available.

There is some uncertainty as to when the majority of the potato crop is harvested in some tropical countries, and therefore which years of observed yield data should be associated with crop model simulations. Future potato model simulations could alter the years associated with the observed yield data (as in Müller et al., 2017) to see if results in these areas improve. These issues are an example of those that come from using national scale yield data – related issues include differing yield variability across spatial scales.

Future work should focus on improving the treatment of potato growing seasons (perhaps by subdividing large countries into important potato growing areas), improving the impacts of heat stress on potato yields and developing more sophisticated irrigation and flooding parameterisations. With more detailed information on potato irrigation, a less crude method could be used that takes into account the differing amounts of irrigation across regions. With a flooding parameterisation, regions such as eastern Europe – that show a negative observed yield-rainfall relationship due to excessive rainfall during part of the growing season (Schleyer, 2017) – may be better simulated.

Some crop models simulate the impacts of pests and diseases on crops directly, although this is rare (Rivington and Koo, 2011). Future work using SimCastMeta could include a resistant potato variety (in addition to the susceptible potato variety used in this analysis), to see how much this could mitigate the projected increases in blight risk. Future work would also be enhanced by simulating other potato pests of global importance, or of particular importance in key potato growing areas. Linking predictive models of likely blight risk to levels of yield loss is also a priority, as this would allow us to quantify the impacts of pests on production and therefore food security. This would require sufficient data to validate causal relationships between pest stresses and yield losses, however, and data are famously lacking in the field (no pun intended) of biotic stresses (Donatelli et al., 2017; Bale et al., 2002).

Agricultural revolution could render current modelling studies obsolete by mid-century. The purpose of this work is to point to likely climatic limitations and opportunities, however, rather than perfectly predict the state of potato agriculture by 2050. Future work could make use of climate suitability algorithms that predict future suitable potato growing areas (Schafleitner et al., 2011) to further enhance these efforts. Scenarios of varying optimism regarding technological improvements could also be included. Different adaptation scenarios that explore the extent to which planting dates and varieties are allowed to be varied in different regions could inform adaptation options with greater sophistication.

This study shows that yields in important potato growing areas in the northern hemisphere could increase by over 50% by the mid-21st century. This number is subject to uncertainty from climate models, $CO_2$ fertilisation and ozone damage however. The largest source of uncertainty comes from the climate model inputs (varying substantially per country), with smaller (c. 10%) uncertainty over the parameterisation of $CO_2$ fertilisation and ozone damage. Therefore, although the sign of yield change in Europe is relatively certain, the magnitude of the effect is not. Globally, the sign of yield change is less certain due to smaller projected yield gains with adaptation (c. 30%), the aforementioned uncertainties and poor model skill in important production regions of the USA, India and China.

It is important to note the predicted increases in blight attack in these regions, however. Whilst these blight increases cannot currently be translated into impacts on production, blight is commonly responsible for substantial yield losses that can be as high as 30% (Dowley et al., 2008; Oerke, 2006). Such decreases in yields from unchecked pests and diseases could reduce expected yield gains from $CO_2$ fertilisation and adaptation to climate change.

# Chapter 7

# The influence of climate change on crop pests and diseases: pesticide analysis

## 7.1 Introduction

Pests and diseases (hereafter collectively referred to as "pests") are moving polewards in response to increasing temperatures (Bebber et al., 2013) and are increasingly present in the areas in which their host crops are found (Bebber et al., 2014a). As a result, changes to the magnitude and frequency of pest outbreaks – rather than distribution – are likely to be of more importance to food security in the coming decades. Modelling of pest distributions based on climate variables remains more common, however (e.g. see Sutherst, 2014).

Temperature is usually an important climatic variable in determining the intensity of disease and insect pest outbreaks (Cammell and Knight, 1992). Minimum temperatures are of particular importance in temperate areas, with low winter temperatures being an important limiting factor to survival (Ziska, 2014; Bale et al., 2002). Research into the impacts of precipitation is not as common (Bale et al., 2002), although humidity (and therefore precipitation) is especially important for the intensity of fungal pathogen outbreaks (Bebber, 2015), which are among the most important in terms of crop losses (Bebber and Gurr, 2015; Oerke, 2006). The oomycete late blight *Phytophthora infestans* is an example of a fungal-like disease of global important to potato agriculture specifically. Both temperature and relative humidity are important for determining the intensity of blight outbreaks. See Chapter 6 for an analysis of how this disease responds to climate change specifically. See Chapter 1 for more on pests, climate and crops.

Relationships at large spatial extents (i.e. greater than the province or farm level) between pests and climate (as well as socio-economic factors) have been demonstrated, primarily concerned with warming and range expansions (Bebber et al., 2014b, 2013), including at the continental and global level (Parmesan and Yohe, 2003). Pest distributions are significantly predicted by per capita Gross Domestic Product (GDP), for example (Bebber et al., 2014b). Globally comprehensive pest abundance and damage data are lacking, however, that would enable us to validate models that assess risk of pest attacks (Donatelli et al., 2017).

Pest management will have to adapt in future to respond to changes in pest outbreaks. Pest management techniques include cultural (e.g. crop rotation or selection of pest-resistant varieties), biological (e.g. natural enemies) and chemical (i.e. pesticide) control. Pesticides are a very common form of pest control and are arguably the most important component of Integrated Pest Management (Alyokhin et al., 2015; Guedes et al., 2016). Pesticides remain vital for crop production and their use is increasing (FAO, 2016) despite potential toxicity to humans and other (non-targeted) organisms when poorly regulated (Coats, 1994). The level of pesticide use in a country is a function of legislative limits, economic access, agricultural technology (Law, 2001) and area as well as environmental factors, including the abundance and intensity of pest outbreaks (Delcour et al., 2015).

Maximum Residue Limits (MRLs) are the primary means by which pesticides are regulated across the globe (Delcour et al., 2015; Handford et al., 2015). MRLs are defined by the European Food Safety Authority as "the upper legal levels of a concentration for pesticide residues in or on food or feed based on good agricultural practices (GAP) and to ensure the lowest possible consumer exposure". They aim to restrict the maximum amount of pesticides that are present in foodstuffs to ensure consumer safety.

The economic conditions in a country can influence the level of pesticides applied through various means. Pesticide companies primarily target major crops to maximise profits as only few crops (wheat, rice, maize and potato for example) dominate global agricultural production (FAO, 2016; Delcour et al., 2015). There are therefore fewer pesticides available for the small-scale farming systems more commonly found in poorer countries (Collier and Dercon, 2014). More obviously, the rate at which pesticides will be applied will largely be determined by prices and application costs (Delcour et al., 2015).

Pests are rarely modelled explicitly in crop models (Rivington and Koo, 2011 – see Chapter 1), so even simple modelling options that estimate the impacts of climate change on pest pressures at large scales are scarce. Modelling on larger scales is of increasing importance as the agricultural sector becomes ever-more globalised, resulting in the proliferation of pest species across continents (e.g. Hulme, 2009). Global climate data sets are becoming increasingly common (e.g. Sheffield et al., 2006, Ruane et al., 2014, Hempel et al., 2013), allowing large-scale analyses of pests with climate variables to take place (e.g. Sparks et al., 2011), although large scale pest data sets remain rare (Donatelli et al., 2017). Smaller-scale, non-climatic processes can average out at larger scales, allowing climate to become a more important determinant of pest outbreaks (Parmesan and Yohe, 2003). Pest severity will increase in some species and decrease in others, making broad conclusions and policy recommendations difficult at large scales (Newbery et al., 2016).

Models that seek to represent pest impacts on crops and changing pest pressures vary in complexity and scope. They range from simple statistical models to complex process-based models; from site-based analyses to global simulations (see Chapter 1). An example of a simple statistical approach is that used by Ziska (2014). In this study, the relationship between daily minimum temperatures and pesticide application rates on soybean was used to predict changes in pest pressures in response to climate for seven locations in the mid-west United States. An attraction of using pesticide data as a proxy for pest pressure data is that it is readily available at the country scale (FAO, 2016) in many areas - data can be a limiting factor to more complex modelling approaches (Jagtap and Jones, 2002), making larger scale analyses difficult. Pesticide data also represent multiple pest species, in that their use at large scales is not commonly associated with a single pest.

Ziska (2014) related minimum temperature to pesticide data at each location using regression analysis. Ziska (2014) also separately examined insecticide, herbicide and fungicide use per area data in order to disaggregate the statistical relationships found in different pest groups. In doing so, the impacts of climate change on pests can be shown by proxy. Ziska (2014) found that there were positive relationships with temperature for all pesticide classes, with warming linked to potential increases in pest pressures in the USA.

An earlier study of Chen and McCarl (2001) used a similar statistical approach to link both temperature and precipitation to pesticide cost, again across the United States. This study found that increases in temperature and precipitation resulted in an increase in pesticide cost for the majority of crops in the US. This was attributed to increasing severity of pest outbreaks, resulting in more pesticide use being predicted with climate change. The work of Ghimire and Woodward (2013) linked pesticide data to various social, economic and climate variables, but did not estimate changes to pesticide use with climate change. This study suggested pesticides are being under-used in developing countries and over-used in developed countries.

The complexities of the impacts of climate on pesticide use are described in Delcour et al. (2015). The general pattern is for usage to increase with rising temperatures due to increasing pest pressures and in some cases enhanced crop growth (Delcour et al., 2015). Pesticide efficiency is affected by changes in climate through temperature increases leading to increased toxicity, but warming also increases chemical degradation (Noyes et al., 2009). Precipitation increases lead to enhanced pesticide run-off (Noyes et al., 2009).

The objective of this chapter is to examine the potential of simple statistical modelling for informing our understanding of how climate change influences global pesticide use (and by proxy the intensity of pest pressures). Given the links between pests and climate at large scales, it is hypothesised that significant relationships between pesticide use and climate variables exist that can be used to estimate the impacts of climate change on pesticide use. This chapter complements the late blight modelling work in Chapter 6 as it uses data to evaluate global scale pesticide-climate relationships. These relationships are also broader than those associated with the single (albeit important) pest species modelled in Chapter 6.

This work therefore provides an analysis of the impacts of climate change on pests - are the intensity of pest pressures on crops likely to increase with increasing temperatures and changing precipitation patterns? The previous studies of Ziska (2014) and Chen and McCarl (2001) related climate variables to pesticide use and extrapolated for future climate scenarios in specific sites in the United States. Ghimire and Woodward (2013) looked at how pesticide use is related to climate and socio-economic variables across 94 countries. This work builds upon these previous studies by relating pesticide use to these variables and extrapolating future climate impacts on pesticide use globally for the first time.

### 7.1.1 Research questions

1. Is there a relationship between pesticide use and climate at large spatial scales?
2. Is there a stronger relationship between pesticide use and climate when taking into account GDP?
3. Is there more variability in pesticide use between countries or temporally within countries?
4. How will climate change affect pesticide use?

## 7.2 Methods overview

### 7.2.1 Summary

This work consists of two analyses: the correlation analysis looking at both within- and between-country variability in pesticide data (Section 7.3) and the statistical model analysis (Section 7.4) that looks at climate change impacts on pesticide use. See Table 7.1 for a summary of the analyses and Table 7.2 for a summary of variables used in these analyses.

**Table 7.1:** Summary of the analyses in this chapter.

| Analysis | Description |
|---|---|
| **Correlation analysis: within countries** Methods - Section 7.3.1 Results - Section 7.3.2.1 | Correlations of pesticide use with time series of climate and economic variables for each country time series. |
| **Correlation analysis: between countries** Methods - Section 7.3.1 Results - Section 7.3.2.2 | Correlations of pesticide use with climate and economic variables averaging time series for each country and correlating variables for each continent. |
| **Statistical models** Methods - Section 7.4.1 Results - Section 7.4.2 | Statistical models calibrated on baseline climate and pesticide data and used to project pesticide use with future climate data. |

**Table 7.2:** Variables used in the correlation and statistical model analyses.

| Variable | Definition (unit) | Section |
|---|---|---|
| $P$ | Pesticide use per area data (tonnes 1000ha$^{-1}$) | 7.2.2.1 |
| $Tm$ | Mean temperature (°C) | 7.2.2.2 |
| $R$ | Precipitation (mm day$^{-1}$) | 7.2.2.2 |
| $GDP$ | Gross Domestic Product (US$) | 7.2.2.3 |
| $GDP_{\%}$ | Percentage of GDP from agriculture (%) | 7.2.2.3 |
| $GDP_{A1}$ | GDP per agricultural area (US$ 1000ha$^{-1}$) | 7.2.2.3 |
| $GDP_{A2}$ | GDP per arable land and permanent crop area (US$ 1000ha$^{-1}$) | 7.2.2.3 |
| $MRL$ | Maximum Residue Limit (mg kg$^{-1}$) | 7.2.2.3 |

The correlation analysis relates historical climate and GDP variables to pesticide data within and between countries to answer research questions one, two and three.

Mean temperature $Tm$, precipitation $R$, $GDP$ and $MRL$ variables are correlated with pesticide data $P$ to answer research question one. Relationships are examined for each country-level time series, focusing on the relationships between pesticide use and climate for each country (the “within country” analysis). The “between country” analysis examines data between countries by continent, averaging the pesticide and climate variables for each country and examining the between-country variability in pesticide data.

Correlations inform which of the four GDP variables tested is used to answer research question two and in the climate change statistical models. The aim is to select one variable for modelling as they are not independent of each other. This is because they are largely comprised of the same GDP data, therefore explaining the same variation in pesticide use and not being independent variables.

To address research question two, correlations are examined for different groups of countries based on their GDP variable value. Countries with a higher GDP should be able to afford to use more pesticides on their crops, all other things being equal. It is therefore hypothesised that a stronger climate-pesticide relationship would emerge when looking at the highest countries with respect to the GDP variable.

The data are examined between countries in an analysis by continent, averaging the pesticide and climate variables for each country and examining the inter-country variability in pesticide data to address research question three. This informs how best to measure pesticide-climate relationships for the subsequent climate change modelling work. It is hypothesised that more pesticide variability exists between, rather than within, countries, and that this greater variability is due to climate-pesticide relationships being more of a determinant of pesticide variability at larger scales.

In Section 7.4, multiple linear regression models are defined and used to answer research question four - assessing the impacts of climate change on pesticide use. Following the calibration of these models using baseline climate data (Section 7.4.2.1), future climate data from 2041 to 2050 are used to extrapolate future pesticide use levels (Section 7.4.2.2). The GDP data are included in this modelling framework by analysing regressions based on all the data and separately using data from countries associated with high values of the GDP variable only.

### 7.2.2 Input data

#### 7.2.2.1 Pesticide data

Pesticide data $P$ are available from FAOSTAT (FAO, 2016). The pesticide data are collected by reporting national statistics of the quantities (in tonnes of active ingredients) of pesticides used in or sold to the agricultural sector for crops and seeds. Data are unavailable for individual crops such as potato, so all-crop pesticide use per area data are used. Pesticide use per area data are calculated by finding the total pesticide use for each country and dividing it by the total arable land and permanent crop area (also available from FAOSTAT). These data are available for 149 countries with varying lengths of time series, from some countries with a single year of data to 16 countries with a time series between 1990 to 2010. The average length of time series is 11.34 years. Eight countries are excluded from the analysis as they have time series of less than three years. Six countries have time series of three years, 14 have time series of four years and 103 have time series of five or more years (see Figures 7.1 and 7.2). Short time series in some regions helped to inform which variables to include in the statistical models – see Section 7.4.1.

The pesticide data were analysed for trends through time using a robust regression technique. Robust regression was used to fit models to the data using the R package "robust" (Wang et al., 2014), as this is superior to ordinary least squares regression when data contain outliers or otherwise break the assumptions associated with linear models (Finger, 2010). A previous study found no significant trends of pesticide data through time (Chen and McCarl, 2001). Here, 59 of the 149 countries showed significant linear trends through time – 19 in Europe (50% of European countries), 15 in Asia (44% of Asian countries), 11 in Africa (29% of African countries), 9 in South America (75% of South America countries) and 5 in North America (28% of North America countries). 43 of the trend countries showed a positive relationship through time, i.e. pesticide use has significantly increased through time. Detrending of these time series was not undertaken as the purpose of this would be to remove trends that result from factors not included in modelling. Relationships between pesticide use and the factors included in the models (weather and socio-economic variables) weakened in all cases following detrending, so detrending was not performed.

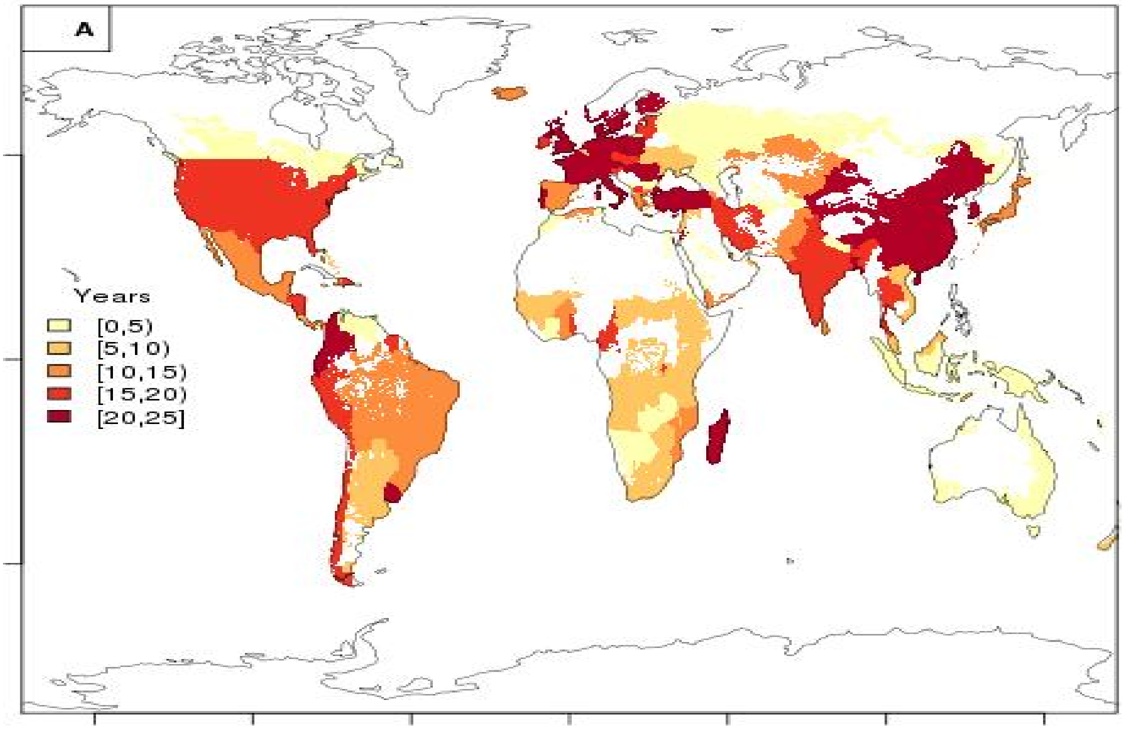



**Figure 7.1:** Length of pesticide use time series across countries.

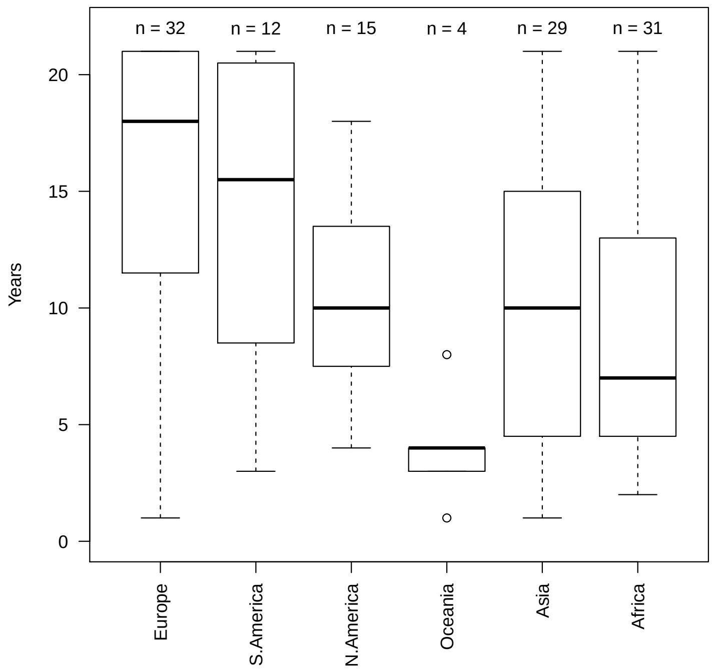



**Figure 7.2:** Length of pesticide time series across continents. n = number of countries in each continent.

#### 7.2.2.2 Climate data

The AgMERRA (Agriculture Modern-Era Restrospective analysis for Research and Applications) data set (Ruane et al., 2014) at 0.5° resolution is used for baseline climate data in the correlation analyses of Sections 7.3.2.1 and 7.3.2.2. These data are representative of years 1990 to 2010 to match the available pesticide data period. See Chapter 3, Section 3.2.1.2 for further description of these data.

ISI-MIP (Inter-Sectoral Impact Model Intercomparison Project) bias-corrected input data at 0.5° resolution are used for climate changes from the baseline to the future (Hempel et al., 2013) in the statistical model analysis of Section 7.4. Future climate data are compared to historical ISI-MIP data for extrapolation of pesticide use into the future. See Chapter 6, Section 6.2.2.1 for a description of the ISI-MIP data.

The climate data are used from the above data sets only from grid cells where agriculture is present. The crop land area data from the year 2000 from NASA's Socio-Economic Data and Applications Center (SEDAC) are used as shown in Figure 7.3 (SEDAC, 2012) at 0.5° resolution. For countries where crop land area data are absent, the climate data are averaged over all grid cells in that country (these countries were the Bahamas, Barbados, Cape Verde, Cook Islands, Fiji, French Polynesia, Iceland, Malta, Mauritius, New Caledonia, Qatar, St. Kitts and Nevis, St. Lucia, Samoa, Seychelles and Vanuatu). Otherwise, climate data were averaged over the grid cells covered by the crop mask.

Shapefiles from the Database of Global Administrative Areas are used to define country boundaries used in this analysis (www.gadm.org). Gridding and preparation of the data is performed using the statistical package R (R Core Team, 2017).

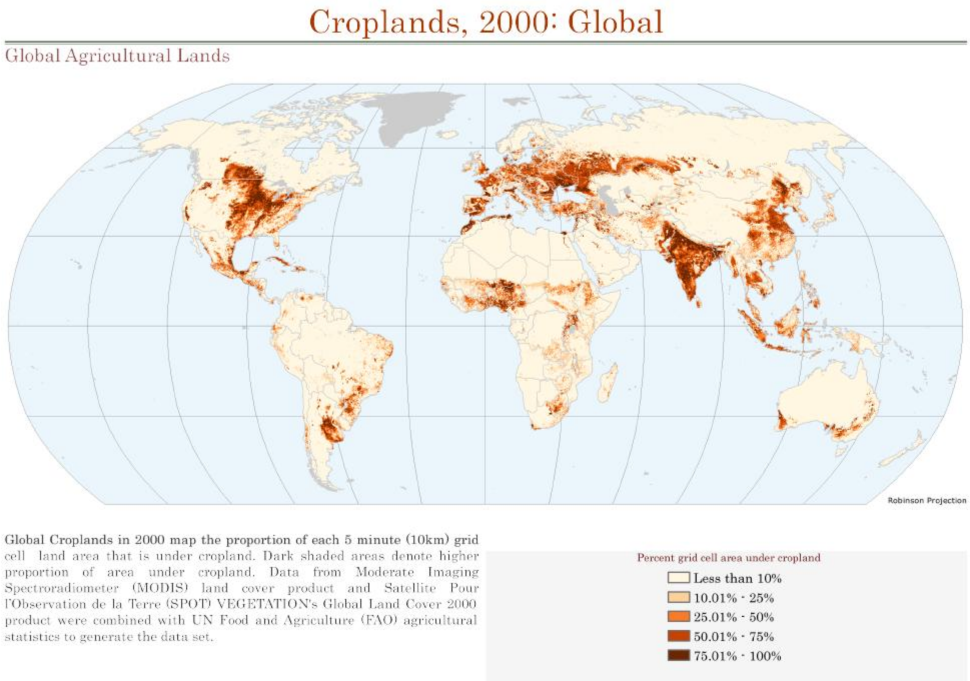



**Figure 7.3:** Map of agricultural land used. Figure taken from SEDAC (2012).

#### 7.2.2.3 Socio-economic data

Four variables (see Table 7.2 in Section 7.2.1) involving agricultural area and economic data are examined in order to explore the relationship between economics and pesticide use. These are Gross Domestic Product $GDP$ from the World Bank (data.worldbank.org), the value added by agriculture $GDP_{\%}$ (as a percentage of GDP, also from the World Bank, www.data.worldbank.org) and two measures of GDP per agricultural area: GDP divided by the total agricultural area including livestock land $GDP_{A1}$ and GDP divided by the arable land and permanent crop area $GDP_{A2}$, both from FAOSTAT (FAO, 2016).

The GDP data are examined across the years for each country that have pesticide data, save for Myanmar and the Cook Islands, where no World Bank data are available. For these two countries, the 2005 value of GDP is used from the UN Statistics Division (http://data.un.org). $GDP_{\%}$ is the net output of the agricultural sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. $GDP_{A1}$ and $GDP_{A2}$ represent the relative size of the economy of a country and the amount of agriculture in that country - how much money can potentially be spent on agriculture when normalised by agricultural area.

Maximum Residue Limit (MRL) data are from the Global MRL database (www. globalmrl.com). MRL data from 82 countries were available at the time of this analysis. The data used in correlations in Section 7.3.2.2 are the mean value of MRLs for each country (averaged across years with pesticide data).

