# Developing robust arable farming systems for multiple benefits: Mathematical programming approach

**By:**

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***"Great things have little beginnings."***

— Asamankese Secondary School (Ghana) motto

This thesis is dedicated to my grandmother (Ms Grace Esi Ampomaa Amoah), my mother (Ms Charlotte Asante), my wife (Alice Odumaa Ahodo) and my beloved daughter (Nana Akua Ampomaa Ahodo). I also dedicate this thesis to the memory of my late father, Mr Ben Moses Kwami Ahodo.

***"Farming is a profession of hope"***

— Brian Brett

## THESIS ABSTRACT

To be able to meet the growing demand for food and ensure food security, arable farming systems need to be made more sustainable. However, making arable farming systems more sustainable could sometimes mean reductions in the use of productivity improving inputs such as fertiliser and pesticide in order to reduce their impacts on the environment. This presents conflicting environmental and economic goals, which increase management complexities in sustainable arable farming systems. An arable farm level model, consisting of four modules, which combines mixed-integer, risk and goal-programming approaches, has been developed to capture many of the complexities in arable farming and optimise farm profit, risk and nitrate leaching. Statistical validation of the model using data from the Farm Business Survey (FBS) showed a good association between model-predicted results and observed farm data. Results of the application of the mixed-integer weighted goal-programming module to estimate aggregate cost of non-chemical (spring cropping) control of black-grass showed that in the short run the strategy could cost the UK arable farming sector, however there could be a long term benefit of reductions in black-grass infestation. On per hectare basis, cost estimates provide indication of possible farm payment to incentivise adoption of the strategy. On individual farm basis, spring cropping could be beneficial dependent on the soil type, rainfall and hectares of land available to the farm. The application of the MOTAD module and randomly generated risk-aversion parameter method showed that arable farmers in England are risk-averse and that farmers in different regions would react to change in policy differently depending on their levels of risk-aversion. The results also showed the need for regional policies and relevance of the model in policy analysis. The model, which has been developed as part of this research adds to the few arable farm level models identified in the UK and bridges model capability gaps identified in arable farm modelling. Given available data for calibration and validation, results generated by the model can be applied to better inform arable farming and policy decisions to enhance the development of robust and sustainable arable farming systems to ensure food security.

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My greatest gratitude goes to the almighty God (Mawu) for giving me the strength to undertake this research.

## STATEMENT OF CONTRIBUTIONS

The greater majority of the ideas, model development and validation, analysis and writing of this thesis are wholly the work of the candidate. However, all chapters in this thesis were developed with support and improvements by input and advice of the supervisory team and/or collaborators. As a result, the personal pronoun "we" is used in this thesis (particularly Chapters 2, 4, and 5).

The general introduction (Chapter 1) was written mainly by the candidate with editorial advice from the supervisory team: Professor Robert Freckleton and Professor David Oglethorpe. Also, editorial advice was given by Dr Dylan Childs who assessed it when the chapter was submitted as a literature review as part of the PhD degree requirement by the Department of Animal and Plant Sciences.

Chapter 2 is a version of a conference paper submitted to 89th Conference of the Agricultural Economic Society. The idea including the model calibration, data collection and analysis was developed by the candidate with suggestions from Professor Robert Freckleton and Professor David Oglethorpe. Also the chapter was written by the candidate with general editorial advice given by Professor Robert Freckleton, Professor David Oglethorpe and Dr Helen Hicks.

The model developed and validated as part of this research was entirely by the candidate with advice and suggestions from my supervisors, Professor Robert Freckleton and Professor David Oglethorpe. Also, in terms of model building some suggestions and advice were given by Mr Eric Audsley and Dr Ira Cooke. The data collection for building and validating the model, writing of model codes were done entirely by the candidate. The chapter on model description and validation (Chapter 3) was written by the candidate with advice and suggestion on review of statistical measures of association and general editorial advice given by Professor Robert Freckleton and Professor David Oglethorpe. Editorial advice was also given by Dr Alexa Varah, who offered to proofread the chapter draft.

Chapter 4 is a version of a manuscript by Kwadjo Ahodo, David Oglethorpe, Helen Hicks and Robert Freckleton, submitted to the Agricultural Systems journal. The idea was suggested by Professor Robert Freckleton and developed by the candidate. The modelling and analysis were also done by the candidate with suggestion on spring crop rotation constraint modelling by Professor David Oglethorpe. The data on black-grass control costs and yield penalties due to black-grass infestation were supplied by Dr Helen Hicks from her work on Black-grass Resistance Initiative project. The chapter was written mainly by the candidate with editorial advice given by Professor Robert Freckleton, Professor David Oglethorpe and Dr Helen Hicks.

Chapter 5 is a version manuscript by Kwadjo Ahodo, David Oglethorpe and Robert Freckleton, submitted to the American Journal of Agricultural Economics. The idea was mainly developed by the candidate, with advice from Professor David Oglethorpe to focus on methodology and policy, and support from Professor Robert Freckleton. Data collection from the Farm Business Survey, modelling, model runs and analysis of results were done entirely by the candidate. The chapter was written mainly by the candidate with support, suggestions and editorial advice by Professor David Oglethorpe on the drafting of the section on utility theory and model application to policy analysis, and general comments/suggestions and editorial advice by Professor Robert Freckleton.

The general discussion (Chapter 6) was written mainly by the candidate with editorial advice by Professor Robert Freckleton and Professor David Oglethorpe.

## DECLARATION BY AUTHOR

The work presented in this thesis is original and does not contain work or materials, which have been previously written or published by others apart from where references have been made in the text. The contributions of the supervisory team and collaborators to all aspects of the research or thesis have been indicated above. The contents of this thesis are results from work I undertook from the beginning of my research and it can be sated that it does not contain any work submitted to qualify for any other type of degree in any institution. Sections of the thesis, which have been published or submitted for publication have been shown and I am aware that where applicable the copyright of the thesis content resides with the copyright holder(s) of that material.

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# 1 GENERAL INTRODUCTION

*This section presents a review of literature on arable farming systems modelling beginning with the concept of sustainable agriculture as the foundation for the need for innovative and multifunctional agricultural systems. It continues with a review on sustainable farm management practices in soil/nutrient, pest/weed, water, machinery/labour management and crop rotation as well as the policies such as the Common Agricultural Policy (CAP), which influence farming decision. Some of the challenges, opportunities, objectives, constraints and complexities in sustainable arable farming as well as the main research aim and objectives are presented. The section also presents a review of mathematical programming/modelling approaches beginning with the choice of mathematical programming, specifically linear programming based approaches as a means of modelling and testing out innovative farming systems. This is followed by a review of existing farm models to identify model capability gaps and continues with the research framework, research aim and thesis chapter specific research questions, identified research data needs and finally the key messages.*

## 1.1 Sustainable agriculture

The United Nations Department of Economic and Social Affairs (UN-DESA, 2013) projected the world population to increase by 34% by 2050, meaning that demand for food will continue to increase. However, as agricultural production becomes intensive due to high demand for food, agricultural inputs also increase resulting in externalities to the economy, environment as well as society. Externalities from agriculture such as nitrate leaching, pollution of water sources, emission of greenhouse gases (GHG), depletion of soil fertility and loss of biodiversity (Tait and Morris, 2000; Tilman *et al.*, 2002; Rodríguez and Wiegand, 2009; Vasileiadis *et al.*, 2011; Skevas *et al.*, 2013; Skevas and Lansink, 2014) have caused society to raise concerns over how intensive agriculture affects the natural environment, society and the economy, and the need for more sustainable agricultural systems (Tait and Morris, 2000 and Tilman *et al.*, 2002). The emergence of the sustainable development concept (WCED, 1987) has also promoted sustainable agriculture, which is being adopted by governments as part of agricultural policies or strategies (Gafsi *et al.*, 2006; Defra, 2011). This is because externalities from agriculture have the potential to reduce agricultural productivity, food security as well as compromise the benefits that will be derived from the environment in the future (Perman *et al.*, 2011).

The American Society of Agronomy (ASA, 1989) defined sustainable agriculture as “one, that over the long term, enhances environmental quality and the resources based on which agriculture depends, provides for basic human food and fibre needs, is economically viable, and enhances the quality of life for farmers and society as a whole.” According to Hansen and Jones (1996) sustainable agriculture is “the ability of farming systems to continue into the future” whereas Tilman *et al.* (2002) defined it as “practices that meet current and future societal needs for food and fibre, for ecosystem services, and for healthy lives, and that do so by maximising the net benefit to society when all costs and benefits of the practices are considered.” From all the above definitions, it can be said that sustainable agriculture seeks to promote environmental (ecological) well-being of society or holistic approach to food production with economic, environmental and societal goals. Sustainable agriculture is thus multifunctional (Rossing *et al.*, 2007).

### 1.1.1 Sustainable farm management practices

The shift from conventional to a more sustainable agriculture involves the adoption of sustainable management/agronomic practices. Sustainable farming practices promote efficiency in input utilisation—efficiency in the use of land/soil, fertiliser, water, pesticide, labour and machinery (ten Berge *et al.*, 2000). Also, there must be efficiency in farm husbandry practices such as crop rotation and soil tillage. There are measures or strategies, which can be adopted to ensure sustainability of arable farms (Tait and Morris, 2000). This section therefore, focuses on practices, which enhance sustainable input use—efficient use of fertilisers, pesticides, water, labour and machinery.

#### 1.1.1.1 Sustainable land/soil and nutrient management and fertiliser use

Land or soil for agriculture is very important in arable crop production because the type of soil on a particular land, and the location of the land can influence the level or the scheduling of farm operations, input use and yield obtained from an arable system. How the land is used can impact on the quality of the landscape and biodiversity or its ecosystem functions (Doran, 2002; Rounsevell *et al.*, 2003; Audsley *et al.*, 2006). Glendinning (2009) found that land use is one of the most important factors that determine system-wide sustainability. Soil health or quality changes over time as a result of natural events or human impact however, it can be enhanced by management and land use practices, which focus not only on the productivity function of soil but on multiple functions of soil (Doran and Zeiss, 2000; Doran, 2002).

Nitrogen is the most dynamic nutrient due to its being water soluble, mobile and easily leached in the soil and as a result has to be applied annually to ensure enhanced and sustainable yields (de Wit, 1992). Nitrogen use efficiency (NUE)[1] is significant in cereal systems, which provide over 60% of human dietary needs. Thus, there should be efficient nutrient management to reduce nutrient losses through leaching, erosion, denitrification, ammonia and nitrous oxide volatilisation (King, 1990; Cassman *et al.*, 2002). King (1990) recommended that maximising nitrogen (N) input through biological N fixation, utilization of the nutrients present in the soil and the ability to recycle nutrients from off-farm sources could make agricultural systems more sustainable. Growing crops that use the applied nutrient efficiently can reduce nitrate leaching, or cover crops can be grown to reduce nutrient loss through erosion, leaching and volatilisation (King, 1990; Tilman et al., 2002). Crop rotations as part of the integrated management practices has been found to enhance soil fertility and influence soil aggregation, bulk density, microbial biomass and water infiltration and extraction (Francis and Clegg, 1990; Dogliotti et al., 2003). Growing clover crop as part of the rotation can reduce the input of fertiliser as well as farm cost in arable farming systems (Williams *et al.*, 2010) (see Section 1.1.1.5 for more benefits of crop rotation).

#### 1.1.1.2 Sustainable pest management and pesticide use

Pests such as weeds compete with crops for soil nutrients, water and sunlight; and other pests and diseases also destroy crops, hence reduce the yield or yield potential of arable crops. It is thus imperative to prevent or control pests (weeds,

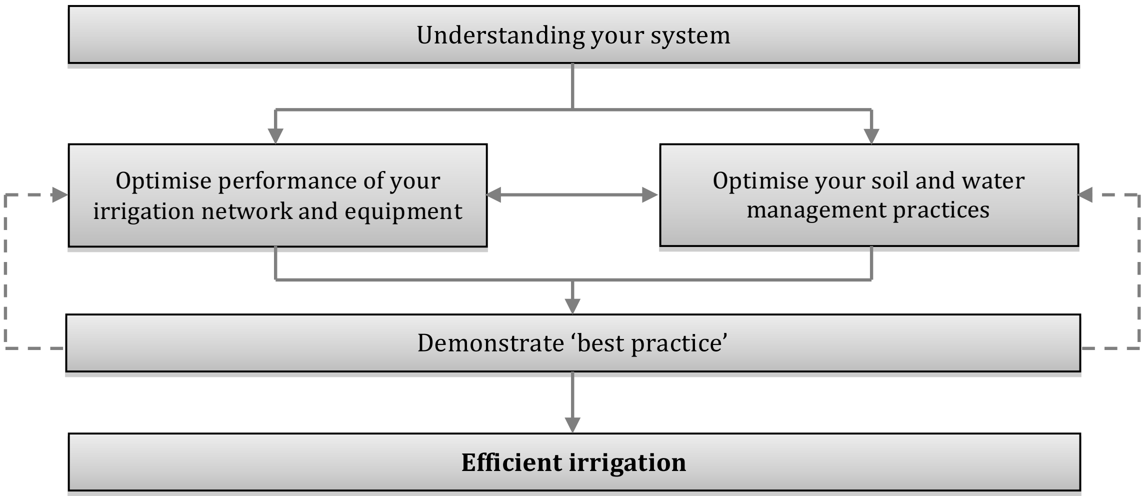
[1] NUE is the ratio of fertiliser N removed from the field by the crop and the amount of fertiliser N applied.

insects, fungi, rodents) in arable systems. The normal practice over the years has been the use of chemicals (pesticides and herbicides) to control pests, resulting in pollution of water sources or the environment (Wijnands, 1997; Carvalho, 2006; EC, 2007). The European Commission's (EC, 2008) proposed strategy to ensure safer use of pesticides became mandatory in 2014 and it requires each member state creating the conditions necessary for implementing Integrated Pest Management (IPM) system.

The IPM system prescribes minimum, or sometimes no use of chemicals or prevents the use of chemicals with certain active ingredients or substances (Wijnands, 1997; Hillocks, 2012). Hillocks (2012) provided some possible IPM alternatives to pesticides. Bürger *et al.* (2012) found that winter wheat fields managed by IPM strategies such as late seeding and resistant cultivars were treated with lower pesticide intensity. Integrated Weed Management (IWM) has also been created as part of IPM to promote sustainable ways of managing weeds (Chikowo *et al.*, 2009; Pardo *et al.*, 2010). One of the sustainable means of managing weeds and pests with less or without chemicals is through crop rotation to break the reproductive cycle of disease pathogens, insects and weeds (Francis and Clegg, 1990; Salassi *et al.*, 2013). The use of crop rotation with spring crops is also being encouraged as non-chemical means of controlling weeds such as black-grass which has developed and continue to develop resistance to many herbicidal active ingredients (Moss and Lutman, 2013). Although, the adoption of such strategy could reduce arable farm profit in the short term, it has a long term benefit of reducing weed infestation and reducing chemical cost (see Chapter 4).

#### 1.1.1.3 Sustainable water use and irrigation

Water is a very important resource in arable crop production and in areas of low rainfalls or soils with poor water retention capacity irrigation is used to supplement rainfall. One strategy of sustainable water use in arable farming systems is by achieving irrigation efficiency (see Figure 1-1 for pathway to achieve irrigation efficiency) through efficient irrigation scheduling. Irrigation efficiency is about putting the right amount of water onto crops in the right place and the right time with minimal wastage (Knox and Kay, 2008). However, according to Anadranistakis *et al.* (2000) factors such as atmospheric demand for water vapour, plant traits and soil characteristics should be considered for proper irrigation scheduling to achieve efficiency. About 80% of UK farmers use judgements not based on measurements in deciding when to irrigate, but such judgements are prone to consideration errors (Defra, 2011; McBurney, 2011). For crops like potatoes, poorly timed irrigation can result in potato crops developing scabs; whereas over irrigation can cause wastage of water, labour and energy (Mackerron, 1993; Hess *et al.*, 2009). In England, demonstrating irrigation efficiency is now a requisite for renewing irrigation water abstraction licence (Knox *et al.,* 2012).




Source: Re-drawn from Knox and Kay (2008) and Knox *et al.* (2012)

Figure 1-1: Pathway to achieve irrigation efficiency

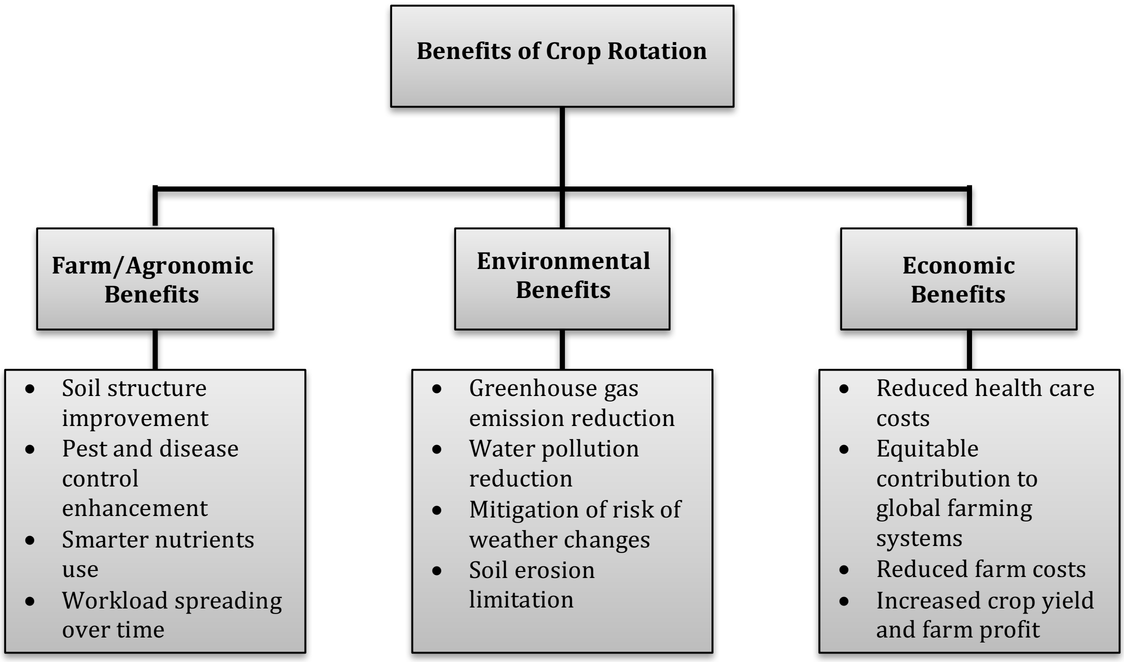
#### 1.1.1.4 Sustainable labour and machinery use

Sustainable crop production also depends on efficient labour and machinery use in order to achieve the desired yields and possibly reduce carbon emission (from machinery). This can be achieved through better knowledge of the production process, a considerable management effort and an efficient planning or timing of all farm operations (de Wit, 1979). Also, methods for increasing machinery efficiency should be enhanced against its detrimental effect on biodiversity (Rodríguez and Wiegand, 2009). Management practices adopted by farmers as well as the prevailing weather conditions and soil type can affect labour and machinery use efficiency in arable systems (Pardo *et al.*, 2010). For example, the soil type and rainfall can affect timing of ploughing due to their influence on the work rate and the workable hours available to the farmer. Efficient crop rotation, soil management, water management etc. can impact positively on efficient labour and machinery use efficiency. Pardo *et al.* (2010) found that farms implementing reduced tillage benefit from lower labour requirement and Rodriguez and Wiegand (2009) found that machinery efficiency could also be achieved with local operators of machinery who have much information about the farm areas.

#### 1.1.1.5 Crop rotation and sustainable arable crop production

Over the years, farmers worldwide have practised crop rotation and with the myriad benefits associated with it, proper and efficient crop rotation plans can be very significant or pivotal in sustainable arable farming systems. The benefits of crop rotation in farming systems have been well documented (e.g. Francis and Clegg, 1990; Dogliotti *et al.*, 2003; Baldwin, 2006; Schonhart *et al.*, 2011; APRODEV, 2012; Salassi *et al.*, 2013). These benefits cut across all aspects of the farming system—crop rotation has agronomic and economic as well as environmental benefits and as a result influences the sustainability of agricultural systems (Baldwin, 2006; Schonhart *et al.*, 2011; APRODEV, 2012). In the case of soil quality, crop rotation has the potential to increase the soil organic matter, soil structure improvement, soil degradation reduction, translating into long-term higher yields and greater farm profitability (APRODEV, 2012). Crop rotation also influences soil aggregation, bulk density, microbial biomass and water infiltration and extraction (Francis and Clegg, 1990; Dogliotti *et al.*, 2003). The improvements in soil organic matter also have the potential to reduce the use of synthetic fertiliser, which is one of the objectives in sustainable arable farming system. Crop rotation can be used to control weeds, pests and diseases by breaking the reproductive cycle of diseases pathogens, insects and weeds (Francis and Clegg, 1990; APRODEV, 2012; Salassi *et al.*, 2013; HGCA, 2014). Crop rotation also impacts positively on the environment by reducing greenhouse gas emission (GHG) and water pollution, and in terms of economic or financial benefits, crop rotation affects farm income and cost through changes in yield and input variation (Schonhart *et al.*, 2011; APRODEV, 2012).

According to Schonhart *et al.* (2011) diversifying crops however, can limit economies of scale and can result in reductions in expected farm net revenues. Notwithstanding, the benefits of crop rotation summarised in Figure 1-2 indicate the importance of crop rotation in sustainable arable farming systems. Due to these benefits, crop rotation has either been explicitly or implicitly modelled in farm models using different approaches to support the decision of farmers as well as policy makers at different scales (e.g. El-Nazer and McCarl, 1986; Annetts and Audsley, 2002; Rounsevell *et al.*, 2003; Detlefesen and Jensen, 2007; Schonhart *et al.*, 2011; Salassi et al., 2013). Examples of crop rotation models are ROTAT (Digliotti *et al.*, 2003), ROTOR (Bachinger and Zander, 2007) and CropRota (Schonhart *et al.*, 2011).

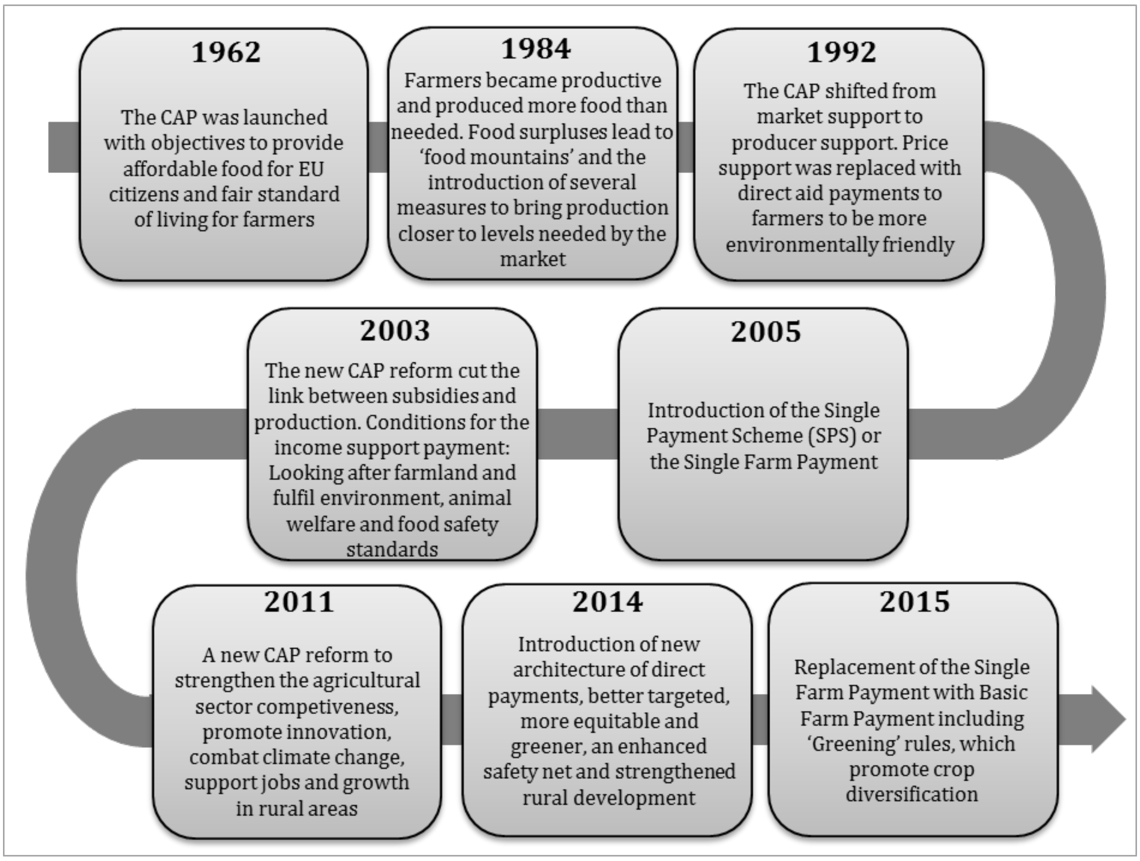



Source: Based on information from APRODEV (2012)

Figure 1-2: Benefits of crop rotation

#### 1.1.1.6 Policies associated with sustainable agriculture: Common Agricultural Policy (CAP) reforms

In 1962, the CAP was launched as a partnership between agriculture and society—between Europe and its farmers to improve agricultural productivity in order for consumers to have stable supply of affordable food and ensuring that EU farmers make a reasonable living (EU, 2012; Balaceanu, 2013). Since its launch, the CAP has undergone many reforms (see Figure 1-3 for a summary of CAP reforms from 1962 to 2015) by moving the CAP from product to producer support and now a more land-based approach, which provides safety net for farmers, environmental integration improvements and rural development support (EU, 2013).