Whilst technological development is important for rates of pesticide application (see Section 7.1), it is assumed that as it is related to GDP (e.g. see Mowery and Rosenberg, 1991) it was not necessary to include in this analysis; the short pesticide variable lengths in this analysis necessitate relatively few variables in modelling.

## 7.3 Correlation analysis

### 7.3.1 Methods

Pesticide data are correlated with AgMERRA climate and socio-economic data to assess research question one - is there a relationship between climate and pesticide use? Two methods of correlating the data are used: "between-countries" and "within-countries" to assess research question three - is there more variability between or within countries? Time series of pesticide use for each country are examined for the within-country work. For between-country work, the variables are averaged for each country and a single correlation calculated for each continent. Oceania is excluded from between-country work due to a lack of GDP data in many countries. The two methods of analysis aim to see if there is more pesticide variability – and potentially stronger climate-pesticide relationships – between or within countries. In all cases, correlations are Pearson's product moment correlations using the base statistical package of R (R Core Team, 2017).

MRL and GDP data are correlated with pesticide data to assess their importance for predicting pesticide use. MRL data are excluded from the within-country analysis as only one value is associated with each country (i.e. there is no temporal variability in the data). The four GDP variables (see Section 7.2.2.3) are correlated with pesticide data in order to see which is the best predictor of pesticide use to include in the subsequent statistical modelling framework.

To test the hypothesis that higher GDP countries show a stronger relationship with climate variables (research question two), different GDP bins are tested in the between country correlation analysis. The countries are examined as part of three different groups: the lowest 33%, middle 33% and highest 33% GDP variable countries (subsequently referred to as low, medium and high GDP bins).

### 7.3.2 Results

#### 7.3.2.1 Within countries

Within-country correlations are presented in Table 7.3 and Figures 7.4 to 7.9.

Slightly more significant correlations within countries are associated with precipitation rather than temperature (see Figures 7.4 and 7.5). Most of the significant correlations with climate variables are positive – higher temperatures and wetter conditions more often than not are associated with higher pesticide usage rates. The temporal variability is dominated by the GDP signal, however (see Figures 7.6, 7.7, 7.8, and 7.9 for $GDP$, $GDP_{\%}$ $GDP_{A1}$ and $GDP_{A2}$ correlations respectively), with relatively few significant correlations with climate variables. The significant correlations with climate variables that are found are concentrated in tropical areas, with very few being in temperate countries. There are more positive than negative significant correlations with GDP variables apart from $GDP_{\%}$, which shows more negative correlations with pesticide use.

The within-country correlations show that $GDP_{A1}$ is more of a predictor of pesticide use than the other GDP variables tested (see Table 7.3). This was therefore chosen as the GDP variable used in subsequent climate change statistical modelling (Section 7.4.1 describes the models). A different GDP variable to $GDP_{A1}$ had a significantly higher correlation in only 30% of countries. $GDP$ and $GDP_{A2}$ are also significantly correlated with pesticide use in a large number of cases – the GDP data being the largest determinant of pesticide use found in this study, more so than legislative or climatic data.

**Table 7.3:** Mean within-country correlations between pesticide use and GDP variables. $GDP$ is the Gross Domestic Product, $GDP_{\%}$ is the percentage of value added by agriculture, $GDP_{A1}$ is GDP normalised by agricultural area including livestock areas and $GDP_{A2}$ is GDP normalised by arable agricultural area.

| Continent | $GDP$ | $GDP_{\%}$ | $GDP_{A1}$ | $GDP_{A2}$ |
|---|---|---|---|---|
| Europe | 0.20 | -0.01 | 0.21 | 0.21 |
| South America | 0.76 | -0.39 | 0.76 | 0.73 |
| North America | 0.35 | -0.11 | 0.34 | 0.33 |
| Oceania | 0.48 | -0.02 | 0.49 | 0.45 |
| Asia | 0.18 | -0.08 | 0.18 | 0.18 |
| Africa | 0.17 | -0.16 | 0.23 | 0.21 |
| Global | 0.36 | -0.13 | 0.37 | 0.35 |

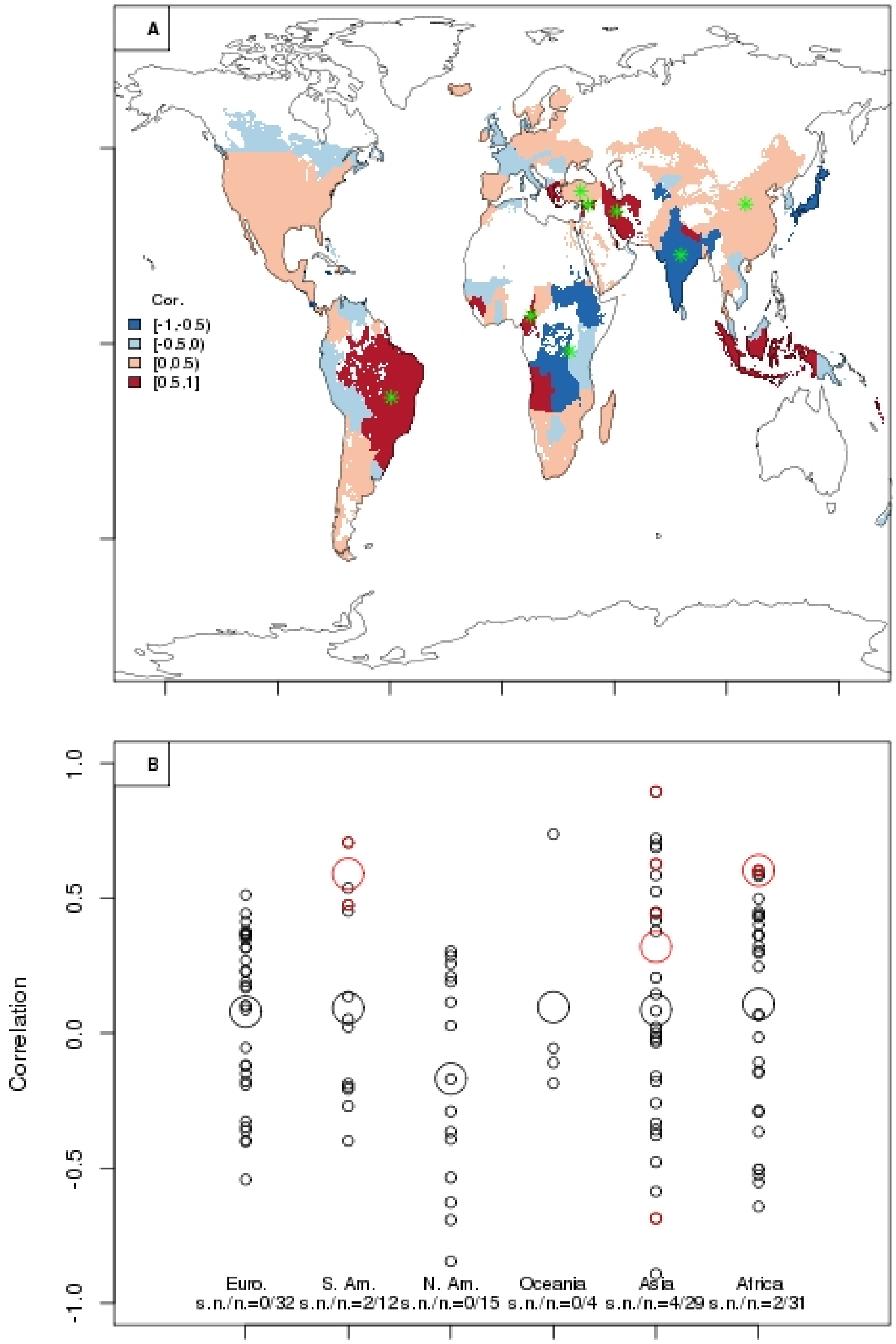



**Figure 7.4:** Correlations of $P$ data with mean temperature $Tm$. A: mapped correlations. Green stars indicate significant correlations. B: correlations of each country shown by continent. Small red circles indicate countries with significant correlations. The large black circle indicates the mean correlation across countries for each continent. The large red circle indicates the mean significant correlation. "n." refers to the number of countries, "s.n." refers to the number of significant countries.

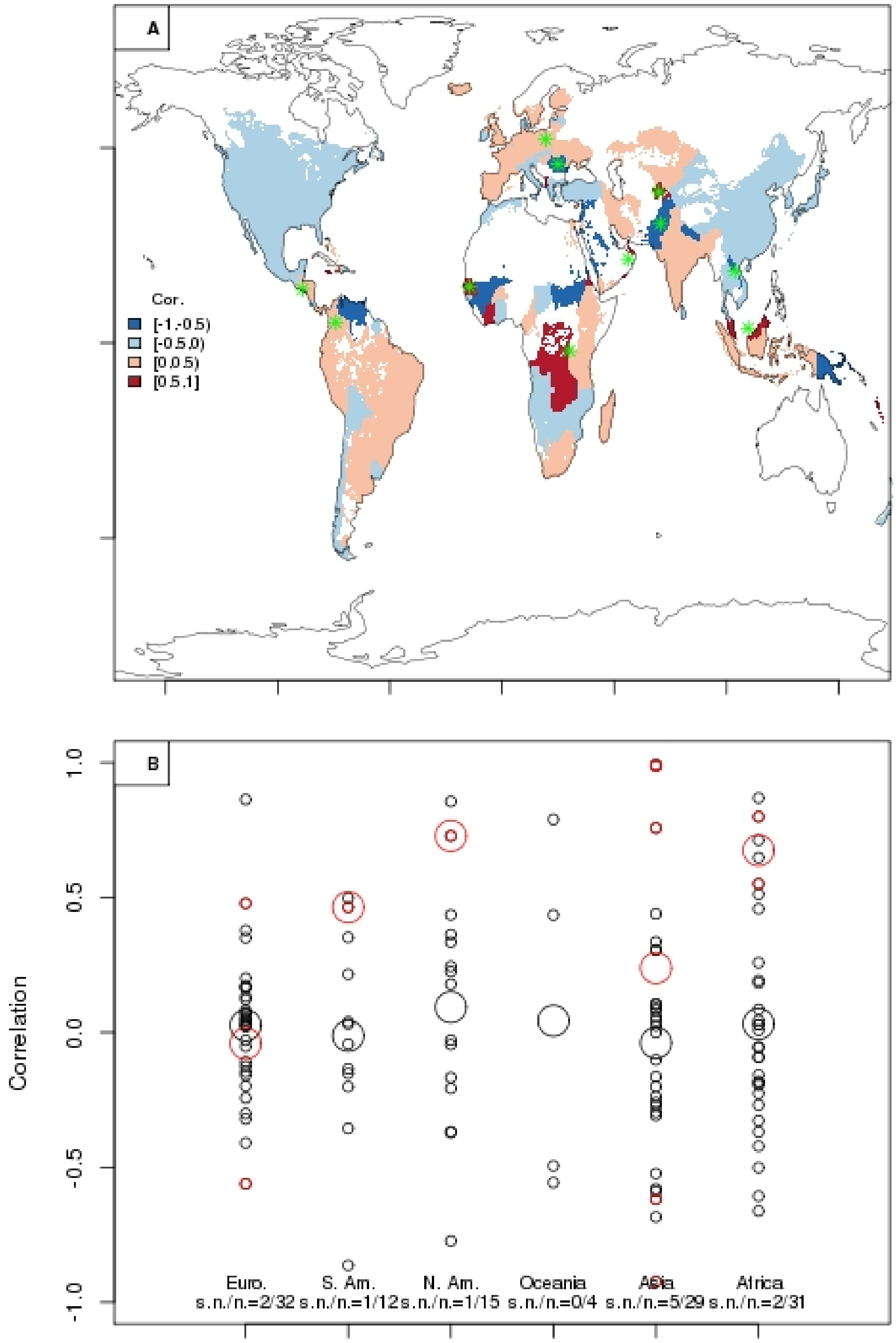



**Figure 7.5:** Correlations of $P$ data with precipitation $R$. A: mapped correlations. Green stars indicate significant correlations. B: correlations of each country shown by continent. Small red circles indicate countries with significant correlations. The large black circle indicates the mean correlation across countries for each continent. The large red circle indicates the mean significant correlation. "n." refers to the number of countries, "s.n." refers to the number of significant countries.

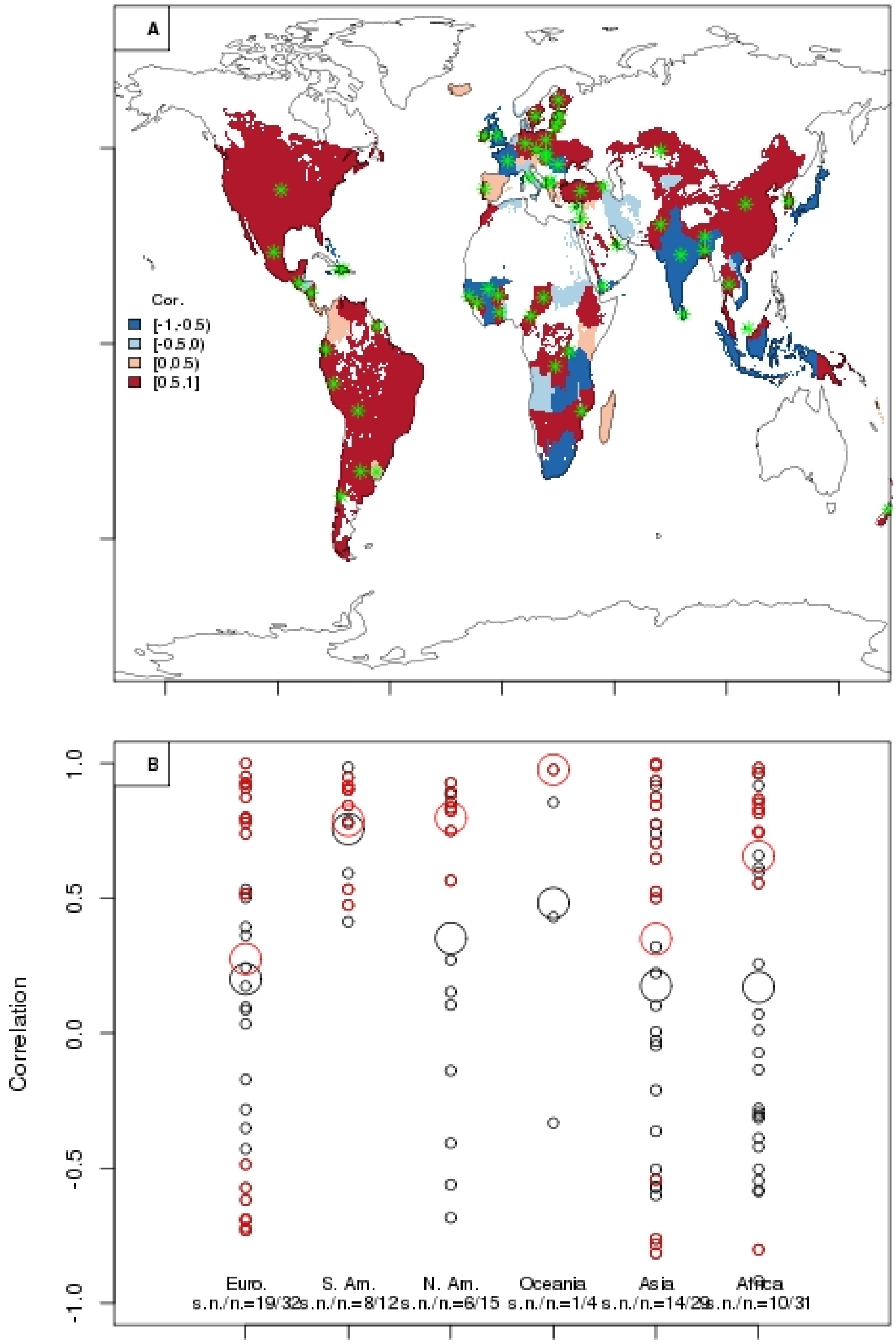



**Figure 7.6:** Correlations of $P$ data with $GDP$. A: mapped correlations. Green stars indicate significant correlations. B: correlations of each country shown by continent. Small red circles indicate countries with significant correlations. The large black circle indicates the mean correlation across countries for each continent. The large red circle indicates the mean significant correlation. "n." refers to the number of countries, "s.n." refers to the number of significant countries.

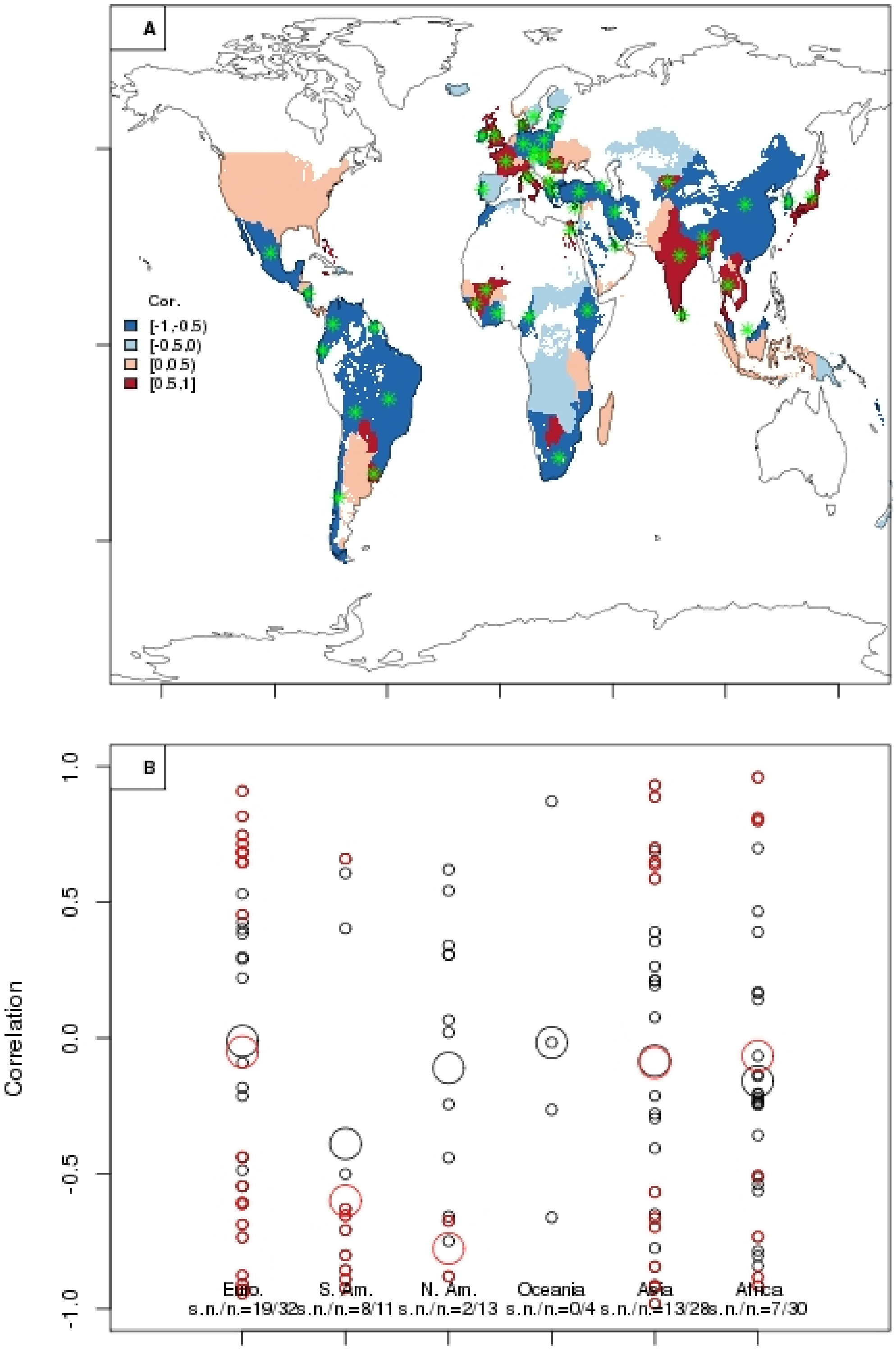



**Figure 7.7:** Correlations of $P$ data with $GDP_{\%}$. A: mapped correlations. Green stars indicate significant correlations. B: correlations of each country shown by continent. Small red circles indicate countries with significant correlations. The large black circle indicates the mean correlation across countries for each continent. The large red circle indicates the mean significant correlation. "n." refers to the number of countries, "s.n." refers to the number of significant countries.

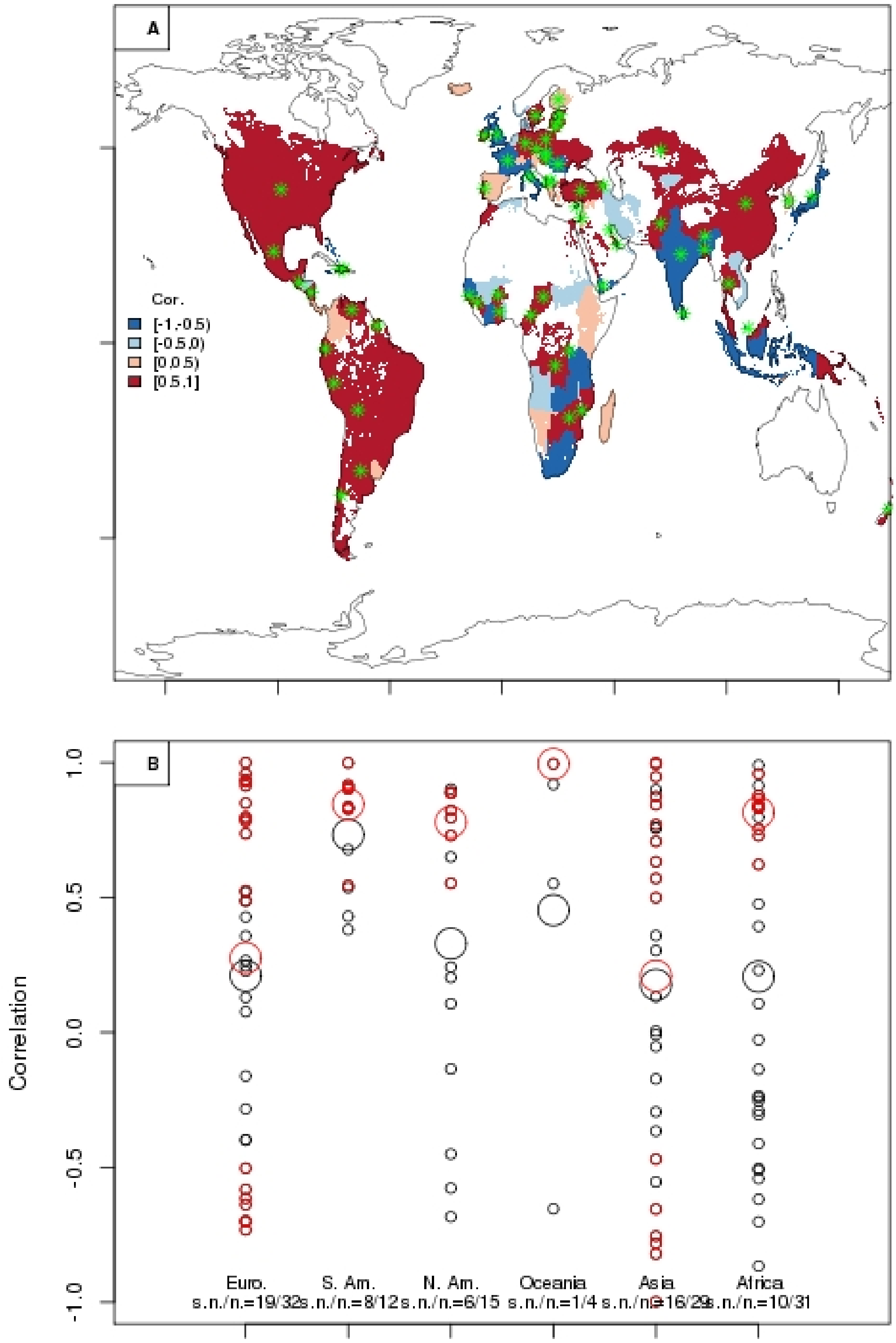



**Figure 7.8:** Correlations of $P$ data with $GDP_{A1}$. A: mapped correlations. Green stars indicate significant correlations. B: correlations of each country shown by continent. Small red circles indicate countries with significant correlations. The large black circle indicates the mean correlation across countries for each continent. The large red circle indicates the mean significant correlation. "n." refers to the number of countries, "s.n." refers to the number of significant countries.

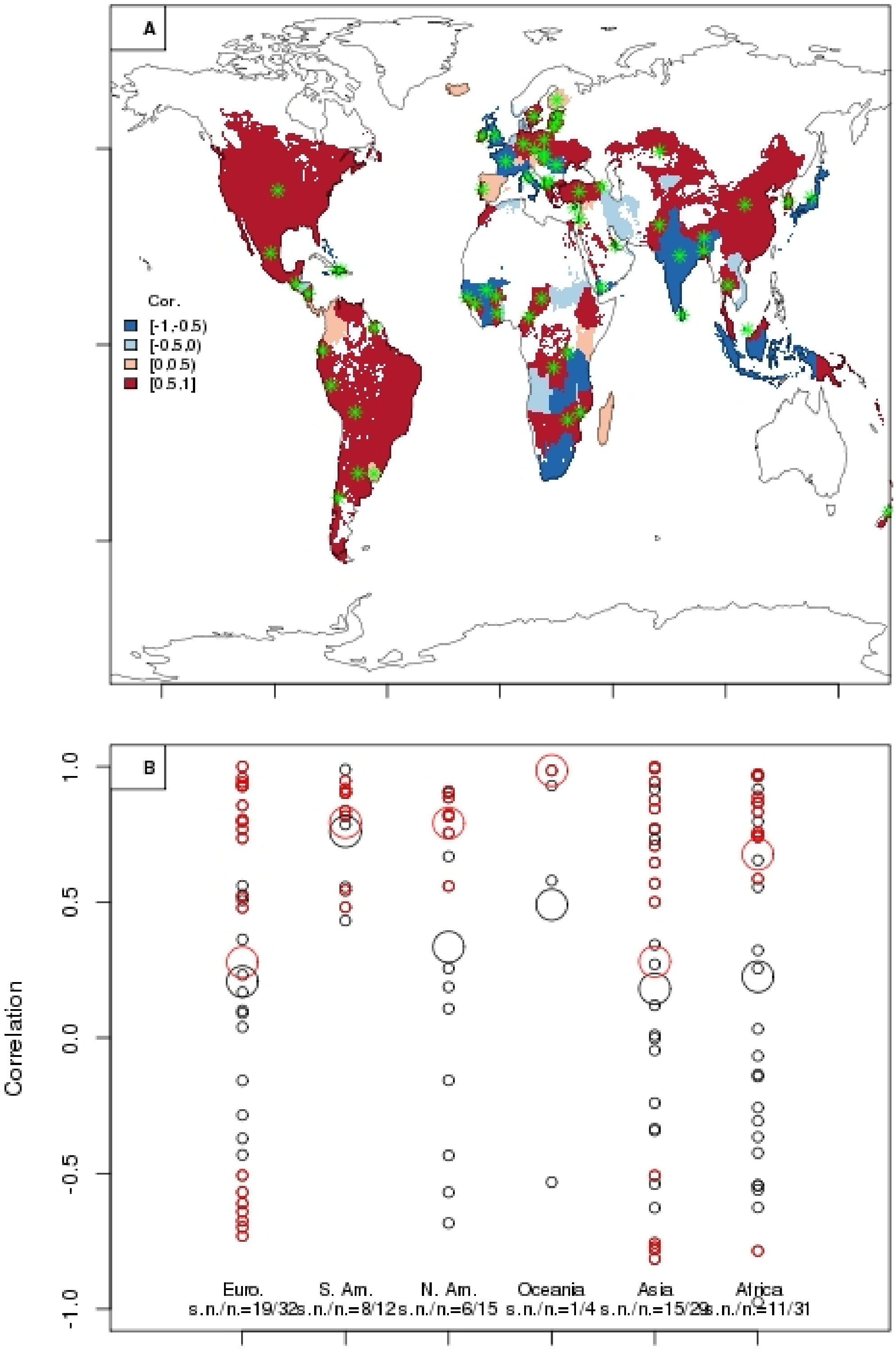



**Figure 7.9:** Correlations of $P$ data with $GDP_{A2}$. A: mapped correlations. Green stars indicate significant correlations. B: correlations of each country shown by continent. Small red circles indicate countries with significant correlations. The large black circle indicates the mean correlation across countries for each continent. The large red circle indicates the mean significant correlation. "n." refers to the number of countries, "s.n." refers to the number of significant countries.

#### 7.3.2.2 Between countries

Tables 7.4 and 7.5 and Figure 7.10 show correlation results between countries.

There is most often more variability in pesticide use between than within countries. The exception to this is in South America, where there is higher variability within country time series. This is the result of GDP variables predicting high variability within South American time series. In three continents, however, variability is at least an order of magnitude higher between countries (Table 7.4). As a result of this greater variability in between-country pesticide use variables, correlations with climate variables are, on average, higher. Whilst GDP is still a strong determinant of pesticide use between countries, the magnitude of the correlations between pesticide use with climate variables is comparable to those with the GDP variables.

The different GDP bins show some evidence of stronger correlations with mean temperature and pesticide use as you go from low to high bins (see Figure 7.10). Europe and Asia especially show this, with correlations becoming significant in the high bin. North America also shows a less strong sign of the same pattern. There is no such trend with precipitation correlations, however, with significant correlations appearing in the low, medium and high bins in different continents.

**Table 7.4:** Mean variability $(t/ha)^2$ across countries in pesticide use per area data and the variability in pesticide use per area data at the continental level.

| Continent | Country | Continent |
|---|---|---|
| Europe | 1.06 | 12.04 |
| South America | 18.49 | 15.74 |
| North America | 28.26 | 402.64 |
| Asia | 1.51 | 18.03 |
| Africa | 0.27 | 0.41 |

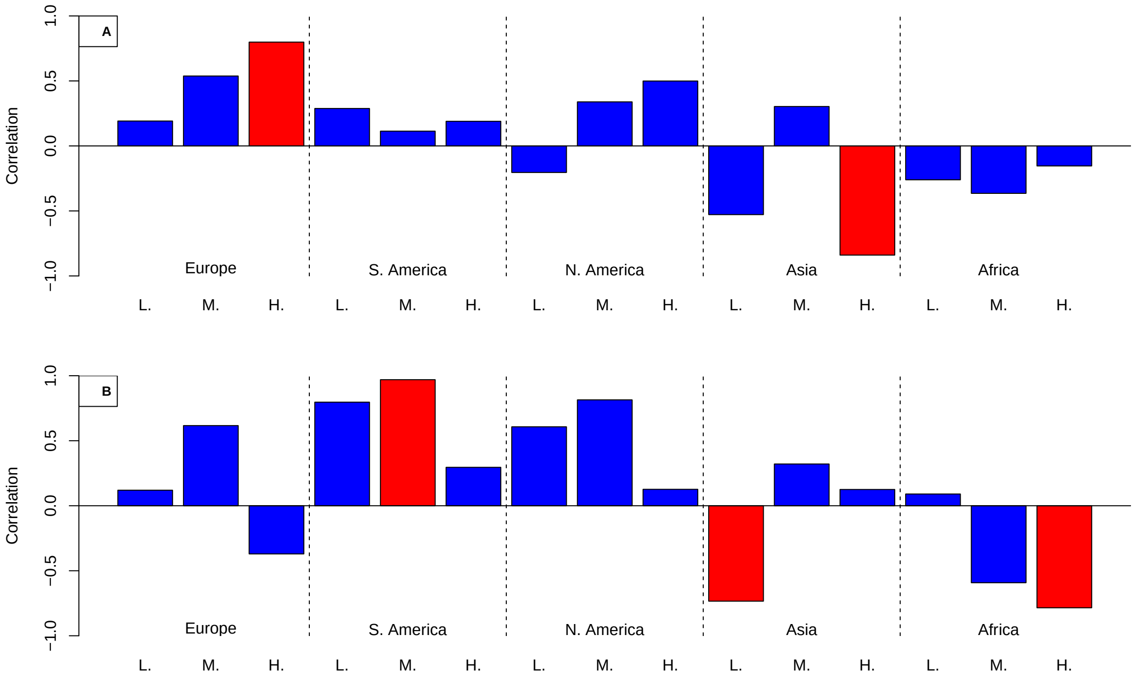



**Figure 7.10:** Correlations of mean temperature (A) and precipitation (B) with pesticide use across continents for different GDP bins. Red bars are significant correlations at the 0.05 level L., M. and H. refer to Low, Medium and High GDP bins respectively, which are the lower, middle and upper 33% of countries within each continent when ranked by GDP.

Maximum Residue Limits (MRLs) are found to have insignificant correlations with pesticide use across continents (and globally) save for Africa, which has a significant negative correlation (see Table 7.5) – this is expanded upon in Discussion. All MRL values are identical in European countries, as they are subject to European Union legislation (therefore no correlation can be calculated). The only other continent to show a large positive correlation is Oceania, but this is insignificant (only being comprised of three observations in the MRL data set). As there is only one significant correlation observed between countries and no varying data for Europe, MRLs are not included in the statistical model framework.

The between country correlations of pesticide use with $GDP_{A1}$ are shown in Table 7.5. GDP remains a strong determinant of pesticide use. These are significant at the 5% level apart from Oceania (where there are only four observations) and South America. In South America, GDP is an important determinant of pesticide use but there is relatively low variability in the GDP variable, resulting in an insignificant correlation between countries.

**Table 7.5:** Correlations between $P$ and MRL and $GDP_{A1}$ between countries for each continent. p-values in brackets.

| Continent | $MRL$ | $GDP_{A1}$ |
|---|---|---|
| Europe | n/a | 0.50 (<.01) |
| South America | 0.06 (0.89) | 0.41 (0.19) |
| North America | 0.23 (0.43) | 0.95 (<.01) |
| Oceania | 0.97 (0.17) | -0.10 (0.90) |
| Asia | -0.31 (0.21) | 0.39 (0.03) |
| Africa | -0.83 (0.02) | 0.80 (<.01) |
| Global | 0.19 (0.08) | 0.36 (<.01) |

## 7.4 Statistical models

### 7.4.1 Methods

This section describes the creation of statistical models that are used to address research question four – what are the impacts of climate change on pesticide use? Statistical models are first calibrated on baseline ISI-MIP climate data (results in Section 7.4.2.1) and then used to extrapolate future pesticide use using future ISI-MIP climate data (results in Section 7.4.2.2).

The correlation analysis shows that there are limited significant relationships between climate and pesticide use within countries, but between countries this climate signal is stronger. The statistical models are therefore "between-country" models, following the between-country correlations - comprising of country-level data that are averaged for each country and modelled at the continental level. Oceania was excluded from this work due to a lack of GDP data in many countries.

The least limiting countries with respect to GDP (i.e. the high GDP bin countries - see Section 7.3.1 for a description of the bins) are examined independently for changes to future pesticide use, as these countries showed a stronger temperature-pesticide use correlation in some cases (Section 7.3.2.2).

Two multiple linear regression models are therefore created for each continent – one comprising of all the country data for that continent, the other made up of data from only high GDP bin countries. Following the methods of Ziska (2014), each data point in these models represents a temporally- and spatially-averaged country of pesticide and climate data - i.e. the data are averaged over the years that pesticide data are available and across the grid cells in that country that have agriculture. Given the limited data that make up each regression (maximum $n$ of 32 for the European model – see Figure 7.2 in Section 7.2.2.1 for time series length) only a small number of variables can be included in each model to avoid overtuning. As discussed in Babyak (2004), including too many variables in regressions comprised of limited data can lead to estimates varying wildly given different samples taken from a population – i.e. we can have less confidence in coefficients obtained when looking at small sample sizes. Babyak (2004) suggest 10-15 observations per variable in linear regression analyses (although this is dependent on the effect size as well as other factors, rather than meant as an explicit rule to follow). Therefore only mean temperature $Tm$ and precipitation $R$ are included in models (these being important climatic variables for pest distribution and abundance, and shown to have relationships with pesticide data between countries in this chapter):

$$P(c) = Tm(c) + R(c) + e \tag{7.1}$$

where $P$ is pesticide use per area, $c$ is each country and $e$ is a Gaussian error term.

Using the models represented by Equation 7.1, the impacts of climate change on pesticide use are assessed using mean temperature and precipitation changes from the baseline period to the period of 2041 to 2050. The models are calibrated on baseline climate data from five climate models and then run using future climate data to project future pesticide use.

### 7.4.2 Results

#### 7.4.2.1 Baseline climate

Significant regression models are found in all continents save North America – i.e. significant variability in pesticide use is predicted by the models in the baseline period (Table 7.6). There are significant relationships with temperature in all continents save North America and Africa. Significant relationships with precipitation are found in South America and Africa. Temperature explains the majority of variation in pesticide use in Europe and Asia, whereas precipitation explains the majority in South America and Africa. The baseline climate data used are shown in Figure 7.11.

Despite the coefficients associated with mean temperature and precipitation in North America being insignificant, they are substantial in magnitude – larger than those of other continents. This results from the variability in the North American pesticide data being much higher than other continents (see Section 7.3.2). Indeed, the mean R squared value of 0.66 associated with the high GDP bin North American model is higher than some other significant models. This North American model is still insignificant as it contains a small number of data points.

All continents save South America show a higher R squared value for the higher GDP bin models. This is due to more variation being explained by temperature in the high GDP models. The high bin models are not always more significant, however, as a result of these models having fewer data points. The difference in precipitation variation explained by the high bin model is not so clear. South America shows a reduction in precipitation variation explained, resulting in this being the only continent to show a decrease in R squared for the high bin model. In contrast, the African model shows a substantial increase in precipitation variation explained by its high bin model, which is the main reason why this model has a higher R squared value.

**Table 7.6:** Regression results for each continent for both all data and the high GDP bin data (H.) models. Variable variation explained (Var.), coefficients (Coef.), p-values associated with coefficients (P.Val.), model R squared (R.Sq.) and model p-value (P.Val). Asterisks indicate significant models. Results shown are averaged across climate models, with ranges across models shown in brackets.

| Continent | R.Sq. | P.Val. | $T_m$.Var. | $T_m$.Coef. | $T_m$.P.Val. | $R$.Var. | $R$.Coef. | $R$.P.Val. |
|---|---|---|---|---|---|---|---|---|
| Europe* | 0.32 (0.31, 0.33) | <.01 (<.01, <.01) | 0.27 (0.26, 0.28) | 0.57 (0.55, 0.59) | <.01 (<.01, <.01) | 0.05 (0.04, 0.06) | 1.09 (1.00, 1.23) | 0.17 (0.11, 0.21) |
| Europe H.* | 0.64 (0.62, 0.65) | 0.02 (0.02, 0.02) | 0.62 (0.61, 0.63) | 0.97 (0.95, 0.99) | 0.01 (0.01, 0.02) | 0.02 (0.01, 0.02) | 0.86 (0.70, 0.98) | 0.56 (0.51, 0.63) |
| South America* | 0.62 (0.56, 0.67) | 0.01 (0.01, 0.02) | <.01 (<.01, <.01) | -0.54 (-0.57, -0.48) | 0.02 (0.01, 0.02) | 0.62 (0.56, 0.67) | 3.08 (2.81, 3.21) | <0.01 (<.01, 0.01) |
| South America H. | 0.14 (0.06, 0.38) | 0.92 (0.79, 0.97) | 0.05 (0.04, 0.05) | -0.16 (-0.57, 0.17) | 0.85 (0.63, 0.96) | 0.1 (0.01, 0.33) | 1.05 (-0.73, 3.12) | 0.82 (0.6, 0.92) |
| North America | 0.10 (0.07, 0.13) | 0.54 (0.43, 0.67) | 0.06 (0.06, 0.06) | 1.08 (0.65, 1.31) | 0.31 (0.21, 0.50) | 0.04 (0.00, 0.07) | -2.20 (-3.51, 0.78) | 0.54 (0.34, 0.84) |
| North America H. | 0.66 (0.43, 0.81) | 0.34 (0.19, 0.57) | 0.27 (0.26, 0.27) | 4.26 (3.63, 5.02) | 0.20 (0.10, 0.37) | 0.39 (0.16, 0.54) | -27.25 (-34.72, -19.27) | 0.28 (0.14, 0.53) |
| Asia | 0.01 (0.01, 0.01) | 0.89 (0.87, 0.91) | 0.01 (0.00, 0.01) | -0.05 (-0.05, -0.04) | 0.66 (0.64, 0.69) | <.01 (<.01, <.01) | 0.10 (0.10, 0.12) | 0.77 (0.73, 0.79) |
| Asia H.* | 0.72 (0.72, 0.73) | 0.01 (0.01, 0.01) | 0.72 (0.72, 0.73) | -0.75 (-0.75, -0.74) | <.01 (<.01, <.01) | <.01 (<.01, <.01) | -0.02 (-0.07, 0.03) | 0.95 (0.87, 0.99) |
| Africa* | 0.27 (0.25, 0.28) | 0.01 (0.01, 0.02) | 0.11 (0.10, 0.12) | -0.04 (-0.05, -0.04) | 0.17 (0.12, 0.27) | 0.16 (0.14, 0.18) | -0.21 (-0.22, -0.20) | 0.02 (0.01, 0.03) |
| Africa H.* | 0.77 (0.72, 0.81) | 0.01 (<.01, 0.01) | 0.02 (0.01, 0.02) | 0.08 (0.06, 0.10) | 0.11 (0.05, 0.22) | 0.76 (0.71, 0.79) | -0.57 (-0.63, -0.50) | <.01 (<.01, <.01) |

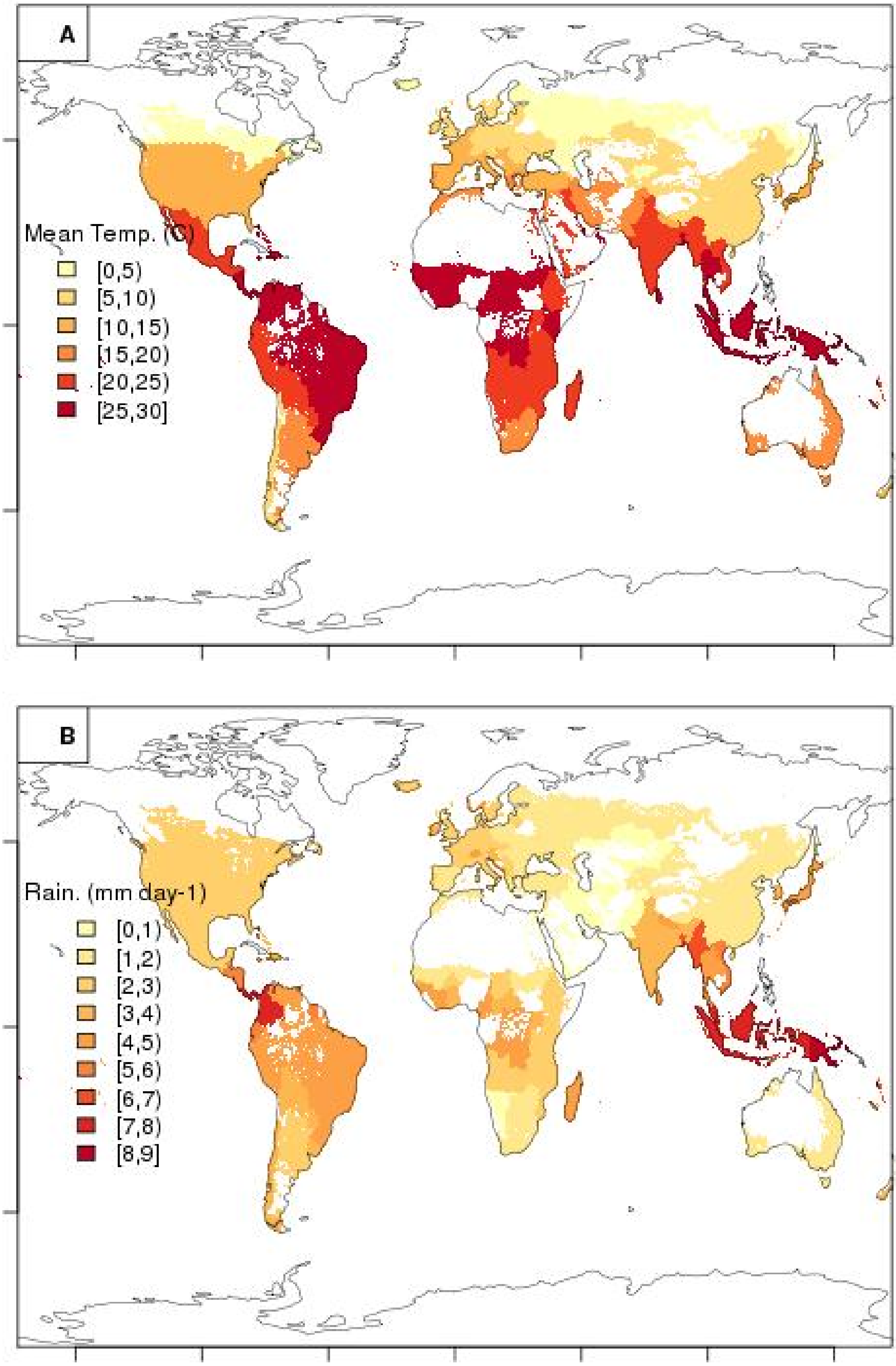



**Figure 7.11:** Mean daily baseline climate data across growing seasons and grid cells used in analysis (means across climate models). A = Mean Temperature, B = Precipitation.

#### 7.4.2.2 Future climate

Projected percentage changes to pesticide use are shown in Figure 7.12. The percentage changes, along with climate changes and model coefficients, are shown in Table 7.7. Future climate changes are shown in Figures 7.13 and 7.14.

Pesticide use in 2041-2050 is projected to increase in Europe and North America and decrease in South America and Asia (see Figure 7.12). African pesticide use is projected to decrease when looking at all countries – when looking at the high GDP bin, pesticide use is projected to increase. Temperature changes drive the majority of future changes in pesticide use (Figure 7.13). As a result, particular confidence can be associated with the models that are both significant and have a significant relationship with temperature. These are both European models, the South America all country model and the Asia high GDP bin model (see Table 7.7).

Focussing on those models that are significant in the baseline climate: in the European models, significant positive temperature coefficients lead to increases in future pesticide use. For the significant South America and Asia models, the predicted reductions in future pesticide use are the result of the models having significant negative temperature coefficients. This results in any increase in temperature being associated with decreased pesticide use, as an increase in temperature is multiplied by a negative temperature coefficient, leading to a negative change in pesticide use. The significant African model for all countries shows the same pattern of a negative temperature coefficient, but as this coefficient is insignificant this result should be treated with caution. The high bin African model explains more variation and has a lower p-value, however the temperature coefficient is still insignificant at the 0.05 level. As a result, increases in future temperatures are predicted to result in future increases in African pesticide use, but again this should be treated with caution (Figure 7.12).

**Table 7.7:** Climate change regression results for each continent for both all data and the high GDP bin data (H.) models. Predicted mean percentage change in pesticide use, coefficients (Coef.) and mean changes in mean temperature $T_m$ and precipitation $R$ variables from a baseline to future climate (averaged across climate models, ranges across models in brackets). Asterisks indicate significant models that are significant in a baseline climate.

| Continent | % Change | $T_m$.Change | $T_m$.Coef. | $R$.Change | $R$.Coef. |
|---|---|---|---|---|---|
| Europe* | 38 (25, 50) | 2.14 (1.43, 2.77) | 0.57 (0.55, 0.59) | <0.01 (-0.04, 0.04) | 1.09 (1.06, 1.23) |
| Europe H.* | 37 (24, 53) | 1.98 (1.32, 2.62) | 0.97 (0.95, 0.99) | 0.06 (-0.02, 0.24) | 0.86 (0.70, 0.98) |
| South America* | -23 (-33, -13) | 1.79 (1.44, 2.20) | -0.54 (-0.57, -0.48) | -0.06 (-0.23, 0.13) | 3.08 (2.81, 3.21) |
| South America H. | -7 (-31, -1) | 1.78 (1.37, 2.26) | -0.16 (-0.57, 0.17) | -0.03 (-0.27, 0.15) | 1.05 (-0.73, 3.12) |
| North America | 22 (8, 34) | 1.59 (1.23, 1.95) | 1.08 (0.65, 1.31) | -0.39 (-0.90, 0.04) | -2.20 (-3.51, 0.78) |
| North America H. | 71 (45, 100) | 1.81 (1.15, 2.48) | 4.26 (3.63, 5.02) | -0.26 (-0.59, -0.01) | -27.25 (-34.72, -19.27) |
| Asia | -4 (-5, -2) | 2.08 (1.53, 2.60) | -0.05 (-0.05, -0.04) | 0.03 (-0.12, 0.15) | 0.10 (0.10, 0.12) |
| Asia H.* | -24 (-30, -17) | 2.05 (1.46, 2.61) | -0.75 (-0.75, -0.74) | 0.02 (-0.20, 0.18) | -0.02 (-0.07, 0.03) |
| Africa* | -20 (-31, -12) | 1.82 (1.33, 2.36) | -0.04 (-0.05, -0.04) | 0.04 (-0.11, 0.18) | -0.21 (-0.22, -0.20) |
| Africa H.* | 16 (10, 24) | 1.85 (1.34, 2.36) | 0.08 (0.06, 0.10) | -0.01 (-0.12, 0.09) | -0.57 (-0.63, -0.50) |

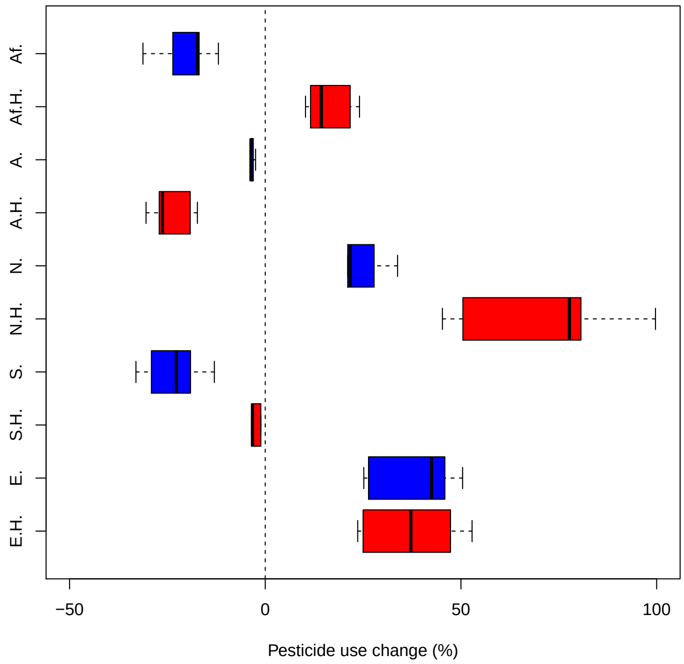



**Figure 7.12:** Pesticide use percentage change from present day to 2041-2050. E = Europe, S = South America, N = North America, A = Asia, Af. = Africa. The letter H. and the red bars correspond to percentage changes taken from models with data from high GDP bin countries only. Blue bars are for percentage changes taken from models using all data. Range shown is across climate models. Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