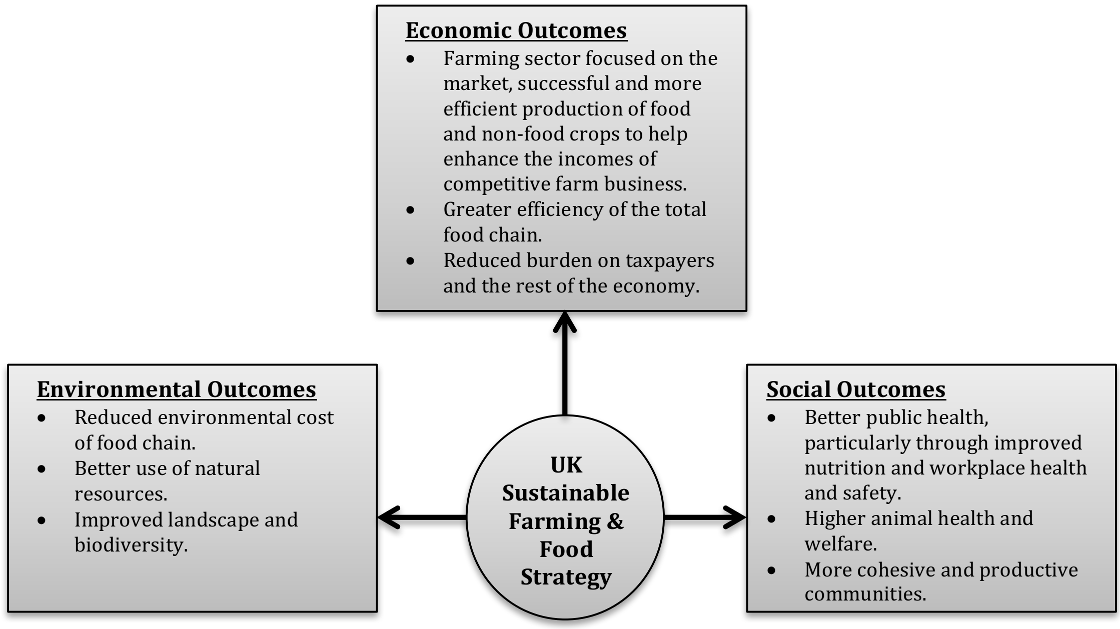

Source: Drawn with information from Defra (2014) and EU (2012, 2013)

Figure 1-3: Reforms to the Common Agricultural Policy (CAP)

In the UK, agricultural support to farmers is mainly provided through the CAP (Nix, 2014). One of the major reforms to the CAP, decoupling was introduced in 2005. With this reform, farm payment was delinked from what was being produced on the farm and led to the introduction of the Single Payment Scheme (SPS) to support farm businesses. The eligibility for the single payment was linked to the Statutory Management Requirements and keeping the land in 'Good Agricultural and Environmental Condition' (Nix, 2014). In terms of crop rotation, the reform post 2013 requires that on an arable area between 10ha and 30ha and a minimum of two crops are required (Nix, 2014). In 2015 the Single Farm Payment (SFP) was replaced with the Basic Farm Payment, which includes the 'greening' rules to promote crop diversification (Defra, 2014; RPA, 2015, 2016).

### 1.1.2 Challenges, opportunities, objectives, constraints, complexities and trade-offs examples in sustainable arable farming systems

With the focus of sustainable agriculture being increasing productivity (food production and profitability) whiles reducing its impact on the environment as well as serving as a source of livelihood especially in rural areas, the opportunities associated with sustainable farming systems can be said to include the provision of ecosystem services, improvements in environmental quality indicators such as water quality, and the provision of jobs and improvements in the rural economy. Thus in the UK, the emergence of the sustainable development concept has driven the need for a more sustainable agriculture or farming systems, which are environmentally or ecologically responsible and still produce affordable food (Living Countryside, 2014). In 2002, the UK Sustainable Farming and Food Strategy (SFFS) was published and the overall aim of the strategy consists of economics, social and environmental outcomes (summarised in Figure 1-4) (Defra, 2002; 2006). With farmers seen as custodians of the farm environment, subsidies (farm payments) received by arable farmers in the UK as part of the sustainable farming strategy, have been linked to the satisfaction of Statutory Management Requirements and keeping of farmland in Good Agricultural and Environmental Condition (Nix 2014). An arable farm in the UK has to achieve sustainability by integrating economic, ecological and social aspects of sustainability, or in other words a sustainable arable farm in the UK must combine both economic and environmental goals without losing sight of social aspects (Ikerd *et al.*, 1998; den Biggelaar and Suvedi, 2000).




Source: Based on information from Defra (2002; 2006)

Figure 1-4: Outcomes of the UK Sustainable Farming and Food Strategy (SFFS)

However, the conflicting nature of simultaneously achieving the economic, environmental and social objectives in sustainable farming systems pose big challenges (Pannell, 1999, Godfray *et al.*, 2010). Economically, a sustainable farming system should be able to provide sustainable income to farmers through the provision of sustainable crop yield levels. However, to reduce the environmental impact, there is the need for efficient input use, which may sometimes require reduction in inputs such as fertilisers and chemical, which are used to safeguard crop yield even in light of soil fertility and weed infestation problems. Thus environmentally, the challenge is to reduce externalities such as nitrate leaching and diffuse pollution whiles maintaining yield levels to provide stable income for farmers. The primary aim of farming is to produce food and thus a sustainable farming system should be able to provide food to feed the growing population.

The world's population projected to increase by 34% by 2050, the social challenge in sustainable farming is to produce enough food to ensure food security for growing population whiles improving incomes levels of farmers and reducing environmental impact. With stagnant yield potential being the main impediment of arable farming systems underpinned by sustainable agricultural principles (Tilman *et al.*, 2002), the question is how can the growing population be fed (or ensure food security) with farming systems underpinned by sustainable agricultural principles? For example, how can cereals (e.g. wheat) be produced with less application of nitrogen (N) fertiliser and chemicals, which are vital in arable crop production? Reducing nitrogen application will reduce yield and applying more nitrogen in order to increase yield can cause nitrate leaching, which pollutes water sources and eventually affect aquatic biodiversity. Also, reducing chemical input could lead to lower yield levels due to weed infestation. Thus the overall issue in sustainable farming is the simultaneous achievement of conflicting economic, environmental and social objectives, which are themselves constraints to one another and increase the complexities in sustainable farming systems.

Some of the farmers' objectives in sustainable arable systems are maximising profit, minimising risk associated with different cropping systems, dealing with crop management complexities, maximising organic matter (OM) balance, minimising labour cost and minimising nitrogen losses through nitrate leaching. Thus, the arable farming objective could be high financial return and environmental goals to safeguard the sustainability of the system (Groot *et al.*, 2012). The move from conventional to a more sustainable agriculture could be associated with risks and makes some farmers risk-averse. Rounsevell *et al.* (2003) found farmers' risk revealed in the choice of crop division and techniques through diversification and adoption of crops with low profit variability. The results generated by the risk model application in Chapter 5 also reflect the influence of risk aversion on crop choices and diversification. Sustainable arable farming objective could sometimes be a trade-off between profit maximisation and risk minimisation.

Arable farming objectives are affected by many constraints: economic, biophysical or environmental, legislative, pests (e.g. weeds), inputs, soil types as well as farm operations (Pretty and Bharucha, 2014). The use of fewer inputs such as fertiliser, pesticides and water in sustainable agriculture is itself a constraint to farmers. Farmers willing to increase farm size may be constrained by availability of land; farmers shifting to new cropping systems could be constrained by soil type as well as the skills (agronomic knowledge) needed for the new system. The type of soil and prevailing weather conditions (e.g. rainfall pattern) affect the workable hours as well as influence the scheduling of farm operations (Rounsevell *et al.*, 2003). This could increase labour and machinery cost and hence reduces farmers' profit. Again, the location of a farm, environmental factors, risk of diseases, fertiliser and labour requirements affect the performance and profitability of farms (Rounsevell *et al.*, 2003).

Complexities exist in sustainable arable systems in terms of inputs use, soil types and soil processes, farm management practices and the number of crops grown (Cooke *et al.*, 2013). Annetts and Audsley (2002) gave an example of such complexities with respect to timing of farm operations as follows: farmers have best times to grow winter wheat in order to obtain a higher yield because late planting of the crop may result in low yield but will decrease the use of chemicals. Less use of chemicals is beneficial to the environment and cost saving for the farmer. Late planting also increases the risk of nitrate (which could have been used by crops) leaching from the soil. Early cropping can lead to higher yields however, this is dependent on the climate, which in turn affects the workability of the soil. Williams *et al.* (2003) also found that slurry spreading increases ammonia losses however, switching to slurry injection reduced ammonia volatilisation by 7%, net profit by £13/ha and slightly increased leaching by 2%. Also, rapid incorporation after broadcasting was more effective and reduced ammonia emission by 17% but reduced profit by £17/ha and increased leaching and nitrous oxide emissions by 3% and 2% respectively. The IWM-based cropping systems (e.g. spring cropping to control black-grass) have been found to reduce herbicides usage and potential environmental impact however, it can increase the system's complexities and impact on labour and profitability (Pardo *et al.*, 2010). The constraints and complexities in arable farming can influence the trade-offs made by farmers. Groot *et al.* (2012) found trade-offs between operating profit and labour balance and between OM balance and N losses with the lower labour balance often associated with lower soil N losses.

In terms of analysis and evaluation of sustainable farming systems, modelling approaches through the use of mathematical programming have been found to be fit for purpose due to their ability to allow for the consideration and analysis of multiple objectives and conflicting resource use, complexities as well as policy analysis (Hazell and Norton, 1986). Thus the overall aim of the research is to develop a modelling tool that can be used for evaluating the and economic as well as environmental (ecological) viability and riskiness of alternative cropping systems that may be adopted to deal with increased pressure on input use. The study focuses on commercial arable farming systems due to their economic importance as well as their impact of the environment. Also, the scope of the research is at the farm level. As part of the overall research aim, other specific objectives have been set with specific research questions (see Section 1.6 for the thesis chapter specific research questions).

In sustainable farming, efficient input use is vital in that the manner in which inputs are used determine the farming outcome. For example, achieving efficiency in N fertiliser use can impact crop yield and nitrate leaching. Farm location determines the soil type and the prevailing weather condition and as a result the location of a farm can influence farming outcomes. Also, as part of the effort to make farming systems more sustainable, policies have been formulated to guide farming. Thus input, farm and policy factors can influence the sustainability arable farming in terms of impact on the achievement of the socio-economic and environmental goals. One of the specific objectives is therefore to investigate how variations in input, output, farm and policy factors impact on farm profit, management complexities and risk.

Weed infestation can impact negatively on the sustainable farming effort in the sense that weeds compete with crops and reduce crop yield, and with the common approach to weed management being chemical application, achievement of the environmental objective of sustainable farming in terms of minimising pesticide use can be impeded. For arable farming systems to be sustainable there is the need to develop sustainable weed management strategies to achieve the socio-economic goal of producing more food to ensure food security whiles reducing environmental impact of water pollution through intensive herbicide application. One of such strategies is the use of spring cropping in the control of black-grass, which is a very important weed in UK arable farming. Another objective of the research is therefore to investigate how the use of spring cropping as a weed control strategy impact on arable farming economic and risk outcomes.

The move to make arable farming systems more sustainable is associated with risk in that new farming strategies, innovation and technologies with unknown or uncertain outcomes have to be adopted. In some instances, inputs such as fertiliser and chemicals used by farmers to safeguard yield have to be reduced in order to achieve the environmental objective of sustainable farming. How such strategies are adopted can be influenced by the level of risk aversion behaviour of farmers. Thus the issue of risk aversion or risk in general is important in sustainable farming. Risk aversion and cropping decision of arable farmers in England are therefore investigated as part of the research objectives.

### 1.1.3 Section summary/conclusion

To be able to feed the growing population, there is the need to shift from conventional agriculture, which normally results in externalities to the environment, economy and society, to a more sustainable one. Thus, developing multifunctional farming systems should be underpinned by the principles of sustainability, which will enhance the production of more and quality food to ensure food security, without damaging the environment for both current and future generations. Arable farming systems underpinned by principles of sustainability rely on sustainable management of soil, fertiliser, pest (weed) and pesticide, labour and machinery use as well as efficient crop rotation and policy, which in turn affect efficient and sometimes limited use of farming inputs. Variations in soil types also influence the crop selection, fertiliser use, labour and machinery use and hence farm productivity and revenue. Again, sustainable farming systems are associated with stagnant yield potential and this coupled with the rising food demand due to population increase can impede the move from conventional systems to more sustainable ones. These raise pertinent research questions with respect to multifunctional arable farming systems underpinned by sustainability principles. For example, how do variations in soil types, farm inputs/outputs and policy affect arable farming objectives/goals such as profit maximisation and risk minimisation? Also, how does the adoption farm management strategies such as weed management strategies impact on farm revenue? How does the risk aversion of arable farmers influence crop selection due to associated farm management practices?

There is the need for continuous research using mathematical modelling approaches, which are relatively less expensive and can capture many of the complexities and farm management strategies as well as policies to answer the research questions in order to better inform arable farming decisions and policy. In UK context, the use of mathematical modelling approaches, particularly goal and risk programming approaches to investigate and answer the research questions such as the ones asked above and in the thesis are still lacking. Thus the overall aim of the research is to develop a modelling tool that can be used for evaluating the economic as well as environmental viability and riskiness of alternative cropping systems that may be adopted to deal with increased pressure on input use.

## 1.2 Mathematical modelling as a means of analysing and testing out new and innovative farming systems

Complexities exist in arable farming systems and with the aim of making arable farming systems more sustainable, there is the need for analysing and testing out new and innovative farming systems to improve farming productivity, reduce environmental impact and risk and ensure food security as well as inform policies, which influence what and how farmers should farm. Testing out or analysing farming systems can be done using field trials however, such trials could be expensive and as result there is need for simulating experiments and farming systems using modelling approaches. Modelling approaches such as econometric models and artificial intelligence can be useful in analysing or testing innovations in arable farming systems and as with field trials, although they may have their strengths, they have some limitations in terms of farm level or farming systems modelling. Econometric approaches may suffer from data difficulties in terms of capturing data on resources shared by competing crops and changes in economic structure in terms of production technologies, policies and prices (Hazell and Norton, 1986). For example, in Chapter 2 the effect of price variation and single farm payment (SFP) on farm profit are demonstrated by simulating changes in crop prices and farming inputs with and without the SFP, taking into consideration constraints to farming activities. Results from such simulation may be difficult to obtain with econometric approaches. In the case of artificial intelligence (AI), its approaches may have to be coupled with mathematical programming approaches to achieve the real advantage of AI (McBride and O'Leary, 1993; Vossen *et al.*, 1999). The disadvantages of such coupling approaches have been listed in McBride and O'Leary (1993). For example, coupling AI and mathematical programming may mean replacing the role an operational research analyst plays in terms of data gathering, formulation and interpreting results and in terms of farming systems, certain changes in factors, which affect farming may not be recognised by a modelling approach based on AI. This could lead to reformulation of the whole problem in order to incorporate such changes, which may be time consuming.

The limitations of the above methods make mathematical modelling (programming) more appropriate method in testing and analysing farming systems because its structure suit production economic theory (Fragoso *et al.*, 2008). Mathematical modelling also provides a framework for organising quantitative information about the supply side of agriculture be it at the farm or sector level and in the case of the farm level, it is useful in terms of evaluating the implications of different resource endowments, improved or new farming strategies (Hazell and Norton, 1986). Again, the availability of well-known and applied mathematical modelling approaches (see examples in Kaiser and Messer, 2010) makes it possible to draw on the strengths of different approaches as well as already existing models to create robust models for farm analysis. The features of mathematical programming models make interpretability of their results relatively easy compared to approaches like AI, which has limited applications with respect to farm level optimisation modelling and econometric models, which are unsuitable for constrained optimisation.

Thus in this study, mathematical modelling (programming) method is adopted to answer pertinent research questions with respect to arable farming systems due to the fact that apart from the advantages highlighted above, with mathematical modelling, multiple objectives in arable farming systems can be investigated (e.g. Annetts and Audsley, 2002; Cooke *et al.*, 2013). Also, to develop a sustainable farming system, integrated modelling approaches should be adopted to encompass both the ecological or environmental and socio-economic aspects of agriculture or land use (Cooke *et al.*, 2009), hence the use of mathematical modelling to optimise multiple farming goals.

## 1.3 Mathematical modelling approaches (MMAs)

The choice of modelling approach is influenced by the outcome the researcher or the modeller is seeking, as well as the capability of the particular approach being adopted. Mathematical programming models can be deterministic or stochastic, dynamic or static, mechanistic or empirical, and these types of models can either be linear or non-linear (Chalabi, 1998; Thornley and France, 2007). Models used to describe agricultural systems are mainly mechanistic or empirical (Chalabi, 1998). Table 1-1 presents a comparison of mechanistic and empirical models in terms of their capabilities. Non-linear models, compared to their linear counterparts are less restrictive because the equations may have both linear and non-linear forms (Kaiser and Messer, 2011). Figure 1-5 shows some of the MMAs applied in agricultural land use modelling with examples of approaches under linear and non-linear models. Table 1-2 also shows some of the practical application of MMAs found in literature. The user groups of the model/approaches were determined based on what the model or the approach could be used for. ***Farmers (F)*** means the output of the model can inform farmer decision or assist farmer decision-making; ***Policy (P)*** means it can assist policy makers or provide policy makers with information during policy formulation and ***Others (O)*** means it can be used by other researchers or modellers. The double plus (++) means the main user group and a plus (+) means it can provide information to the user group.

Table 1-1: Comparison of mechanistic and empirical models

| Mechanistic models | Empirical models |
|---|---|
| They can simulate systems behaviour outside the range of observed data in ways consistent with established scientific understanding. | Prediction of the future is based on an extrapolation of historical time series of observed past behaviour and description of past technologies. |
| Good for investigating important biological relationships by carrying out sensitivity analysis on the model parameters. | They do not have close link with the physical systems. |
| They are usually defined by many parameters, which are often highly correlated. | Have simpler structure, less number of parameters. |
| They cannot be used easily for optimisation and control purposes. | They are easier to use for optimisation and control purposes. |

Source: Chalabi (1998) and Janssen and van Ittersum (2007)

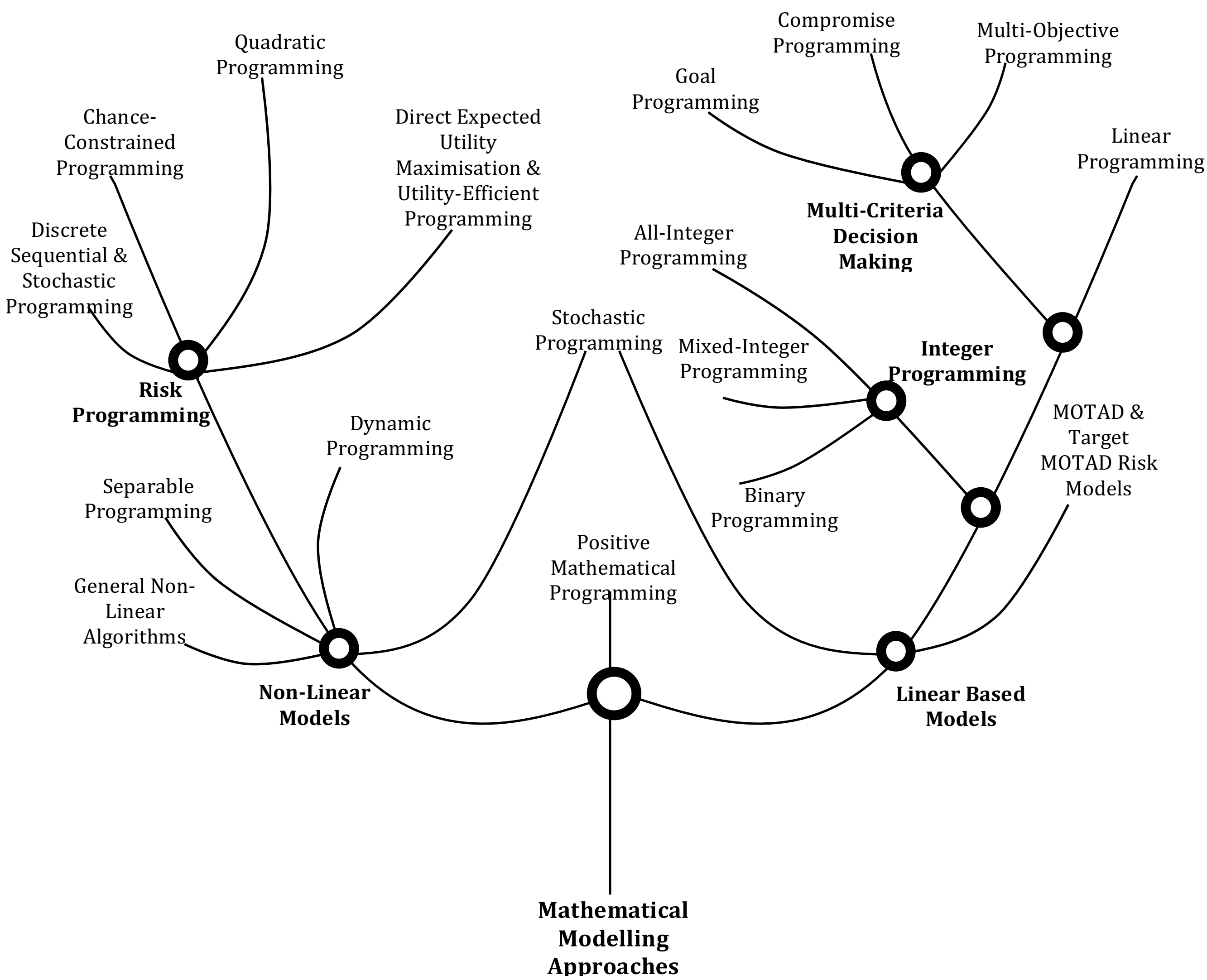



Figure 1-5: Mathematical modelling approaches

### 1.3.1 Linear programming (LP) models

Since its use was reported by Heady (1954) LP application in agriculture to assist in the decision making process of farmers and policy makers has been popular. According to Acs *et al.* (2010) LP provides a means to examine the micro-level effect of policy changes on farmers' behaviour across different farm types. In general, all LP models have in them four general properties (Kaiser and Messer, 2011): the objective to be optimised, the constraints restricting the activities, linearity of all equations and non-negativity of all activities or decisions variables. The assumptions of LP are summarised by Hazell and Norton (1986) as: optimisation, fixedness, finiteness, determinism, continuity, homogeneity, additivity and proportionality. A generalised LP model for an arable farmer who is seeking to maximise gross margin can be expressed as follows:

$$\text{Max } Z = \sum_{j=1}^{n} c_j x_j \tag{1-1}$$

Subject to:

$$\sum_{j=1}^{n} a_{ij} x_j \leq b_i \qquad i = 1\ to\ m \tag{1-2}$$

$$x_j \geq 0 \quad j = 1\ to\ n \tag{1-3}$$

Where $Z$ is the gross margin to be optimised (maximised), $x_j$ is level of $j$th activity, $c_j$ is the gross margin of the $j$th activity, $a_{ij}$ is the $i$th resources needed to produce the $j$th activity and $b_i$ is amount of resources available to the farmer.

LP has been applied in arable farming systems modelling to identify optimum farming objectives such as profit and crop management complexity (e.g. Annetts and Audsley, 2002; Rounsevell *et al.*, 2003; Audsley *et al.*, 2006). Although the application of LP is very popular, it has some limitations in terms of the linearity of constraints and fixed input-output coefficients and computational problems of infeasibility, unboundedness and degeneracy (Kaiser and Messer, 2011; Osgathorpe *et al.*, 2011). These limitations of LP have led to the development of other modelling approaches.

### 1.3.2 Integer programming (IP) models

Integer programming (IP) is similar to LP however, IP has been developed to deal with the problem of infeasibility, which may occur in rounding activities up or down in LP problems (Kaiser and Messer, 2011). With IP all (all-integer programming) or some of the variables (mixed-integer programming, MIP) can be integers. Like LP, IP models also have objective functions to be optimised subject to constraints however, IP has some advantages over LP (see Butterworth, 1985). IP can produce an optimum plus one or more suboptimal solutions to select from, whereas LP produces a single optimal solution. There are three main approaches to solving linear IP problems (Genova and Guliashki, 2011): cutting planes approach, which is an algorithm based on polyhedral combinatorics, the enumerative approaches (branch-and-bound, branch-and-cut and branch-and-price) and the relaxation and decomposition approaches. According to Kaiser and Messer (2011) the branch-and-bound approach is the most effective IP solution. With the branch-and-bound, the maximum percentage error estimated based on the upper and lower bound optimal solutions give maximum possible error (see Kaiser and Messer (2011) for the steps involved in the branch-and-bound approach). IP (MIP) approaches have been applied in farming systems or land use modelling (e.g. Makowski *et al.*, 2001; Viaggi *et al.*, 2010; Cooke *et al.*, 2013). The model described in Chapter 3 uses an MIP approach.

### 1.3.3 Multi-criteria decision making (MCDM)

In sustainable arable farming systems, farmers (decision makers) normally have to make trade-offs among different goals or objectives. For example, an arable farmer is faced with multiple goals of maximising profits, minimising risks, reducing nitrate leaching and herbicide use. One of the tools able to capture these different goals simultaneously is the MCDM approach. Schniederjans (1995) defined MCDM as a "means to solving decision problems that involve multiple objectives". MCDM models were developed to deal with the single objective limitations of programming models such as LP (Oglethorpe, 2010). Examples of MCDM approaches are multiple objective programming (MOP), compromise programming (CP) and goal programming (GP).

According to El-Gayar and Leung (2001) MOP is recommended when two objectives are being considered, however, CP is recommended when the number of objectives is greater and targets are unknown because it searches for a best compromised solution among the effective solutions and presents it to the planner. Goal programming (GP) on the other hand is applied in a situation in which the decision maker faces multiple goals because it optimises multiple goals simultaneously by minimising the deviations in the levels of targets (Schniederjans, 1995; El-Gayar and Leung, 2001; Kaiser and Messer, 2011). GP does this through the summation of positive and negative deviation variables allowing for either over or under achievement of goals (see Kaiser and Messer, 2011).

With GP, goals are specified or targets are set and the GP solution gives the optimum solution close to the target or goals. The possibility of underachievement of a maximisation goal target or the overachievement of minimisation goal targets is sometimes seen as a limitation of the GP approach. Notwithstanding, GP has been applied extensively in agriculture and land use planning or modelling (e.g. Tamiz *et al.*, 1998; Tiwari *et al.*, 1999; El-Gayar and Leung, 2001; ten Berge *et al.*, 2000; Oglethorpe, 2010). In Chapter 4 a mixed-integer weighted goal-programming model is applied to investigate effect of controlling black-grass with spring cropping on farm profit.

### 1.3.4 Positive Mathematical programming (PMP)

The PMP is an approach introduced by Howitt (1995) to calibrate programming models. The emergence of the PMP was due to the fact that the predictive accuracy of early explicit models was found to be limited, lack of validation of existing models (Heckelei and Britz, 2005) and its popularity is due to the fact that it can be constructed from minimal data set (Howitt, 1995). PMP makes supply response agricultural models more realistic by allowing perfect calibration to observed based year and avoiding the provision of a more smooth simulation response compared to LP models (Helming, 2005; Heckelei *et al.*, 2012). According to Cooke *et al.* (2013) some aspects of the system that are difficult to quantify may get incorporated in the error term in PMP models however, this limits the ability of the model to make predictions of the reference data. PMP calibration starts with an optimisation LP problem. The two steps of model calibration using PMP is summarised as follows (see Heckelei and Britz, 2000; Heckelei and Britz, 2005): Step 1: The LP model is extended by adding calibration constraints with associated dual values. Step 2: The dual values of the constraints are employed to specify a non-linear objective function to make the marginal cost of the preferable activities equal to their respective prices at the base year. Examples of PMP application can be found in Howitt (1995); Heckelei and Britz (2000); Preckel *et al.* (2002) and Heckelei *et al.* (2012).