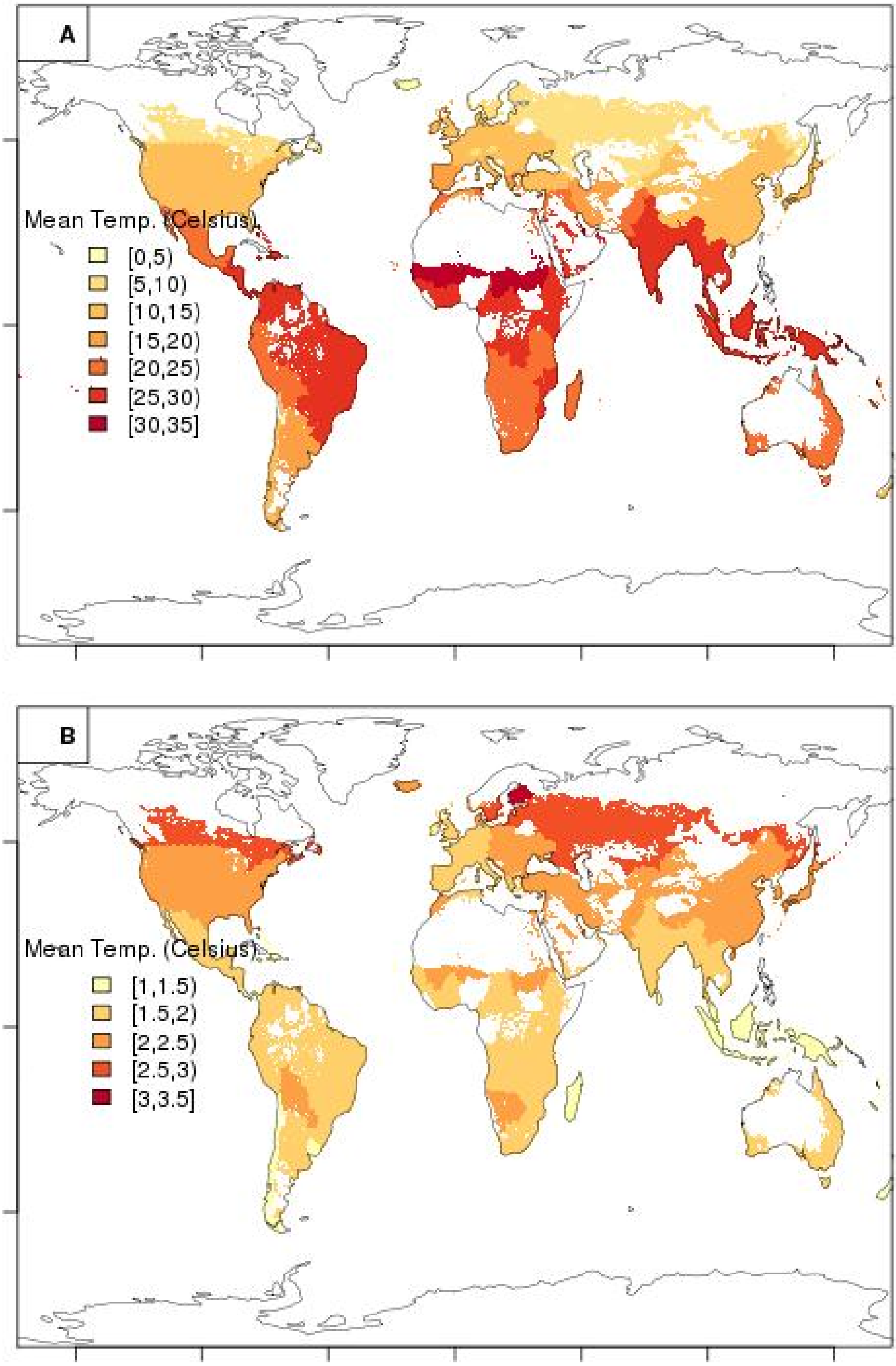



**Figure 7.13:** Mean daily future climate data across growing seasons and grid cells used in analysis (means across climate models). A = Mean temperature in future climate, B = Change in mean temperature from baseline to future climate.

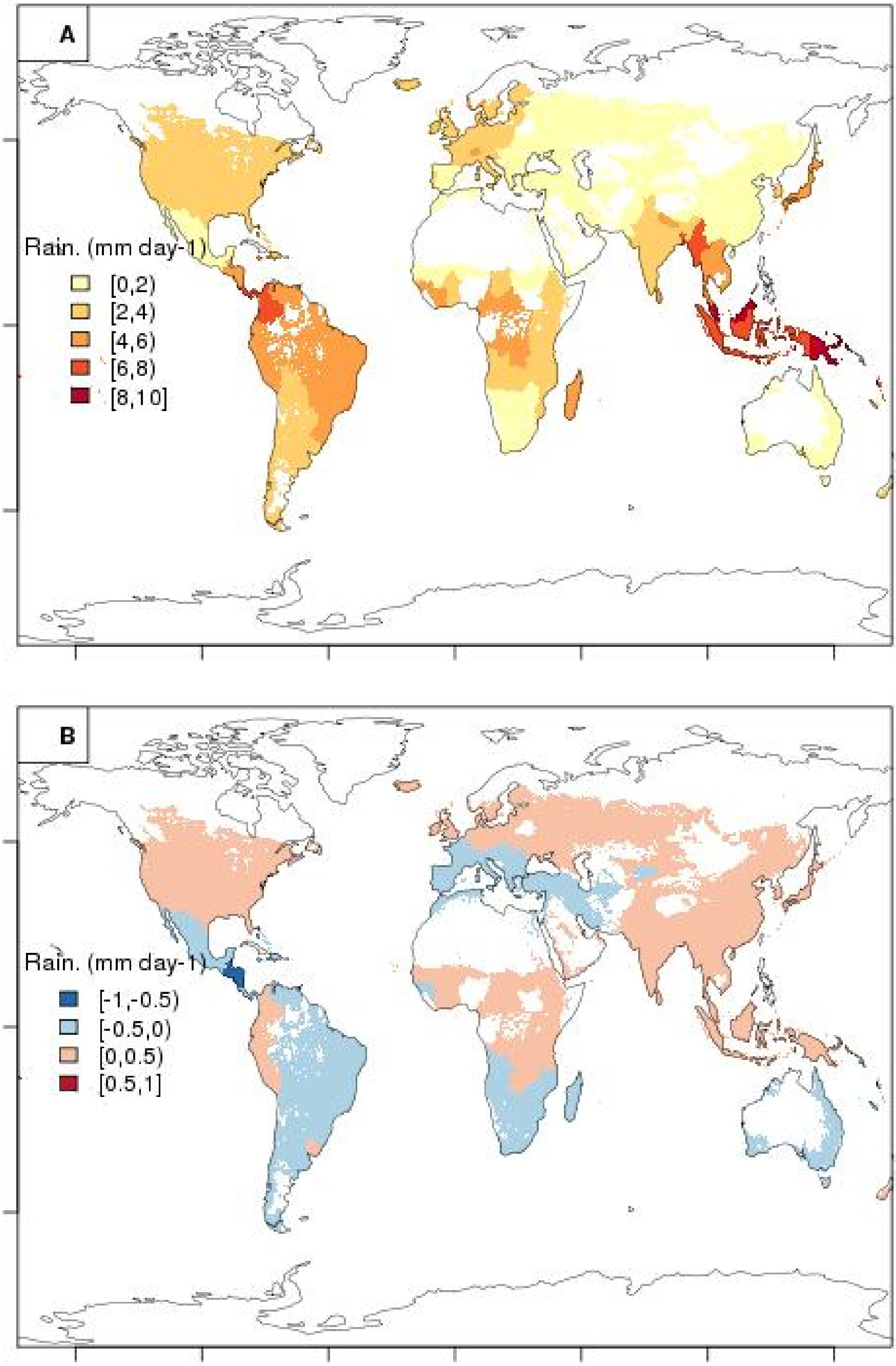



**Figure 7.14:** Future climate data used in analysis (means across climate models). A = Precipitation in future climate, B = Change in precipitation from baseline to future climate.

## 7.5 Discussion

This work had four research questions:

1. Is there a relationship between pesticide use and climate at large spatial scales?
2. Is there a stronger relationship between pesticide use and climate when taking into account GDP variables?
3. Is there more variability in pesticide use between countries or temporally within countries?
4. How will climate change affect pesticide use?

Large scale relationships between pesticide use and climate are significant in some cases and can help us to understand how pesticides will be used in a future climate. This gives us an indication of the intensity and distribution of future pest attacks. Temperature is shown to be an important predictor of pesticide use in temperate areas, leading to warming resulting in increases in future pesticide use of up to 50%. In warmer areas, pesticide use is predicted to decrease with warming. Precipitation is shown to be of importance for predicting pesticide use in tropical regions. However, this work shows that economic access to pesticides is of primary importance in the majority of countries as opposed to climatic factors alone, supporting previous work that shows the importance of economic variables for predicting pesticide use (Ghimire and Woodward, 2013). When accounting for GDP, temperature especially is shown to be an important predictor of pesticide use.

When looking at the data between countries, a stronger relationship between climate and pesticide use is seen. This is because there is a higher variability in pesticide use between countries than within them, and the majority of variation within most time series of pesticide use is explained by the GDP variable. Between countries, climate becomes a more important driver of pesticide use. The variability between the climate of countries is larger than within countries, leading to stronger correlations between climate and pesticide use between countries. Within countries in temperate areas (primarily Europe) for example, legislative and economic variables are most important for predicting pesticide use and there are few significant correlations with climate variables. Significant relationships emerge when looking at between country correlations.

In agreement with previous studies (Ziska, 2014; Chen and McCarl, 2001), correlations between-countries show that temperature is the most important driver of pesticide use in temperate areas - here shown by the relatively colder region of Europe. Precipitation was more important in South America and Africa. In temperate areas, minimum temperature is more often the limiting climatic factor behind the intensity of pest outbreaks as it determines the over-wintering capacity of pest populations, faster development, extended distributions and potentially additional generations of pests in a growing season (Bale et al., 2002; Cammell and Knight, 1992). Comparatively little has been published about the impacts of changing precipitation patterns on pests but there are suggestions that increases in precipitation can lead to increased insect mortality (Bale et al., 2002). Humidity is particularly important for fungal diseases also, so changes to both the magnitude and timing of precipitation could be important for the intensity of fungal outbreaks (Bebber and Gurr, 2015).

The strongest relationship found between GDP variables and pesticide use is with $GDP_{A1}$, which is GDP normalised by agricultural area including livestock. In general, this variable accounts for more information than $GDP$ alone or $GDP_{\%}$ (the value added by agriculture) as it takes into account the extent of agriculture in a country; it accounts for the potential amount a country can invest in agriculture. The inclusion of livestock crop areas is thought to be beneficial as large amounts of pesticides are used on feed crops for animals as well as on the grazing areas of the livestock themselves, resulting in an impact on pesticide use. The $GDP_{\%}$ variable shows more negative correlations with pesticide use compared to the other GDP variables. This is likely to do with this variable not being a direct measure of wealth. It is often the case that the GDP of poorer countries is highly dependent on agriculture. As such, a high value of $GDP_{\%}$ could be associated with the country being relatively poor and therefore having less money available to spend on pesticides.

Data representing the level of pesticide legislation in countries show largely insignificant correlations with pesticide use. Legislation is becoming stricter globally, however, and is likely to be (if anything) of more importance for determining future pesticide use levels (Klatt et al., 2016; Handford et al., 2015). In Europe, pesticide legislation is most stringent and pesticide use is tightly bound to these limits (Handford et al., 2015). Neonicotinoids (an insecticide), for example, were banned in Europe in 2014 (Klatt et al., 2016). It will therefore be hard to sustainably deal with the predicted increases in pest pressures in the future.

The African MRL-pesticide relationship is the only region to show a significant correlation. It is at first glance a surprising result, being a negative correlation: it suggests that the tighter the pesticide legislative limitations imposed, the more pesticides are applied to crops. However, there is evidence to suggest that pesticide legislation is poorly enforced in Africa (Matthews et al., 2011). Whilst developing countries are increasingly establishing stringent legislation to comply with the limitations imposed by countries they are exporting to, the legislation often lacks detail and the capacity to be enforced effectively (Handford et al., 2015). There is a significant positive correlation between GDP and pesticide use also. This could mean that richer African countries that can afford more pesticides are associated with more stringent legislation but do not enforce it.

Grouping based on the GDP variable results in stronger relationships between pesticide use and temperature. This supports the hypothesis that when economic access is less of a limiting factor, climate becomes a larger determinant of pesticide use. This is probably due to the level of pest outbreaks being a relatively larger determinant of pesticide use when money is non-limiting, with pest outbreaks being related to climate in turn (e.g. see Bale et al., 2002). Precipitation shows less of such a relationship with GDP. This is potentially due to temperature - rather than precipitation - being the important climatic determinant of pest outbreaks (Cammell and Knight, 1992) in the richer temperate countries. The regions where precipitation is a more important predictor of pesticide use (e.g. South America and Africa) tend to be poorer and are perhaps less able to respond to pest attacks. Precipitation is also implicated in other processes that affect pesticide use, such as runoff (Noyes et al., 2009). Indeed, the results here suggest that precipitation is more of a determinant of pesticide use than temperature in a majority of countries, albeit showing mostly insignificant correlations within countries.

As described in Conn et al. (2015), the reliability of extrapolations using statistical models depends on factors such as sample size and how far the prediction data are from the observed range. If we extrapolate beyond the range of observed data we cannot know whether observed relationships will hold. For example, a temperature-pesticide linear relationship may be non-linear outside the range of the data on which it was calibrated. This could result from warming leading to a tipping point at a temperature threshold for a pest species (Lenton, 2013; Salis et al., 2016). In this analysis we assume this to be an acceptable extrapolation given the relatively modest climatic changes predicted to 2045 (around an average 2°C rise in temperature and small precipitation changes), resulting in the extrapolations being largely within the range of the calibration baseline data.

Extrapolations of future pesticide use show that in temperate areas (i.e. Europe and North America), increases in temperatures are likely to lead to an increase in pesticide use. This pattern is also true for the African high GDP model. In tropical regions (i.e. Asia and South America), a negative relationship with temperature is predicted to lead to reductions in pesticide use. Both directions of change are the result of opposing relationships with temperature and pesticide use in the baseline climate. Higher temperatures lead to more pesticide application in colder areas; lower temperatures lead to more pesticide application in warmer areas. The European, Asian and African models were made up of the most data and provided the majority of the significant models in the baseline climate. The temperature coefficients of the European and Asia high GDP bin models were significant and drove the changes in future pesticide use. We can therefore have the most confidence in these extrapolations. Whilst there is modest uncertainty across climate models in the predicted pesticide use change, the sign of change is the same across climate models in all cases.

Correlation is not causation; we cannot determine with these data how much the pesticide-climate relationship is due to the pest-climate relationship. However, as discussed above, temperature is the most important climatic determinant of pests in temperate areas. As well as the positive impacts of warming on pests in temperate areas outlined previously, warming could have some negative consequences for pests when temperatures exceed upper lethal limits for growth and development (Bale and Hayward, 2010). In tropical areas, pests can be limited by high temperatures at the edges of their range (as species in temperate regions are limited by cold temperatures) and are less likely to adapt if they occupy specialist niches, as many species do in the tropics (Boucher-Lalonde et al., 2014).

### 7.5.1 Limitations

Pesticides are being under-used in developing countries and over-used in developed countries (Ghimire and Woodward, 2013). It is unlikely that pesticide use will in reality increase in economically developed areas such as Europe (Handford et al., 2015). Projections of 50% increases in Europe reflect the extrapolation of current temperature-pesticide relationships that in turn partly reflect projected temperature-biotic stress relationships. These projections serve as an indication of future pest pressures rather than future predictions of pesticide use, as it is uncertain what future legislative and economic limitations will be in place. We can, however, state with confidence that pesticide use is unlikely to increase significantly in future in Europe as current levels are in danger of not being sustainable already – e.g. see the recent European ban on Neonicotinoids (an insecticide) in 2014 (Klatt et al., 2016).

There are adverse implications for increases in pesticide use. Impacts on non-target creatures can be detrimental to ecosystem health (Leach and Mumford, 2008). Insect biodiversity has recently declined, with increases in pesticide use partially responsible (Evans et al., 2018; Goulson et al., 2015).

Over-use of pesticides can lead to negative economic impacts as well as environmental problems (Khan et al., 2002). Monitoring costs for damaged ecosystems can increase and impacts on non-target creatures can be detrimental to ecosystem health (Leach and Mumford, 2008). Pimentel (2005) estimated US annual costs of $1.1 billion due to adverse impacts on public health, $1.4 billion due to crop yield losses, $2.2 billion due to bird losses, $1.5 billion due to pesticide resistance and $2 billion due to ground water contamination.

Monitoring costs for damaged ecosystems can increase also (Leach and Mumford, 2008).

In general, a simple modelling approach is adopted to avoid model overtuning given limited data (e.g. see Babyak, 2004 and Section 7.4.1). If given more data on pesticide use (both longer time series and more countries) then more variables could be included in the statistical models, such as those discussed below. With more data, model coefficients can be treated with greater confidence, resulting in more confidence in the relationships shown between pesticides and climate. That being said, the regions where significant models and temperature coefficients (i.e. Europe and Asia) are shown can be treated with some confidence in that the direction of change predicted is unlikely to change with more data and variables - more that the strength of the signal is uncertain and could change.

The complexity of changing pest pressures over time are such that simple models cannot fully capture changes in the relationships between pesticides and climate (e.g. see Welch and Harwood, 2014). Both abiotic and biotic factors are implicated in these responses (Delcour et al., 2015). An interaction between temperature and precipitation is not included for model simplicity, but can be a significant climatic driver of pests, for example affecting overwintering (Pan et al., 2014).

Changes in extreme weather events are likely to have a significant impact on the scale of future pest outbreaks (Boggs, 2016) – further work could include variables in statistical models that assess the impacts of changing extremes of climate on pesticide use (e.g. number of days above a temperature threshold during the year). The rate and scale of pest evolutionary responses to climate and other selection pressures are not considered (being commonly neglected in such studies – Bale et al., 2002) despite their potential importance (e.g. see Atallah et al., 2014).

The relationships seen here between pesticide use and temperature are also likely due to factors other than pest-climate relationships. Delcour et al. (2015) detail how complex the direct and indirect impacts of temperature on pesticide use can be, such that predictions of the direction of pesticide use change are still uncertain. Not all the causes of changes in pesticide use are accounted for – technological developments, crop characteristics and efficiency of pesticide application are potentially important factors (Delcour et al., 2015).

Lastly, different varieties of pesticides are not distinguished here - for example, insecticides examined alone may have a stronger temperature signal if they are representative of insect pest pressures and the relationship of insects to climate. Herbicides often make up the majority of pesticide applications (FAO, 2016) and therefore may dull the temperature-pesticide signal relative to insecticides alone. This analysis highlights some likely trends in pesticide use (and hence pest pressures) with future climate, but also shows the need for further work using more data to enable more complex modelling studies.

### 7.5.2 Conclusions

Pesticide legislation is becoming stricter in most regions, limiting the quantity and type of pesticides applied (Klatt et al., 2016; Handford et al., 2015). Chen and McCarl (2001) found that increasing temperatures lead to higher pesticide costs. Therefore both legislative and economic limitations are likely to be increasingly imposed in the future.

This work has shown that there are likely to be increases in pesticides required due to increased pest pressures in certain regions. It is therefore important that future pest management scenarios look into the sustainability of future pesticide use levels from both a legislative and economic perspective. At present it is likely that higher GDP regions are over-using and poorer areas under-using pesticides (Ghimire and Woodward, 2013).

Chapter 6 features an analysis of the impacts of climate change on blight. Blight was projected to increase in Europe when the disease was allowed to adapt to warming conditions. The blight work is an example of a more specific climate-biotic stress analysis, featuring a single disease of potato and the adaptation of changing growing seasons and pest evolution in response to warming. The more generic pesticide-climate analysis in the present chapter supports the conclusions of Chapter 6, with most confidence associated with the European region in both analyses. Both chapters point to future difficulties in sustainably managing pest outbreaks in Europe.

To conclude, this work shows that although GDP is the most important predictor of intra-country pesticide variability, climate is an important factor when economics have been taken into account, especially at large spatial scales. With warming, temperate areas are likely to see required increases in pesticide use and warmer areas may see a decrease.

# Chapter 8

# Summary and conclusions

The objectives set out in Chapter 1 were as follows:

1. Develop a process-based crop model suitable for simulating large scale potato-weather relationships (Chapter 2).
2. Evaluate the process-based potato model in contrasting climates using regional data and parameter information (Chapter 3).
3. Evaluate the potato model parameter set up at the national scale for use in global simulations (Chapter 4).
4. Compare the model skill of the global and regional simulations (Chapter 5).
5. Assess the impacts of climate change on global potato yields (Chapter 6).
6. Assess the impacts of climate change on global potato biotic stress (Chapter 6).
7. Use proxy data (on pesticide use) to evaluate the links between climate and pests and predict the influence of climate change on pests globally (Chapter 7).

The main results from each chapter are summarised in turn with the exception of Chapter 2, which describes the model used in subsequent analysis chapters, fulfilling Objective 1. After results are summarised, conclusions relating to the above objectives are stated. Section 8.2 then summarises future research recommendations.

## 8.1 Results summary and conclusions

### 8.1.1 Chapter 3 - GLAM-potato regional evaluation

Chapter 3 fulfils Objective 2: evaluate GLAM-potato in the temperate and tropical climates of the UK and Colombia using regional planting date information and optimisation of parameters.

For both the UK and Colombia, GLAM-potato was shown to satisfactorily simulate potato development, growth and yield in most cases. The model shows the ability to capture inter-annual variability in observed yields. Certain regions of Colombia and years in the UK time series show poor skill in simulating yields due to unrealistic simulated planting dates and varieties. Model skill was higher in the UK due to a longer time series, more parameter optimisation and more specific information concerning planting dates.

It was therefore concluded that GLAM-potato is an adequate tool for regional scale potato simulations, given that it performs satisfactorily in simulating potato weather-yield relationships, growth and development in these temperate and tropical regions.

### 8.1.2 Chapter 4 - Variety and management parameterisation for global simulations

Chapter 4 fulfils Objective 3: test a parameterisation of GLAM-potato designed to simulate potatoes across large (global) scales with minimal parameter information. These tests were performed in the UK and Colombia using national yield data.

Simulations showed realistic model outputs of planting dates, durations and leaf area index. Model skill of simulating observed yields was poor, however, primarily due to the lack of significant observed weather-yield relationships. The relationships with rainfall were well represented. Temperature relationships with observed yields were very weak. Significant differences in relationships between observed and simulated yields and weather variables were not identified, however.

UK results showed a negative relationship between simulated yields and temperature that was not in observations. This was likely due to early season temperatures having more of an impact on growing season length than seen in simulations. The most important impact of temperature on crops is usually on crop development (i.e. durations). As temperature-yield relationships were so weak in the UK time series, and due to confidence in their representation in the regional UK time series, the model was deemed adequate for simulating these relationships.

Colombian results showed similar problems with simulating solar radiation relationships. The relationship between rainfall and observed yields was weak, resulting in solar radiation being the limiting factor for simulating yields rather than the rainfall relationship – i.e. there was a positive relationship between simulated yields and solar radiation, when the observed yields show a negative relationship with solar radiation.

It was therefore concluded that GLAM-potato is an adequate tool for potato simulations at the global scale, given that it performs satisfactorily in simulating potato weather-yield relationships using no regionally-specific parameter information and national scale yield data.

### 8.1.3 Chapter 5 - Model skill in regional and global studies

Chapter 5 fulfils Objective 4: compare the skill of the regional and global model evaluations in the UK and Colombia. This provides an improved understanding of why model skill is different in regional and global simulations.

Regional simulations in the UK and Colombia showed better model skill more often than global simulations using national scale yield data. The main source of this difference in model skill was parameter differences between the studies; regional studies used parameter optimisation to better simulate phenology and featured regionally-specific information on planting dates. Simulations using regional yield data were also associated with higher model skill than simulations using national scale data in some cases. Confidence in these results is necessarily limited by the small number of countries examined, low model skill and few years of data analysed.

It was concluded that the limited planting date and phenology information available to global studies is an important limiting factor to model skill. To improve global crop modelling, better quality information on planting dates and varieties needs to be made available.

### 8.1.4 Chapter 6 - The impacts of climate change on potato agriculture: global analysis

Chapter 6 presented the global potato yield simulations alongside the global blight simulations. This chapter fulfils Objectives 5 and 6, which assess the global impacts of climate change on potato yields and potato biotic stress respectively.

When considering both agricultural adaptations and $CO_2$ fertilisation, yield changes were mostly positive. Global mean yield changes shown across climate models were -6 to 16% without adaptation and 33 to 47% increases with adaptation. Decreasing these ranges by mean projected ozone damage to yields leads to global mean yield changes of -18 to 4% without adaptation, and 21 to 35% with adaptation. These results are also uncertain due to the uncertain size of the $CO_2$ fertilisation effect, although this is unlikely to change the sign of change when taking into account adaptation.

Other model studies show less favourable yields in the future, although these do not include both adaptation to climate change and $CO_2$ fertilisation. Other studies also fail to report crop model outputs such as LAI and duration, or feature detailed assessments of model skill in simulating inter-annual variability. Results in this chapter show that European yields are typically accurately simulated, although model skill is frequently poor elsewhere.

When accounting for the adaptation of blight to warming temperatures, blight units were projected to increase by 2050. This increase was particularly large in the northern hemisphere. Results showed that blight may subside in key potato growing areas by mid-century if it does not adapt to warming.

It was concluded that potato yields are likely to increase in the future in the important potato growing areas of Europe and Russia by 2050. Increased blight pressures could reduce expected potato yield gains, however, if not sustainably managed. Further modelling is needed to speak with confidence on potato yield changes in other key potato growing regions such as India, China and the United States.

### 8.1.5 Chapter 7 - The influence of climate change on crop pests and diseases: pesticide analysis

Chapter 7 fulfils Objective 7: to present a global analysis of the impacts of climate change on pest pressures, using pesticide use data as a proxy for pest pressures. This analysis complements the global crop-climate modelling of Chapter 6 by taking a broader, data-based look at the impacts of climate change on pest pressures.

Warming resulted in higher projected pesticide use in temperate areas, with Europe showing projected increases as high as 50%. Tropical regions show a decrease in projected pesticide use in some cases, with precipitation also important in leading to varied pesticide changes. Within countries, however, GDP is shown to be the most important driver of pesticide use. When this is accounted for, a clearer climate signal emerges that can be used to assess the impacts of climate change on pesticide use.

In agreement with the more specific late blight climate change analysis in Chapter 6, it was concluded that pest pressures are likely to increase in future due to warming in temperate areas. Due to the increasingly stringent pesticide legislation in place in many countries (as well as economic constraints), it is important that sustainable plans are made to deal with likely increases in pest pressures due to climate change.

## 8.2 Research recommendations

In order to improve future forecasts of the impacts of climate change on abiotic and biotic stresses of potato, we can improve the skill and quantification of uncertainty associated with the modelling used in this thesis. It is also important to make better use of the information such modelling provides by expanding the system boundary of the study – i.e we can put potato yield and blight change projections into more comprehensive and wide-ranging assessments of future food security. Both of these modelling and contextual improvements are discussed below.

Results in Chapter 6 point to various improvements for future potato modelling work. Uncertainties not taken into account include crop model structural and parametric uncertainty, as well as input data uncertainty (soil, growing area and irrigation information).

FAOSTAT input data are associated with the year of harvest. In larger countries, these data may be misleading if different regions harvest at different times. In the absence of yield data at the sub-national level, future studies should make use of agro-ecological zones to subdivide larger countries in an effort to accurately model the correct growing season, and therefore have more representative observed yield data locally.

In terms of improvements to GLAM-potato, more detailed parameterisations of heat stress and the impacts of excessive soil moisture may improve results in some countries such as India. More information on irrigation could improve results in important production countries such as the United States. For this type of global gridded analysis, it is important to take into account other crop seasons so that, for the crop of interest, the correct growing season is simulated that is representative of observations.

Further work is needed to assess the changes to model skill between regional and global studies. Results here suggest that more detailed parameter information is particularly important in leading to better model skill at regional scales. These results were only based on two countries, however, with few years of yield data available and often insignificant national scale weather relationships with observed yields. Therefore, further work would ideally use regional data of longer time series across more countries. Different spatial extents and levels of parameter detail should also be explored. Accurate and comprehensive data sets on planting dates, harvest dates and phenology parameters would be of great benefit to future global crop modelling.

Future modelling of potato pests and diseases within climate impacts studies would be improved by simulating other global potato pests, or those of particular importance in key potato growing areas. There is also a need to link the results of models such as SimCast (that forecast measures of risk of biotic stress) to yield changes, so the impacts of pests on food security can be directly estimated. In both of these cases, however, data is a limitation and a priority in terms of future research needs. In the pesticide analysis, more pesticide data would enable more variables to be included in statistical models and improve confidence in results.

The changes described above would potentially improve crop and blight model simulations and allow us to have more confidence in projections. There is also a need to improve the range of scenarios projected, as well as putting projections into a broader, more comprehensive context. Simulations in this thesis have started to do this by incorporating biotic stresses into a climate impacts framework, but more is needed.

Projections depend on the scenarios on which they are driven and only one socio-economic scenario is used here (RCP 8.5). Incorporation of other scenarios would provide a range of projections on which policy decisions could be based. Adaptation scenarios could also be investigated that look at different adaptive capacities and technologies. Mitigation of climate change is not considered and future potato agricultural scenarios cannot be labelled sustainable until they are demonstrably "climate smart" – i.e. that they adapt to climate change to produce sufficient food whilst not exacerbating the cause of the problem. Land use change is not investigated and scenarios of different land use could be used to provide further information on future global potato production.

The simulation of other crops would allow dietary choice scenarios to be investigated – food security in any region is about more than the production of a single crop. Dietary nutrition, access to food and the sustainability of food production are also critical. Integrated assessments of socio-economics, food production and climate change are in their infancy, but such studies are necessary to develop a more accurate sense of how climate change will impact people's lives and shape policy. This thesis has developed and evaluated a global crop modelling framework, a necessary component in such an analysis. Whilst potatoes are important and neglected in modelling communities, it is vital that future studies take into account more than just the humble potato to assess the risks and opportunities that climate change poses to food security.

# Appendix A - GLAM-potato regional evaluation

Below in Figures A1 to A10 are the time series of observed yields, simulated GLAM yields and simulated statistical model yields for the 10 evaluation regions of Colombia. Also included in plots are summary statistics for model performance and for the test of significant difference between GLAM and statistical model correlation coefficients with observed yields.

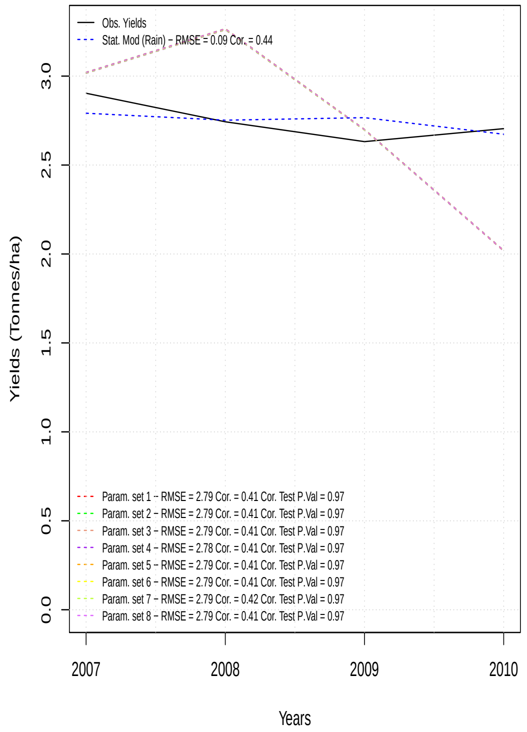



**Figure A1:** Boyacá comparison of GLAM and statistical model skill.

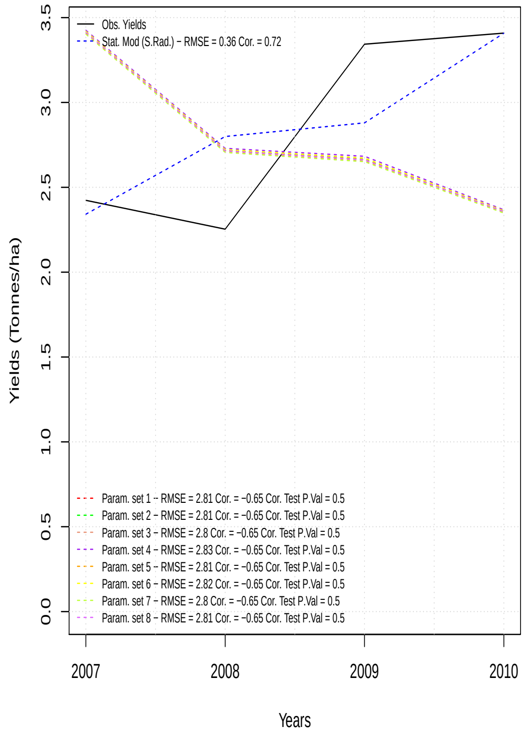



**Figure A2:** Caldas comparison of GLAM and statistical model skill.

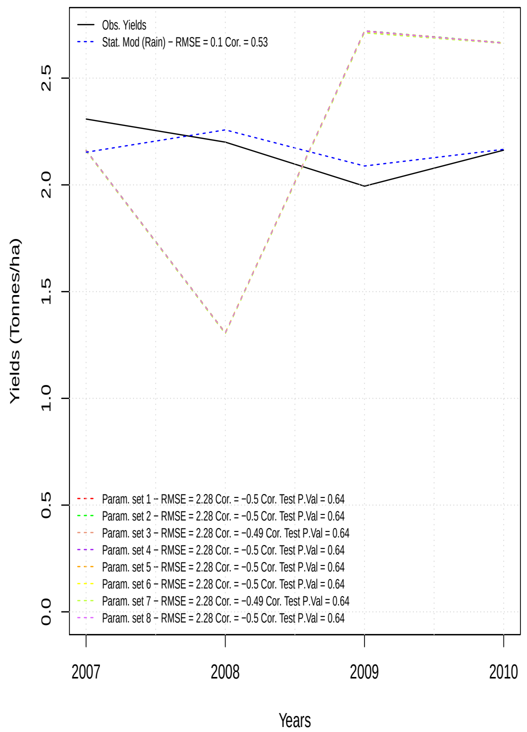



**Figure A3:** Cauca comparison of GLAM and statistical model skill.

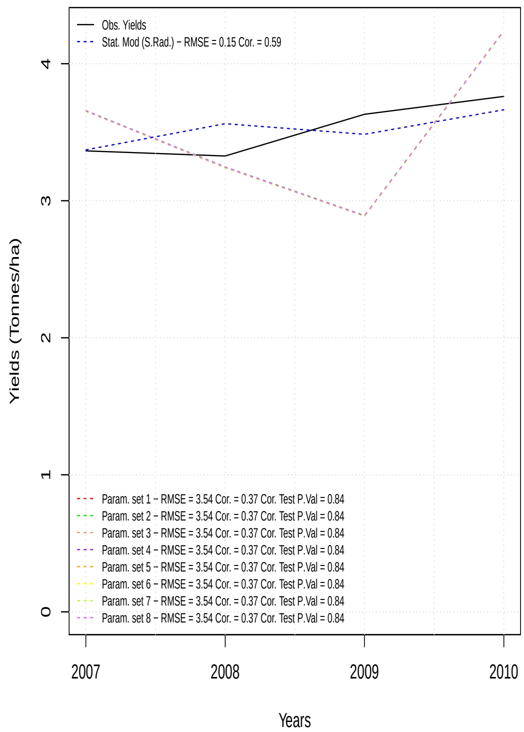



**Figure A4:** Cundinamarca comparison of GLAM and statistical model skill.

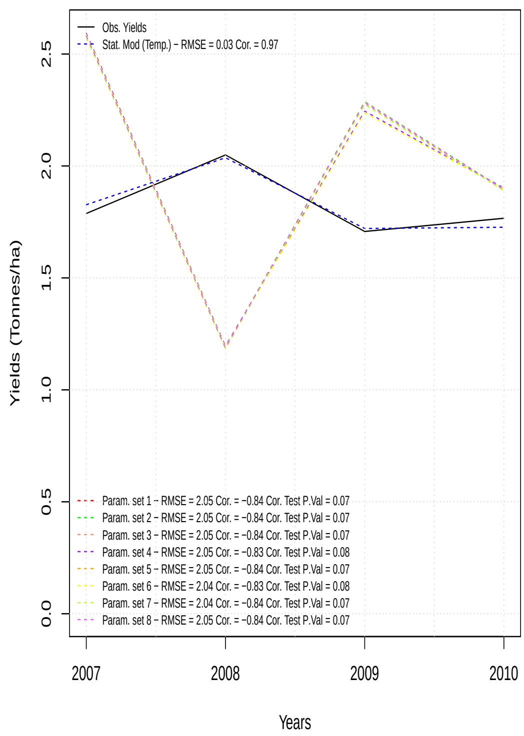



**Figure A5:** Huila comparison of GLAM and statistical model skill.

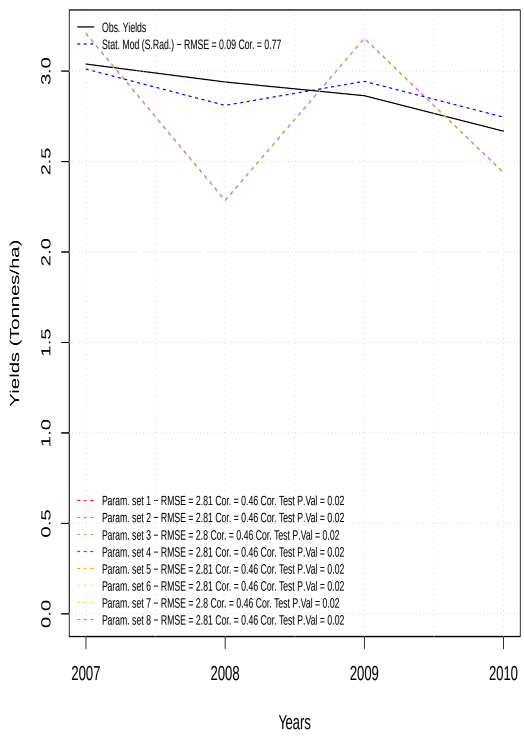



**Figure A6:** Nariño comparison of GLAM and statistical model skill.

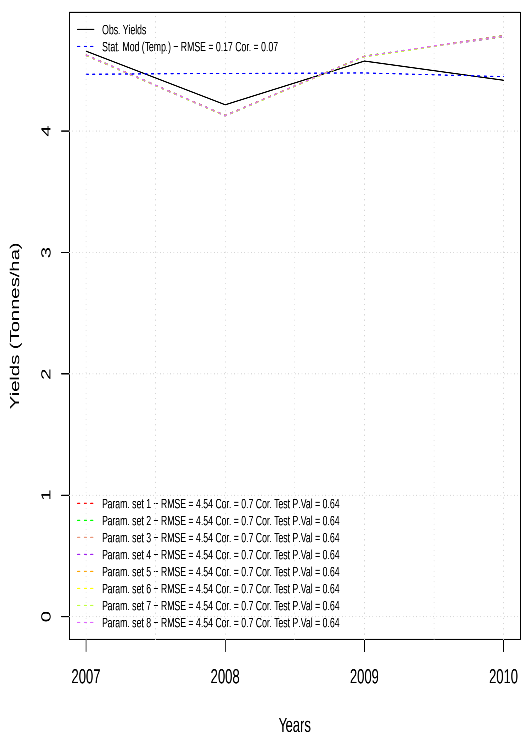



**Figure A7:** N. Santander comparison of GLAM and statistical model skill.

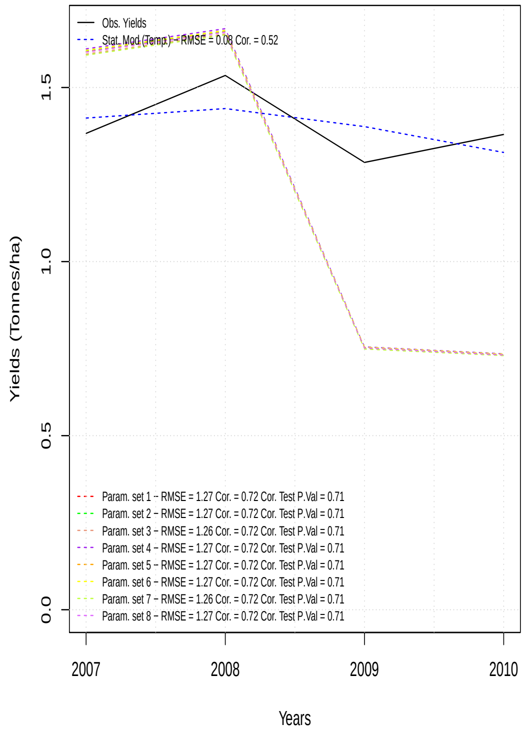



**Figure A8:** Quindío comparison of GLAM and statistical model skill.

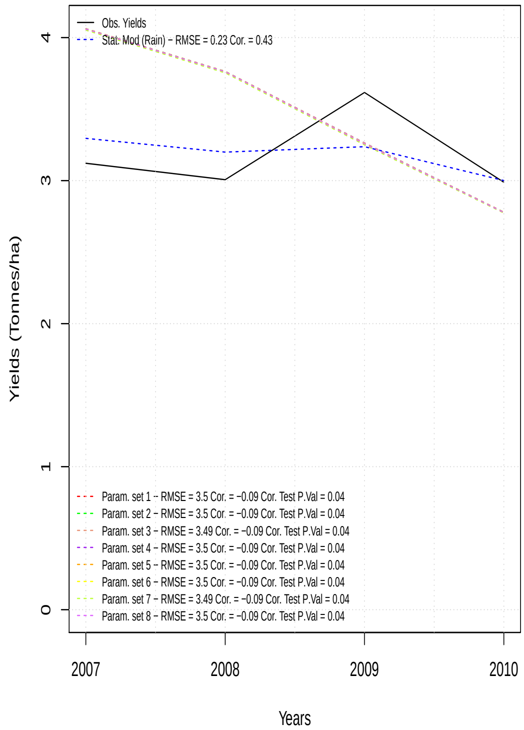



**Figure A9:** Santander comparison of GLAM and statistical model skill.

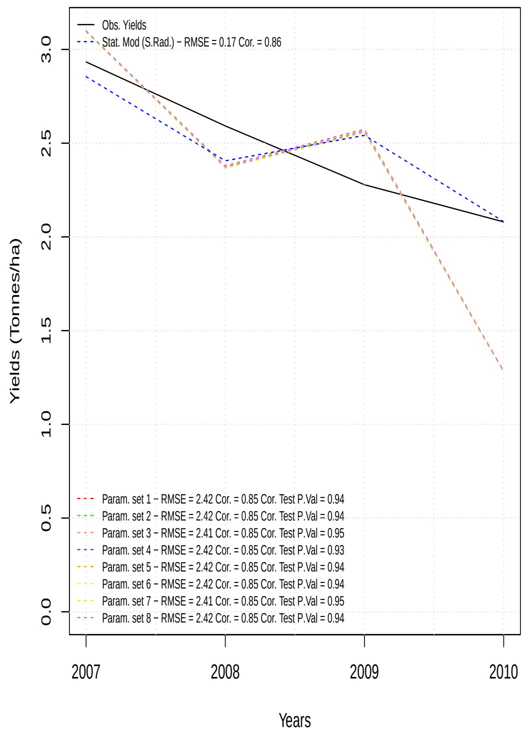



**Figure A10:** Tolima comparison of GLAM and statistical model skill.

Below in Figures A11 to A20 are boxplots showing evaluation test 2 variables for all years and grid cells (biomass, harvest index, maximum leaf area index and duration). Boxplots show medians, interquartile ranges and the whiskers extend to 1.5 times the interquartile range.