### 1.3.5 Risk programming (RP)

The existence of risk in arable farming systems influence farmers' decision making and due to the risk-averse nature of arable farmers, they normally choose farm plans that provide a satisfactory level of security (Hazell and Norton, 1986). For instance, an arable farmer may choose cropping systems which are less risky over those which are riskier (e.g. potato production). Risk programming models applied in farming system modelling include quadratic risk programming, QRP (mean-variance analysis), minimisation of total absolute deviation (MOTAD or target MOTAD), chance-constrained programming and discrete sequential programming (Kaiser and Messer, 2011). The most RP applications in agriculture are based on the MOTAD or the mean-variance decision criteria (Tauer, 1983). MOTAD was developed as an approximation of expected value-variance (Hazell, 1971) and its solution can be generated by LP algorithms (McCarl and Önal, 1989). In MOTAD, linear approximation of expected variability is used instead of non-linear variance-covariance measure of risk. The objective function is linearized through the use of mean absolute deviation (MAD) (Hazell and Norton, 1986; Adesina and Ouattara, 2000). Although the linear approximation may be less effective than with quadratic programming (Kaiser and Messer, 2011), in some instances where the enterprise income distributions are skewed, the MAD may outperform sample variance in quadratic programming (Hazell and Norton, 1986; Adesina and Ouattara, 2000).

MOTAD results are not second-degree stochastic dominant[2] and as a result Tauer (1983) developed the target MOTAD, a two-attribute risk and return model, which has additional constraint that sets a target. Notwithstanding, MOTAD has been used extensively to model risk in farming systems especially in situations where solvers for quadratic programming are not available or difficult to obtain. Examples of MOTAD and other RP model applications in farming system modelling can be found in Dorward (1999); Adesina and Ouattara (2000) and Flaten and Lien (2007), Others can be found in Martins and Marques (2007), Visagie *et al.* (2007)

[2] Under the Second-degree Stochastic Dominance (SSD) concept, a decision maker's choice between two risky alternatives is predicted without a prior knowledge of the decision maker's utility function except that it displays risk aversion. The necessary and sufficient conditions on the two risky prospects are provided in order for one to be preferred or indifferent to the other by all risk averse decision makers (Meyer, 1977).

and Cooke *et al.* (2013). In Chapter 5 a mixed-integer MOTAD model is applied to investigate arable farmers risk aversion in England.

### 1.3.6 Dynamic/recursive programming

The dynamic nature of some aspects of arable farming has influenced the development and application of dynamic programming (DP). Dynamic programming is used to solve large and complicated problems by dividing them into smaller sub-problems and the approach begins by looking at the final stage or period and then work back to the initial or current period (Barnard and Nix, 1973). Dynamic programming has some advantages over traditional LP in that it can handle non-linear and integer problem, incorporate stochastic elements as well as has advantage in solving inventory and decision-tree type problems (Barnard and Nix, 1973; Kaiser and Messer, 2011). Thus DP can be said to relax the linearity, divisibility and deterministic assumptions of LP (Kaiser and Messer, 2011).

However, unlike LP models, DP models are very difficult to generalise and it also suffers from *curse of dimensionality* as the number of computations can increase exponentially with increase in the number of stages or state variables (Barnard and Nix, 1973; Kaiser and Messer, 2011). Thus constructing a DP model for an arable system, incorporating more stages or periods can be tedious and time consuming.

In some instances, DP may be applied without the introduction of the element of time and in such situation, DP can best be described as a recursive programming (Kaiser and Messer, 2011). Recursive programming deals with sequences of interrelated decisions however, the approach does not seek to devise optimal rules for decision-making but explains only the changes that occurs (Barnard and Nix, 1973). Notwithstanding, the drawbacks associated with DP and recursive programming, examples of their application can be found in agricultural systems modelling (e.g. Pandey and Medd, 1991; Wallace and Moss, 2002; Viaggi *et al.*, 2010; Kennedy, 2012; Shrestha *et al.*, 2015; Liu *et al.*, 2016).

### 1.3.7 Stochastic programming

Uncertainty exist in agriculture due to factors the existence of factors, which farmers do not have control over. For example, farmers do not have control over rainfall, which influence farm operation scheduling as well as crop yield. Also, farmers do not have control over the farm input and output prices. Thus in some instances, there is the need to capture uncertainty and variability associated with input, weather and other factors, which introduce risk in farming. This can be done through the application of stochastic programming, which allows for the consideration of uncertainty as well as probability distribution associated with data (Shapiro and Philpott, 2007). This means stochastic programming can be said to relax the deterministic assumption of in LP models.

However, the drawback of stochastic programming is that probability distributions has to be estimated for items in the model matrix likely to be associated with random variation and this can be tedious and time consuming (Barnard and Nix, 1973). Also, stochastic programming models tend to be complicated (Kall and Wallace, 1994). Examples of stochastic programming approaches with respect to agricultural systems van be found in: Jacquet and Pluvinage (1997), Clancy *et al*. (2012) and Finneran *et al*. (2012).

Table 1-2: Practical examples of mathematical modelling approaches

| References/study location | Modelling approaches/model name | Scale/ level | Objectives | Constraints | Agricultural/land use activities | End user groups | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | F | P | O |
| Cooke *et al.* (2013)<br><br>UK | Mixed-integer programming<br><br>**farmR** | Farm | Multiple objectives:<br>Profit<br>Risk minimisation<br>Crop management complexity preferences | Cropping area (land)<br>Sequenced operation<br>Crop rotation<br>Labour and machinery<br>Soil type and rainfall<br>Workable hours | Arable farming systems | ++ | + | + |
| Salassi *et al.* (2013)<br><br>USA | LP<br>Crop rotation network flow model<br><br>**MOTAD (Target MOTAD)** | Farm | Net returns maximisation | Equal area for each crop in the rotation<br>Limit on crop area<br>Risk constraint | Arable cropping systems | + | | + |
| Bergez *et al.* (2012)<br><br>France | Integration of bio-decision models<br>Dynamic models<br>Simulation<br><br>**MODERATO** | Farm and Regional | Water use optimisation | Equipment constraints<br>Resource constraints<br>Regulatory or human constraints | Cropping systems | ++ | ++ | + |
| Groot *et al.* (2012)<br><br>Netherlands | Multiple objective programming<br><br>**FarmDESIGN** | Farm level | Multiple objectives:<br>maximisation of profit and organic matter balance.<br><br>Minimisation of labour requirement and N losses | Crop areas<br>Feed balance<br>Frequency of cultivation<br>Crop rotation<br>Labour requirement | Mixed organic farming | ++ | ++ | + |
| Howitt *et al.* (2012)<br><br>USA | PMP<br><br>**SWAP** | Regional (State) | Regional profits maximisation through land and water optimisation | Resource availability:<br>Land<br>Water | Agricultural and environmental water systems | | ++ | + |

Table 1-2 Continued

| References/study location | Modelling approaches/model name | Scale/ level | Objectives | Constraints | Agricultural/land use activities | End user groups | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | F | P | O |
| Osgathorpe *et al.* (2011)<br><br>UK (Scotland) | Multiple objective programming | Farm | Multiple objective:<br>Gross margin maximisation<br>Biodiversity (bumble bee conservation) | Labour availability<br>Labour requirement<br>Fertiliser and fodder requirement<br>Subsidy payment constraints<br>Rotational constraints | Crofting<br>Arable and livestock systems<br>Grazing | + | ++ | + |
| Viaggi *et al.* (2010)<br><br>Italy | Dynamic Integer programming<br><br>Simulation | Farm | Multiple objectives:<br>Household worth<br>Consumption<br>Uncertainty<br>Debt-asset ratio<br>Diversification | Labour<br>Investment on capital<br>Payments<br>Policy | Arable cropping systems | + | ++ | + |
| Matthews (2006)<br><br>Website:<br>http://www.macaulay.ac.uk/PALM/ | Simulation modelling<br><br>**PALM** | Landscape | Economic and environmental | No constraint were explicitly stated | Farming systems<br>Landscape<br>Livestock | | ++ | + |
| Berntsen *et al.* (2003)<br><br>Denmark | LP<br>Scenario modelling<br>Simulation<br><br>**FASSET** | Farm | Economic and environmental | Total arable area<br>Space for animals<br>Crop sequence | Arable cropping systems<br>Pig production | + | ++ | + |
| Dogliotti *et al.* (2003)<br><br>Netherlands | LP<br>Crop rotation model<br>Prototyping of Dutch organic arable farming<br>Simulation<br><br>**ROTAT** | Farm | Multiple objectives:<br>Gross margin maximisation<br>Environmental: crop rotation to reduce pesticide use, reduce erosion | Agronomic principles and farmer specific constraints | Arable cropping systems | ++ | + | + |

Table 1-2 Continued

| References/study location | Modelling approaches/model name | Scale/ level | Objectives | Constraints | Agricultural/land use activities | End user groups F | P | O |
|---|---|---|---|---|---|---|---|---|
| Rounsevell *et al.* (2003)<br><br>UK | LP<br>Spatial modelling (GIS)<br>Simulation<br><br>**SFARMOD**<br>**ACCESS** | Regional | Profit maximisation | Resource constraints<br>Operation sequencing<br>Crop rotation | Arable cropping systems | ++ | ++ | + |
| Annetts and Audsley (2002)<br><br>UK | LP<br>Scenario modelling<br><br>**SFARMOD** | Farm | Multiple objectives:<br>Economic and environmental objectives | Machinery time<br>Cropping area (land)<br>Crop rotation<br>Livestock grazing and feed | Arable cropping and livestock systems | ++ | ++ | + |
| El-Gayar and Leung (2001)<br><br>Egypt | Multi-criteria decision making (MCDM) model<br><br>**CP**<br>**WGP** | Regional | Regional availability of protein<br>Employment<br>Foreign exchange earnings | Resource constraints:<br>Land<br>Labour<br>Water<br>Capital | Aquaculture | + | ++ | + |
| Makowski *et al.* (2001)<br><br>Netherlands | Mixed Integer Linear Programming (MILP) | Farm | Multiple objectives:<br>Economic (gross margin) and environmental | Cropping area<br>Crop frequencies<br>Crop sequencing<br>Mineral balance, Labour | Cropping systems<br>Fallow | + | + | ++ |
| ten Berge *et al.* (2000)<br><br>Netherlands | Multiple Goal LP (MGLP)<br><br>The model is a prototype farm model | Farm | Multiple objectives:<br>Economic (Gross margin)<br>Environmental (nitrogen and phosphorus surpluses) | No rented land<br>Reduced nitrogen and pesticide use | Arable cropping systems<br>Bulb production systems<br>Dairy systems | + | ++ | + |
| Zander and Kächele (1999)<br><br>Germany | Multiple goal LP (MGLP)<br><br>**MODAM** | Regional | Multiple objectives:<br>Economic and ecological goals | Other goals serve as constraints | Arable cropping and livestock systems | + | ++ | + |

Table 1-2 Continued

| References/study location | Modelling approaches/model name | Scale/ level | Objectives | Constraints | Agricultural/land use activities | End user groups | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | **F** | **P** | **O** |
| Howitt (1995)<br><br>USA | Positive mathematical programming (PMP)<br><br>Non-linear optimisation | Farm<br>Regional<br>Sectorial | Gross Margin | Land | Arable cropping systems | | | ++ |
| McCarl and Onal (1989)<br><br>USA | Non LP (NLP) and LP Linear Approximation<br>Separable programming<br><br>**MOTAD** | Farm | Profit maximisation | Tractor times<br>Sequenced operation | Arable cropping systems | | | + |

### 1.3.8 Section summary/conclusion

Myriad of MMAs exist in agricultural land use modelling however, the choice depends on the modelling objective as well as the capabilities of the modelling approach. Different modelling approaches have their strengths and weaknesses (limitations). LP models are more popular as far as optimisation of farming objectives is concerned however, it has limitations, which makes its application unsuitable in certain scenarios. LP is restrictive due to its linearity of constraints and fixed input-output coefficient, it is also associated with problem of infeasibility. The limitations of LP led to the development of other approaches. IP deals with the problem of infeasibility in LP models due to rounding up and down of activities. IP can incorporate integers into the model and can also produce both optimal and suboptimal solutions. MCDM modelling approaches such as GP is able to handle multiple objectives simultaneously and this makes it suitable for modelling multiple arable farming objectives. However, there is the possibility of over or under achievement of goals. RP approaches such as MOTAD deals with the linear approximation of expected value-variance. Although approximation can be less effective, in a situation where solvers for quadratic risk programming are not available or difficult to obtain, MOTAD models are more suitable since they can be solved by LP solvers. PMP is able to calibrate programming models, and one of its strength is that it can be constructed from minimal data but the data needs to be of good quality, and also, there is the possibility of the PMP model failing to make predictions of the reference data.

Existing MMAs have their strength and limitations and therefore when developing a robust multifunctional farming system models, there is the need for a modelling approach, which draws on the strength of different MMAs to create a more robust model. With the main research aim of developing a farm level model to evaluate economic as well as environmental and riskiness of alternative cropping systems, an arable farm model, which draws on the strength of mixed-integer, weighted goal and risk (MOTAD) programming approaches is developed. Also, as part of the thesis aims, the model is applied in Chapter 4 to investigate and answer research questions on the economic viability (and risk) of using crop rotation with spring cropping to control black-grass (weed). The model is also applied in Chapter 5 to investigate and answer research questions on risk aversion behaviour of arable farmers in England (see Section 1.7 for research and thesis aims).

## 1.4 Model review

This section presents some of the existing models related to agricultural land use, which have been created based on some of the MMAs shown above. The level of interactions of the models were assessed based solely on information in literature in terms of what the model is used or has been used for. Few of the models are introduced below this section (see Table 1-6 under Chapter Appendix for other examples) and Table 1-3 shows models identified with their level of interaction. The information presented about the models is mainly brief description however, references are provided, which can be referred to for more information.

The four levels of interaction are shown below. The **plus (+)** means the model falls under that level of interaction.

1. ***Policy—agricultural land use level (P-L):*** means models can predict or simulate changes in agricultural land use due to changes to policy.
2. ***Land use—environment level (L-E):*** means model can show or simulate how changes in land use or type of land use (activities) affect the environment.
3. ***Climate—agricultural land use level (C-L):*** means model can show or simulate the changes in agricultural land use due to variability in climate.
4. ***Modelling framework (MF):*** means whether or not the model is a modelling framework or provides a framework for building other models.

Table 1-3: Existing model examples and their levels of interaction

| Model | Model type/class | Level of interaction | | | |
|---|---|---|---|---|---|
| | | P-L | L-E | C-L | MF |
| **SFARMOD** (Silsoe Whole Farm Model) | Comparative-static | + | + | + | |
| **MODAM** (Multi-objective Decision support tool for Agro-ecosystem Management) | Comparative-static (MCDM) | + | + | + | |
| **FSSIM** (Farm System Simulator) | Comparative-static | + | + | + | |
| **CAPRI** (Common Agricultural Policy Regionalised Impact analysis) | Recursive dynamic/ Comparative-static | + | + | | |
| **SEAMLESS-**IF (Environmental and Agricultural Modelling: Linking European Science and Society Integrated Framework) | Comparative-static/ Dynamic | + | + | + | + |
| **ROTAT** (a tool for generating crop rotation) | Comparative-static | | + | | |
| **ROTOR** (crop ROTation in ORganic farming systems) | Comparative-static | + | + | | |
| **SWAP** (California Statewide Agricultural Production Model) | Comparative static | + | + | + | |
| **FASSET** (Farm ASSEssment Tool) | Dynamic | + | + | | |
| **PALM** (People and Landscape Model) | Dynamic | + | + | + | |
| **MODERATO** | Dynamic | + | | | |
| **FarmDESIGN** | Comparative-static | + | + | | |

### 1.4.1 SFARMOD (Silsoe Whole Farm Model)

This is a multiple objective LP model developed for a variety of farming scenarios including UK and European arable and mixed arable and livestock farms for farmers and decision makers to determine the best cropping, machinery and labour options. It is particularly for looking at future climate and economic scenarios and their impact on land use, and has a comprehensive database. References: Annetts and Audsley (2002); Williams *et al.* (2003); Audsley *et al.* (2006); Cranfield University (2013).

### 1.4.2 MODAM

MODAM (Multi-Objective Decision support tool for Agro-ecosystem Management) is a multiple-criterion decision-making LP used on multiple-objective land use issues. It is an instrument, which can generate a solution for competing groups and land users; and it allows the depiction of economic and ecological spatial problems at variable scales. MODAM served as interface and focused in interdisciplinary research during its development. References: Zander and Kächele (1999); Janssen and van Ittersum (2007); Schuler and Sattler (2010).

### 1.4.3 FSSIM (Farm System Simulator)

The FSSIM is an optimisation model developed as part of the integrated modelling framework of the System for Environmental and Agricultural Modelling: Linking European Science and Society (SEAMLESS) project and its target is integrated assessment of agricultural systems in 27 member states of the EU. It has components representing farmer objectives, risk, policies, calibration, current activities, alternative activities and different activity types. It uses the estimated prices and calculates supply responses of farms to price shocks in a selection of EU 27 regions and enable detailed regional integrated assessment of agricultural and environmental policies, innovations on farming practices and the sustainability of farming systems. References: Janssen *et al.* (2010); Louhichi *et al.* (2010).

### 1.4.4 ScotFarm model

The ScotFarm is a dynamic farm level model with generic linear programming set up to optimise net farm margin. The model consists of four modules: livestock, crop, feed and grass modules. The livestock module consists of dairy, beef and sheep production systems. The feed module determines monthly feed requirements for each of the animals on a farm based on type, age and production cost of the animal. The crop module assumes that decision making is based on yield and gross margin whereas the grass module divides fixed total land into arable, grassland and rough grazing. The model outputs include farm margin, land use, animal numbers, feed use, production level, cost of production and marginal costs. References: Shrestha *et al.* (2015); SRUC[3].

[3] Scottish Rural College (SRUC): https://www.sruc.ac.uk/downloads/file/3167/scotfarm

### 1.4.5 MEETA (Managing Energy and Environment Trade-offs in Agriculture) model

The MEETA model, developed by researchers at the University of Nottingham combines bio-economic modelling and life cycle analysis (LCA) approaches to investigate the trade-offs between energy, emissions and finances at the farm level in England. The model is a linear programming optimisation model, which uses a single year time frame to represent multi-year cropping and rotational aspects in arable farming and its outputs include optimal crop areas, farm gross margin, greenhouse gas emission and net energy generated from the farm. References: Glithero *et al*. (2012); Glithero *et al*. (2015).

### 1.4.6 Section summary/conclusion

From the review of the existing models, it can be said that each of the models has its strength and limitations, specific objectives and targets different user groups. Some of the models can be classified as biophysical and others as bio-economic models, which can inform farmers' decision as well as policy making at the farm, regional and sectorial levels. Combination of biophysical and bio-economic models can result in more robust arable farming system model. In terms of research gaps, from literature, it has been observed that the models identified have specific focus and target different user groups, hence variation in their capabilities. For example, SFARMOD was found to be based on formulating LP as a multi-objective model however, such formulation could be prone to generating infeasible results due to the fact that other objectives expressed as inequality constraints must be enforced. Other models such as ROTAT and ROTOR focus mainly on crop rotation and even those designed for multiple farming objectives such as MODAM and FASSET normally focus on environmental indicators such as nitrate leaching, pesticide and fertiliser use and soil erosion. Comparisons[4] of the capabilities of the models identified and linked to research questions (see Table 1-4) indicate that there is still model capability gap. With respect to the overall research and thesis aims, not many models exist in which risks in arable systems are explicitly modelled. Also, not many models evaluating the economic and environmental (ecological)

[4] The capabilities of models were identified based primarily on literature.

objectives—specifically profit and nitrate leaching using goal programming were identified.

The main gaps identified are that not many of the models identified modelled arable systems at the farm level and focused on optimising farm profit, nitrate leaching and explicitly incorporated risk especially in UK context. For example, while the ScotFarm (Shrestha *et al*., 2015) has dynamic element to it, it does not explicitly incorporate risk and also does not take into consideration timeliness penalty due to sub-optimal operations and rotations. Also, depending on the modeller's objective, some of the models are combined with others in order to achieve the desired outcomes (e.g. Rounsevell *et al.*, 2003; Bergez *et al.*, 2012).

With the research gaps identified coupled with the thesis aims (see Section 1.7), there is the need for research to develop a robust arable farm level model, which draws on the strengths of different mathematical modelling approaches and existing models. An arable farm level model, which combines mixed-integer, weighted goal and MOTAD (risk) programming approaches and draws on the strengths of other existing models is developed to optimise three arable farming objectives (profit maximisation, nitrate leaching and risk minimisation). Thus the model has the capability to evaluate economic benefits (profit), farmers' risks and ecological/environmental benefits (nitrate leaching minimisation). The model is applied in Chapters 4 and 5 to address research questions with respect to weed control and risk aversion (see Section 1.6 for research questions for Chapters 4 and 5).

Table 1-4: Comparison of capabilities of identified models to study objectives

| Model | Model capability[5] | Research Questions* | | |
|---|---|---|---|---|
| | | **C2** | **C4** | **C5** |
| SFARMOD | Determination of cropping, labour and machinery, which optimises multiple objectives of profit, risk and environmental burdens or criteria. | + | - | - |
| farmR | Determine cropping, labour and machinery which optimises profit, risk and crop complexities | + | - | + |
| MODAM | Economic and ecological benefits of farming systems Simulation of trade-offs scenarios of economic and ecological outcomes of farming systems | + | - | - |
| FSSIM | Assessment of agricultural and environmental policies on farm performance and sustainable indicators at the farm level. Optimisation of farm income and risk. | + | - | + |
| FASSET | Comparison with experimental data and exploring consequences of environmental and management changes for farm productivity and environmental impacts. | - | - | - |
| FarmDESIGN | Configuration of farm types to show alternative farms with best economic and environmental benefits Generating results of trade-offs between environmental and economic benefits | + | - | - |
| PALM | Simulation of flows of carbon, water, N through and within household as well as economic and labour flows. | - | - | - |
| SWAP | Optimisation of water use in agricultural production at the state level | - | - | - |
| MODERATO | Simulations of irrigation block functioning. | - | - | - |
| CAPRI | Assessment of the effect of the common agricultural policy (CAP) at the EU level | - | - | - |

A plus (+) indicates that the model is capable of generating a result on answers similar to what a research objectives seek; a minus (-) means model not capable of generating results similar to what the research objectives seek. * C2 = Research questions asked under Chapters 2((1) How do changes in rainfall at a farm location and moving from one soil type to the other affect farming objectives? (2) How do changes in N fertiliser under different soil types and rainfall affect the arable farming objectives? (3) Can increase in crop prices influence farmers to apply N above N max and forgo the Single Farm Payment (SFP) if farmers have the right to do so? (4) Is there any difference in the objectives of farms applying the N max and receiving the SFP and those who may apply above the N max and forgo the SFP?). C4 = Research questions asked under Chapters 4 ((1) What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring barley rotation? (2) What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring beans rotation? (3) Is there any effect of controlling black-grass with spring cropping on farm risk? (4) What are the effects of controlling black-grass with spring cropping on farm costs?). C5 = Research questions asked under Chapters 5 ((1) Are arable farmers in England risk averse? (2) Are there any differences in risk aversion across regions in England? (3) Do the levels of risk aversion influence cropping decisions? (4) What is the effect of policy change on farmers with different levels of risk aversion?).

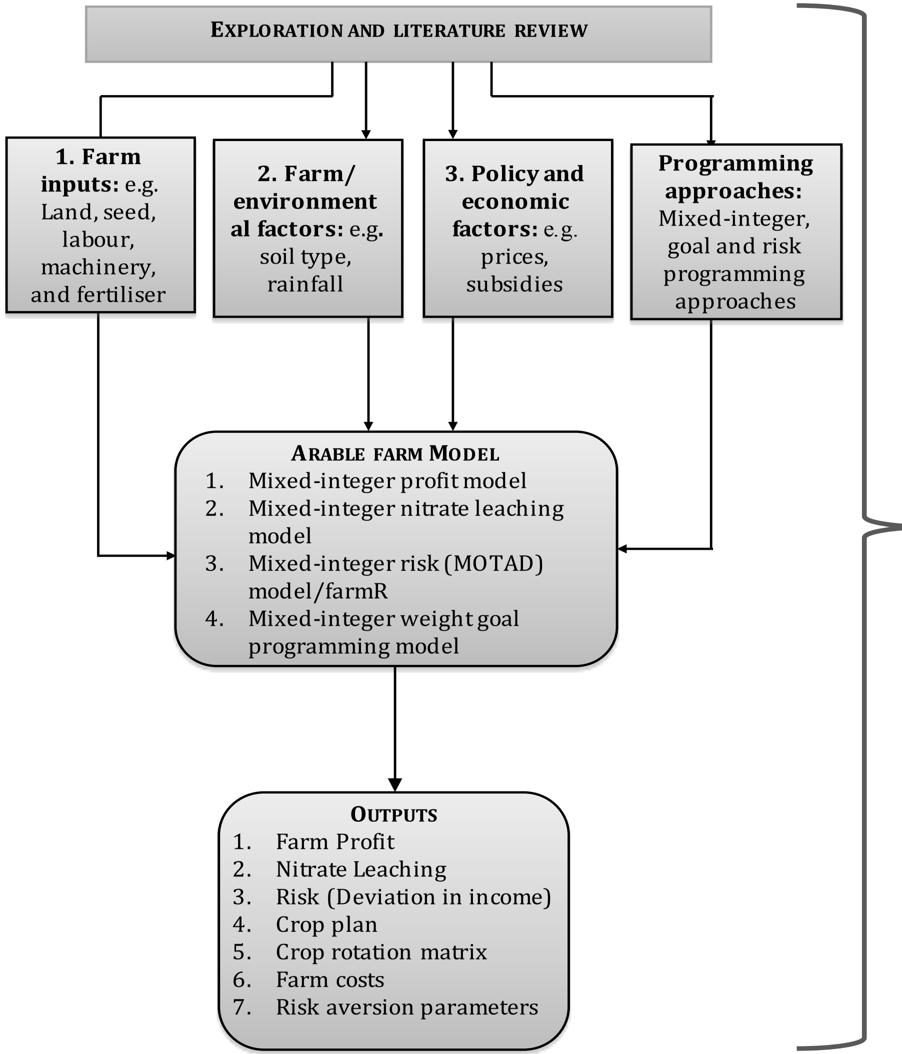
[5] The capabilities of models were identified based primarily on literature.