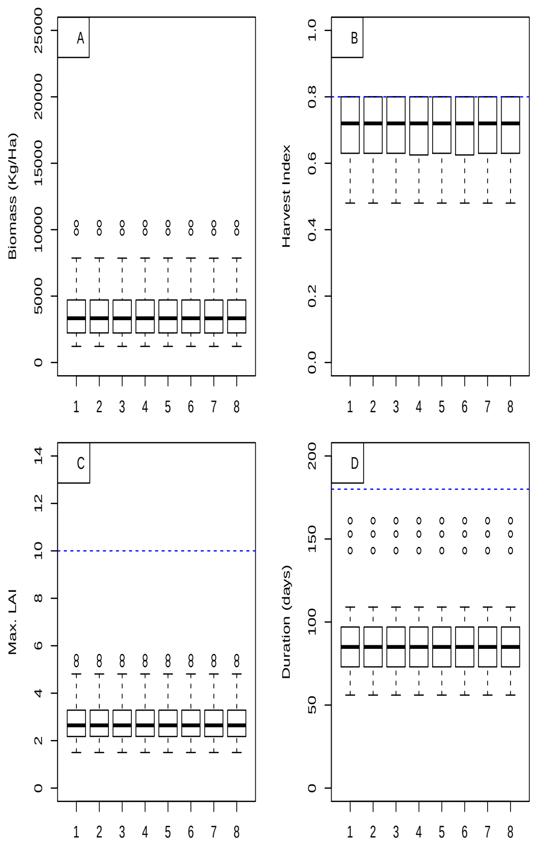



**Figure A11:** Boyacá variables across all years and grid cells.

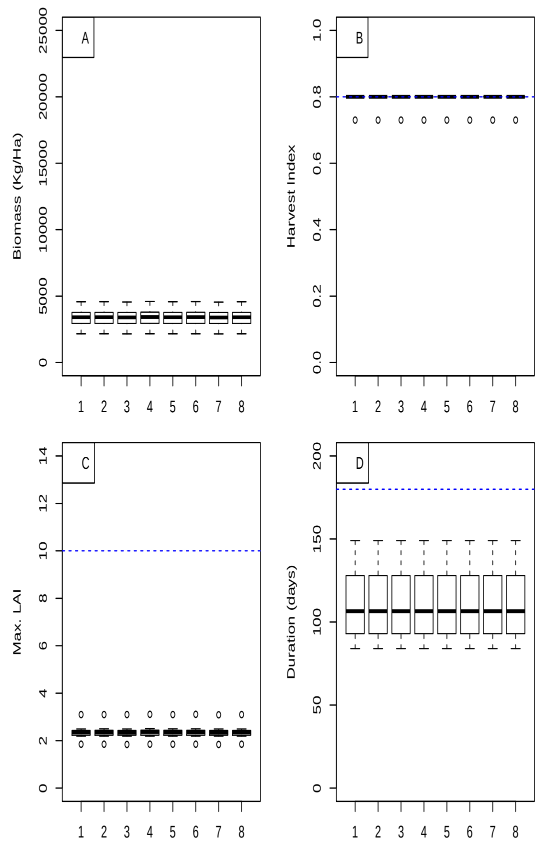



**Figure A12:** Caldas variables across all years and grid cells.

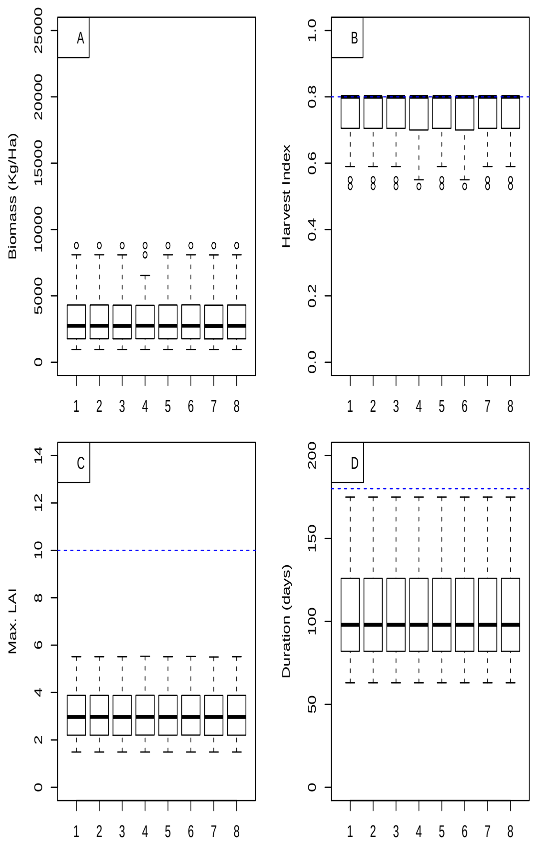



**Figure A13:** Cauca variables across all years and grid cells.

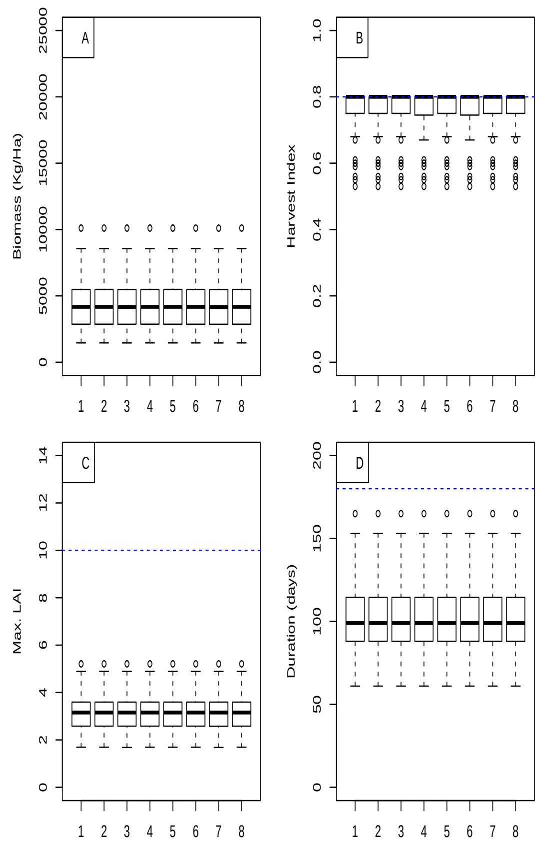



**Figure A14:** Cundinamarca variables across all years and grid cells.

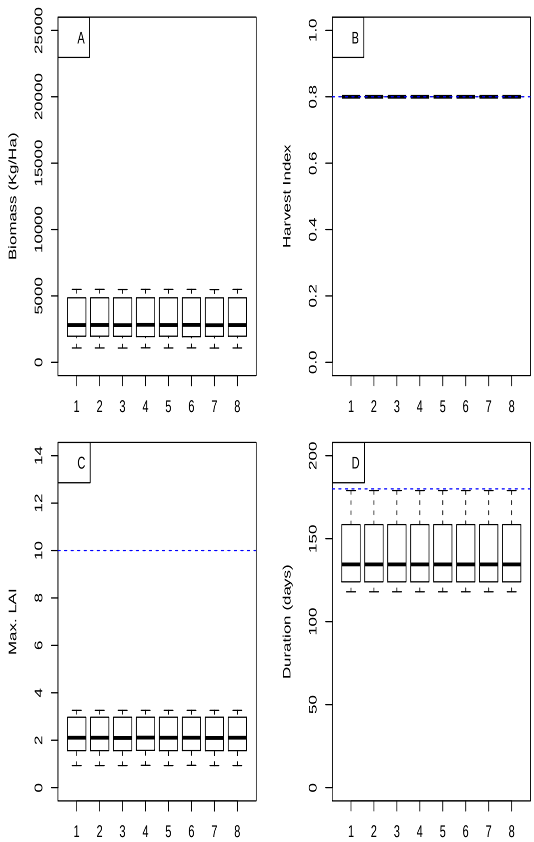



**Figure A15:** Huila variables across all years and grid cells.

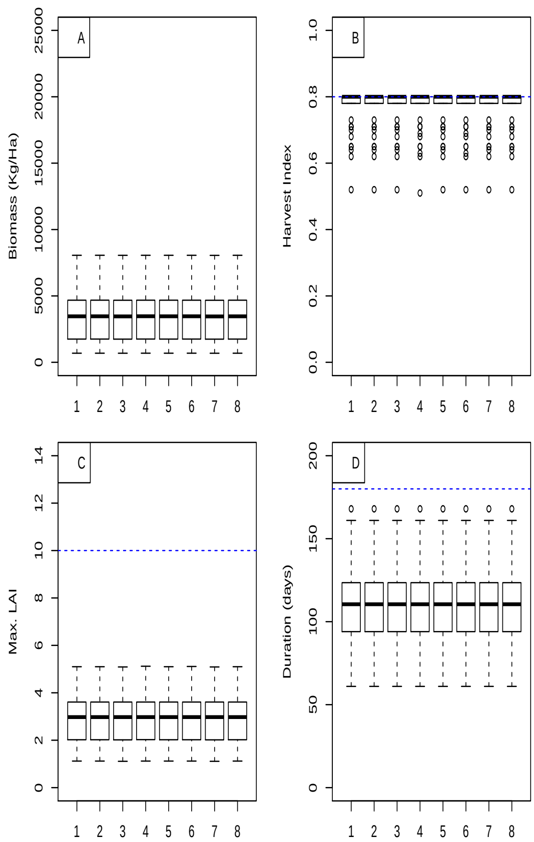



**Figure A16:** Nariño variables across all years and grid cells.

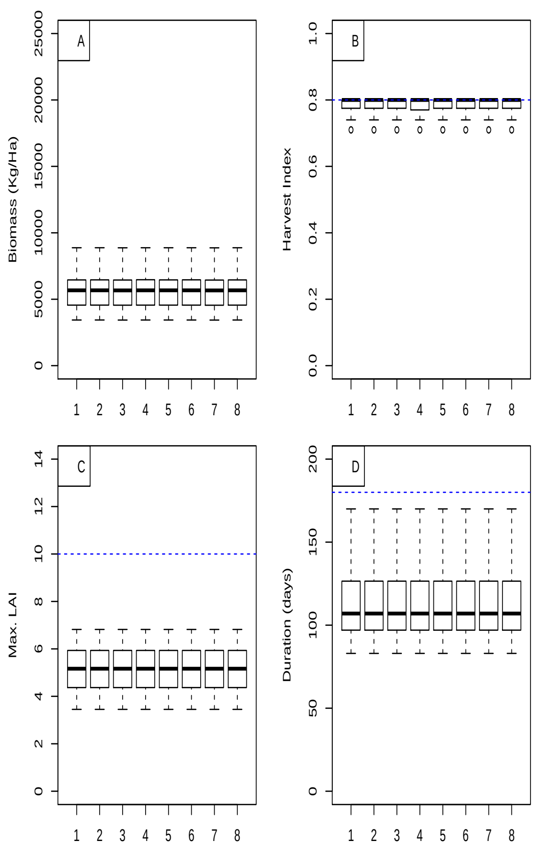



**Figure A17:** N. Santander variables across all years and grid cells.

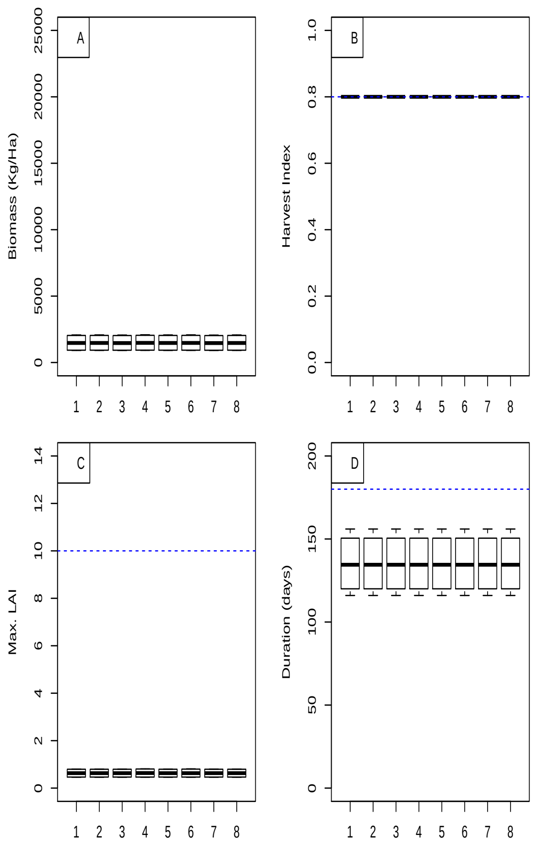



**Figure A18:** Quindío variables across all years and grid cells.

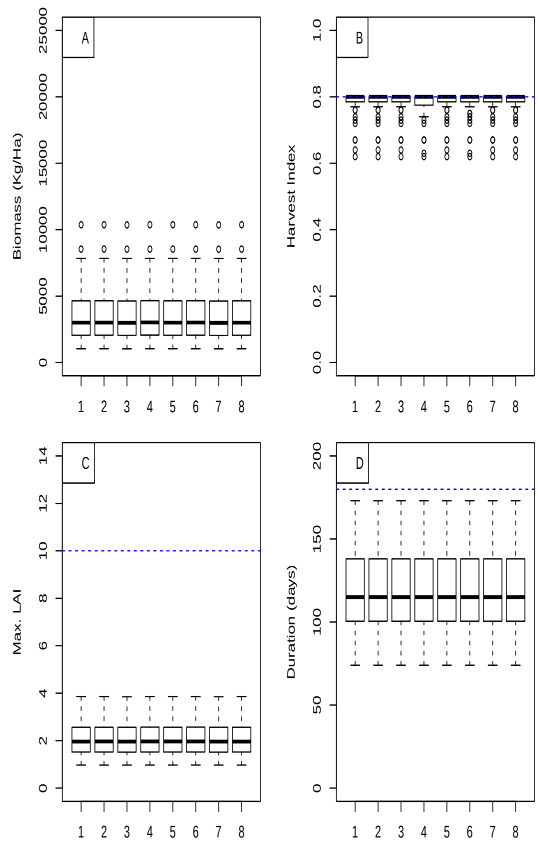



**Figure A19:** Santander variables across all years and grid cells.

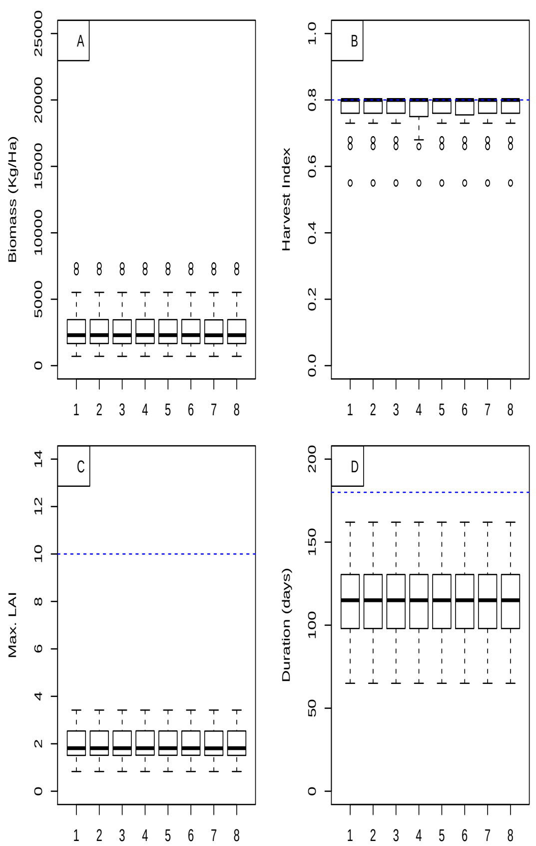
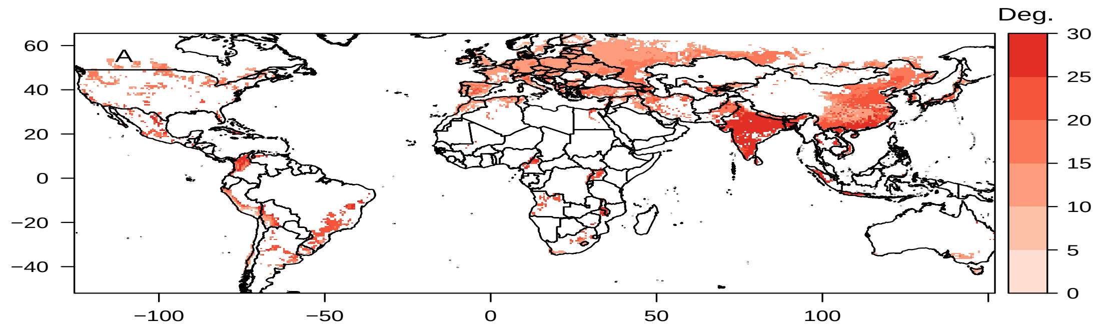



**Figure A20:** Tolima variables across all years and grid cells.

# Appendix B - The impacts of climate change on potato agriculture: global analysis

Figure B1 shows mean temperature, rainfall and solar radiation for the baseline evaluation simulations.



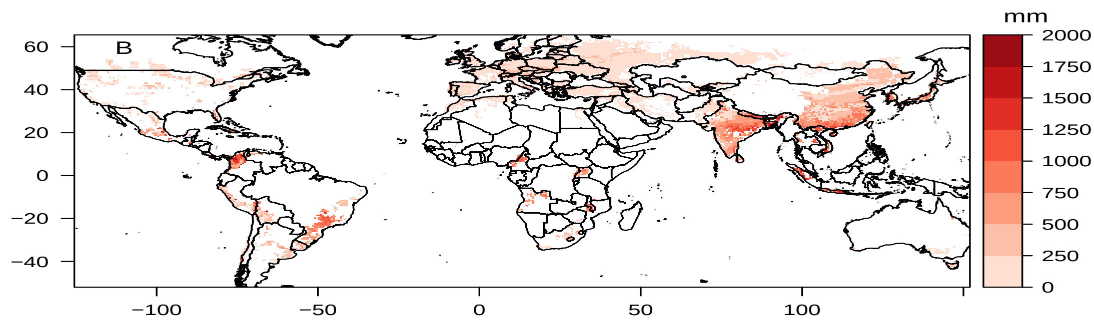
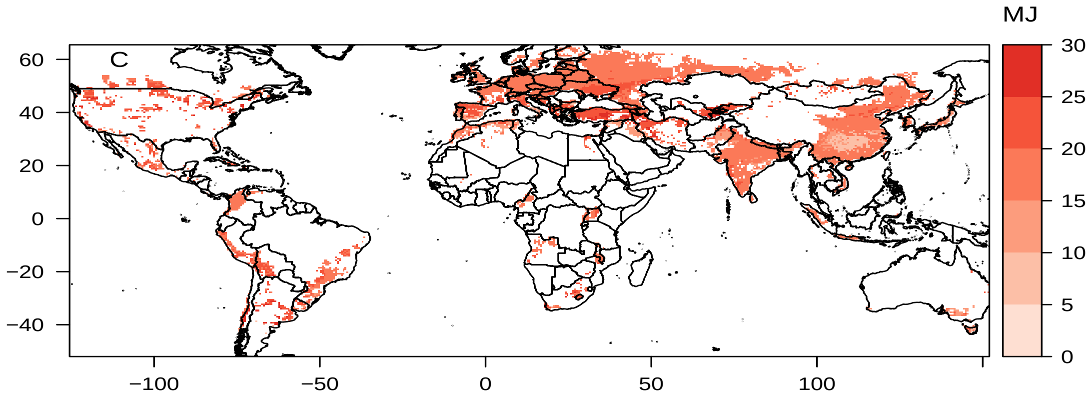




**Figure B1:** A. Mean temperature. B. Mean total rainfall during the growing season. C. Mean solar radiation (next page).




| Country | Years Simulated | Why Excluded | Detrending |
|---|---|---|---|
| Afghanistan | Na | S | Na |
| Albania | 1980-2009 | Na | ND |
| Algeria | 1980-2009 | Na | ND |
| Angola | 1993-2009 | F | ND |
| Argentina | 1980-2009 | Na | ND |
| Armenia | 1992-2009 | Na | ND |
| Australia | 1980-2009 | Na | Linear |
| Austria | 1980-2009 | Na | Quadratic |
| Azerbaijan | 1992-2009 | Na | ND |
| Bahrain | Na | R | Na |
| Bangladesh | 1980-2009 | Na | ND |
| Belarus | 1992-2009 | NA | Quadratic |

| | | | |
|---|---|---|---|
| Belgium | 2000-2009 | Na | ND |
| Belize | Na | A | Na |
| Benin | Na | S | Na |
| Bermuda | Na | R | Na |
| Bhutan | Na | S | Na |
| Bolivia | 1980-2009 | Na | ND |
| Bosnia | 1992-2009 | Na | Linear |
| Botswana | Na | Y | Na |
| Brazil | 1980-2009 | Na | ND |
| British Virgin Islands | Na | Y | Na |
| Brunei Darussalam | Na | Y | Na |
| Bulgaria | 1980-2009 | Na | ND |
| Burkina | Na | S | Na |
| Burundi | Na | S | ND |
| Cabo | Na | R | Na |
| Cambodia | Na | Y | Na |
| Cameroon | 1980-2009 | Na | ND |
| Canada | 1980-2009 | Na | Quadratic |
| Cayman Islands | Na | Y | Na |
| CAR | Na | S | Na |
| Chad | Na | S | Na |
| Channel Islands | Na | Y | Na |
| Chile | 1980-2009 | Na | Quadratic |
| China Hong Kong SAR | Na | Y | Na |
| China Macao SAR | Na | Y | Na |
| China | 1980-2009 | Na | ND |

| | | | |
|---|---|---|---|
| ChinaT | 1980-2009 | Na | ND |
| Colombia | 1980-2009 | Na | ND |
| Comoros | Na | R | Na |
| Congo | Na | S | Na |
| Cook Islands | Na | Y | Na |
| Costa | 1980-2009 | Na | ND |
| Ivory Coast | Na | Y | Na |
| Croatia | 1992-2009 | Na | Quadratic |
| Cuba | 1980-2009 | Na | Linear |
| Cyprus | Na | A | Na |
| Czech | 1993-2009 | Na | ND |
| Czechoslovakia | Na | P | Na |
| DPRK | Na | S | Na |
| DR Congo | Na | S | Na |
| Denmark | 1980-2009 | Na | ND |
| Djibouti | Na | Y | Na |
| Dominica | Na | A | Na |
| Dominican R | Na | S | Na |
| Ecuador | Na | S | Na |
| Egypt | 1980-2009 | Na | ND |
| El Salvador | Na | S | Na |
| Equatorial Guinea | Na | Y | Na |
| Eritrea | Na | S | Na |
| Estonia | 1992-2009 | Na | Quadratic |
| Ethiopia | Na | S | Na |
| Ethiopia PDR | Na | Y | Na |
| Faroe Islands | Na | R | Na |
| Fiji | Na | A | Na |
| Finland | 1980-2009 | Na | ND |

| | | | |
|---|---|---|---|
| France | 1980-2009 | Na | Quadratic |
| French Guiana | Na | Y | Na |
| French Polynesia | Na | R | Na |
| Gabon | Na | Y | Na |
| Gambia | Na | Y | Na |
| Georgia | 1992-2009 | Na | ND |
| Germany | 1980-2009 | Na | Quadratic |
| Ghana | Na | Y | Na |
| Gibraltar | Na | Y | Na |
| Greece | 1980-2007 | F | ND |
| Greenland | Na | Y | Na |
| Grenada | Na | Y | Na |
| Guadeloupe | Na | Y | Na |
| Guam | Na | Y | Na |
| Guatemala | Na | S | Na |
| Guinea | Na | A | Na |
| Guinea-Bissau | Na | Y | Na |
| Guyana | Na | Y | Na |
| Haiti | 1989-2009 | F | Linear |
| Holy See | Na | Y | Na |
| Honduras | 1980-2009 | Na | Quadratic |
| Hungary | 1980-2009 | Na | ND |
| Iceland | Na | A | Na |
| India | 1980-2009 | Na | ND |
| Indonesia | 1980-2009 | Na | ND |
| Iran | 1980-2009 | Na | ND |
| Iraq | 1980-2009 | Na | ND |
| Ireland | 1980-2009 | Na | ND |
| Isle of Man | Na | Y | Na |
| Israel | 1980-2009 | Na | ND |

| | | | |
|---|---|---|---|
| Italy | 1980-2009 | Na | ND |
| Jamaica | 1980-2009 | Na | Na |
| Japan | 1980-2009 | Na | ND |
| Jordan | 1980-2009 | Na | ND |
| Kazakhstan | Na | S | Na |
| Kenya | Na | S | Na |
| Kiribati | Na | Y | Na |
| Kuwait | Na | S | Na |
| Kyrgyzstan | 1992-2009 | Na | ND |
| Laos | Na | S | Na |
| Latvia | 1992-2009 | Na | Quadratic |
| Lebanon | 1980-2006 2009-2009 | F | ND |
| Lesotho | 1982-2009 | F | ND |
| Liberia | Na | Y | Na |
| Libya | Na | S | Na |
| Liechtenstein | Na | Y | Na |
| Lithuania | 1992-2009 | Na | ND |
| Luxembourg | 2000-2009 | Na | Quadratic |
| Madagascar | Na | S | Na |
| Malawi | 1980-2009 | Na | ND |
| Malaysia | Na | Y | Na |
| Maldives | Na | Y | Na |
| Mali | 1990-2009 | Na | Quadratic |
| Malta | Na | R | Na |
| Marshall Islands | Na | Y | Na |
| Martinique | Na | Y | Na |
| Mauritania | Na | A | Na |
| Mauritius | Na | R | Na |
| Mayotte | Na | Y | Na |

| | | | |
|---|---|---|---|
| Mexico | 1980-2009 | Na | ND |
| Monaco | Na | Y | Na |
| Mongolia | 1980-2009 | Na | ND |
| Montenegro | Na | Y | Na |
| Montserrat | Na | R | Na |
| Morocco | 1980-2009 | Na | ND |
| Mozambique | 1980 1985-2009 | F | ND |
| Myanmar | Na | S | Na |
| Namibia | Na | A | Na |
| Nauru | Na | Y | Na |
| Nepal | 1980-2009 | Na | ND |
| Netherlands | 1980-2009 | Na | Quadratic |
| New Caledonia | Na | S | Na |
| New Zealand | Na | S | Na |
| Nicaragua | Na | S | Na |
| Niger | Na | S | Na |
| Nigeria | Na | S | Na |
| Niue | Na | Y | Na |
| Norfolk Island | Na | Y | Na |
| Northern Mariana Islands | Na | Y | Na |
| Norway | 1980-2009 | Na | Quadratic |
| Occupied PT | Na | S | Na |
| Oman | Na | S | Na |
| Pacific Islands Trust Territory | Na | Y | Na |
| Pakistan | 1980-2009 | Na | ND |
| Palau | Na | Y | Na |
| Panama | 1980-2009 | Na | ND |
| Papua NG | Na | A | Na |

| | | | |
|---|---|---|---|
| Paraguay | Na | A | Na |
| Peru | 1980-2009 | Na | ND |
| Philippines | Na | S | Na |
| Pitcairn Islands | Na | Y | Na |
| Poland | 1980-2009 | Na | ND |
| Portugal | 1980-2009 | Na | ND |
| Puerto Rico | Na | Y | Na |
| Qatar | Na | A | Na |
| Korea | 1980-2009 | Na | ND |
| Moldova | 1992-2009 | Na | Quadratic |
| Reunion | Na | A | Na |
| Romania | Na | S | Na |
| Russia | 1992-2009 | Na | Quadratic |
| Rwanda | 1980-2009 | Na | Quadratic |
| Saint Kitts | Na | R | Na |
| Saint Lucia | Na | Y | Na |
| Saint Pierre and Miquelon | Na | Y | Na |
| Saint Vincent and the Grenadines | Na | Y | Na |
| Samoa | Na | Y | Na |
| San Marino | Na | Y | Na |
| Sao Tome and Principe | Na | Y | Na |
| Saudi Arabia | Na | S | Na |
| Senegal | Na | A | Na |
| Serbia | Na | Y | Na |
| Seychelles | Na | Y | Na |
| Sierra Leone | Na | Y | Na |
| Singapore | Na | Y | Na |

| | | | |
|---|---|---|---|
| Slovakia | 1993-2009 | Na | ND |
| Slovenia | 1992 1995-2009 | F | Linear |
| Solomon Islands | Na | Y | Na |
| Somalia | Na | Y | Na |
| South Africa | 1980-2009 | Na | ND |
| South Sudan | Na | Y | Na |
| Spain | 1980-2009 | Na | ND |
| Sri Lanka | 1980-2009 | Na | Quadratic |
| Sudan | Na | S | Na |
| Suriname | Na | Y | Na |
| Swaziland | 1989-2001 2004 2007-2009 | F | ND |
| Sweden | 1980-2009 | Na | ND |
| Switzerland | 1980-2009 | Na | ND |
| Syrian Arab Republic | 1980-2009 | Na | ND |
| Tajikistan | 1992-2009 | Na | ND |
| Thailand | 1980-1998 2001-2009 | F | Quadratic |
| Macedonia | 1992-2009 | Na | ND |
| Timor-Leste | 1980-1994 1997-2005 2008-2009 | F | ND |
| Togo | Na | Y | Na |
| Tokelau | Na | Y | Na |
| Tonga | Na | Y | Na |
| Trinidad and Tobago | Na | Y | Na |
| Tunisia | 1980-2009 | Na | ND |
| Turkey | 1980 1983-2009 | F | ND |
| Turkmenistan | Na | S | Na |

| | | | |
|---|---|---|---|
| Tuvalu | Na | Y | Na |
| Uganda | 1980 1983-2009 | F | ND |
| Ukraine | 1992-2009 | Na | ND |
| UAE | Na | A | Na |
| UK | 1980-2009 | Na | ND |
| Tanzania | Na | F | Na |
| USA | 1980-2009 | Na | ND |
| Uruguay | 1980-2009 | Na | ND |
| USSR | Na | P | Na |
| Uzbekistan | 1992-2009 | Na | ND |
| Vanuatu | Na | Y | Na |
| Venezuela | 1980-2009 | Na | ND |
| Vietnam | 1980-1994 1997-2004 2007-2009 | F | ND |
| Western Sahara | Na | Y | Na |
| Yemen | Na | S | Na |
| Yugoslav SFR | Na | P | Na |
| Zambia | Na | S | Na |
| Zimbabwe | 1980-2009 | Na | ND |

**Table B1:** Details of countries simulated, countries/years excluded and reasons for doing so and the model used for detrending (if applicable). Key: F = Flatline (consecutive years of same yield data so years listed excluded) Y = Yield (fewer than 6 years of data for simulations so country excluded) R = Resolution (country too small for resolution simulated so excluded) P = Political (outdated country, represented by extant country/countries, so excluded) S = multiple-state (time series with multiple sections of yield data at different mean levels so excluded) L = Length (section of time series chosen due to more years of data in multi-state time series) W = Weather (section of time series chosen due to stronger relationship between observed yields and weather data) A = Area (Country excluded as no grid cells with sufficient potato growing area) O = Data Outlier (year excluded as it is an outlier that is more than two standard deviations from mean of time series and is not supported by the corresponding production and area data) ND = not detrended due to weakened correlations with weather variables. Na = not applicable - e.g. not detrended as country not simulated.

Figures B2 to B5 show sowing windows and varieties selected in future climate for climate models gfdl-esm2m, ipsl-cm5a-lr, miroc-esm-chem and noresm1-m respectively.