## 1.5 Research framework

The main objective of sustainable arable farming systems or arable farming systems for multiple benefits is to increase food production to ensure food security whiles reducing the negative externalities from farming systems due to intensive input use. However, farming systems underpinned by sustainable farming principles may be associated with lower productivity and high risk due to reductions in the use of inputs such as fertiliser and chemicals, which are used by farmers to safeguard crop yield but could impact negatively on the environment. Thus for such farming systems to be adopted, there are questions that need to be answered or addressed in terms of how inputs, output and policy variations affect arable farming outcomes; how adoption of sustainable farming strategies affect farming outcomes and how the risk aversion behaviour of arable farmers influence cropping decisions and reaction to policy change. To be able to address such questions, a research framework through the use of mathematical modelling/programming approach is used.

The research framework (simplified in Figure 1-6) begins with exploration and review of literature (in Chapter 1) based on which the overall research aim as well as the research questions is set. The exploration and literature review stage is used to identify the type of inputs used in arable farming systems, farm managements/agronomic practices adopted by arable farmers, as well as environmental/farm specific, policy and environmental factors which influence farmer's decision on input combination. That is, the framework identifies the input used by arable farmers (e.g. land, seed, labour, machinery/fuel, and fertiliser), the environmental/farm specific factors (e.g. soil type and rainfall), policy and economic factors (e.g. nitrate vulnerable zones directive, farming subsidies (single farm payment, now basic farm payment), input and crop prices) and farm management practices (e.g. crop rotation, sequential operations). The level of farm inputs such as fertilisers and chemicals safeguard crop yields whereas seed rates determine the crop population on the field and hence potential yield. The area of land available to the farmer determines the scale of production and hence possible crop rotation plan that can be adopted. Farm/environmental factors such as soil types and rainfall influence farm planning and could result in timeliness penalties as well as determine the levels of other inputs such as fertilisers that need to be applied. Farm policies influence how and what farmers should produce whereas prevailing crop prices influence farming decisions. Consideration of such factors in farm analysis is vital and thus the effects of some of the factors identified on farming objectives are further investigated in Chapter 2 using sensitivity analysis.

As part of research framework existing mathematical programming approaches are identified and the information informs the development of a suitable model, which draws on the strength of existing approaches and models to select and analyse multifunctional farming systems. The interactions between inputs, the farm factors and farm practices identified constitute an arable farming system, and based on these the data needed for the research (farm data) are identified and collected. An arable farm level model consisting of four modules is thus developed (see Chapter 3 for more details) to help answer some of the questions raised above. The model is defined to generate the data (results) from the farm data (a secondary data). The model is validated with a different data set from the Farm Business Survey (FBS) and the predicted results compared with observed data as presented in Chapter 3. With some of the problems in sustainable arable farming identified as unknown outcomes of some adopted farming strategies, the model mixed-integer goal programming model is then applied to investigate and answer questions with respect to the effect of using spring cropping as a black-grass (weed) control strategy on farm income and risk (see Chapter 4). Also, with risk aversion behaviour of farmers vital in farm planning and decision making in farming, a mixed-integer risk (MOTAD) model is applied to investigate and answer questions on how risk aversion influence cropping decision and how farmer may react to policy change (see Chapter 5).




| QUESTIONS ADDRESSED | Inputs | | | TOOLS (FARM MODELS) | | | | OUTPUTS | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1. How do variations input, farm and policy factors affect arable farming objectives? (Chapter 2)* | + | + | + | | | + | | + | | + | + | | | |
| 2. Validation: How do model results compare with real farming outcomes (Chapter 3) | + | + | + | + | + | + | + | + | + | + | + | | + | |
| 3. How does the adoption of spring cropping impact on farm revenue/cost and farm risk? (Chapter 4) | + | + | + | | | | + | + | | + | + | | + | |
| 4. How does risk aversion influence cropping decision? How do farmers react to policy change based on their level of risk aversion? (Chapter 5) | + | + | + | | | + | | + | | + | + | | | + |

* The tool applied was modified farmR model with similarities with the mixed-integer MOTAD model developed as part of the research. The plus (+) means the inputs and tools were applied in answering the research questions and the type of outputs that were generated.

Figure 1-6: Framework of the research.

## 1.6 Overall research aim and thesis aims

The overall aim of the research is to develop a modelling tool that can be used for evaluating the and economic as well as environmental (ecological) viability and riskiness of alternative cropping systems that may be adopted to deal with increased pressure on input use. Although the overall research aim is as stated above, in this thesis some research questions were answered as part of the overall research and thesis aims.

***Chapter 2: Investigation of factors affecting arable farming profit, crop complexity and risk under the single farm payment policy***

In Chapter 2, the effect of some of the factors related to arable farming systems (identified through literature review) on the goals or objectives of arable farming are investigated under the single farm payments policy through a sensitivity analysis with a focus on nitrate vulnerable zones. This is done under an assumption that farmers have been given the right to apply N fertiliser above the prescribed N limits and forgo the single farm payment if they choose to do so.

The following research questions are answered:

1. How do changes in rainfall at a farm location and moving from one soil type to the other affect farming objectives?
2. How do changes in N fertiliser under different soil types and rainfall affect the arable farming objectives?
3. Can increase in crop prices influence farmers to apply N above N max and forgo the Single Farm Payment (SFP) if farmers have the right to do so?
4. Is there any difference in the objectives of farms applying the N max and receiving the SFP and those who may apply above the N max and forgo the SFP?

***Chapter 3: Arable farm models for optimising farm profit, nitrate leaching and risk: Model description, verification and validation***

Models need to be validated to give potential model users some level of confidence. Thus in Chapter 3 the model built based on the overall research aim is validated through statistical validation using the Farm Business Survey (FBS) data of 281 lowland arable farms.

The following research questions are answered:

1. What is the degree of association between model predicted crop areas and observed crop areas (land use)?
2. What is the degree of association between model predicted fertiliser amounts and observed fertiliser amounts (input use)?
3. What is the degree of association between model predicted revenues/costs and observed revenues/cost?

***Chapter 4: Sustainable weed control with rotational management: Estimating the aggregate cost of controlling black-grass (Alopecurus myosuroides) with spring cropping in UK arable farming***

Weed management is very important in arable farming systems due to their impact on farm productivity. In the UK the control of black-grass through chemical means normally become ineffective due to the weed constantly developing resistance to a variety of herbicidal active ingredients. As a result, the use of non-chemical control strategies such as spring cropping is being encouraged to ensure sustainable weed management in arable fields. Thus in Chapter 4, the mixed-integer goal programming module of the model developed as part of the overall research aim is applied to estimate the aggregate cost of black-grass control using crop rotation with spring cropping.

The following research questions are answered:

1. What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring barley rotation?
2. What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring beans rotation?
3. Is there any effect of controlling black-grass with spring cropping on farm risk?
4. What are the effects of controlling black-grass with spring cropping on farm costs?

5. Is there any policy implication of the results?

***Chapter 5: Risk in agriculture: Modelling spatially-referenced farmer risk behaviour using an evolved mixed-integer MOTAD approach***

Risk aversion influences farming decision and policy and thus in Chapter 5 the mixed-integer MOTAD module of the model developed as part of this research is applied to estimate risk aversion coefficients using data of arable farmers in England and randomly generated risk aversion parameters. Also, policy analysis relevance of the method applied as well as the reaction to policy changes due to differences in risk aversion is demonstrated.

The following questions are answered:

1. Are arable farmers in England risk averse?
2. Are there any differences in risk aversion across regions in England?
3. Do the levels of risk aversion influence cropping decisions?
4. What is the effect of policy change on farmers with different levels of risk aversion?

## 1.7 Identified model data and research data needs

This section presents the research data needs informed by data used in the models identified through literature review. The research used farm management data (FMD) mainly from farm management literature and existing models, supplemented by data from the UK Farm Business Survey (FBS) and biophysical data from existing models. Some of the data identified in the other models were at the farm level whereas others were at the regional level. Other model data were from pilot or experimental farms (see Table 1-7 under Chapter Appendix for the data used in some of the models identified). The research data needs in relation to the overall research aim and thesis aims/research questions under Section 1.6 are summarised in Table 1-5.

Table 1-5: Data needs, sources and collection methods in relation to research questions

| Overall aim of research/thesis aims | | Data needs | Data sources | Methods of collection |
|---|---|---|---|---|
| Overall aim of the research | | | | |
| Develop a farm level mathematical (optimisation) model that can be used to evaluate economic as well as ecological/environmental viability and riskiness of alternative cropping systems. | | Farm management data, e.g. yield, price and cost data, subsidy payments<br><br>Soil type, Rainfall data<br><br>Machine work rate for farm operations<br><br>Workable hours<br><br>Model formulation and programming information | Farm management pocket book, Farm Business Survey (FBS), agriculture literature, existing model data (e.g. farmR model data) | Literature review, Secondary data, Communication with model development experts |
| **Thesis aims/research questions** | | | | |
| 1 | Chapter 2: What are the factors affecting arable farming objectives? | Data on N fertiliser limits in Nitrate Vulnerable Zones | Defra, farmR Model and data | Literature review, Secondary data |
| 2 | Chapter 3: What are the degrees of association between model predicted results and observed data? | Farm output data, Farm and crop area data, soil type and rainfall. Information on validation | FBS, Met Office, Soilscapes® website | Literature review, Secondary data |
| 3 | Chapter 4: What is the aggregate cost of black-grass control with spring crops in UK arable farming? | Data on input use, farm output data, soil type, rainfall, rotation plans | FBS, Farm management pocket books, Data from farmR model | Literature review, Secondary data<br><br>BGRI project (http://bgri.info/) |
| 4 | Chapter 5: How do farmers' risk-aversion behaviours influence their decision? | Data/information on farmers risk preferences, crop yield and price data, soil type and rainfall data | Literature, FBS data, Met office, Soilscapes® website | Literature review, Secondary data |

## 1.8 Key Messages

- Sustainable farming systems rely on efficient farm management practices and resource use. Therefore, the development of robust multifunctional arable farming systems should be underpinned by the principles of sustainability. This will enhance the production of more and quality food to ensure food security without damaging the environment for both current and future generations.
- Efficient crop rotation can be pivotal in sustainable arable farming systems.

- Complexities exist in arable farming systems in terms of field operations, input use, farm management practices, and farm outputs. Arable farming systems are also associated with risks in terms of crop type, yield and prices, adoption of new farming systems and technology. Trade-offs are normally between economic and environmental goals as well as between farm income and risk.
- Different types of mathematical modelling approaches exist, and each has its strength and limitations. When modelling arable farming systems, different approaches can be combined to draw on their strengths in order to develop a more robust model.

- In the case of the UK, not many arable farm models based on optimisation approaches were identified and even those identified, it was the SFARMOD, which was found to have included environmental aspects such as nitrate leaching. There is thus model capability gap and the need for further research.

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# Appendix

Table 1-6: Model packages/framework examples

| References | Model | Model information |
|---|---|---|
| van Ittersum *et al.* (2008)<br><br>SEAMLESS Project: www.seamless-ip.org | SEAMLESS-IF (Environmental and Agricultural Modelling: Linking European Science and Society Integrated Framework) | This is a modelling framework part which aims at integrated framework to support integrated assessment of agricultural systems at different scales, and to provide analytical capabilities for economic, environmental, social and institutional aspects of agricultural systems. Thus, it focuses on agricultural land-use activities and their interactions with the environment, economy and rural development. Its components include a quantitative model, database, indicators and software infrastructure. |
| Britz *et al.* (2007) | CAPRI | It is a EU quantitative agricultural sector modelling system with the main objective of assessing the effect of the CAP policy instruments at the EU, member state and sub-national levels. It consists of databases, a methodology, software for implementation and development, maintenance and applications team. CAPRI also allows the comparability of its results.<br>The model reports are presented in interactive maps and the technical solution is based on GAMS modelling language. The graphical user interface (GUI) is now in C, interacting with FORTRAN code and libraries, which deal with database management. |
| Dogliotti *et al.* (2003) | ROTAT | This was designed to generate crop rotation based on agronomic criteria and it does that by combining crops from a predefined list to generate all possible rotations. The possible number of crop combinations is limited by a number of user-controlled filters, which are designed based on expert knowledge to eliminate crop successions, which are agronomically feasible. If no limitations are imposed, ROTAT can generate 71,824 rotations varying from one to six years. |
| Backinger and Zander (2007) | ROTOR | ROTOR targets nitrogen (N), weed management and phytosanitory issues using rule-based static approach. It has some similarities with ROTAT. ROTOR works by putting together a set of crop production activities semi-automatically from a site and crop specific field operations using a database. It then generates all the possible sequences of crop production activities from within the crop generation module, linked to 3-8 year initial crop rotations. |

Table 1-6 Continued

| References | Model | Model information |
|---|---|---|
| Berntsen *et al.* (2003)<br><br>FASSET website: http://www.fasset.dk/ | FASSET | This is a whole farm dynamic model used to evaluate results of changes in regulations, management, prices and subsidies on a range of indicators for sustainability at the farm level. It has two major components—planning (based on LP) and simulation modules. The planning module generates management plans to be implemented annually and simulated afterwards. The simulation results are used as environmental and economic indicators. The simulation is implemented in C++. |
| Howitt *et al.* (2010)<br>Howitt *et al.* (2012) | SWAP | It is a PMP model of California irrigated agriculture, which is multi-input and output model of agricultural production. The model can calibrate itself using PMP to a base year of land use and input allocation data by using exogenous elasticities and assumed profit maximisation behaviour of farmers. The model covers more than 93% of irrigated agriculture in California. In SWAP, non-linear cost function is calibrated to observed values of input use in agricultural production. It is written in the GAM software language and solved using the non-linear third party solver, CONOPT-3. Through SWAP, water managers and policy makers get insight into the economics of water use and agricultural production at the state level. |
| Matthews (2006)<br><br>Website:<br>http://www.macaulay.ac.uk/PALM/ | PALM | It is an object-oriented programming, which consists of a number of agents representing households, landscape and livestock. The landscape is made up to a number of similar land units, each represented by an object containing data, methods and properties applicable to the field. The model is spatially explicit; operates at the landscape level and it is constructed as a number of nested classes and simulates the flows of carbon, water and N through and within households as well as economic and labour flows. The model is written in Delphi and runs on a daily time-step using daily weather data as driving variables. |
| Bergez et al. (2001)<br>Bergez et al. (2012) | MODERATO | This is bio-decisional model developed to simulate an irrigation block functioning and for irrigation advisors to address irrigation at the block level with limited amount of irrigation water. It includes the main constraints related to irrigation and simulates the plant-soil system with a dynamic biophysical model taking into consideration the in-field variability that results for sequentially irrigating the plots in a block of irrigation. |

Table 1-7: Data used in existing models

| Reference | Model | Data used in model | Data availability | Remarks |
|---|---|---|---|---|
| Annetts and Audsley (2002); Rounsevell *et al.* (2003) | SFARMOD | MAFF data (based on annual census data, secondary crop data, soil data | - | MAFF data not available but crop data can be obtained from FBS, FMD. |
| Cooke *et al.* (2013) | farmR | FBS (149 low land arable farms in England and Wales) | + | FBS data can be parameterised at the farm level |
| | | Farmer interview (stated preferences on risk) | - | Data on farmers preferences on risk needed (not used). |
| Zander and Kächele (1999) | MODAM | Farm data from different regions<br>Data from 32 farms in one region and 40 farms in another region | - | Data pertains to Germany but can inform research data needs |
| Louhichi *et al.* (2010) | FSSIM | Farm Accountancy Data Network (FADN) data | + | FADN can be obtained when needed and can be parameterised at the farm level. |
| | | Farm survey data | - | Survey data specific for France and Netherlands |
| Howitt *et al.* (2012) | SWAP | Agricultural production data from 27 regions in California | - | Data may not be applicable in the UK but its information can inform research data needs |
| Berntsen *et al.* (2003) | FASSET | Data from Danish Farm Account Statistics | + | Data shares some similarities with the FBS but it pertains to Denmark |
| Dogliotti *et al.* (2003) | ROTAT | Farm data from 10 pilot farms | - | Data was obtained from experimental farms |

Note: The plus (+) in *data availability* column indicates that some components of the model data are similar to some components of the Farm Business Survey (FBS) and can be obtained. The minus (-) indicates data does not pertain to the UK, but either informs research data needs or may not be possible to obtain.

***"That's what the Single Farm Payment is all about. If farmers got that payment on time, maybe they could afford tractors with lower emission engines and that sort of thing."***

— Richard Haddock

# 2 FACTORS AFFECTING ARABLE FARMING OBJECTIVES (GOALS)

*In the preceding chapter, a review of literature on sustainable agriculture was conducted to identify some of the farm management practices and policies, objective/goals, complexities and trade-off examples related to sustainable farming systems, which can be incorporated into farm models. Also a review of mathematical programming approaches and existing models was conducted to identify gaps in modelling approaches and model capabilities. The review showed the existence of modelling approaches and model capability gaps and in the UK context, with exception of the SFARMOD and farmR models, not many arable farm level models were identified. Thus there is the need for research to develop a model, which draws on the strength of the modelling approaches and existing models and incorporate some of the factors of production and farm management practices identified.*

*Again as part of the model development aim of this research, in this chapter, some of the factors related to arable farming systems such as soil type, rainfall, nitrogen fertiliser application, crop price, Single Farm Payment (SFP), identified through literature review are further investigated quantitatively in the context of Nitrate Vulnerable Zones (NVZs) and under different soil-rainfall interactions to examine their effect on arable objectives. The selected factors normally serve as model parameters or constraints in farm models and impact on model results, hence the need to investigate their effect on farming objectives. Also, in terms of sensitivity analysis studies with respect to the selected factors, farming objective, optimisation models, soil-rainfall interaction, NVZs and SFP, not many were identified especially in UK context, hence the need for the study. Part of the aim of this chapter is to investigate whether or not farmers will be better off applying more nitrogen fertiliser above the prescribed amounts for NVZs to increase crop yield if they are given permission to forfeit the SFP and apply more nitrogen fertiliser.*

*A version of the study presented in this chapter was submitted, accepted and presented at the 89th Annual Conference of the Agricultural Economics Society on 13th April 2015.*

# Investigation of factors affecting arable farming profit, crop complexity and risk under the single farm payment policy

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## Abstract

In this chapter we investigate the effect of variations in soil type, rainfall, nitrogen (N) fertiliser amount and crop prices on the objectives of arable farms operating in Nitrogen Vulnerable Zones (NVZs) and receiving the Single Farm Payment (SFP). Sensitivity analysis was carried out using a mixed-integer programming (MIP) arable farm model (farmR). The farmR model estimates three arable farming objectives of interest: farm profit, crop complexity and risk. Applying the 2014 SFP flat rate and the maximum N limits (N max) values (prescribed in the NVZ guidelines) to each crop, N max was varied under different soil types and rainfall interactions. Crop prices were also varied to illustrate the effectiveness of the SFP under a scenario of high crop prices. The results showed that although applying N above N max increases farm productivity under all soil and rainfall interactions, under a scenario where farmers have been given the right do so and forgo the SFP, would reduce farm productivity and increase risk. The SFP thus acts as a payment for the opportunity cost to farms for not being able to apply N above N max. However, under a scenario of crop price increases, applying above N max and forfeiting the SFP could generate higher productivity than at the N max level.

## 2.1 Introduction

Agricultural policy instruments have been designed to regulate production, make it more efficient and sustainable by promoting efficient input use or to provide financial support to farmers. Regulation, government intervention or changing policy in agriculture is probably the most critical driver in agricultural land use due to its influence on what and how farmers can produce (Halloran and Archer 2008; Angus *et al*., 2009). In the UK, one such policy instrument is the Single Farm Payment (SFP) under the Common Agricultural Policy (CAP), which provides financial support to arable farmers. In order to receive this payment, farmers are required to adopt environmentally friendly agronomic practices or technologies with the aim of making arable farming more sustainable. For arable farmers to receive the SFP, some Statutory Management Requirements (SMRs) have to be satisfied and the farmland has to be kept in Good Agricultural and Environmental Condition (GAEC) (Nix, 2014).

Under some circumstances GAEC can only be achieved if the application of inputs such as nitrogen (N) fertiliser is restricted. In NVZs there are limits to the amount of N that can be applied (Defra, 2013). However, reduced N inputs can clearly lead to reduced crop yields and hence profit margins. Thus, shifting to more sustainable arable farming systems through the adoption of new agronomic technologies or practices under the SFP policy could influence input as well as outputs levels, which in turn could influence the farming objectives whether profit or non-profit (Clark *et al*., 1999; Halloran and Archer, 2008; Hanson *et al*., 2008). Bojnec and Latruffe (2013) found that the provision of subsidies was negatively related to the technical efficiency but positively related to farm profitability. In this study, the effects of variations in soil types, rainfall, N amounts and crop prices on the objectives of arable farms in NVZs receiving the SFP are investigated.

Apart from policies such as SFP influencing the farming decision through the adoption of SMRs and GAEC, farm specific and climatic factors such as soil types and rainfall and economic factors such as crop prices could also influence input use. In NVZs, to receive the SFP, farmers are constrained by maximum N amounts limits (N max) prescribed in the NVZ guidelines although some farms may be allowed to apply slightly above N max (Defra, 2013). Factors such as soil type, prevailing rainfall could determine the amount of N to apply and in turn influence farmers to apply either above or below the N max. This implies that under the SFP scheme, variation in N amount influenced by the above-mentioned factors could impact on farm productivity or farming objectives. Also, economic factors such as crop prices have direct relationship with farm productivity and therefore could influence farmers' decision on input use. Again, variation or volatility in crop prices can increase the risk faced by farmers (Harwood *et. al.*, 1999). Thus, how do variations in these factors affect the arable farming objectives? How different are the objectives of farms applying the N max and receiving the SFP and those who may apply above the N max and forgo the SFP assuming farmers have been given the right to do so? Can increase in crop prices influence farmers to apply N above N max and forgo the SFP if farmers have the right to do so?

Soil types and rainfall are farm location specific and affect the scheduling of farm operations leading to yield reductions due to timeliness penalties (Webster *et al.*, 1977; Reith *et al.*, 1984; Rounsevell *et al.*, 2003; Cooke *et al.*, 2013). Soil characteristics such as soil depth, water holding/retention capacity, bulk density, nutrient levels and organic matter define the soil type, which in turn determines its suitability for supporting certain farm enterprise (Draycott and Bugg 1982; Reith *et al.*, 1984). Variations in rainfall have been found to cause variations in yield and hence affect farm profitability and make farming business risky (Peterson *et al.*, 1990; Rao *et al.*, 2011; Brown *et al.*, 2013). With the effects of climate change and soil degradation on rainfall patterns and soil fertility respectively, it is important to understand mechanistically how changes in rainfall at a farm location and moving from one soil type to the other affect farming objectives.

Changes in fertiliser amounts have been found to affect crop yield, which is a significant determinant of farm profit (e.g. Greenwood *et al.*, 2001; Sylvester-Bradley *et al.*, 2008; Zhang *et al.*, 2009; Jannoura *et al.*, 2014). However, the effect of fertiliser on crop yields has a diminishing effect with increasing use. From an economic viewpoint, in order to maximise profit, marginal revenue obtained for applying fertiliser on a crop must equal the marginal cost of applying the fertiliser (Farquharson, 2006). Thus, in this chapter we seek answers to the following question: how do changes in N fertiliser under different soil types and rainfall affect the arable farming objectives?

The effects of soil types, rainfall and N fertiliser on farming objectives especially through crop yield variability detailed by other studies are normally tested using field experiments (e.g. Sylvester-Bradley *et al.*, 2008), biophysical crop response (e.g. Zhang *et al.*, 2009) or econometric/statistical (e.g. Browne *et al.*, 2013) models. Such analyses, based on the results of field trials and data, are useful in highlighting possible short-term effects, but less useful in generating long-term predictions or considering the effects of varying multiple parameters at the same time. However, optimisation or linear programming based farm models have the capability to generate long-term predictions by capturing many of the complexities in arable farming systems and also providing a framework for organising quantitative information about the supply side of agriculture at different levels (Hazell and Norton, 1986). Again, with farm models a much wider spectrum of alternative conditions as well as external factors such as policy and farm environment can be examined mathematically (ten Berge *et al*., 2000).

Farm models have been developed as part of the efforts to promote efficient farm management to help in decision-making at the farm as well as to explore the effects of changing external factors. Such models include arable farming system factors as parameters. It is therefore imperative to investigate how these factors affect the farming objectives with respect to the arable farming objectives. In the farmR model, fertiliser amount serves as an input parameter with N fertiliser used in the determination of simulated crop yields with exception yield for the leguminous crops. Soil types and rainfall serve as constraint parameters, which affect the sequencing of crop rotation, farm operations and scheduling leading to yield reduction due to rotational and timeliness penalties. Thus, changes in the parameters in farmR can result in the variations of the arable farming objectives estimated by the model.

In summary, variations in soil type, rainfall, N fertiliser and crop prices have been found to influence farm productivity and hence farming objectives. Fertiliser amount can affect the arable farming objectives through yield and farm cost variability. There is therefore the need to investigate the effect of its variation on the arable farming objectives. Although the literatures reviewed above give insight or some evidence into how variations in the above-mentioned factors affect arable farming productivity and hence the farming objectives, the findings are normally based on field experiments which seek to measure effect on crop yield. Also, with respect to the SFP, studies that link it to the interactions and variations in the above-mentioned factors are still lacking. Therefore, investigating the effect of farm and economic factors on the arable farming objectives under farm payment policy using an arable farm model (farmR) fit the purpose of this chapter. In this chapter, we attempt to answer the questions raised above. The study research questions can be summarised as follows:

1. How do changes in rainfall at a farm location and moving from one soil type to the other affect farming objectives?
2. How do changes in N fertiliser under different soil types and rainfall affect the arable farming objectives?
3. Can increase in crop prices influence farmers to apply N above N max and forgo the SFP if farmers have the right to do so?
4. Is there any difference in the objectives of farms applying the N max and receiving the SFP and those who may apply above the N max and forgo the SFP?

## 2.2 Methods

### 2.2.1 FarmR model structure

This section gives a brief description of the farmR model. Detailed description of the model design and description of the model objectives and parameters can be found in Cooke *et al*. (2013). The farmR model is a mixed-integer programming (MIP) implementation of previous models by Annetts and Audsley (2002) and Rounsevell *et al*. (2003). It is based on the assumption that a selected decision optimises a weighted contribution of all relevant objectives. The model optimises the overall farmers' utility, which comprises multiple objectives and each objective is the sum of contribution from each of the quantities of the various units. The three main objectives investigated by Cooke *et al*. (2013) were adopted: profit, risk and crop complexity, which according to Cooke *et al.* were ranked as the three most important objectives respectively by farmers. The model is summarised in Figure 2-1 below in terms of the assumptions, objectives and constraints which come together to form the model as well as the model type of output generated by the model.

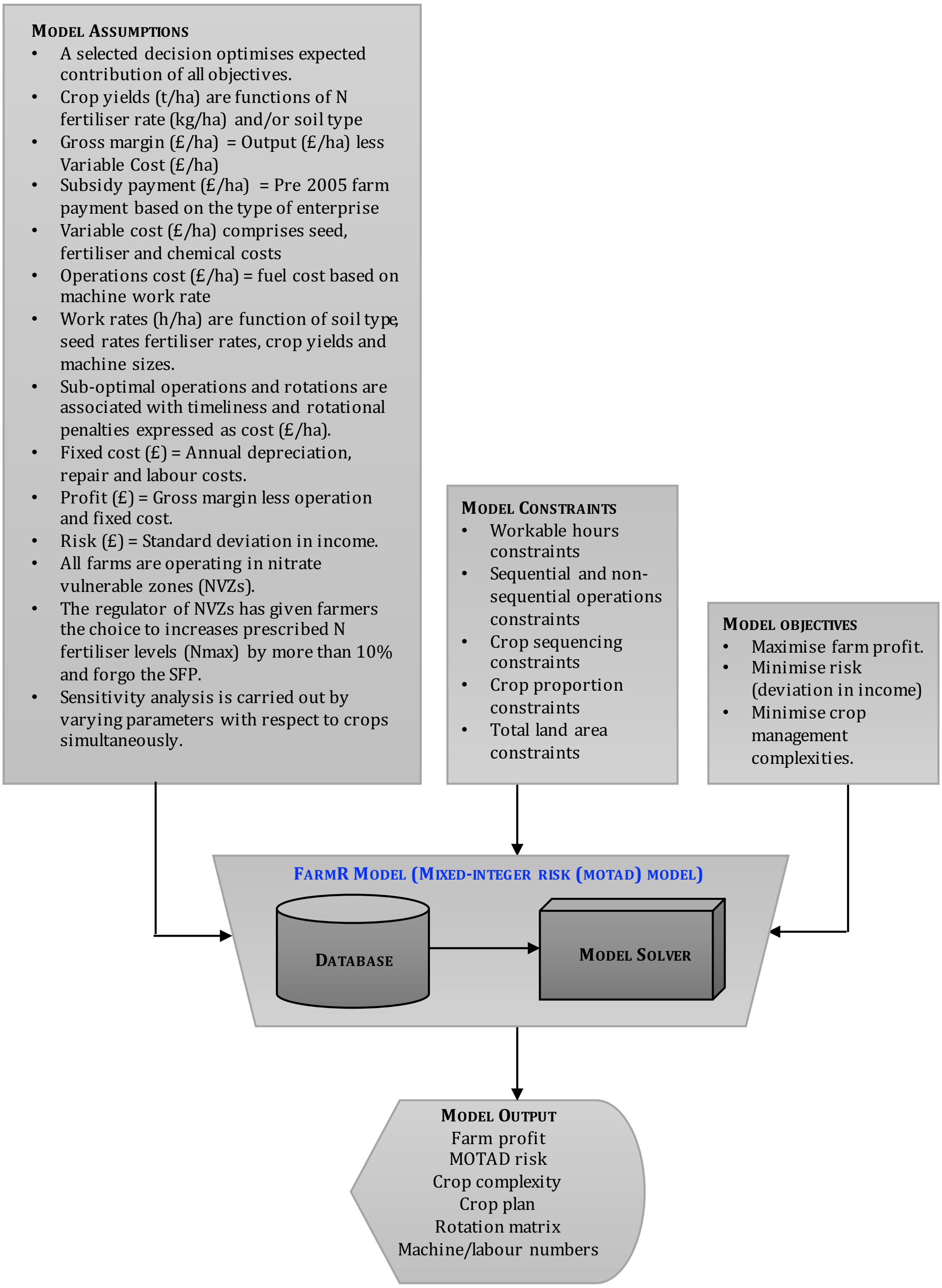


Figure 2-1: Flow diagram representation of the farmR model

The profit objective was defined in farmR as the annual net gross margin—the sum of gross margin of each crop less the cost of operations, machines and labour for each crop, subject to series of constraints (see Rounsevell *et al.*, 2003; Cooke *et al.*, 2013), subject to constraints similar to the constraints under Section 3.3. The objective can be stated as follows:

$$O_{profit} = \sum_{i} G_i a_i - \sum_{ijk} C_{ijk} x_{ijk} - \sum_{m} C_m n_m \qquad (2\text{-}1)$$

Where $G_i$ is the gross margin for the *i*th crop, $a_i$ is the area of crop *i*, $C_{ijk}$ is the cost of the *j*th operation on the *i*th crop in period *k* and $x_{ijk}$ is the area of *j*th operation on the *i*th crop in period k. $C_m$ is the cost of machinery and labour required to perform field operations and $n_m$ is the number of machines of types *m* required to perform the field operations.

It should be noted that the gross margin estimates are based on crop yield values, estimated using response functions, which take into consideration soil types and N fertiliser amounts. For the legume crops the yield response curve took into consideration only soil type. Also, for crops such as ware potatoes and sugar beet, the response functions were based on N fertiliser amounts. The response function for all the crops (with exception of legumes) based on heavy soil and under different levels of N fertiliser rates are shown in Figure 2-2 below.

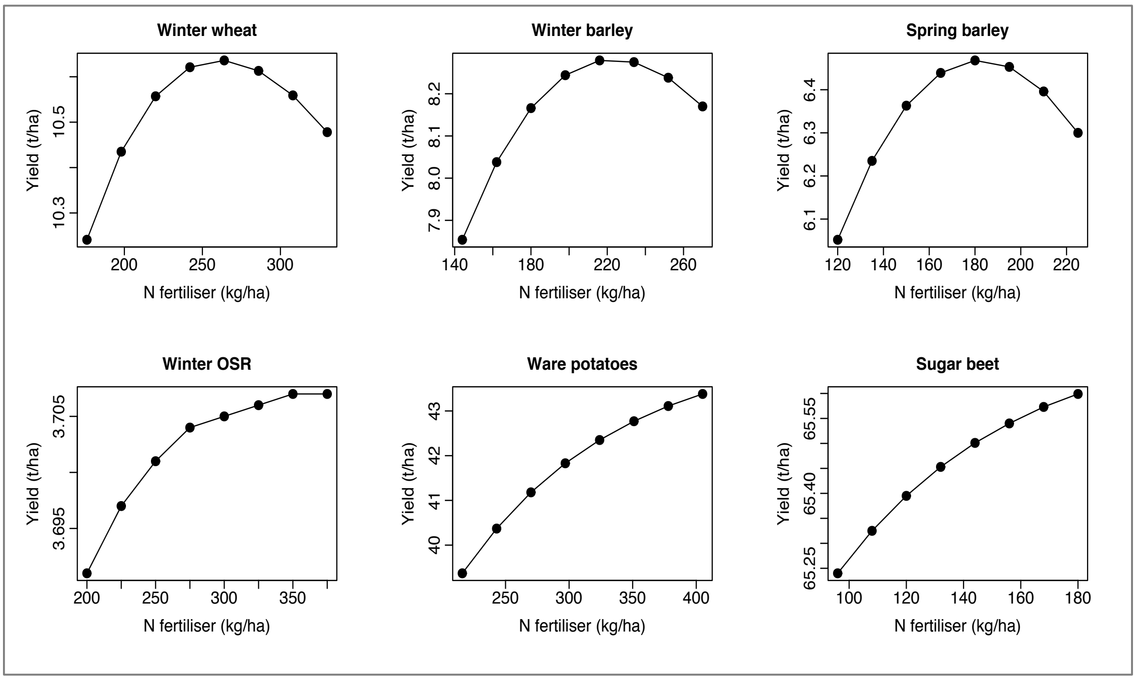


Figure 2-2: Response function based on which the crop yield in the farmR model were estimated.

The risk minimisation objective was based on the principle of minimisation of total absolute deviation (MOTAD) (Tauer, 1983; McCarl and Önal, 1989) in profits. It is the summation of the product of *i*th crop area ($a$) and the standard deviation in output per hectare for the *i*th crop ($\sigma$), multiplied by a constant factor (λ=1) (Cooke *et. al.*, 2013). The λ=1 gave the best model fit when the model was run under different values of λ ranging from 0.5 to 2 at an interval of 0.5 (Cooke *et. al.*, 2013). The risk objective can be stated as:

$$O_{risk} = \lambda \sum_{i} a_i \sigma_i \tag{2-2}$$

The risk values are linked to farmer satisfaction and represent the best or worst possible farm income deviation a farmer would expect over a 5-year period. The number of crop types grown is associated with a number of different operations and a level of difficulty in farm management. Thus in the farmR model crop complexity was less formally defined as the level of difficulty associated with running a number of crop enterprises and operations simultaneously within the farm and were derived based on farmer interviews (Cooke *et al.*, 2013).

In terms of validation, the output of the farmR socioeconomic model was compared with empirical data using the Farm Business Survey. For farmers' preferences on profit, risk and crop complexity, an interview was conducted using multi-criteria decision analysis framework with 47 farmers in England (Cooke *et al.*, 2013). From the responses of the survey and through a recalibrated utility function, achieving 0% satisfaction meant a profit of £60,000 and 100% satisfaction meant £180,000 based on 250 ha farm. This implies that as profit increases from £60,000, farmers' satisfaction begin to rise.

The crops used in farmR and adopted in this chapter were winter wheat, spring and winter beans, spring and winter barley, ware potatoes, winter oilseed rape (here after WOSR) and sugar beet. Also, set-aside land was included. The model codes were written in Java programming languages and initially implemented as a package in the open source statistical environment, R. The model still runs using R but on a Linux Ubuntu Virtual Machine and it uses the COIN-LP numerical library (http://www.coin-or.org/) to solve the underlying MIP model. The farm R model codes can be found through the following link: https://bitbucket.org/iracooke/javawfm. The farmR package being command based, made it suitable for the purpose of this chapter in the sense that the XML file which contains the parameters can be written into to change any of the parameters of interest.

### 2.2.2 Sensitivity analysis

Each parameter or combination of parameters in farmR contributes to the production of an output and with sensitivity analysis, any or all of the parameters of interest can be varied (Pannell, 1997). The sensitivity analysis was carried out following approaches and strategies in line with the ones suggested in Pannell (1997). To be able to achieve the aim of this chapter using sensitivity analysis, the following assumptions were made:

1. We assumed that all arable farms are operating in NVZs and have to comply with the SMRs and GAEC as well as apply the N max amounts in order to receive the SFP. However, some farms may be allowed to apply slightly above the N max (see Defra, 2013) and as a result, in this study, we assumed

that farmers in NVZs are only allowed 10% above the N max limit and that farms increasing the N amount above 10% would lose the SFP.

2. We assumed further that the regulator of the NVZ directive has given farmers who want to increase N max more than 10% the right to do so and forgo the SFP.

3. In order to simplify the analysis, N amounts and prices of all crops were varied simultaneously even though in reality a farmer may decide the N amount of which crop to alter or prices of different crops may not increase by the same margin.

### 2.2.3 Parameter selection and range of variation specification

In NVZs, arable farmers have to follow certain guidelines in order to receive the SFP. As part of the guidelines, farmers are required to apply N up to the prescribed N max however, the type of soil and prevailing rainfall could also influence N application. While the type of soil could determine the amount of N to apply, rainfall could influence the scheduling of N application. This means that soil type-rainfall-N interactions could influence farming decision and hence farming objectives. The three factors were therefore selected and varied. In terms of the range of variation, the N max amount for each crop was varied between -20% and +50%. To illustrate how economic factors affecting the farming objectives under SFP, crop prices were varied to determine whether or not increase in crop prices could influence farmers to apply N above N max and forgo the SFP. Crop prices in the model were increased from 5% to 30% by setting N amount at 40% above N max and SFP to zero. The range of variation for crop prices was informed by wheat price projection by Willenbockel (2011). Table 2-1 shows the three soil types and three rainfall classes (used in Defra, 2010) and the N max amounts chosen for the sensitivity analysis.

Table 2-1: Parameters used for the sensitivity analysis

| Parameters | Crops | N max limit (kg N/ha) |
|---|---|---|
| N fertiliser amount | Spring barley (SBAR) | 150 |
| | Winter barley (WBAR) | 180 |
| | Winter beans (WBEA) | 0 |
| | Spring beans (SBEA) | 0 |
| | Winter wheat (WWHT) | 220 |
| | Sugar beet (SBEE) | 120 |
| | Ware potatoes (WPOT) | 270 |
| | Winter oilseed rape (WSOR) | 250 |

| Soil/rainfall | Soil types/rainfall amounts | Assigned values |
|---|---|---|
| Soil type | Light soil (LS) | 0.5 |
| | Medium soil (MS) | 1.5 |
| | Heavy soil (HS) | 2.5 |
| Rainfall | Low rainfall (mm) (LR) | 550 |
| | Moderate rainfall (mm) (MR) | 650 |
| | High rainfall (mm) (HR) | 750 |

### 2.2.4 Factor variations/interactions and model runs

To ensure soil-rainfall-N interactions, N max was varied under soil and rainfall interactions, with and without SFP to compare variations in the arable farming objectives. In all nine soil type-rainfall interactions were generated. The N max data were obtained from Defra (2013) whereas the soil types and rainfall values were based on information from the farmR model (Cooke *et al.*, 2013) and Defra (2010) respectively. In farmR, soil types ranged from 0.5 through 2.5 representing specific soil types from light through heavy soils (Audsley *et al*., 2008; Rounsevell *et. al.*, 2003) and out of these soil types, the three shown in Table 2-1 above were selected. Crop price data were obtained from the farmR model. In order to capture the SPF in the farmR model, the 2014 flat rate for lowland farmers in England (£207/ha) (Nix, 2014) was applied to each crop enterprise and the model was run under each soil type-rainfall interaction for each variation in N amount and crop price.

## 2.3 Results and discussion

### 2.3.1 Effect of N variations under light soil and rainfall interactions

An increase in N amount under all light soil and rainfall interactions increased the profit however, increasing the N max by more than 10% and forgoing the SFP reduced the profit (see Figure 2-3). For example, applying N max and receiving the SFP generated a profit of £169,265 however, increasing N max by 40% and forfeiting the SFP reduced profit to £127,976 (24% decrease). The results imply that although there is room for arable farmers to increase farm productivity (yield and hence profit) by applying N above N max, doing so will reduce profits (farm income) due to loss of the SFP.

Crop complexity remained unchanged at four indicating that under light soils and rainfall interactions, with or without the SFP the number of crop selected by farmers may not be affected by N variations. The risk increased with increase in N under all interactions meaning that risks associated with N levels equal to or below Nmax are lower. This result can be related to the finding of Monjardino *et al.* (2013) that, higher N rates contributed to higher yields but were associated with higher yield variance translating into higher economic risk. Thus, aiming to receive the SFP by applying below or up to the N max could reduce farm risk.

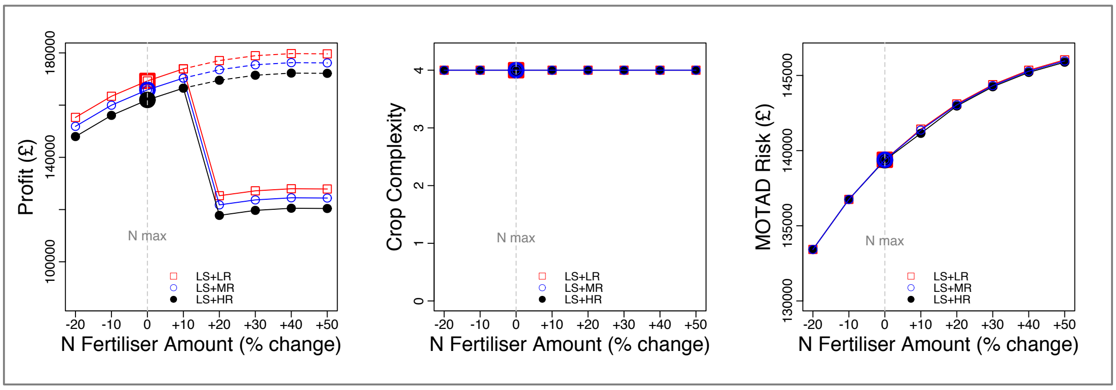


Figure 2-3: Variations in arable farming objectives due to N fertiliser amount variations under light soil-rainfall interactions. The dashed red, blue and black lines represent the profit levels assuming farmers are still receiving SFP after increasing Nmax above 10%.

### 2.3.2 Effect of N variations under medium soil and rainfall interactions

Applying N max under medium soil and low rainfall interaction generated a profit of £136,794 (lower than profit under light soil at N max level) whereas increasing N max by 40% reduced the profit to £93,373 (32% reduction) (see Figure 2-4). The result shows that compared to light soils, farms operating on medium soils have lower profits and the implication is that such farms will be better off operating at N max level and receiving the SFP even if farmers have the right to apply above N max.

Again, crop complexity remained mainly unchanged by increasing N max by 40%. Since farms receive SFP irrespective of the crop grown, it is possible that on a medium soil the number of crops selected by farms may not depend on whether or not farms receive SFP. Increasing the N max by 40% increased the risk by 4% and this may be due to the fact that the estimation of the MOTAD risk was based on farm output (yield and price) and that any increase in farm output will translate into increase in the associated risk (Monjardino *et al.*, 2013). Thus, farmers will be better off by at most fertilising crops at the N max level associated with low risk.

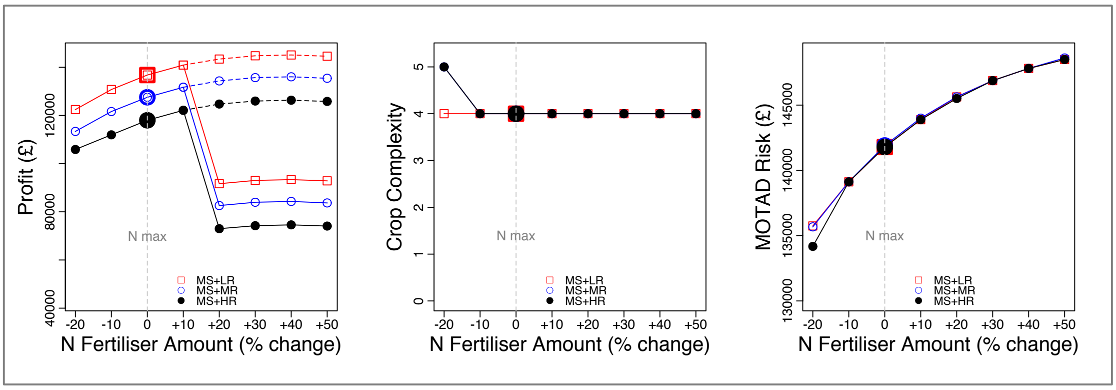


Figure 2-4: Variations in arable farming objectives due to N fertiliser amount variations under medium soil-rainfall interactions. The dashed red, blue and black lines represent the profit levels assuming farmers are still receiving SFP after increasing Nmax above 10%.

### 2.3.3 Effect of N variations under heavy soil and rainfall interactions

Applying N max generated a profit of £85,237 whereas increasing the N max by 30% reduced profit to £39,243 (54% decrease) (see Figure 2-5). With or without SFP, farms operating on heavy soils recorded the lowest profits. Thus, under a scenario of no SFP, farms on heavy soils would be worse-off. A 30% increase in N max under heavy soil and low rainfall changed crop complexity from six to seven but remained unchanged under heavy soil and moderate rainfall. Under heavy soil and high rainfall, it reduced from seven to six. The changes in crop complexity were mainly driven by the interactions of heavy soil, rainfall and N fertiliser, which determine the types of crops to be grown and not due to receipt of the SFP. The risks associated with N max levels were lower than risks associated with increasing N max by 30%. For example, the risk for applying N max was £144,202 whereas that of 30% increase in N max was £148,496 (3% increase). The implication is that applying the N max on a heavy soil and receiving the SFP would be associated with lower risk. The SFP can therefore be said to reduce farm risk.

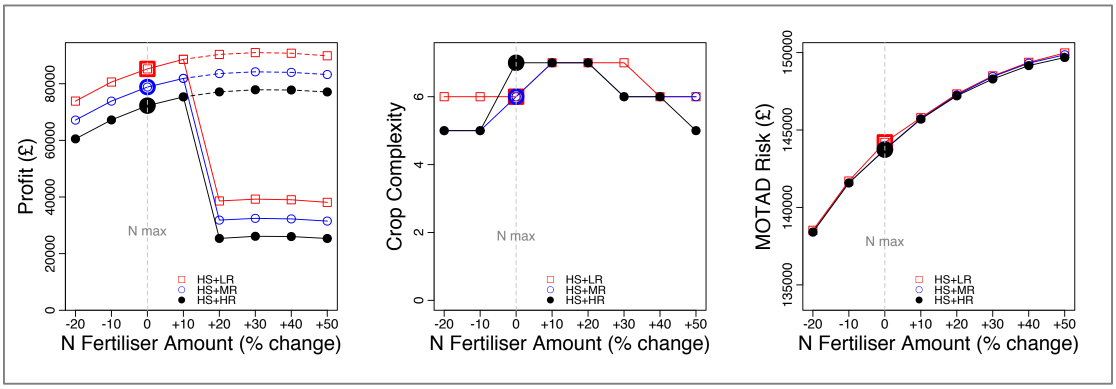


Figure 2-5: Variations in arable farming objectives due to N fertiliser amount variations under heavy soil-rainfall interactions. The dashed red, blue and black lines represent the profit levels assuming farmers are still receiving SFP after increasing Nmax above 10%.

### 2.3.4 Effect of crop prices on farming objectives under the SFP

This section illustrates how economic factors such as crop prices affect farming objectives with respect to the SFP. Under heavy soil and higher rainfall interaction, the results (see Figure 2-6) showed that with 15% increase in crop prices, applying 40% above N max and losing the SFP, farm profit (£91,695) was higher than the profit (at the base crop prices) for applying the N max and receiving the SFP (£72,260). Under the same scenario, crop complexity was lower (six) however, MOTAD risk was higher (£171,209) than the risk at the base crop prices (£149,159). The implication is that higher crop prices can influence farmers more than the other factors to apply N above the N max level and forgo the SFP if they are given the right to do so, since doing so will increase farm productivity (profit) and reduce management complexity than applying N max and receiving the SFP.

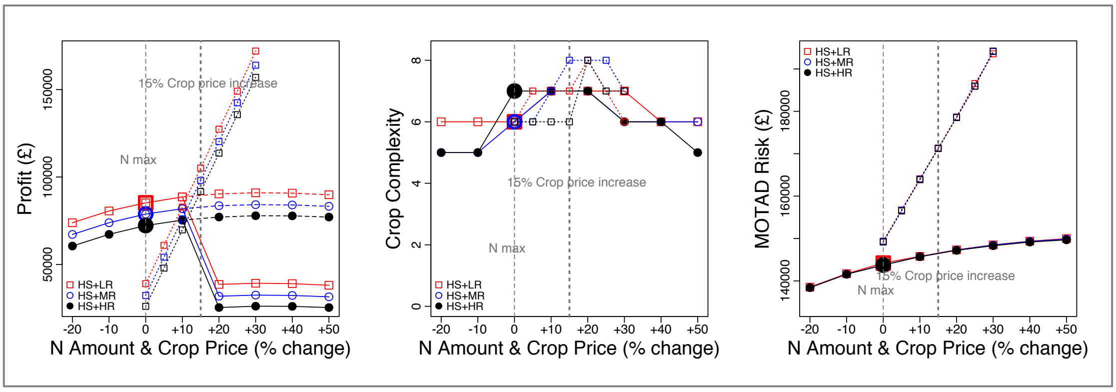


Figure 2-6: Variations in arable farming objectives due to N amount and crop price (red, blue and black dotted lines) variations under heavy soil-rainfall interaction. The dashed red, blue and black lines represent the profit levels assuming farmers are still receiving SFP after increasing Nmax above 10%.

## 2.4 Conclusion

In this chapter, we have investigated the effect of variations in soil type, rainfall, N fertiliser amount and crop prices on the objectives of arable farms operating in Nitrogen Vulnerable Zones (NVZs) and receiving the Single Farm Payment (SFP). Sensitivity analysis was carried out using a mixed-integer programming (MIP) arable farm model (farmR) under an assumption that farmers in NVZs have been given options to apply prescribed N fertiliser (N max) amounts and receive the SFP but can apply above N max and forgo the SFP. The model estimates three arable farming objectives: profit maximisation, crop complexity and risk minimisation. Applying the 2014 SFP flat rate for lowland farmers in England to all crop enterprises and the maximum N limits (N max) values to each crop, N max and crop prices were varied under different soil types and rainfall interactions.

We showed that the profits of farms applying the N max and receiving the SFP were higher than that of farms applying above the N max and losing the SFP, and that farms on heavy soils would be worse-off. There were more variations in crop complexity under heavy soil and rainfall interactions. The risk increased with increase in N under all interactions implying that risks at N max level or below are lower. We also showed that farms in NVZs have potential to increase farm productivity by applying N above N max under all soil and rainfall interactions however, doing so and forgoing the SFP reduces farm productivity and increases farm risk. There is thus an opportunity cost to farms for not being able to apply N above N max to increase productivity however, the SFP acts as a payment (compensation) for the opportunity cost to farmer to cut nitrate leaching by applying low levels of N. The SFP can be said to bring some form of Pareto efficiency in that farms benefit through the SFP scheme and society also benefit from an environment with less nitrate pollution. However, increase in crop prices could influence farmers to increase N amount above N max and forgo the SFP in the sense that increase in crop prices contributed more to farm profit than the SFP. The implication is that although the SFP may be a good support or compensation scheme, its effectiveness could be affected due to the influence of the factors considered especially crop prices on farming decisions and hence the farming objectives. Going forward, future farm payments could be estimated taking the factors looked at into consideration. Also, more discussions as well as research on the formulation of a payment scheme linked to variations in soil types, climate (rainfall) and prevailing crop prices are needed to better inform both farmers and policy makers.