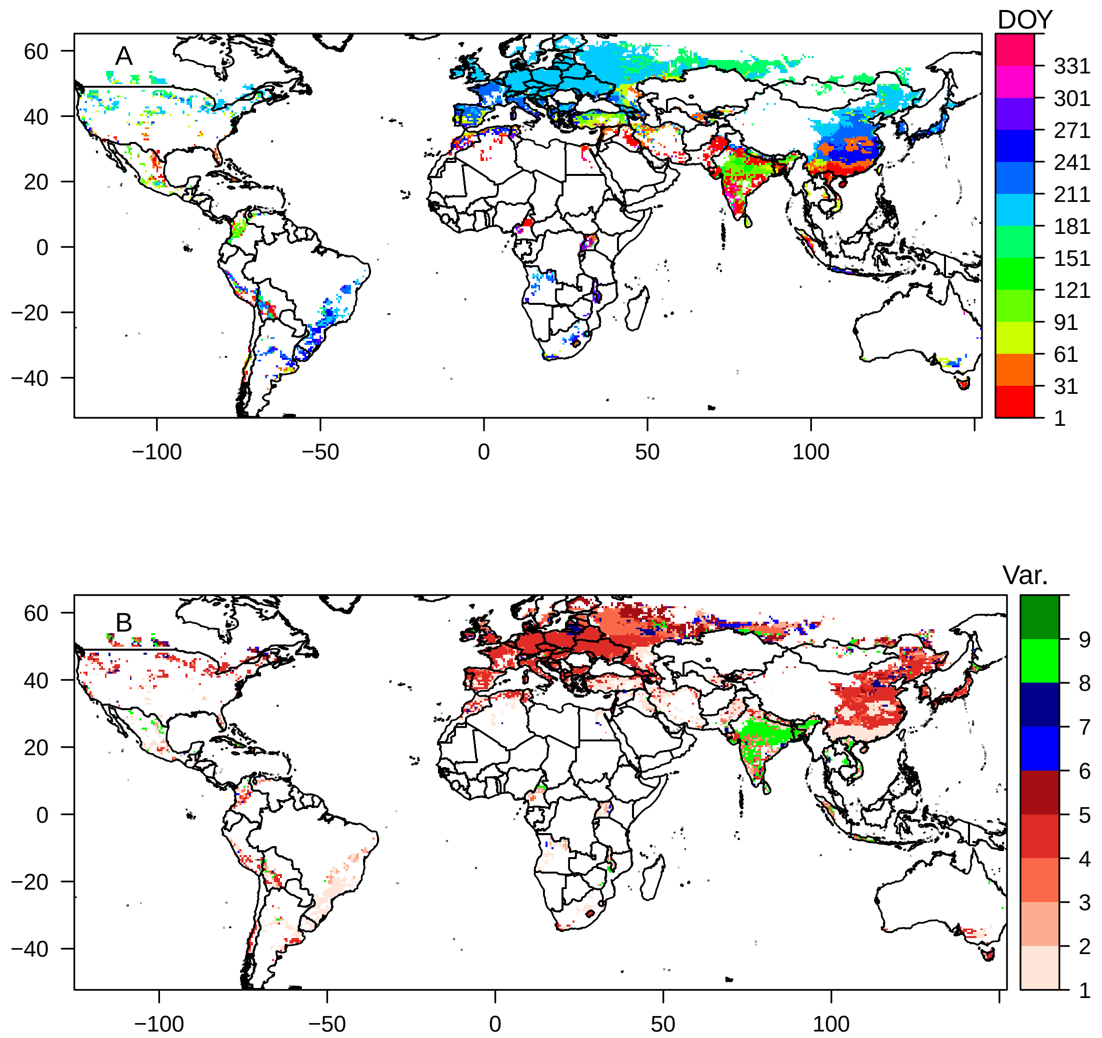



**Figure B2:** A. Start of the sowing window and B. varieties chosen for 2041-2050 using the gfdl-esm2m model.

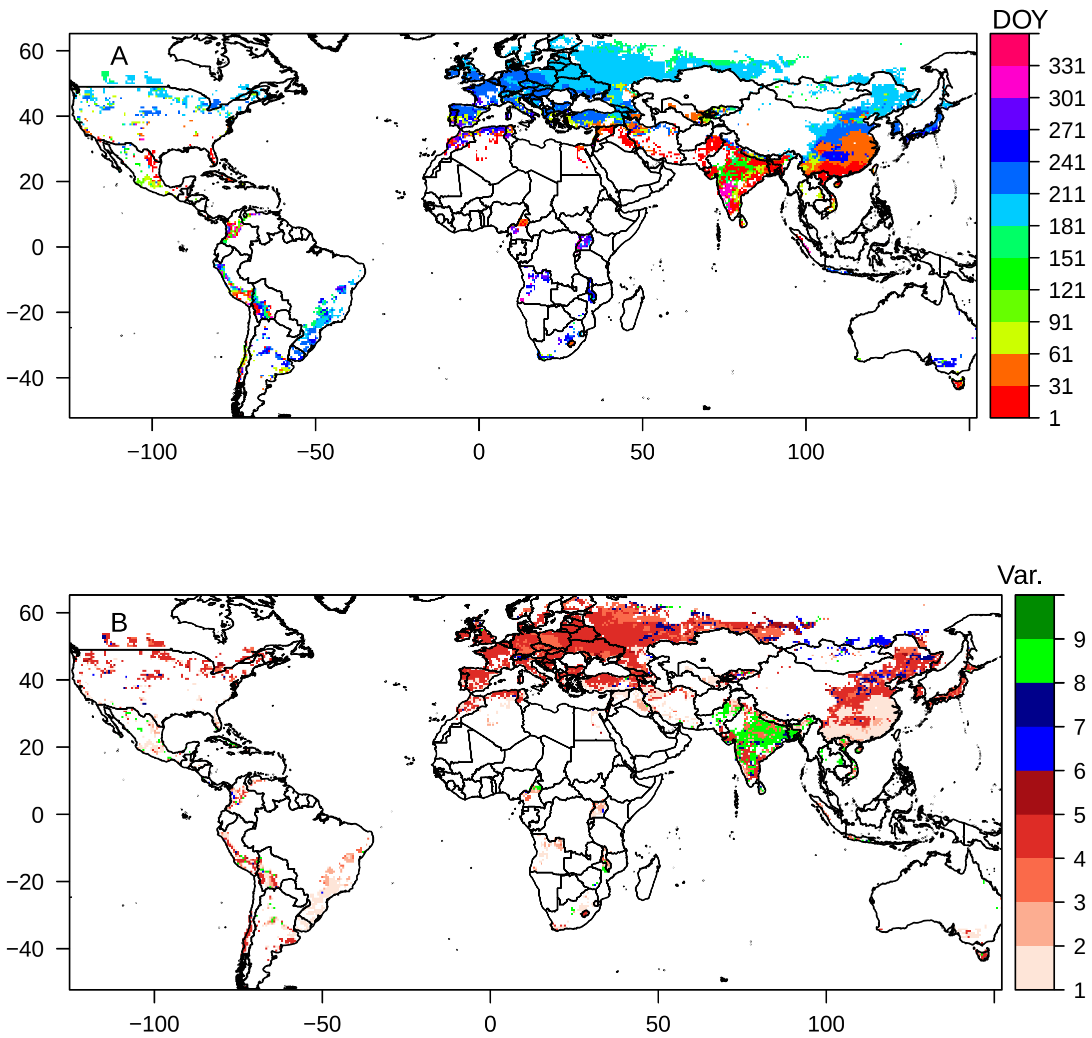
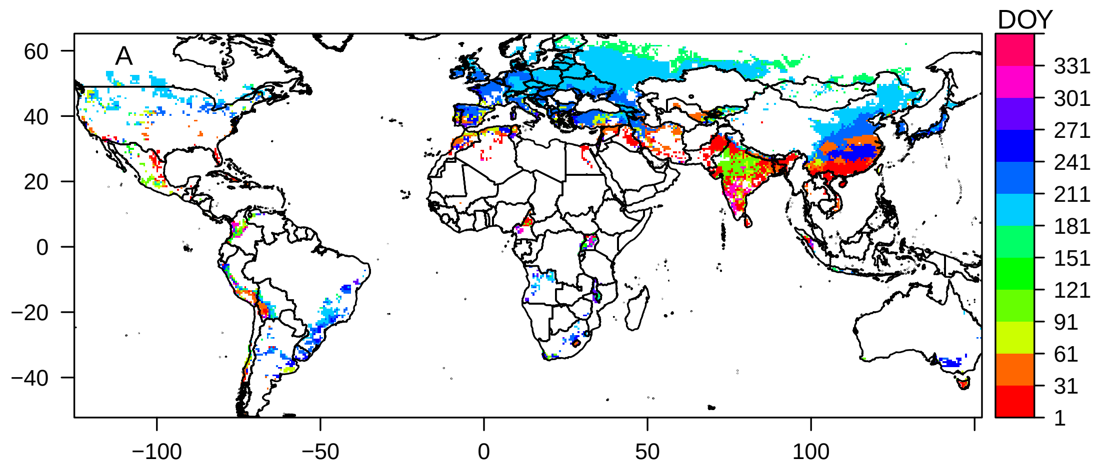



**Figure B3:** A. Start of the sowing window and B. varieties chosen for 2041-2050 using the ipsl-cm5a-lr model.



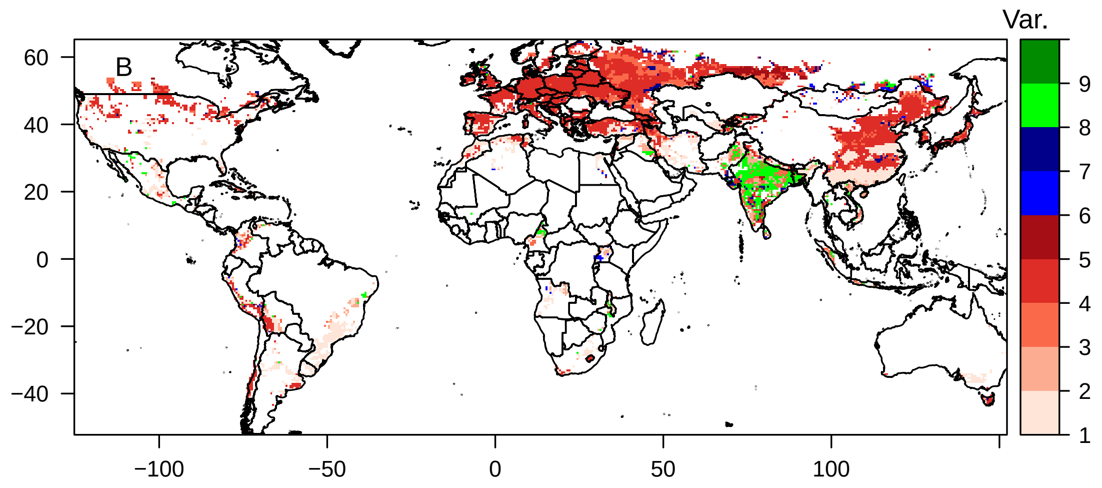




**Figure B4:** A. Start of the sowing window and B. varieties chosen for 2041-2050 using the miroc-esm-chem model.

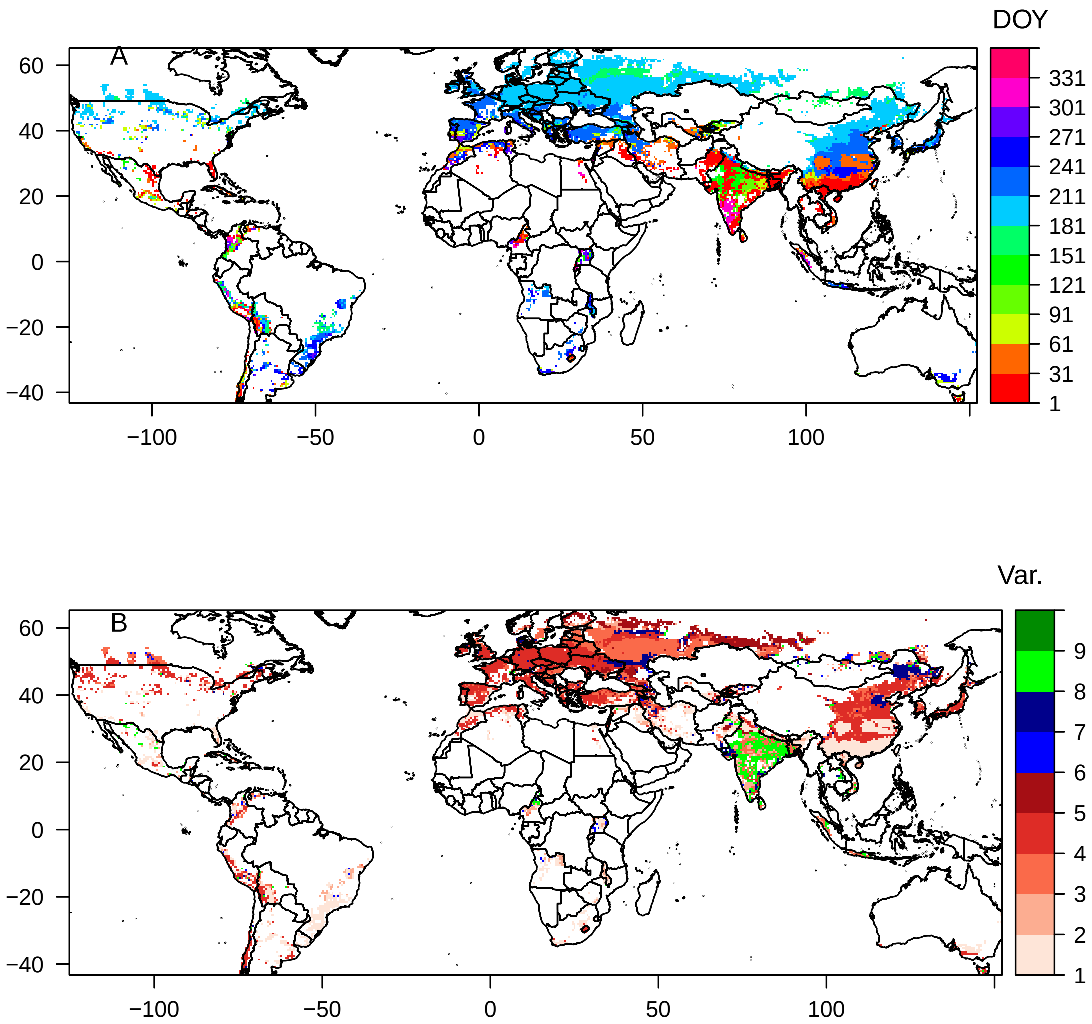



**Figure B5:** A. Start of the sowing window and B. varieties chosen for 2041-2050 using the noresm1-m model.

Figures B6 to B10 show yield changes from baseline to future climate without and with adaptation for climate models gfdl-esm2m, hadgem2-es, ipsl-cm5a-lr, miroc-esm-chem and noresm1-m respectively.

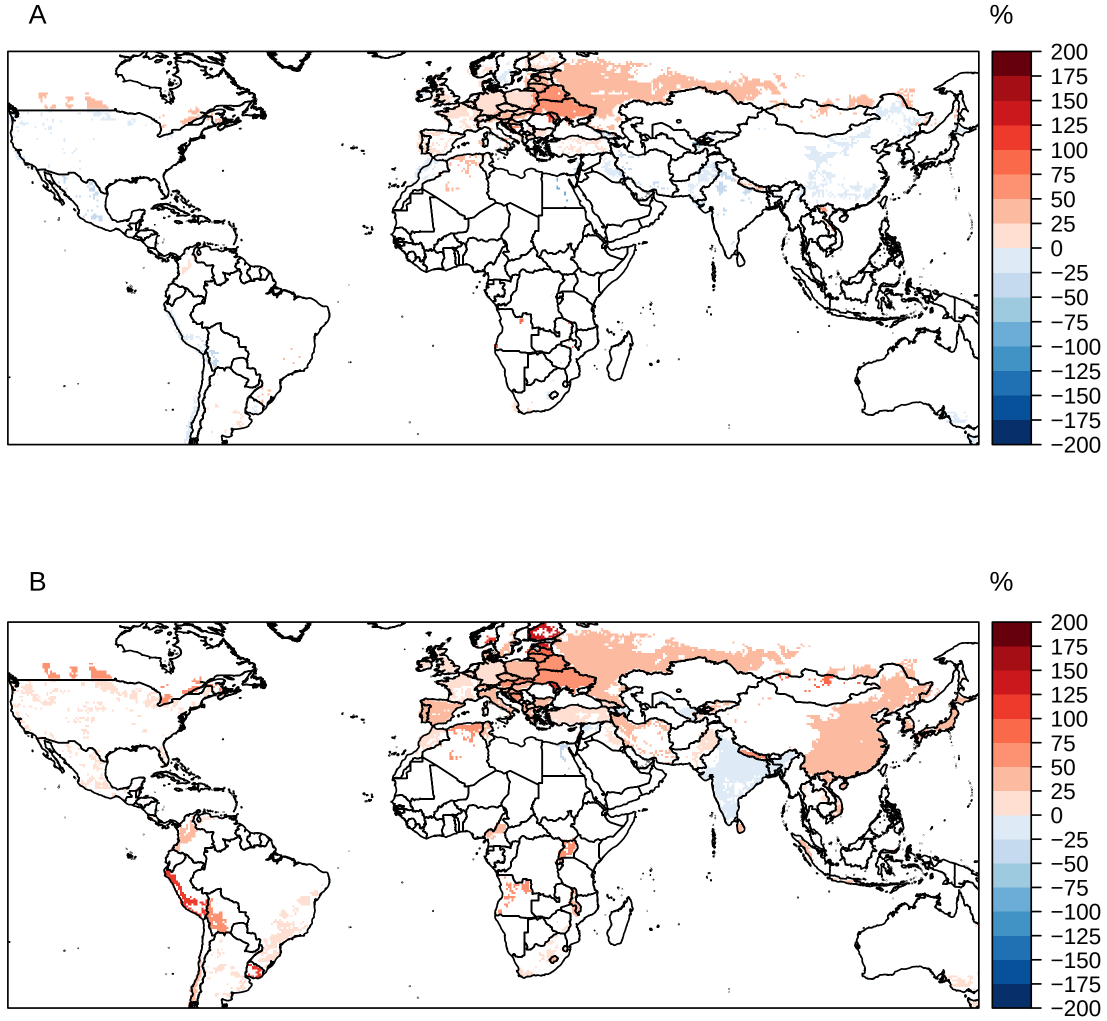



**Figure B6:** Yield changes from baseline to future climate for the gfdl-esm2m model with A. no adaptation and B. adaptation.

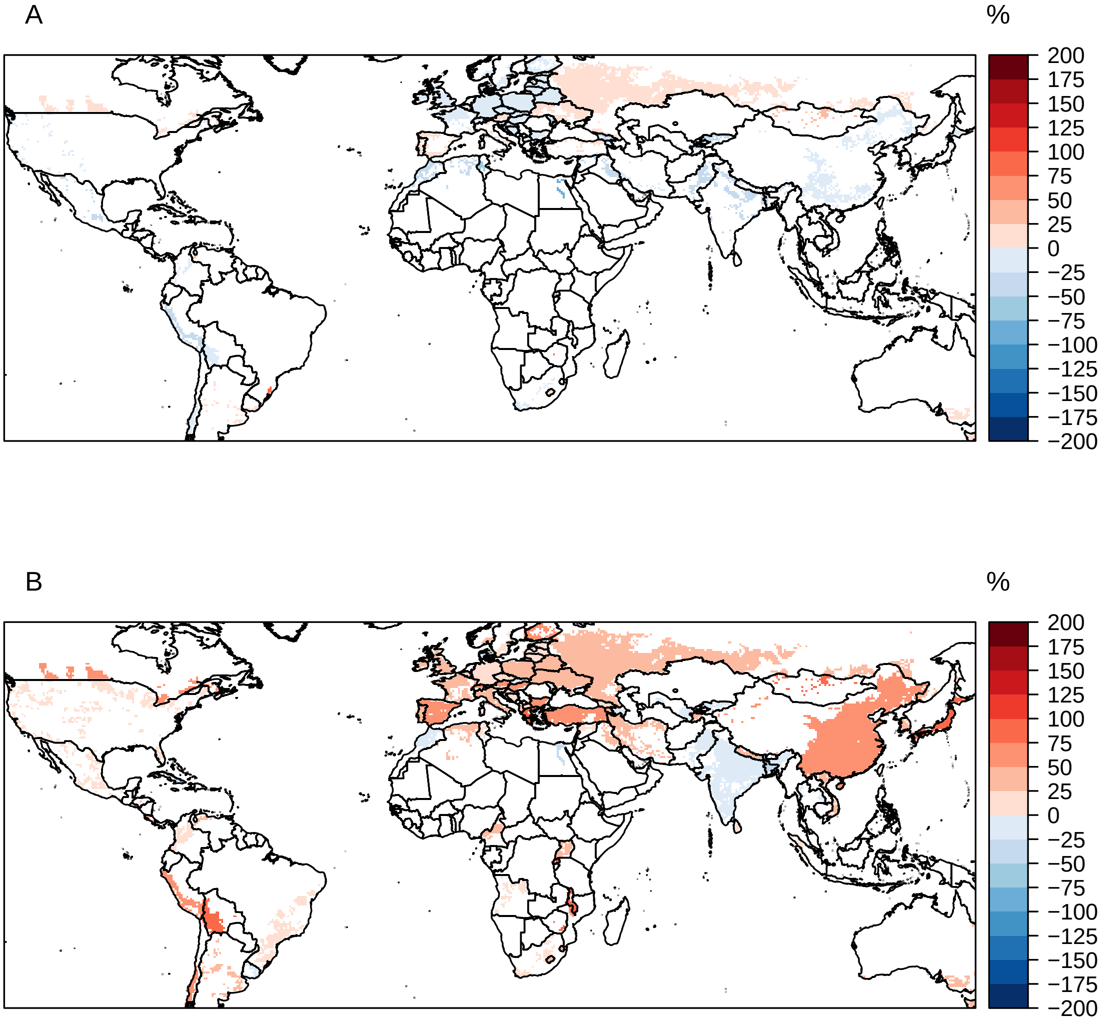



**Figure B7:** Yield changes from baseline to future climate for the hadgem2-es model with A. no adaptation and B. adaptation.

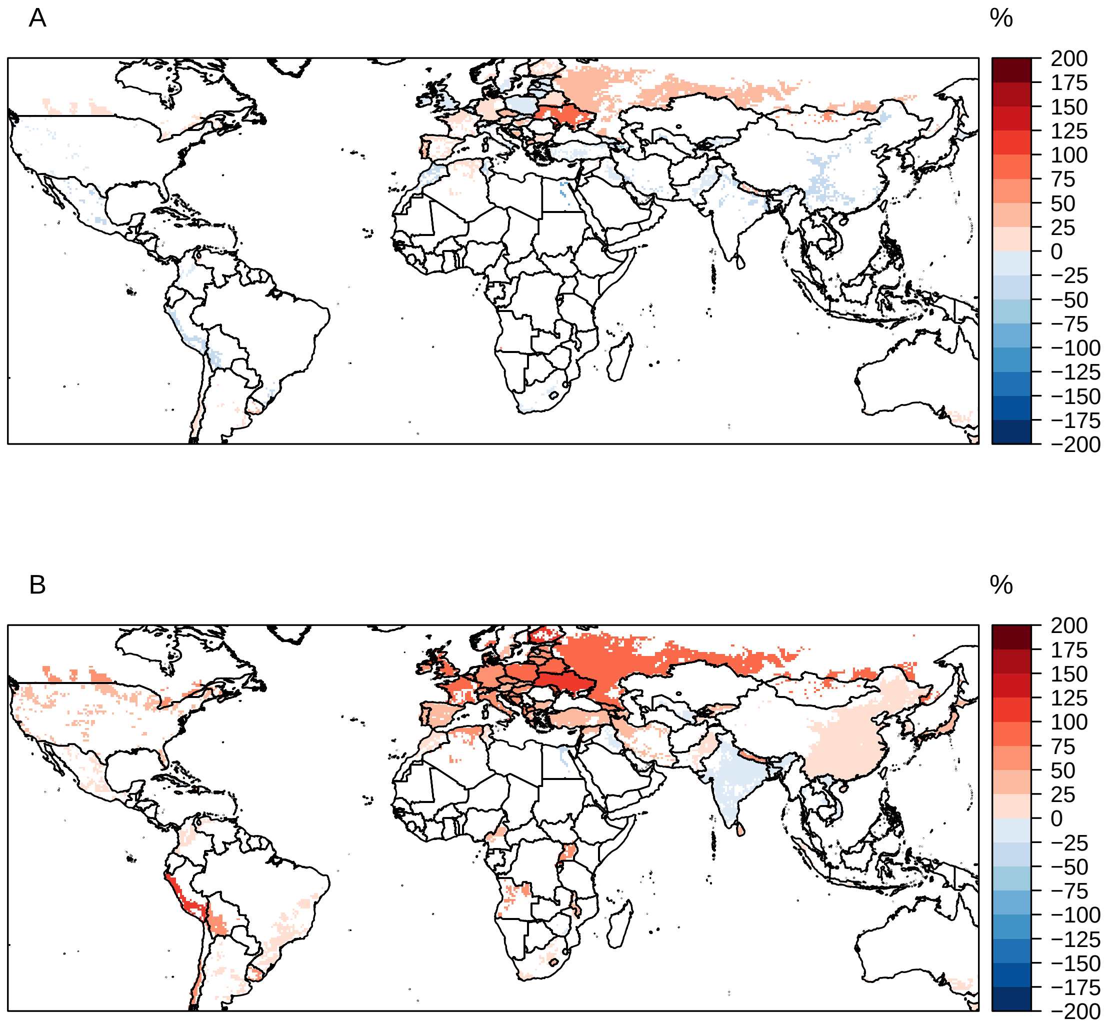



**Figure B8:** Yield changes from baseline to future climate for the ipsl-cm5a-lr model with A. no adaptation and B. adaptation.