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***“You can't plow a field simply by turning it over in your mind.”***

— Gordon B. Hinckley

# 3 MODEL DESCRIPTION, VERIFICATION AND VALIDATION

*In Chapter 2 the effect of some of the factors related to arable farming systems identified through literature review (e.g. soil, rainfall, crop prices, N fertiliser amount and Single Farm Payment (SFP)) on arable farming objectives have been investigated using a mixed-integer arable farm model and sensitivity analysis. This was done under an assumption that farmers in NVZs have been given the option to apply N fertiliser above the prescribed amount and forgo the SFP. The factors under consideration normally serve as parameters or constraints in arable farm models and hence the reason for investigating their effect on arable farming goals. The results show that given the option, farmers in NVZs would lose revenue by applying N fertiliser above the prescribed amount and forfeiting the SFP and that farmers on heavy soils would be worse off. Also, risk levels were found to be lower at the prescribed N fertiliser amount. Thus farmers are better off applying the prescribed N fertiliser amounts and receiving the SFP. The SFP can be said to pay for the opportunity cost of farmers in NVZs not being able to apply more N fertiliser to increase yield and thus bring some sort of Pareto efficiency. Also, variations in the factors considered were found to influence arable farming objectives and hence farming decision. Thus there is the need for continuous research to develop a model taking into consideration the factors considered in order to better analyse arable farming systems.*

*In this chapter, an arable farm level model developed incorporating some of the factors and farming objectives identified and investigated in the two preceding chapters is described, verified and validated. The model draws on the strength of some of the modelling approaches and existing models by combining mixed-integer, goal and risk programming approaches. The model is validated using the Farm Business Survey (FBS) data of 281 farms and predictive validation. Validation results showed good association between model predicted results and observed data. The model consists of four modules, which can be used as stand-alone models and thus add and offer alternatives to the few arable farm models in UK context. Two of the modules, the mixed-integer weighted goal programming and mixed-integer MOTAD models are applied in the next two chapters respectively to answer research* *questions on two issues found to be important in arable farming systems, black-grass (weed) control and risk aversion.*

## Arable farm models for optimising farm profit, nitrate leaching and risk: Model description, verification and validation


## Abstract

The increased demand for food has led to intense input use in agriculture and this has driven the need for more sustainable farming systems, which are more productive and environmentally friendly. However, increasing productivity and reducing the environmental impact or risk are conflicting farming objectives, which create complexities in sustainable farming systems. Thus, there is the need to investigate some of these complexities using models. As part of the overall research aim, an arable farm level model consisting of four modules is developed using mixed-integer, weighted goal and risk programming approaches to optimise three arable farming objectives: profit maximisation, nitrate leaching and risk minimisation. In this chapter, the model is described, evaluated and validated to investigate the degree of association between model predicted results and observed farming data. The model is validated using predictive validation and data for 281 farms in the Farm Business Survey. Aggregate level comparison of model results and observed data using statistical measures of association showed positive association between model predicted and observed crop areas. However, estimates of the coefficient of residual mass ($CRM$) showed some level of under-predictions of crop areas by the models whereas estimates of the mean absolute error ($MAE$) ranged between 0.42 and 0.58. In general, the model makes good predictions of crop areas (land use), fertiliser amounts (input use) and farm revenues/costs. Comparison of the modules however, showed that modules in which risk was incorporated made relatively better predictions than the ones in which risk was not explicitly incorporated. With model calibration and validation seen as continuous processes in model development, continued calibration followed by validation and updating of models with detailed data could enhance their predictive powers and performance.

## 3.1 Introduction

### 3.1.1 Background

The increased demand for food due to population increase has intensified agriculture (Tilman *et al.*, 2002; Tilman *et al.*, 2011) and this has driven the need for more sustainable agricultural or farming systems, which are more environmentally or ecologically responsible and still produce affordable wholesome food (Living Countryside, 2014). However, sustainable agricultural principles could impact on farm productivity (Tilman *et al.*, 2002) because such principles prioritise the efficient use of resources, which could sometimes mean reduced levels of inputs (Pretty, 2008). Reductions in inputs such as nitrogen (N) fertiliser could affect crop yield which in turn could cause variations in farm profits and possibly make the farming business riskier. Also, excessive or inefficient use of fertiliser could lead to negative agricultural externalities or impacts such as nitrate leaching (Addiscott *et al.*, 1991). Thus, farmers applying sustainable farming principles are faced with myriad conflicting objectives to meet their goal of profitable and sustainable food production (Wallace and Moss, 2002). Many of these conflicting objectives or complexities in farming systems can be captured and investigated using mathematical models through linear programming based approaches (e.g. Annetts and Audsley, 2002; Cooke *et al.*, 2013).

Since linear programming (LP) was first reported by Heady (1954), its application in agriculture to help in the decision making process of farmers and policy makers has been popular. This is because LP provides a means to examine the micro-level effect of changes in policy and other factors on farmers' behaviour across different farm types (Acs *et al.*, 2010). In general, all LP models have in them four properties as listed in Kaiser and Messer (2011): the objective to be optimised (minimised or maximised), the constraints restricting the activities, linearity of all equations and non-negativity of all activities or decisions variables. The key assumptions of LP can be summarised as: optimisation, fixedness, finiteness, determinism, continuity, homogeneity, additivity and proportionality (Hazell and Norton, 1986). Although LP is popular and has been extensively applied in agricultural land use (e.g. Annetts and Audsley, 2002; Rounsevell *et al.*, 2003), due to integer or binary nature of some management actions there may be problems of infeasibility as a result of rounding up or down of activities (Kaiser and Messer, 2011; Osgathorpe *et al.*, 2011). For example, in machine or labour selection, an LP model may select 3.5 tractors or 0.6 farmer, which although may serve as a guide in farm planning, may not be realistic. With mixed-integer programming (MIP) the problem of infeasibility due to rounding of activities associated with LP can be overcome (Butterworth, 1985; Kaiser and Messer, 2011). Mixed-integer programming models are similar to LP models but have an extra constraint ensuring that some of the activities are chosen as integers and thus overcome the problem of infeasibility due to rounding of activities.

To be able to make trade-offs between economic and environmental goals or conflicting goals as well as deal with the single objective limitation of LP, the multi-criteria decision making (MCDM) modelling approach can be applied. The MCDM approach based on goal programming (GP) has been used extensively in agricultural land use or farming systems modelling (e.g. ten Berge *et al.*, 2000; El-Gayer and Leung, 2001; Oglethorpe, 2010). With GP, the conflicting goals or objectives faced by arable farmers can be optimised simultaneously by minimizing the deviations in goal targets. Also, in terms of modelling farm risk, one of the approaches that has been widely used, is the minimisation of total absolute deviation (MOTAD) (e.g. Hazell, 1971; Adesina and Ouattara, 2000; Cooke *et al.*, 2013). Hazell (1971) developed MOTAD as a linear approximation of the expected value-variance approach, which is a quadratic risk programming (QRP) approach. The MOTAD approach gained prominence in farm risk modelling due to the fact that it solution can be generated by LP or MIP algorithms (McCarl and Onal, 1989) and in particular situations where the enterprise income distributions are skewed, the mean absolute deviation (MAD) in MOTAD may outperform sample variance in QRP (Hazell and Norton, 1986; Adesina and Ouattara, 2000).

In the UK context, two main existing arable farm models were identified. The first one is the Silsoe Farm Model (SFARMOD) (Annetts and Audsley, 2002), which is a multiple objective LP model developed for a variety of farming scenarios. The second is the farmR model (Cooke *et al.*, 2013), which is an MIP implementation of the SFARMOD, but explicitly incorporate risk (MOTAD). Although some of the formulations and data from the above two models were adopted and adapted to build the model described in this chapter (for the purposes of convenience referred to as SAFMOD), there are some differences influenced by the intended use of the model. The SFARMOD optimises profit and environmental outcome (nitrate leaching), however it is an LP model and does not explicitly incorporate risk. The farmR model, although an MIP model and explicitly incorporates risk (MOTAD), does not use a GP approach and does not optimise any environmental outcome or objective. The SAFMOD combines the MIP and weighted goal-programming (WGP) approaches as well as the MOTAD to optimise profit, nitrate leaching and risk. In terms of subsidy, unlike the SFARMOD and farmR, which implemented the pre 2005 farm payment scheme based on the type of crop grown, the SAFMOD implemented the Single Farm Payment (SFP) scheme by applying the flat rate for lowland farms in England to all crop enterprises or activities.

### 3.1.2 Model verification and validation

Models are developed to mimic real systems and as a result during model development many of the significant features and/or complexities of the real systems are captured in the model. To give the model users some level of confidence in using the models, models are verified and validated. Model verification is concerned with whether or not the model is doing what it was intended to do with sufficient accuracy (Gass, 1983; Balci, 1996). Thus model verification deals with building the model correctly—for example the accuracy of transforming the mathematical model formulation into a model specification via computer code (Balci, 1996). Also, solving a linear programming model with two different solvers to ensure consistency in the model results can be considered as a form of model verification. Validation, on the other hand, is concerned mainly with the degree to which the model compares with reality or the real system being modelled. Model validation is thus a significant part or stage of optimisation modelling in the sense that it improves the relevancy of models as well as strengthens the theoretical basis for modelling (McCarl, 1984; Wallach and Goffinet, 1989; McCarl and Apland, 1986; Wossink, 1993; Kelijnen and Sargent, 2000). There are two main methods or approaches through which mathematical programming models can be validated: validation by construct and validation by results.

Validation by construct is concerned with whether or not the right procedures were used in building the model (McCarl and Spreen, 1997). This implies that model description can be considered to be a form of validation by construct in the sense that how the model was formulated as well as how the model parameters and coefficients were estimated is shown. For example, to ensure that the fertiliser amounts used in building the model conform with reality, the amounts used were based on the fertiliser recommended amounts in Defra (2010) and providing such information in the model description allows potential users to judge whether or not the model was built using credible data. With validation by construct, the validity of the model is assumed, not tested, and thus does not appear to be satisfying (McCarl and Spreen, 1997). This limitation of validation by construct makes it necessary for validation by results, which is seen to be a higher-level validation approach than validation by construct.

Under validation by results the model results are compared with real world outcomes (McCarl and Apland, 1986; McCarl and Spreen, 1997). McCarl and Spreen (1997) listed different experiments that can be carried out under validation by results however, prediction experiment (hereafter predictive validation) is the most common validation by results experiment. Predictive validation involves fixing the problem or model data at real world values and then solving the model to generate results. These results are then compared with real world data to investigate the degree of association using statistical measures or indicators of association. Thus predictive validation requires historical data (Balci, 1996).

### 3.1.3 Review of statistical measures of association

The main purpose of predictive validation is to compare the model results with real world data and thus statistical measures or indicators of association are mainly used to show the degree of association between the model's predicted results and the real world data. Different statistical measures or indicators have been used or suggested in literature to compare model data to experimental, observed or historical data (see for example: McCarl and Spreen, 1997; Gaiser *et* *al.*, 2010; Nousiainen *et al.*, 2011; Franko *et al.*, 2011; Cooke *et al.*, 2013; Razzaghi *et al.*, 2013; Gueymard, 2014; Maniruzzaman *et al.*, 2015; Hussain and Al-Alili, 2016). A review of the literature to identify statistical measures of association applied in model validation (see Table 3-1 for review results) found indicators such as correlation coefficients, coefficient of determination ($R^2$), root means square error or difference (RMSE) and mean absolute error (MAE). The coefficient of residual mass (CRM), although not used extensively, was found to be a good indicator of over- and under-prediction by models. Graphical approaches such as scatterplots with regression lines, boxplots and histograms have been suggested and used (e.g. Klein *et al.*, 2012; Fatnassi *et al.*, 2013; Sargent, 2013; Cooke *et al.*, 2013). Other approaches such as Nash-Sutcliffe's model efficiency (NSE), Willmott's index of agreement (WIA) and Legates's coefficient of efficiency (LCE) have been used to measure overall model performance (e.g. Gueymard, 2014).

Table 3-1: Results of literature review to identify statistical approaches to measure association between predicted and observed data

| Reference | Associated model | Statistical Measures of Association Used or Suggested* | | | | | | | | | | | | | | | | | | | | | Remarks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | R (r) | ρ | $R^2$ | NSE | WIA | LCE | RMSE | MAE | CRM | MBE | RE | SSD | K-S | K-W | SBF | L-T | DIC | S-T | H-T | Graphs | U | |
| Gornott and Wechsung (2016) | Statistical crop yield models | + | + | | + | | | | | | | | | | | | | | | | | | The paper presented statistical crop yield models for winter wheat and silage maize |
| Hussain and Al-Alili (2016) | Solar radiation models | | | + | | | | + | + | | | | | | | | | | | | | | The paper mentioned RMSE, MAE and $R^2$ as metrics for evaluating solar radiation model performance |
| Giovanna *et al.* (2016) | A model on rainfall and landslide | | | + | | | | | | | | | | | + | | + | | | | | | The paper presented an automated method for the selection of rainfall data responsible for shallow landslide initiation which mimics expert judgement |
| Maniruzzaman *et al.* (2015) | AquaCrop Model | | | + | + | + | | + | | | | | | | | | | | | | | | The paper presented the calibration and validation of the AquaCrop model under different irrigation regimes |
| Gueymard (2014) | Solar radiation modelling | | | + | + | + | + | + | + | | + | | | + | | + | | | | | | | The paper reviewed validation methodologies and statistical performance of modelled solar radiation data |
| Pulvento *et al.* (2013) | SALTMED model | | | + | | | | + | | + | | | | | | | | | | | + | | SALTMED model for integrated irrigation, crop and field management. Model was applied to irrigation in Italy |
| Razzaghi *et al.* (2013) | SALTMED model | | | | | | | + | + | | + | + | | | | | | | | | | | Model was applied in Denmark. Statistical methods were used to compare measured and simulated soil water content. |

Table 3-1 (Continued)

| Reference | Associated model | Statistical Measures of Association Used or Suggested* | | | | | | | | | | | | | | | | | | | | | Remarks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | R (r) | ρ | $R^2$ | NSE | WIA | LCE | RMSE | MAE | CRM | MBE | RE | SSD | K-S | K-W | SBF | L-T | DIC | S-T | H-T | Graph | U | |
| Sargent (2013) | General Modelling Approaches | | | | | | | | | | | | | | | | | | | | + | + | The paper discussed model verification and validation as part of model development process |
| Cooke *et al.* (2013) | farmR Model | | + | + | | | | | | | | | | | | | | | | + | + | + | farmR model is a mixed-integer linear programming arable farm model which optimises profit, risk and crop complexity |
| Fatnassi *et al.* (2013) | Climate simulation model | | | + | | | | | | | | | | | | | | | | | + | | The model is a dynamic for simulating climate conditions in a green house |
| Abedinpour *et al.* (2012) | AquaCrop | | | + | + | | | + | + | | | | | | | | | | | | | | AquaCrop is a crop growth model |
| Klein *et al.* (2012) | Process-based crop model | | | + | | | | | | | | | | | | | | | | | | + | The paper used the FADN data to calibrate a crop model |
| Franko *et al.* (2011) | Soil organic matter model | + | | | | | | + | + | | | | + | | | | | | | | | | The paper described a carbon balance model |
| Karunarantne *et al.* (2011) | FAO-AquaCrop model | | | + | | | | + | | | | | | | | | | | | | | | The FAO-AquaCrop model is a model for irrigation |
| Nousiainen *et al.* (2011) | Dairy farm nutrient management model | | | + | | | | + | | | | | | | | | | | | | + | | The paper presented a nutrient management model for dairy farms |
| Gaiser *et al.* (2010) | The EPIC model | | | + | + | | | + | + | | + | + | | | | | | | | | | | The Environmental Policy Integrated Climate (EPIC) model is a field scale model designed to simulate drainage but can be as a crop growth |

Table 3-1 (Continued)

| Reference | Associated model | Statistical Measures of Association Used or Suggested* | | | | | | | | | | | | | | | | | | | | | Remarks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | R (r) | ρ | $R^2$ | NSE | WIA | LCE | RMSE | MAE | CRM | MBE | RE | SSD | K-S | K-W | SBF | L-T | DIC | S-T | H-T | Graph | U | |
| Henninger *et al.* (2010) | Computational models in biomechanics | + | + | + | | | | + | | | | | | | | | | | | | | | The paper presented validation in the context of computational biomechanics |
| Krause *et al.* (2005) | Hydrological models | | | + | + | + | | | | | | | | | | + | | | | | | | Paper investigates the utility of efficiency criteria for evaluating hydrological models |
| Zheng and Agresti (2000) | Generalized linear models | + | + | + | | | | | | | | | | | | | | + | | | | | The paper studies summary measures of the predictive power of generalized linear models |
| McCarl and Spreen (1997) | Model validation approaches | + | + | + | | | | | | | | | | | | | | | | | + | + | The paper reviewed validation approaches for linear programming based models |
| Carley (1996) | Computational models | + | | + | | | | | | | | | | | | | | | | | + | | |

* R (r) = Pearson's correlation coefficient; ρ = Spearman correlation coefficient; $R^2$ = Coefficient of determination; NSE = Nash-Sutcliffe's efficiency; WIA = Willmott's index of agreement; LCE = Legates's coefficient of efficiency; RMSE = Root means square error; MAE = Mean absolute error; CRM = Coefficient of residual mass; MBE = Mean bias error; RE = Relative error; SSD = Sum of square difference; K-S = Kolmogorov-Smirnov test; K-W = Kruskal-Wallis test for median; SBF = Slope of best fit; L-T = Levene's test for variance values; DIC = Deviance information criterion; S-T = Sign test; H-T = Hypothesis testing (to compare means and variances); Graphs = mainly scatter plots with regression line (including boxplot and histogram). The plus (+) indicate the statistical measure was applied or suggested in paper; U Theil's U.

Indicators such as RMSE and MAE (referred to as deviance measures) measure dispersion of individual points and provide the most rigorous and useful information about overall model performance (Stunder and Sethuraman, 1986; Gueymard, 2014). A value of zero is for a perfect model and thus the smaller the value and the closer to zero, the better. The CRM shows the tendency of the model to under- or over-predict, a positive value indicates under-prediction whereas a negative estimate means over-prediction (Pulvento *et al.*, 2013). In the case of indicators such as $R^2$, correlation coefficients, NSE, WIA and LCE (referred to as measures of agreement), a value of one is for a perfect model and thus a value close to one is preferred. Also, NSE ranges from $-\infty$ to 1. An NSE of zero is an indication that model predictions are as accurate as the mean of the observed data whereas a negative NSE indicates that the observed mean is a better predictor than the model (Legates and McCabe, 2013). Mayer and Butler (1993) proposed NSE as the best overall measure of model performance. In the case of WIA, a higher WIA for a model means there is lower error in a model compared to others (Stunder and Sethuraman, 1986).

In this chapter, we describe a farm-level mathematical model, which combines mixed-integer, goal and risk programming or modelling approaches to optimise three arable farming objectives: maximise profit, minimise nitrate leaching and minimise risk (deviation in farm income). We also verify and validate the model using predictive validation and compare the predicted results with observed data using some of the statistical measures of association identified in literature (correlation coefficients, $R^2$, MAE, RMSE, CRM, NSE, WIA, LCE and regression analysis). For the purposes of convenience, the model will be referred to as Sheffield Arable Farm Model (hereafter SAFMOD). The research question related to the validation can be summarised as follows:

1. What is the degree of association between model predicted crop areas and observed crop areas (land use)?
2. What is the degree of association between model predicted fertiliser amounts and observed fertiliser amounts (input use)?
3. What is the degree of association between model predicted revenues/costs and observed revenues/cost?

## 3.2 Methods

### 3.2.1 Model outline and description of components

Many linear programming (LP) models have been applied in agricultural land use research however, such models normally optimise a single objective and also there may be a problem of infeasibility due to rounding up or down of activities. Due to these limitations, other approaches such as the mixed integer programming (MIP) and goal programming (GP) were developed. The MIP approach was developed to overcome the problem of infeasibility due to rounding of activities whereas the GP was developed to overcome the single objective limitation of the LP. In terms of incorporating farm risk, the minimisation of total absolute deviation (MOTAD) approach, which is a linear approximation of quadratic risk programming, is convenient since its solution can be generated using LP and MIP algorithms, and in situations where solvers for quadratic programming may not be readily available. Thus the SAFMOD was developed drawing on the strengths of the MIP, GP and MOTAD approaches. Figure 3-1 shows a flow chart linking various components of the SAFMOD.

The SAFMOD was developed based on the assumption that the soil type and weather (rainfall) influence farm planning and input use. Thus the SAFMOD is run by first setting the soil type and rainfall amount. Unlike the farmR model, in the SAFMOD, the soil type is used to determine N fertiliser rates, which in turn determine the yield for each crop in the model. Variation is soil type thus influence variable cost through fertiliser costs as well as farm output, income deviation and nitrate leaching estimates. With the assumption that soil type and rainfall affect farm operation scheduling, both factors are used to determine the workable hours available to the farmer to carry out farm operations.

In the SAFMOD, the soil type and all other information and initial data, informed by the model assumptions (summarised in Figure 3-1) are stored in CSV files from which other model input parameters such as gross margin, work rates and risk are estimated and stored in CSV files. The information from the CSV files are used to construct the model matrix (see Section 3.4 for model parameter estimates). The SAFMOD was developed using the R programming language and the model codes can be found on GitHub through the following link: https://github.com/kwadjoahodo/SAFMOD/blob/master/SAFMOD.R

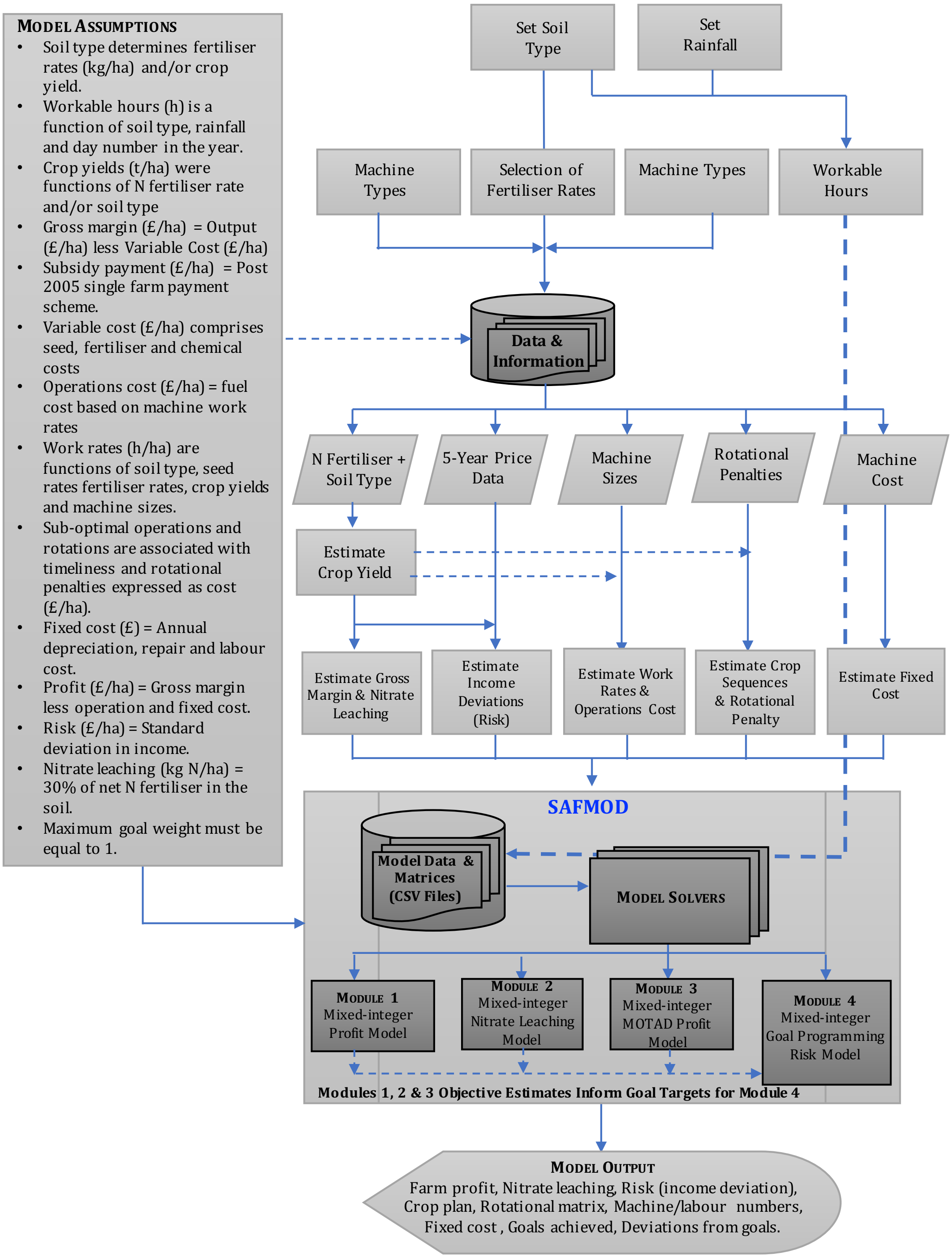



Figure 3-1: Flowchart of the SAFMOD showing the links among various components

The SAFMOD consists of four modules (shown in Figure 3-1) which share common structural constraints as well as parameter estimates (see Section 3.3 and Section 3.4). Each of the modules can be used as a standalone model. The first and second modules are mixed-integer linear programming (MILP) models for profit maximisation and nitrate leaching minimisation respectively. The third module is a mixed-integer MOTAD (MIMOTAD) model for the risk minimisation objective. In the case of GP models targets need to be set for the different goals and therefore the idea of the first three modules is to evaluate targets to inform the target levels for the different goals in the fourth module (the mixed-integer weighted goal programming (MIWGP) model). Descriptions of the four modules are presented below. Some of the formulation approaches used in the SFARMOD and farmR were adopted. Also, adapted versions of relevant algebraic expressions used in Annetts and Audsley (2002); Rounsevell *et al.* (2003) and Cooke *et al.* (2013) were adopted.