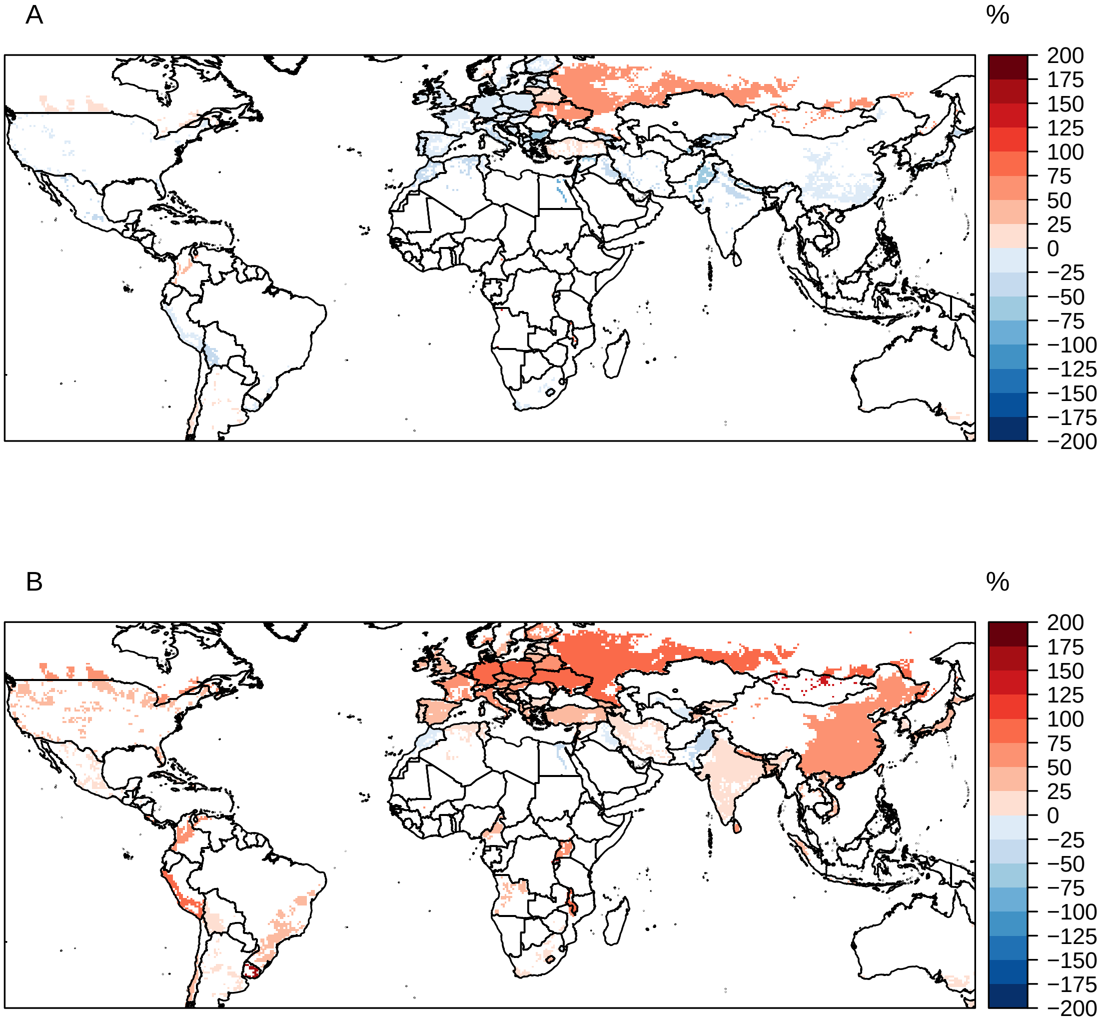



**Figure B9:** Yield changes from baseline to future climate for the miroc-esm-chem model with A. no adaptation and B. adaptation.

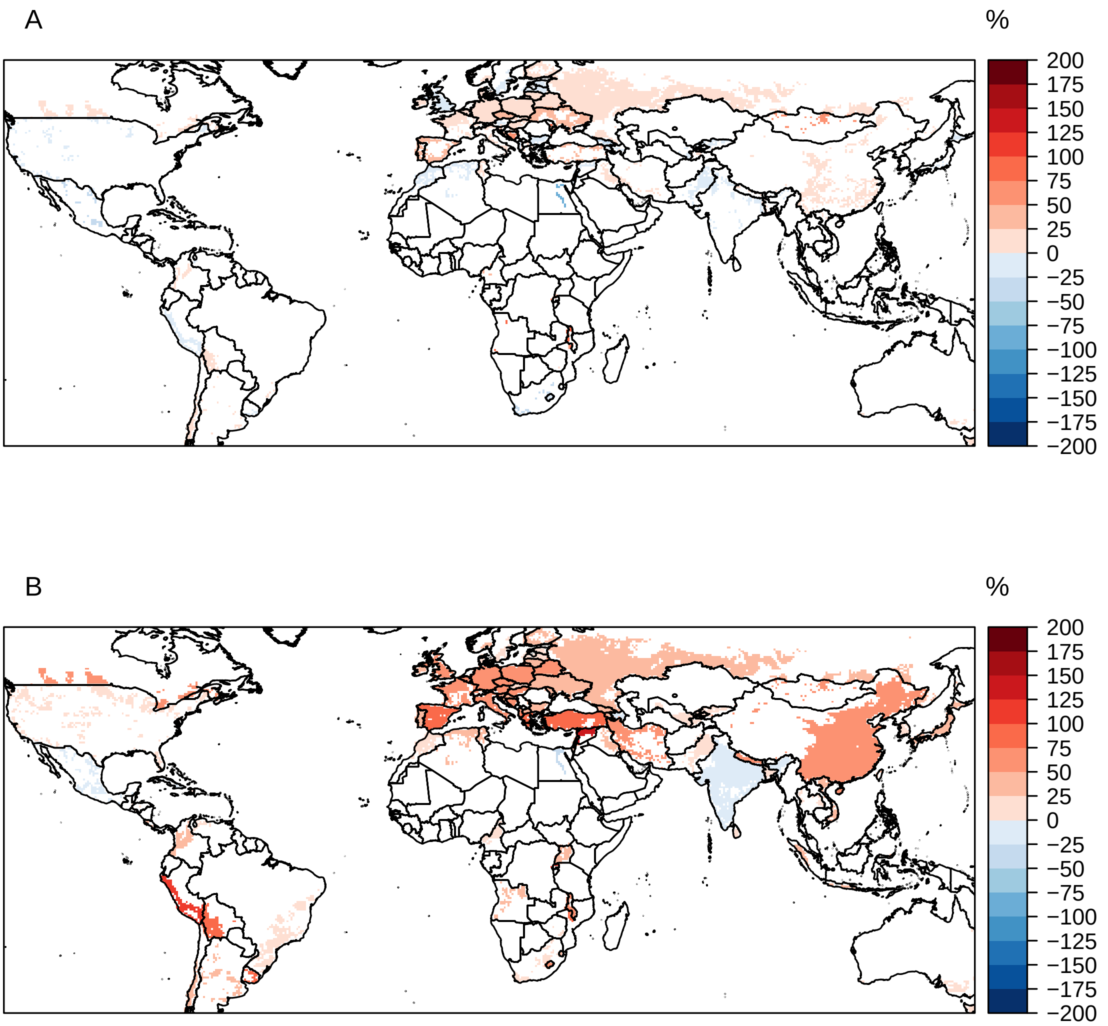



**Figure B10:** Yield changes from baseline to future climate for the noresm1-m model with A. no adaptation and B. adaptation.

# Appendix C - The influence of climate change on crop pests and diseases: pesticide analysis

Model diagnostic plots for pesticide regression models are shown below. 10 figures are shown - two for each continent, representing the models made up of all data and the models using only the high GDP bin data. Diagnostic plots for different climate data typically show very similar trends so not all are shown - diagnostic plots shown here are for the models made up of input data from the GFDL-ESM2 model.

These plots are used to check whether the assumptions of model linearity, constant variance and normality of errors are valid. The "Normal Q-Q" plots show that errors are typically normal. In some regions the plots show that there are likely some extreme values in the upper end of the data (e.g. see Figure C2). The "Residuals vs. Fitted" plots show that there may be some slight increase in variance at larger values (e.g. see Figure C9), but this was also deemed satisfactory given the limited number of data points, making it harder to detect such trends with confidence in the models.

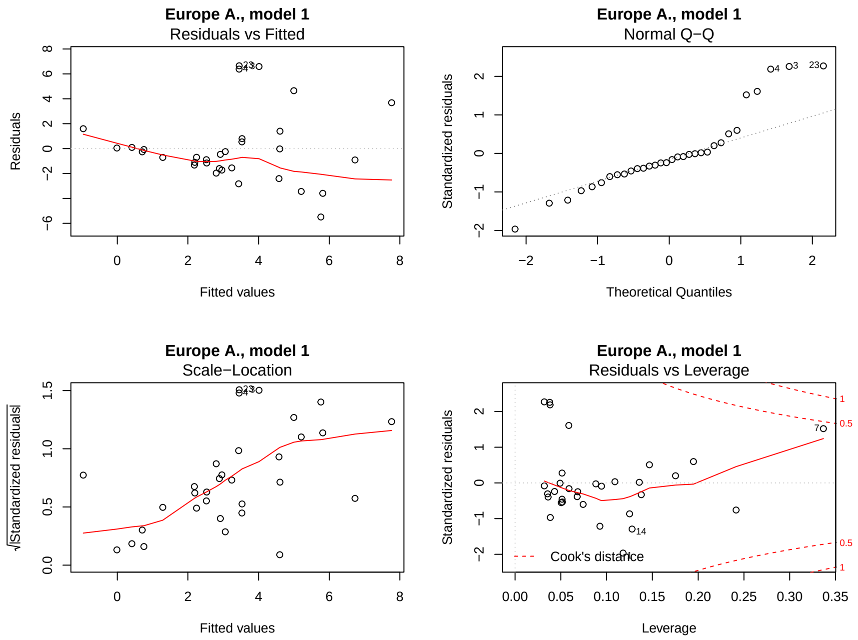



**Figure C1:** Diagnostic plot for European all data model.

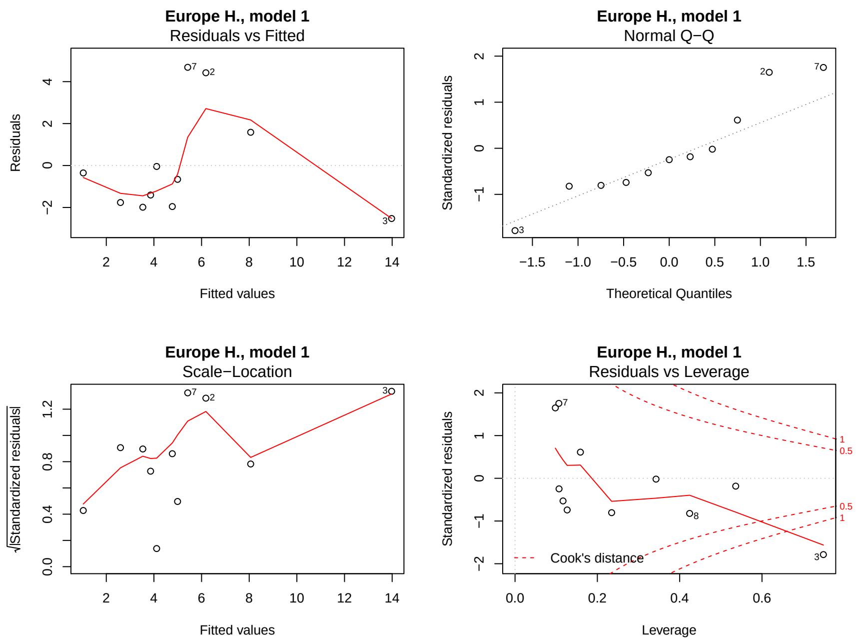



**Figure C2:** Diagnostic plots for European high GDP bin model.

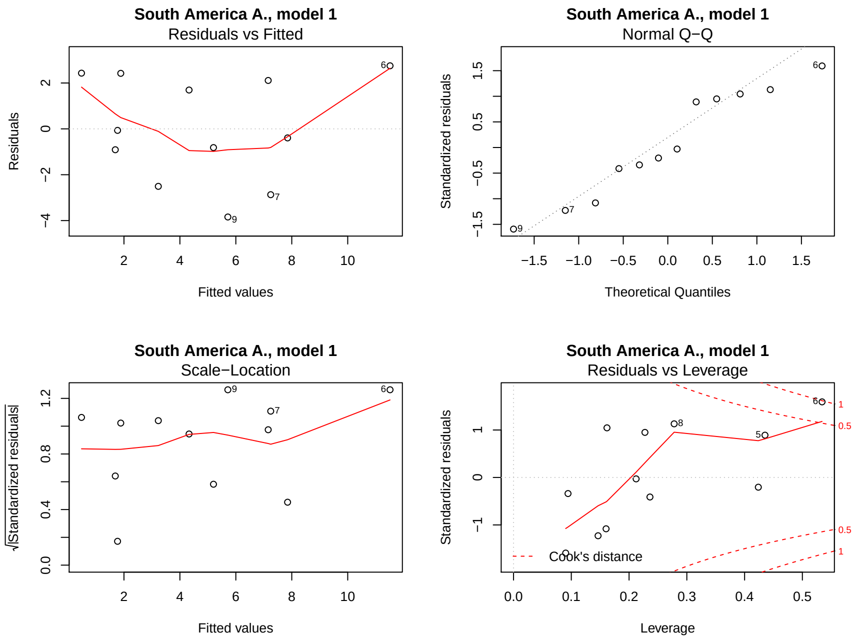



**Figure C3:** Diagnostic plot for the South American all data model.

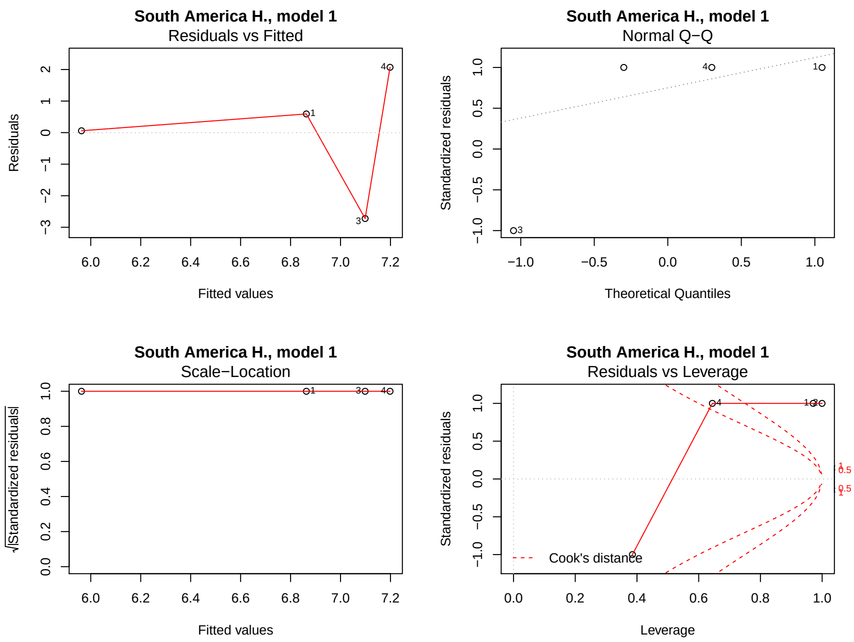



**Figure C4:** Diagnostic plots for the South American high GDP bin model.

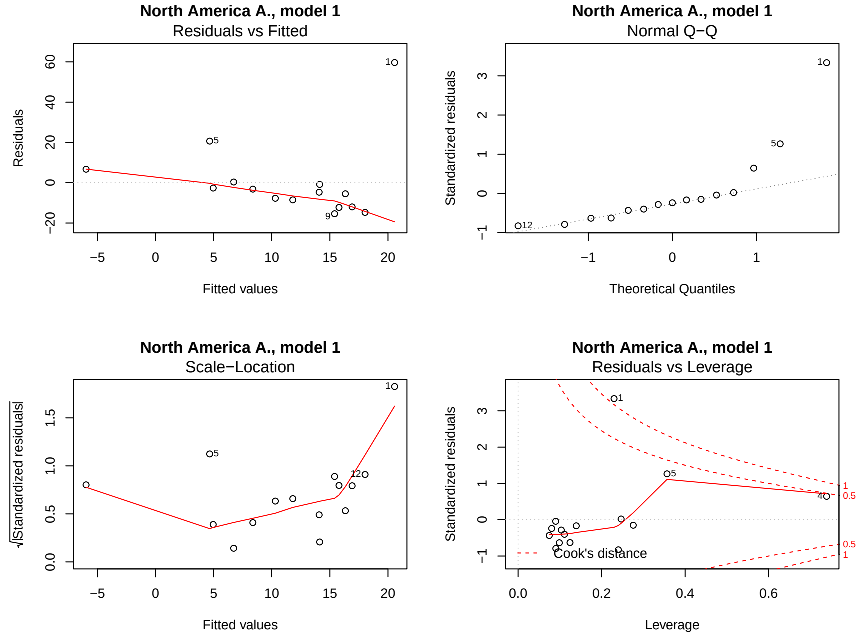



**Figure C5:** Diagnostic plot for the North American all data model.

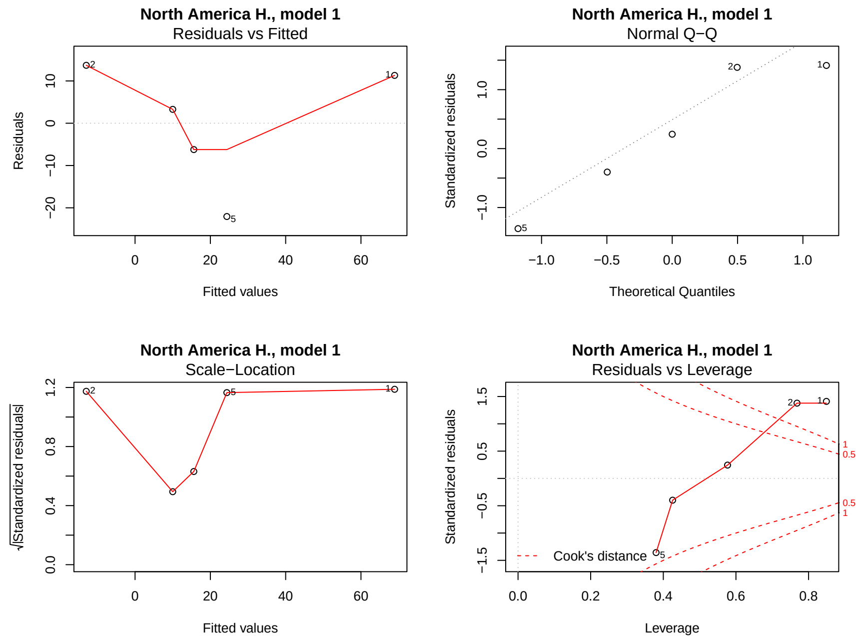



**Figure C6:** Diagnostic plots for the North American high GDP bin model.

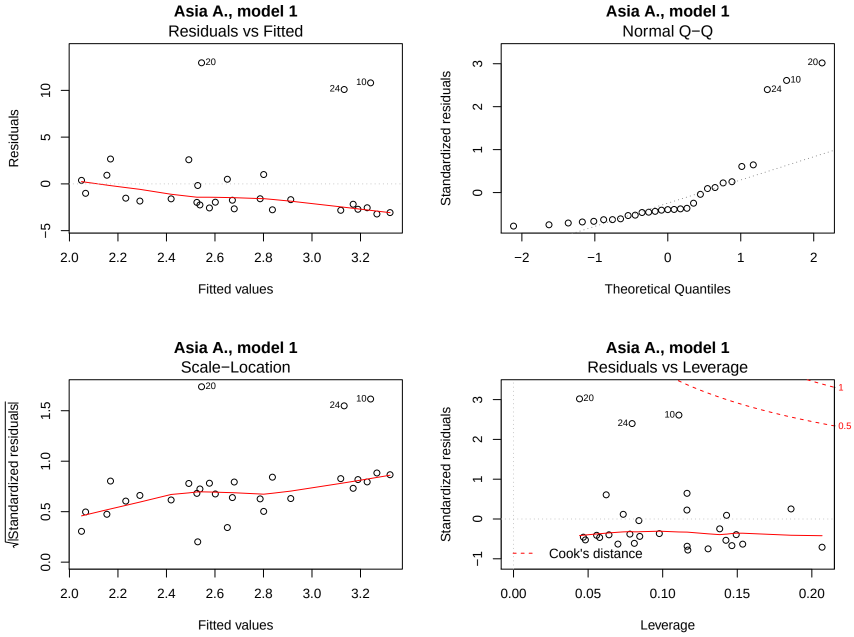



**Figure C7:** Diagnostic plot for the Asian all data model.

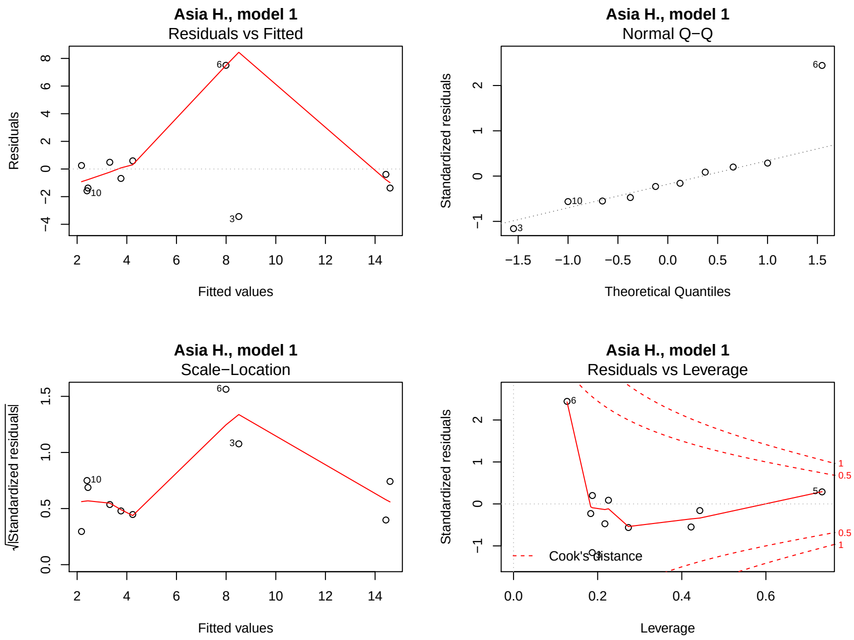



**Figure C8:** Diagnostic plots for the Asian high GDP bin model.

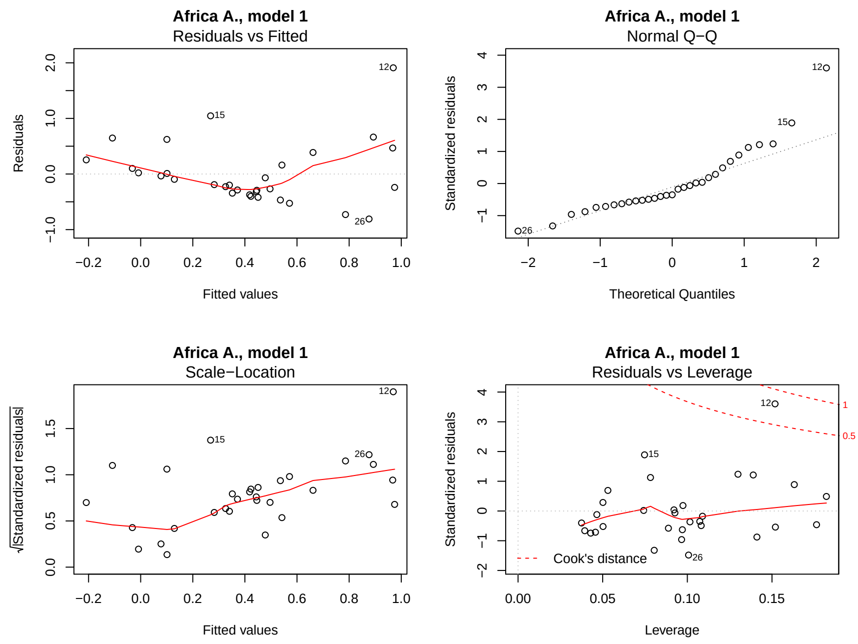



**Figure C9:** Diagnostic plot for the African all data model.

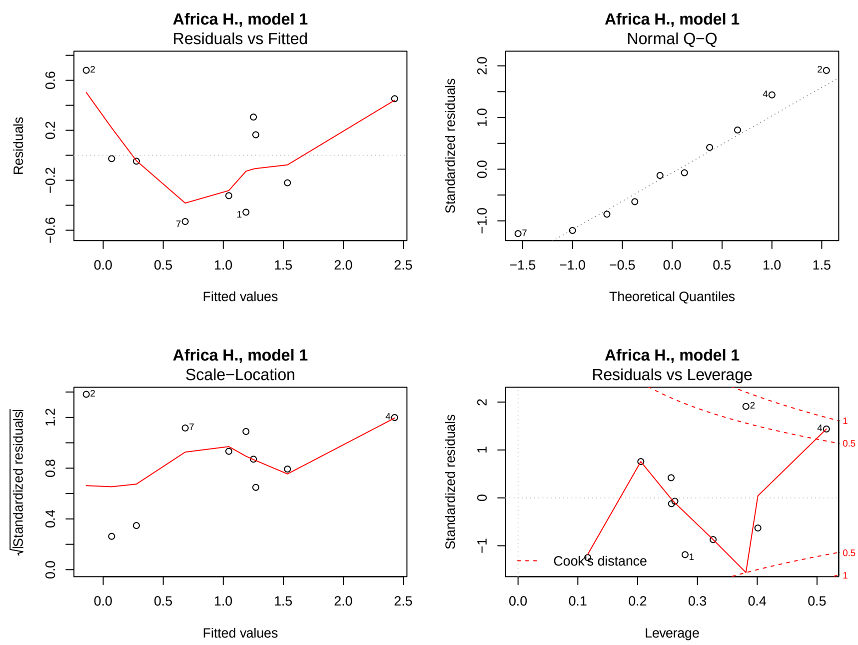



**Figure C10:** Diagnostic plots for the African high GDP bin model.

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