#### 3.2.1.1 Module one: Mixed-integer profit maximisation model

Module one of SAFMOD optimises expected farm profit, the value of which informs the profit target level that can be set in the fourth module. The module is based on the assumption that the farmer is risk neutral and thus interested in only profit maximisation. Module one can also be used to select crop plans as well as machine combinations in a situation where profit maximisation needs to be considered as a single objective (for a risk neutral farmer). The profit maximisation objective can be stated as follows subject to a series of constraints described under Section 3.3.

$$OBJ_{profit} = \sum_{i} \bar{E}_i a_i - \sum_{i}\sum_{j}\sum_{k} C_{ijk} y_{ijk} - \sum_{m} C_m n_m \tag{3-1}$$

$$a_i = \sum_{k} y_{i1k} \tag{3-2}$$

Where $OBJ_{profit}$ is the profit to be optimised, $\bar{E}_i$ is the mean expected gross margin for the $i$th crop, $a_i$ is the area of crop $i$ and it is equal to sum of the area of first ($y_{i1k}$) operation carried on crop $i$ in period $k$ (Eq. (3-2)), $C_{ijk}$ is the cost of the $j$th operation on the $i$th crop in period $k$ and $y_{ijk}$ is the area of $j$th operation on the $i$th crop in period $k$. $C_m$ is the annual cost of machines of type $m$ (annual depreciation, repair cost and annual labour cost) required to perform field operations and $n_m$ is the number of machines of type $m$ (calculated by the model) required to perform the field operations. The model assumes one farmer (integer[6]) in addition to machine and labour numbers, which are also integers but can be set as non-integers depending on the aim of the model user. It should be noted that the cost of operation includes any adjustment to reduction in yield due to improper or suboptimal timing of farm operation and rotations.

#### 3.2.1.2 Module two: Mixed-integer nitrate leaching minimisation model

Module two represents the nitrate leaching minimisation model, the value of which also informs the nitrate-leaching target in module four. Module 2 was based on the assumption that farmer is more concerned with reducing nitrate leaching subject to profit maximisation constraint. Nitrate leaching (kg N/ha) is a function of nitrogen (N) amount in the soil (N applied + atmospheric deposited N + soil N supplied), N uptake by crops, ammonia ($NH_3$) and nitrous oxide ($N_2O$) volatilisation. The objective function for the nitrate leaching model was adopted from Annetts and Audsley (2002) but was adapted due to lack of data on nitrate leaching with respect to farm operation types. As a result, the nitrate leaching model presented minimises the base nitrate leaching with respect to the crops grown using the N balance approach (Wossink, 1993) however, the formulation of the model makes it possible to make any future adjustments to incorporate changes in nitrate leaching due to carrying out farm operations and crop rotation should data become available. Thus, the objective function of the nitrate leaching model can be stated as:

$$OBJ_{nitrate-leaching} = \sum_{i} V_i^e a_i \tag{3-3}$$

Where $OBJ_{nitrate\text{-}leaching}$ is the nitrate leaching to be optimised, $V_i^e$ is the base nitrate leaching from the $i$th crop per hectare and $a_i$ is as defined under Eq.(3-2). Although the nitrate leaching model is formulated to optimise nitrate leaching as a single

[6] The model assumes 1 farmer, which is set as integer and thus primarily makes the model a mixed-integer model. The other machine/labour numbers calculated by the model are also set as integers.

objective, there is a possibility to include the profit objective as a constraint by setting a profit target and solving the model as a multi-objective MIP model.

#### 3.2.1.3 Module three: Mixed-integer risk minimisation (MIMOTAD) model

Module three represents the risk minimisation model using the MOTAD programming approach. The third module was based on assumption that the arable farmer is risk averse and is interested in maximising profit subject to minimising deviation in income (risk). MOTAD is a linear approximation of the quadratic programming (QR) approach and unlike the QR, it uses mean absolute deviation (MAD) instead of variance (Hazell, 1971; Hardaker *et al.*, 1997; Hardaker *et al.*, 2004). Thus MOTAD is a linear approximation of expected farm income variability (Kaiser and Messer, 2011) and the formulation makes it possible to solve a MOTAD problem with LP and MIP algorithms. The MOTAD model (Eq. (3-4)) maximises expected income subject to Eq. (3-5), (3-6) and constraints presented under Section 3.3.

$$OBJ_{profit} = \sum_i \bar{E}_i a_i - \sum_i \sum_j \sum_k C_{ijk} y_{ijk} - \sum_m C_m n_m - \sum_q p_q d_q \tag{3-4}$$

$$\sum_i (E_{iq} - \bar{E}_i) a_i + d_q \geq 0 \quad for\ all\ q \tag{3-5}$$

$$\sum_q p_q d_q \leq M_n,\ M_n \text{ varied} \tag{3-6}$$

Where $E_{iq}$ is the gross margin of the $i$th crop under $q$th state of nature and $\overline{E_i}$ is the mean expected gross margin, $d_q$ is an $s$ by 1 vector of activity levels measuring negative income deviations under $q$th state of nature, $p_q$ is a 1 by $s$ vector of probabilities of the $q$th state of nature and $M_n$ is a measure of mean absolute deviation (MAD) or risk, which can be parametrically varied. The total states of nature ($s$) = 5 (based on 5-year price data). The value of $M_n$ set reflects the level of risk aversion. Although the risk model was formulated to parameterise $M_n$ directly, $M_n$ can be set at its highest value with weight attached to it and parameterise the weight as a measure of risk aversion coefficient or parameter. Also, in the MOTAD model, nitrate leaching objective was incorporated as a constraint and thus the model maximises profit subject to risk and nitrate leaching minimisation, however the nitrate leaching objective target value can be set to zero and the model solved to optimise profit subject to income deviation(risk) constraint as applied in Chapter 5.

#### 3.2.1.4 Module 4: Mixed-integer weighted goal programming model

Mixed-integer linear programming models can be formulated as multi-objective models (e.g. Annetts and Audsley, 2002; Cooke *et al.*, 2013) or, in the case of modules two and three, by maximising or minimising one objective whilst the other objectives are expressed as inequality constraints or whilst the weight attached to the other objective is reduced. However, there can be limitations associated with such formulations because each objective expressed as a constraint must be enforced, otherwise there is a potential of the model generating an infeasible solution (Hazell and Norton, 1986; Zgajnar and Kavcic, 2011). To overcome such limitations, a mixed-integer weighted goal-programming (MIWGP) model was formulated to optimise the three objectives simultaneously based on assumptions that the arable farmer is interested in maximising profit whiles minimising nitrate leaching and risk. Modules 1, 2 and 3 are linked to Module 4 based on assumption that their objective function estimates inform the goal targets in the MIWGP module. The MIWGP (represented by Module 4) allows trade-offs to be made between the goals especially between the economic (profit) and environmental (nitrate leaching) goals or between profit and risk goals and all the goals can be optimised simultaneously without the possibility of generating infeasible solutions. A typical goal-programming (GP) model minimises the deviations from goal targets and can generally be expressed mathematically as:

$$\text{Minimise: } D = \sum_{g=1}^{h} (u_g G_g^- + v_g\, G_g^+) \tag{3-7}$$

subject to $G_g(\mathbf{a}) + G_g^- - G_g^+ = T_g, \quad \mathbf{a} \in Cons$

$\mathbf{a}, G_g^-, G_g^+ \geq 0$

Where $D$ is the total deviation to be minimised, $G_g(\mathbf{a})$ is a linear function or objective (goal) of $\mathbf{a}$, which is a vector of decision variables, $T_g$ is the target set for the $g$th objective or goal informed by results from modules one through three, $G_g^-$ and $G_g^+$ represent the negative (under-achievement) and positive(over-achievement) deviations from goal targets whereas $u_g$ and $v_g$ are the relative weights attached to the deviation variables respectively and *Cons* is a set of rigid constraints (shown under Section 3.3). The weighting scheme described in Kaiser and Messer (2010) was adopted but the weights were normalised with respect to the goal targets (Romero and Rehman, 2003) due to different units for economic and environmental goals. The function, $G_g(\mathbf{a})$ represents each of the objective functions or goals represented by Eq. (3-9), (3-10) and (3-11). It should be noted that for GP problems the goals serve as constraints but are expressed as equations rather than inequalities. Thus the WGP model can be stated as:

$$\text{Minimise: } D = \sum_{g=1}^{3} (u_1 G_1^- + v_1 G_1^+ + u_2 G_2^- + v_2 G_2^+ + u_3 G_3^- + v_3 G_3^+) \tag{3-8}$$

Subject to the goals below and the set of constraints described under Section 3.3.

**Goal 1:** Maximise profit

$$OBJ_{profit} = \sum_i \bar{E}_i a_i - \sum_i \sum_j \sum_k C_{ijk} y_{ijk} - \sum_m C_m n_m + u_1 G_1^- - v_1 G_1^+ = T_1 \tag{3-9}$$

**Goal 2:** Minimise nitrate leaching

$$OBJ_{nitrate-leaching} = \sum_i V_i^e a_i + u_2 G_2^- - v_2 G_2^+ = T_2 \tag{3-10}$$

**Goal 3:** Minimise risk (deviation in profit or income)

$$OBJ_{risk} = \sum_i a_i \sigma_i + u_3 G_3^- - v_3 G_3^+ = T_3 \tag{3-11}$$

Where $a_i$ is the area of the $i$th crop, $\sigma_i$ is the deviation in income for the $i$th crop under all states of nature. Due to the problem of infeasibility in an attempt to incorporate the MOTAD model formulation (Section 3.2.1.3) into the WGP model, the standard deviations in income for the crops were used as measures of risk in the risk minimisation goal instead of income deviations under $q$th state of nature. For maximisation goals, under-achievements are undesirable or detrimental and therefore the minimisation of the deviation is focused on the negative deviations, whereas for minimisation goals over-achievements are undesirable and positive deviations are detrimental, hence the focus of the minimisation in the GP objective function. Thus the objective function, Eq. (3-8) can be revised and stated as Eq. (3-12).

$$\text{Minimise: } D = u_1 G_1^- + v_2 G_2^+ + v_3 G_3^+ \tag{3-12}$$

## 3.3 Model constraints

Decision-making in arable farming is affected by a myriad of constraints and to capture these in the SAFMOD, the constraints presented below were assumed to impact on arable farming decisions. Also, the constraints presented below are imposed in all the four modules but with some modification in model application in Chapter 4.

### 3.3.1 Resource constraints

Resource endowment of arable farms influence the decision taken by farmers and that a farmer can only work with amount of resource available to him/her. Thus this constraint was imposed to ensure that the amount of a resource needed to carry out an operation on a crop does not exceed the amount of the resource available. The resource type considered is the number of workable hours available in a period to carry out an operation and it should be noted that different operations have different workability type and hence different workable hours apply to different operations. The constraint thus ensures that the number of hours a farmer can work cannot exceed the workable hours available in a period. The constraint can be expressed as:

$$\sum_i \sum_j S_{ijkm} y_{ijk} \leq L_{mkw} n_m \qquad \forall m, k, w \tag{3-13}$$

Where, $S_{ijkm}$ is the work rate of operation $j$ carried on crop $i$ using a machine of type $m$ in period $k$ and $y_{ijk}$ area of operation $j$ carried on a crop $i$ in period $k$. $L_{mkw}$ is the amount of resource (workable hours) available in period $k$ to carry out an operation with workability type $w$ using machine of type $m$ and $n_m$ the number of machine type $m$ calculated by the model.

### 3.3.2 Sequential and non-sequential operation constraints

In arable farming some operations must first be performed before another operation can be performed, whereas others are carried based on the crop growth stages. To capture this in the model, a sequential and non-sequential operation constraints were imposed. The sequential operation constraint ensures that an operation is not performed before its preceding operation and that the area of the successor operation ($j$) cannot exceed the area of the preceding operation ($j$-1). For example, a crop has to be planted before it can be harvested and the harvested area cannot exceed the area planted. Table 3-12 (see the chapter Appendix) shows a matrix of crops and the sequential operations. In terms of cost of operation, sequential operation constraint ensures that the model selects not only operations with least costs but operations that can generate optimal profit. The constraint can be expressed as follows:

$$\sum_{k \leq K} y_{ijk} \leq \sum_{k \leq K} y_{i(j-1)k} \qquad \forall\, i, j > 1, k \tag{3-14}$$

Where, $K$ belongs to a set of periods in which an operation can be carried out on a crop. For non-sequential operations, which are carried out based on the stages of crop development Eq. (3-15) ensures that the total area of each operation is equal to the total crop area.

$$a_i = \sum_{k} y_{ijk}. \tag{3-15}$$

### 3.3.3 Crop sequencing or rotational constraint

In sustainable arable farming systems, crop rotation or sequencing is vital however, some crop sequences are deemed beneficial than others—that is some crop sequences are seen as optimal and other sub-optimal and attract penalties (%

yield loss). The yield penalty is imposed in the objective function of the profit maximisation in the column corresponding to the crop sequence. This constraint was imposed to ensure that the total area of a successor crop is equal to the area of the last operation of the predecessor crop. For example, if a farmer decided to grow winter wheat after oilseed rape, the area of winter wheat grown cannot exceed the area of oilseed rape harvested. This can be expressed as follows:

$$\sum_{c} r_{ick} = \sum y_{iJk} \tag{3-16}$$

$$\sum_{k \leq K} y_{c1k} \leq \sum_{c} r_{ick} \tag{3-17}$$

Where, $r_{ick}$ is the area of crop $c$ taking over from (following) crop $i$ in period $k$ whereas $y_{iJk}$ is the area of last or final operation $J$ carried out on crop $i$ in period $k$. The constraint represented by Eq. (3-17) ensures that the area of the first operation of crop $c$ in period $k$ ($y_{c1k}$) does not exceed $r_{ick}$. With respect to non-sequential first operations, the constraint although less restrictive is similar to Eq. (3-17) and is required in a situation where there are no periods overlapping between the last operation of the predecessor crop and the first operation of the successor.

### 3.3.4 Crop area and total cropping area constraints

One of the resources, which influence arable farming business decisions is the availability of land. The hectors of land allocated to a crop mainly depend on the amount of land available to the farmer. Also, the total area land allocated to a crop may be determined by factors such as quota systems, prevailing prices and availability of land. Thus the other constraints considered are crop area and total cropping area constraints. The crop area constraint puts a limit on the area of certain crops. Sugar beet has a quota imposed limiting the area a farmer is allowed to grow. As part of farm planning strategies, some farmers may decide the proportion of the farm area allocated to certain crops. Thus in this study, limitations are put on the area of potatoes (wpot), winter oilseed rape (wosr), legumes (field beans) and sugar beet (sbeet) (see Eq. (3-18) to Eq. (3-21)). In the case of legumes, the model was constrained to select some minimum amount of beans crops however, this constraint can be changed or removed. The crop proportions were formulated in such a manner that it ensures that crops such as winter oilseed rape and sugar beet appear in the rotation cycle 1 in 3 years, reflecting some of the pest management principles of breaking disease cycles using crop rotation. Also, to capture the 'greening' rules with respect to crop diversification as part of the Common Agricultural Policy (CAP) reforms (Defra, 2014a), the crop proportion was formulated in such a way that no one crop can take more than 75% of the crop area and that there will be at least two crops in a rotation. However, the model can also be set up to analyse mono-cropping scenarios.

$$a_{wpot} \leq \frac{1}{4} \times \text{Total cropping area (250ha)} \tag{3-18}$$

$$a_{wosr} \leq \frac{1}{3} \times \text{Total cropping area (250ha)} \tag{3-19}$$

$$a_{beans} \leq \frac{1}{3} \times \text{Total cropping area (250ha)} \tag{3-20}$$

$$a_{sbeet} \leq \frac{1}{3} \times \text{Total cropping area (250ha)} \tag{3-21}$$

The total cropping area constraint ensures the sum of areas of all crops is less than or equal to the total area cropped and for the purposes of this study the total cropped area considered was 250 ha. The total area constraint can be considered as a land use constraint because it ensures that the area of land occupied by a crop or between crops, at any time, must be no more than the total area of land available for crops. The constraint can be expressed algebraically as below where $a_i$ is the area of the $i$th crop:

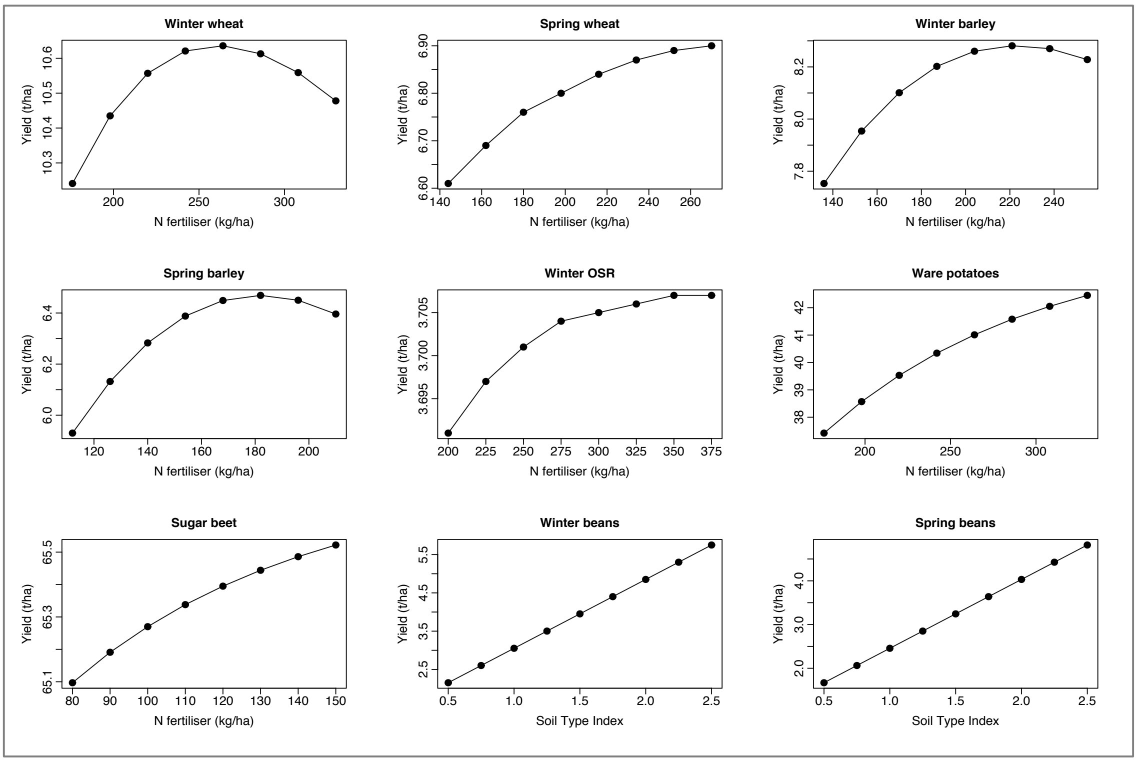
$$\sum_i a_i \leq \text{Total cropping area (250ha)} \tag{3-22}$$

## 3.4 Estimation of model parameters and/or coefficients

The selection, inclusion and estimation of model parameters and coefficients has been borne out of the fact that a farm planning model should ideally contain just sufficient to enable the planning scenarios encompassed realistically (Barnard and Nix, 1973). This consideration is key in LP based modelling in order not to over constrain the model and generate infeasible or unrealistic results. Thus in the SAFMOD, components of model parameter/coefficient estimates considered to be common in farm planning analysis were captured, estimated and incorporated into the model and these are estimated and stored in CSV files. As with all models, such information need to be updated from time to time and model recalibrated to enhance the accuracy of the model.

### 3.4.1 Crop yield estimates

Nitrogen fertiliser and soil types have bigger impact on crop yields and thus in the SAFMOD, crop yields were estimated based yield-response, which take into consideration soil type and N fertiliser rates. The response function allows for the depiction of the diminishing effect N fertiliser application on crop growth and yield. The response functions were adopted from the farmR model however, unlike the farmR model, in the SAFMOD, the soil type determines the N fertiliser rate which is a variable in the response function as well as serves a variable in the response function. Also, in the SAFMOD the N fertiliser rates used to estimate crop yields were based on the recommended N fertiliser rates in Defra (2010). The response functions are shown in Figure 3-2. For crops such as sugar beet and ware potato, the response function was based on N fertiliser rate where as for the legumes they are based on only the soil type. The response function of the other crops such as winter wheat shown in the Figure 3-2 below were based on heavy soil.




Note: For the legume crops the response functions were based on variation in soil type. The soil types are represented by indices ranging from 0.5 through 2.5 at interval of 0.25 representing light soil through heavy soil.

Figure 3-2: Yield response function of crops used in the SAFMOD.

### 3.4.2 Expected gross margins and income deviation (risk) estimates

The expected gross margin ($\bar{E}_i$) for each crop $i$ was estimated based on a 5-year historical price data from 2009 to 2013 (Defra, 2014b). The prices were adjusted for inflation using deflator series from HM Treasury (2014). The expected gross margin was estimated as follows:

$$\bar{E}_i = \left[\left(\frac{\sum_{q=1}^{s} PR_{iq} \times Y_i}{s}\right) - (FE_i + SC_i + OC_i)\right] + Subsidy \tag{3-23}$$

Where, $Y_i$ = yield (t/ha) of the $i$th crop estimated as a function of soil type and N fertiliser amount as indicated above, $PR_{iq}$= price (£/t) of crop $i$ under $q$th state of nature (total of number of states of nature, $s$=5), $FE_i$ = fertiliser (N, P, K) cost (£/ha), $SC_i$ = seed cost (£/ha), $OC_i$ = other costs (£/ha) including chemical and sundry costs of the $i$th crop and $Subsidy$ = Single Farm Payment (SFP) value (£/ha) for lowland farms (Nix, 2014). It should be noted that for sugar beet, transport cost was also considered and added to the variable cost. Table 3-14 (see chapter Appendix) shows example data for gross margin estimate for each of the crops.

In the SAFMOD risk estimates are based on deviations in income. Thus the risk captured in the MOTAD and MIWGP modules are assumed to be output risk and although there is the possibility of input risks, it is assumed that such risks translate into output risk through crop yield levels, hence the focus on output risk. The income deviations (mean absolute deviation and standard deviation estimates) used in the MOTAD and WGP models as representative of risk were therefore estimated using the gross margins under $q$th state of nature for each crop. The income deviations are shown in Table 3-15 (see chapter Appendix).

### 3.4.3 Nitrate leaching estimates

The nitrate ($NO_3^-$) leaching was estimated by adopting the N balance approach used in Wossink (1993). The approach takes into consideration the amount of fertiliser N applied or fixed (inorganic and/or organic) ($N_{App}$), atmospheric N deposition ($N_{Depo}$), crop N uptake ($N_{Uptake}$) and fertiliser evapotranspiration. However, in this study, the fertiliser evapotranspiration was replaced with the volatilisation of ammonia ($Vol_{(NH3)}$) and nitrous oxide ($Vol_{(N2O)}$) and emission factors of 2% and 0.5% were assumed for $Vol_{(NH3)}$ and $Vol_{(N2O)}$ respectively (Professor Roger Sylvester-Bradley, *pers. comm.*). The $N_{Depo}$ value was the average of atmospheric deposited N values obtained from the Air Pollution Information System[7] (APIS) using the grid references for 187 arable fields of farms in England. Also the Soil N Supply (SNS) was taken into consideration in the estimation of total N to the soil. The SNS used for the estimation of nitrate leaching (kg N/ha), $N_{Leach}$ was 80kg/ha, the amount of SNS used to estimate the N uptake efficiency or N capture in Sylvester-Bradley and Kindred (2009). It also reflects the SNS for soils with Soil N Supply Index (SNSI) of one[8] in Defra (2010). The values for $N_{Uptake}$ were estimated by multiplying the total N to the soil by the N uptake efficiency. Thus the N leaching estimates are influenced by N uptake by crops. Based on the N uptake efficiencies used, crops such as sugar beet, potatoes, and winter OSR were found to

[7] APIS website: http://www.apis.ac.uk/search-by-location

[8] The recommended N amounts used in the study were based on soils with SNSI of 1.

have higher N uptake and hence low N leaching estimates (see Table 3-2). Again, in the case of sugar beet, the N leaching estimate was found to be negative due to the higher N uptake efficiency data used although in reality some amount of N leaching may occur on sugar beet fields. The estimates for set-aside were mainly based on the atmospheric deposition and SNS values. The estimation of $N_{Leach}$ can be expressed as:

$$N_{Leach} = \left(N_{App} + N_{Depo} + SNS\right) - \left(N_{Uptake} + Vol_{(NH3)} + Vol_{(N2O)}\right) \tag{3-24}$$

$$N_{Leaching(GW)} = 0.3 \times N_{Leach} \tag{3-25}$$

Where, $N_{Leaching(GW)}$ is the N leaching to groundwater below a depth of 1m adopted from Wossink (1993). According to Cardenas *et al.* (2013) the default values used by the IPCC in estimating the fraction of N leached from the application of both organic and inorganic N is 30% (0.3). Thus the 0.2 factor used by Wossink (1993) was replaced with a factor of 0.3. Again, using a formula in Wossink (1993) the $NO_3^-$ amounts in g/l were estimated using the $N_{Leaching(GW)}$, taking into consideration the annual rainfall amount (mm) and this is shown by Eq. (3-26). The $N_{Leaching(GW)}$ values were used as representative nitrate leaching values in the nitrate leaching objective function and the optimum value converted to $NO_3^-$ (g/l) using Eq. (3-26). The nitrate leaching estimates are linked to soil type—the soil type determines the fertiliser amounts for each crop based on recommended amounts in Defra (2010). The conversion by Eq. (3-26) also links the $NO_3^-$ (g/l) to rainfall amount.

$$NO_3^- \text{in g/l} = \frac{62}{14} \times \frac{N_{Leaching(GW)}}{10 \times Annual\ Rainfall\ (mm/year)} \tag{3-26}$$

Table 3-2: Base N leaching (kg N/ha) estimates for crops and set-aside used in the model

| Crops | N Applied of Fixed (kg/ha) | Total N (kg/ha) | N Uptake Efficiency | N Uptake (kg /ha) | $Vol_{(NH3)}$ (kg/ha) | $Vol_{(N2O)}$ (kg/ha) | N Leaching (GW) (kg N/ha/yr) |
|---|---|---|---|---|---|---|---|
| Winter wheat | 220 | 320 | 0.65 | 208.00 | 6.40 | 1.60 | 31.20 |
| Spring wheat | 180 | 280 | 0.68 | 190.40 | 5.60 | 1.40 | 24.78 |
| Winter barley | 170 | 270 | 0.54 | 145.80 | 5.40 | 1.35 | 35.24 |
| Spring barley | 140 | 240 | 0.39 | 93.60 | 4.80 | 1.20 | 42.12 |
| Winter beans | 285 | 385 | 0.51 | 196.35 | 7.70 | 1.93 | 53.71 |
| Spring beans | 285 | 385 | 0.51 | 196.35 | 7.70 | 1.93 | 53.71 |
| Ware potatoes | 220 | 320 | 0.81 | 259.20 | 6.40 | 1.60 | 15.84 |
| Winter OSR | 190 | 290 | 0.85 | 246.50 | 5.80 | 1.45 | 10.88 |
| Sugar beet | 100 | 200 | 1.07 | 214.00 | 4.00 | 1.00 | -5.70 |
| Set-aside* | -- | 100 | -- | -- | 2.00 | 0.50 | 29.25 |

Note: N deposition (20 kg N/ha/yr) and SNS (80 kg/ha) were added to the N applied to estimate the N update. * N amount was based on N deposition and SNS values. N Fertiliser amounts are based on recommended amounts for a heavy soil

### 3.4.4 Work rates, operations and fixed costs

The work rate (h/ha) of machine types carrying out operations were estimated based on factors such as machine size, soil type, fertiliser or seed amounts, crop yield. For example, the work rate of a combine harvester depends on the crop yield and the size of the combine in terms of power. The work rate for earth-moving operations such as ploughing took into consideration soil type. The formulae for estimating the work rates were obtained from Chamen and Audsley (1993) and are similar to the ones used by Cooke *et al.* (2013) to build the farmR model.

The operation cost took into consideration fuel cost (Eq. (3-27)) based on work rates, fuel consumption, and fuel price. Also, with the possibility farmers hiring seasonal or temporary labour, variable labour cost was assumed to be part of operations cost and as a result, variable labour cost was estimated using an hourly wage rate (£/h) and added to the fuel cost. For operations such as planting and harvesting which attract timeliness penalties, the respective periodic penalties (mainly yield loss) were estimated in terms of cost (£/ha) and added to the cost of operation. Supposing the penalty for harvesting winter wheat in a sub-optimal period is 5% and the average yield and price are 10t/ha and £110/t respectively, the timeliness penalty cost (£/ha) will be £55/ha (0.05 × 10t/ha × £110/t). This value is then added to the cost of harvesting in that period.

$$Fuel\ Cost\ (£/ha) = Fuel\ Consumption\ (l/h) \times Work\ rate\ (h/ha) \times Fuel\ price\ (£/l) \tag{3-27}$$

The fixed cost (*FC*) considered in the study consists of the annual labour cost (*ALC*) and annual machinery cost (*MC*). With the SAFMOD set up to select labour numbers, which are assumed to be permanent labour or workforce, the *ALC* was applied to this type of labour and hence why it was considered under *FC*. The *MC* consists of mainly annual depreciation (*ADep*) and annual repair and maintenance costs (*RCost*). These were estimated based on costs or prices of machinery (*MaC*), rate of depreciation (*DR*), repair cost rate (*RCR*) and replacement years ($n$). Estimates could be adjusted for inflation and to take interest rate (*IR*) into consideration, *ADep* was estimated using the capital recovery factor (*CRF*) (Eq. (3-28) and (3-30)) however, in a situation where interest rate is zero, the *ADep* is recalculated based on Eq. (3-29) where *Dep* is the total depreciation. *RCost* was estimated based Eq. (3-31) and the *MC* based on Eq. (3-32). The *FC* can therefore be expressed as *MC* + *ALC*. In the model, the total fixed cost is calculated using the machine and labour numbers estimated by the model. For example, supposing the *MC* for tractor is £12,000, *ALC* is £18,000 and the tractor and labour numbers selected by the model are 2 and 3 respectively, then the total *FC* will be £78,000 (2×£12,000 + 3×£18,000). Equation shown by Eq. 3-28 to Eq. 3-31 obtained from Iowa State University Extension and Outreach website: https://www.extension.iastate.edu/agdm/crops/pdf/a3-29.pdf.

$$CRF = \frac{IR(1 + IR)^n}{(1 + IR)^n - 1} \tag{3-28}$$

$$Dep = MaC - (MaC \times DR); \quad ADep = \frac{Dep}{n} \tag{3-29}$$

$$ADep = (Dep \times CRF) + (MaC \times IR) \tag{3-30}$$

$$RCost = MaC \times RCR \tag{3-31}$$

$$MC = ADep + RCost \tag{3-32}$$

The machine types and data applied in estimating the $MC$ are shown in Table 3-16 in Chapter Appendix. The work rate, operation and fixed cost estimates by the SAFMOD are based on the assumed machine sizes and prices. In the context of the mixed-integer programming approach, the SAFMOD may select two of the 100kW tractors assumed and used to develop the model. However, it is possible that in reality a farmer with a bigger farm size may use one big tractor, say a 150kW tractor (1.5 of 100kW), which may be give faster work rates and possible relatively cheaper than two 100kW tractors. Thus there could be economy of scale and with the possibility of updating the machine sizes in SAFMOD, the model can be updated to take into consideration bigger machine sizes. Also, with the machine numbers in LP models serving as guide in machinery selection and planning, the machine number selected by the SAFMOD based on the machine types assumed (Table 3-16), can serve as guide in machinery planning in arable farms although in reality other sizes of machine can be selected by the farmer to better optimise profit.

### 3.4.5 Workable hours

Following Annetts and Audsley (2002) and Cooke *et al.* (2013), the cropping year was divided into 26 two-week periods to allow for the analysis of timeliness penalties. Workable hours (*WHs*) represent the number of hours available in a period for a farmer to work. The *WHs* were estimated based on the land type indicator (*LTI*) formula (Tillet and Audsley, 1987) which is a function of the soil type (*ST*), annual rainfall (*AR*) and the day number in the year (*d*) (for example 1st January is considered as day 1). The *LTI* formula makes it possible to solve the models using different soil types and rainfall levels and hence why it was adopted. The estimated *WHs* were multiplied by a factor of 0.85 (adopted from the farmR model by Cooke *et al.* (2013)) to factor in unproductive times.

With differences in the workability of different operations, the *WHs* were revised based on the type of operation (Tillet and Audsley, 1987). For example, spraying has a workability of 60%, thus if the estimated WH = 40h, then with respect to spraying the *WH* will be 24h (40 × 0.6). The *LTI* adopted from Tillet and Audsley (1987) can be expressed as:

$$LTI = 20.6X^2 - 89X + 212 \tag{3-33}$$

Where, $X = (1.257 - 0.257ST)AR + 0.762(ST - 1)$

$ST$ = Soil type (soil type represented by indices from 0.5 to 2.5 at interval of 0.25 to represent light soils through to heavy soils), $AR$ = Annual rainfall (mm).

### 3.4.6 Yield and rotational penalties

Sub-optimal operations and rotations could attract yield penalties (% yield loss), $O_{ypen}$ and $R_{ypen}$ respectively. For example, the optimum time for planting winter wheat is between late September and early October however, planting in early or late December could attract a penalty of about 15%. Legumes (e.g. beans) following winter wheat attracts no penalty and thus considered as optimal rotation. Winter wheat following a barley crop is considered as sub-optimal rotation and could attract a penalty of about 11%. The yield penalty with respect to sub-optimal operations could range from zero to over 20% and the yield penalty with respect to sub-optimal rotation could range from zero to 100% (rotations or crop sequences not allowed). For sub-optimal operations, the yield penalties were expressed as cost ($O_{ypen}$ × crop yield × crop price) and added to the cost of operation in the respective periods (as illustrated under Section 3.4.4). For sub-optimal crop rotations or crop sequences, the yield penalties ($R_{ypen}$ × crop yield × crop price) were assigned to the respective crop sequence or rotations as costs in the profit maximisation objective function. Thus the penalty takes effect if a sub-optimal crop sequence is selected by the model.

In terms of the MOTAD model, it is formulated in such a manner that profit is maximised subject to minimising risk and as a result the effect of yield penalty either due to sub-optimal operations or crop sequences reflects in the profit maximisation objective function but not in the income deviation estimates. This is due to the fact that the risk (income deviation) estimates in the MOTAD model are based on historical and as a result does take into consideration yield and rotational penalty. The effect of yield penalty however, influence the risk estimates of the model indirectly through its direct effect on the profit estimates by the objective function.

## 3.5 Model data

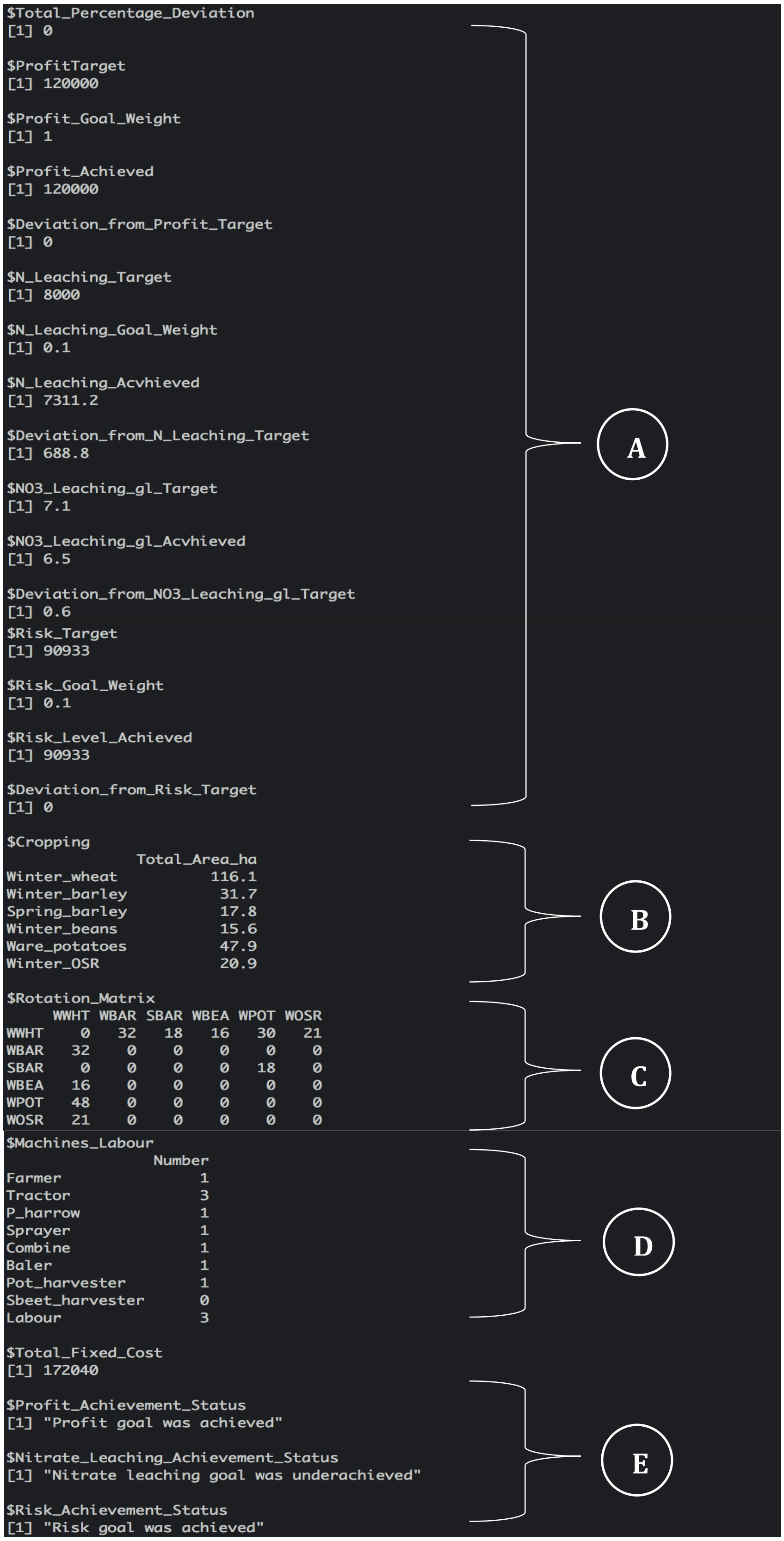
The data used in estimating the model parameters and coefficients were primarily secondary data from farm management books and other existing models (primarily the farmR model). These included data such as farm input and output, soil, rotational penalties as well as information and assumptions used in developing the model and estimating model parameters. The different data types are presented in Table 3-13 (see the chapter Appendix). With some of the data adopted from the farmR model, the sources of such data are stated as farmR and the original references cited by Cooke *et al.* (2013).

## 3.6 Model results example: goal programming module

This section presents an example of the results generated by the SAFMOD—the mixed-integer goal-programming module. The model codes were written in the R programming language (R Core Team, 2015) and solved by the R version of GNU[9] (Gnu's Not Unix) Linear Programming Kit[10] (Rglpk). The codes for the mixed-integer goal-programming model can be found on GitHub through the following link: https://github.com/kwadjoahodo/SAFMOD/blob/master/SAFMOD.R. The example results shown in Figure 3-3 were generated based on a heavy soil, rainfall of 600mm and fixed cost estimates taking into account an interest rate of 0.5%.

[9] GNU: https://www.gnu.org/gnu/gnu.html

[10] GLPK: http://www.gnu.org/software/glpk/
Rglpk: https://cran.r-project.org/web/packages/Rglpk/Rglpk.pdf



```
$Total_Percentage_Deviation
[1] 0

$ProfitTarget
[1] 120000

$Profit_Goal_Weight
[1] 1

$Profit_Achieved
[1] 120000

$Deviation_from_Profit_Target
[1] 0

$N_Leaching_Target
[1] 8000

$N_Leaching_Goal_Weight
[1] 0.1

$N_Leaching_Acvhieved
[1] 7311.2

$Deviation_from_N_Leaching_Target
[1] 688.8

$NO3_Leaching_gl_Target
[1] 7.1

$NO3_Leaching_gl_Acvhieved
[1] 6.5

$Deviation_from_NO3_Leaching_gl_Target
[1] 0.6
$Risk_Target
[1] 90933

$Risk_Goal_Weight
[1] 0.1

$Risk_Level_Achieved
[1] 90933

$Deviation_from_Risk_Target
[1] 0

$Cropping
              Total_Area_ha
Winter_wheat          116.1
Winter_barley          31.7
Spring_barley          17.8
Winter_beans           15.6
Ware_potatoes          47.9
Winter_OSR             20.9

$Rotation_Matrix
     WWHT WBAR SBAR WBEA WPOT WOSR
WWHT    0   32   18   16   30   21
WBAR   32    0    0    0    0    0
SBAR    0    0    0    0   18    0
WBEA   16    0    0    0    0    0
WPOT   48    0    0    0    0    0
WOSR   21    0    0    0    0    0
$Machines_Labour
                Number
Farmer               1
Tractor              3
P_harrow             1
Sprayer              1
Combine              1
Baler                1
Pot_harvester        1
Sbeet_harvester      0
Labour               3

$Total_Fixed_Cost
[1] 172040

$Profit_Achievement_Status
[1] "Profit goal was achieved"

$Nitrate_Leaching_Achievement_Status
[1] "Nitrate leaching goal was underachieved"

$Risk_Achievement_Status
[1] "Risk goal was achieved"
```



Figure 3-3: Model result example generated using the mixed-integer weighted goal programming module in SAFMOD

Part A of Figure 3-3 shows information on the overall deviation (the objective function (in percentage), the goal weights, targets, levels of goals achieved and deviations from goals targets. For example, a weight of 1 was put on the profit maximisation goal with a target of £120,000. The goal was achieved and thus no deviation from goal target. Part B shows the crop proportions whereas Part C shows the rotation matrix. In terms of the crop plan, the time horizon is infinity however, the length of the crop cycle depends on the model solution. The rotation matrix reflects the distribution of crops in fields with the crops in the rows, successor crops and the ones in the columns being the predecessor crops. The results contained in the rotation or crop sequence matrix thus contains implicit rotations or crop sequences rather than explicit fixed period rotation. For example, for the 250ha farm, the crop sequences from Part C can be read as shown in Table 3-3. Part D shows the machines/labour numbers and the total annual fixed cost estimate whereas Part E gives additional information on the whether or not the goal targets were achieved, over or under achieved.

Table 3-3: Crop sequences information contained in the rotation matrix generated by the SAFMOD

| Crop sequence* | Field Area (ha) |
|---|---:|
| WWHT after WBAR | 32 |
| WWHT after SBAR | 18 |
| WWHT after WBEA | 16 |
| WWHT after WPOT | 30 |
| WWHT after WOSR | 21 |
| WBAR after WWHT | 32 |
| SBAR after WPOT | 18 |
| WBEA after WWHT | 16 |
| WPOT after WWHT | 48 |
| WOSR after WWHT | 21 |

* WWHT=Winter wheat; WBAR=Winter barley; SBAR=Spring barley; WBEA=Winter beans; WPOT=Ware potatoes; WOSR=Winter oilseed rape

## 3.7 Model validation steps

Before carrying out the model validation, model verification was carried out to ensure consistency in the results generated by the models. The default models are solved using the R programming software (R Core Team, 2015) version of GNU Linear Programming Kit (Rglpk) however, to ensure consistency in the model results, the models were also solved using the R version of the COIN-OR (Computational Infrastructure for Operations Research) Symphony[11] (Rsymphony) and the results were compared. Both solvers generated the same results. To be able to compare the model results with real farm data, the validation by result approach, which encompasses predictive validation (McCarl and Spreen, 1997) was adopted. Predictive validation is the most common validation experiment, which makes it possible to fix the model data or parameters at real system data levels and run the model, after which the results are compared to respective real data (McCarl and Spreen, 1997). Thus to carry out predictive validation, historical or real data are needed and for the purposes of this study, the Farm Business Survey (FBS) data for arable farms in England and Wales were used (see Section 3.8 for farm selection criteria). The steps for the validation by results can be summarised by Figure 3-4 (designed based on information from McCarl and Spreen, 1997) assuming all model solutions generated via the validation experiment are optimal.

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[11] Symphony: https://projects.coin-or.org/SYMPHONY
Rsymphony: https://cran.r-project.org/web/packages/Rsymphony/Rsymphony.pdf

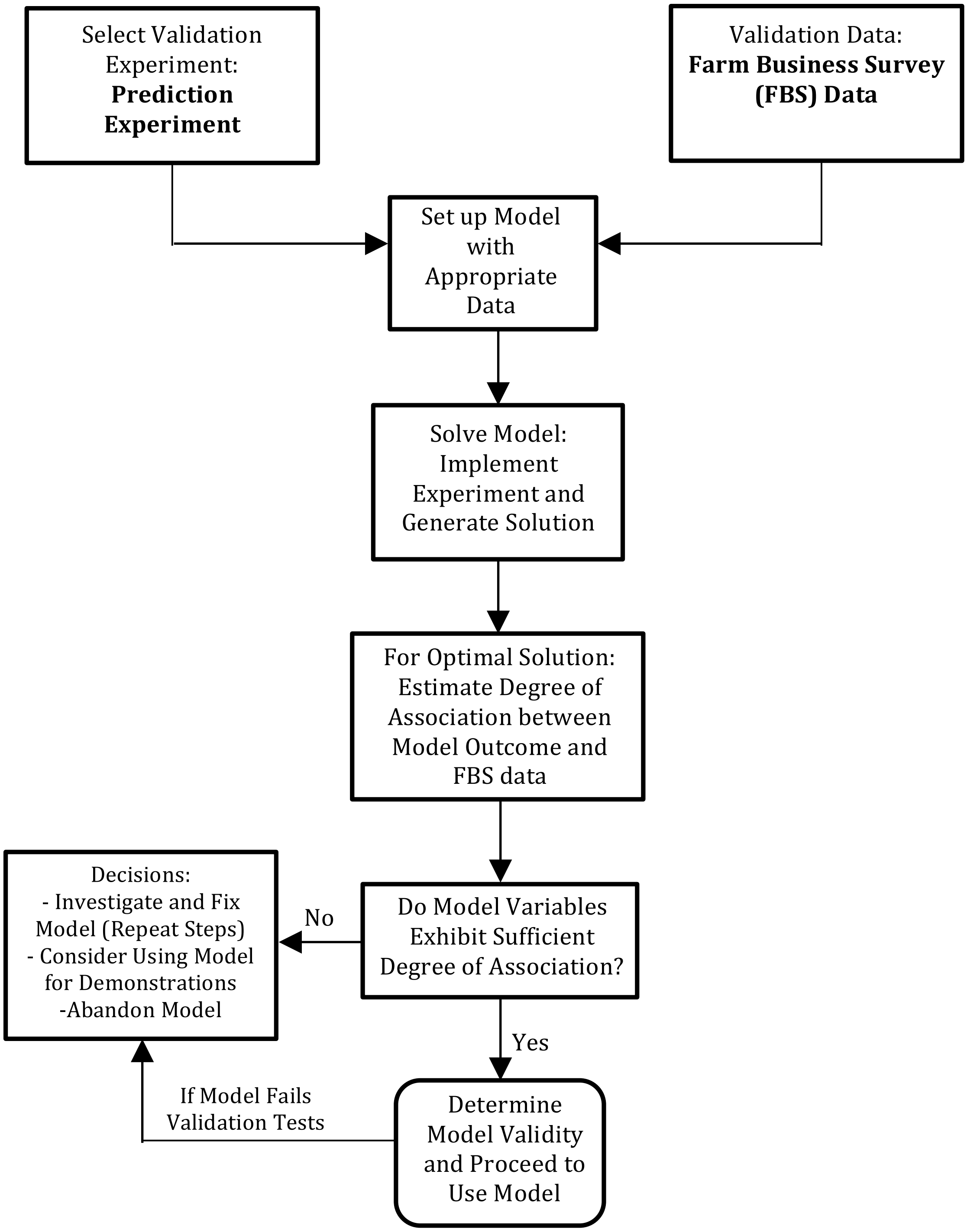



Figure 3-4: Steps for model validation by results

### 3.8 Validation data

To perform a predictive validation, empirical data—the 2009-2013 Farm Business Survey (FBS) data were obtained from the UK Data Archive (UKDA) and used. These data were filtered by selecting farm at an altitude of less than 300m (lowland arable farms) and with arable crops and set-aside[12] areas of greater than or equal to 100ha. Farms with missing data for three or more years with respect to the arable crop and set-aside areas were excluded. Thus 281 farms located in all the FBS defined regions in England and Wales[13] were used for the model validation. Since the yield values from the default model were functions of soil types and N fertiliser amounts, in a situation where the yield data of farms were missing or farms did not grow particular crops, the yields were estimated using the soil type and the respective recommended N fertiliser amounts obtained from Defra (2010). The resultant data were time-averaged (2009 to 2013) crop yields, farm areas, gross margins and profit levels and fertiliser quantities for each of the 281 farms selected. Other data were fertiliser cost, seed cost and fuel cost. In the model, workable hours were estimated based on soil types and rainfall amount. As a result, the dominant soil types (obtained from Soilscapes[14]) for counties in which the farms are located were used as representative soil types for the selected farms. Also the rainfall amounts for the FBS-defined regions[15] in which farms are located were used as representative rainfall amounts for the selected farms. This was done to be able to estimate the workable hours for each of the 281 farms based on their representative soil types and rainfall amounts.

[12] Set-aside areas were areas of un-cropped arable land and areas of voluntary set-aside.
[13] The selected farms from Wales as the result of the criteria were from two counties whereas in England farm selected fell under all the FBS defined regions.
[14] Soilscapes: http://www.landis.org.uk/soilscapes/
[15] Regional rainfall were obtained from Met Office: http://www.metoffice.gov.uk/climate/uk/summaries/datasets

## 3.9 Input for model validation and model runs

The time-averaged crop yields and farm arable areas were used as model input for the validation. The models were then calibrated or set up to allow for the use of the time-averaged crop yields, arable areas, soil types and rainfall amounts for each farm as model inputs while holding all other parameters constant. This means the models were calibrated by fixing crop yields and farm areas at the observed FBS yield and farm area values. Soil types and rainfall amounts were fixed at farm-specific values obtained from Soilscapes and Met Office respectively based on their FBS-defined counties or regions, and the models were run for each of the 281 farms.

In the case of the risk (MOTAD) model, it was run setting the Mean Absolute Deviation (MAD) to £20,000, due to the fact it gave the best fit when predicted and observed crop areas were compared. In terms of the weighted goal-programming model the set of weights and goals which gave the best fit in terms of predicted and observed crop areas comparison (weight for profit maximisation = 0.8, nitrate leaching minimisation = 1, risk minimisation = 0.05), were adopted and used for the validation. It is also possible that other set of weights and goal targets could give better model fit.

To be able to conduct aggregate level comparison using farm average crop yields and areas as model input, the soil type and rainfall were set at heavy soil and 600mm respectively. This type of aggregate level comparison was conducted to enable the models to be solved once, for the 'average' farm and the result compared to average data. Heavy soil and rainfall amount of 600mm were found to give the best fit in terms of comparing predicted and observed crop areas when the models were run at different soil types and rainfall levels.

After model runs, the results of the models were then compared to the observed FBS data using statistical measures of association such as Pearson and Spearman correlation coefficients, coefficient of determination (regression analysis), MAE and RMSE. Other statistical measures of association applied were NIA, WIA, LCE, CRM and t-test.

## 3.10 Statistical measures or indicators of association

After model calibration and model runs, the model results were then compared with the observed FBS data to measure the degree of association using statistical indicators and graphical approaches. According to Loague and Green (1991) model evaluation (validation) should include both statistical criteria and graphical displays in that both approaches can be used to compare the performance between alternative models, hence these two approaches were adopted. Statistical measures are useful for quantitative evaluation of model performance whereas graphical displays are useful for showing trends and types of error distribution patterns which may not be able to be shown using statistical measures (Loague and Green, 1991). Some of the statistical measures or indicators of association identified through the review of measures of association (see Table 3-1) were adopted and applied in the model validation and these are expressed by Eq. (3-34) to (3-39) with a regression model expressed by Eq. (3-40). $O_l$ is the observed data for the $l$th observation of the parameter of interest (e.g. crop areas), $P_l$ is the model-predicted result (data) of the $l$th observation of the parameter of interest (e.g. model predicted or generated crop areas), $O_{av}$ and $P_{av}$ are the means of the observed and predicted data respectively and $N$ is the number of observations. For the regression model shown by Eq. (3-40), $\alpha$ is the intercept, $\beta$ is the slope (slope of best fit line), and $\varepsilon$ is the error term.

$$MAE = \frac{1}{O_{av}}\left(\frac{\sum_{l=1}^{N}|P_l - O_l|}{N}\right) \quad (3\text{-}34)$$

$$RMSE = \frac{1}{O_{av}}\sqrt{\frac{\sum_{l=1}^{N}(P_l - O_l)^2}{N}} \quad (3\text{-}35)$$

$$CRM = \frac{\left(\sum_{l=1}^{N} O_l - \sum_{l=1}^{N} P_l\right)}{\sum_{l=1}^{N} O_l} \quad (3\text{-}36)$$

$$NSE(ME) = 1 - \left(\frac{\sum_{l=1}^{N}(P_l - O_l)^2}{\sum_{l=1}^{N}(O_l - O_{av})^2}\right) \quad (3\text{-}37)$$

$$WIA = 1 - \left( \frac{\sum_{l=1}^{N} (P_l - O_l)^2}{\sum_{l=1}^{N} (|P_l - O_{av}| + |O_l - O_{av}|)^2} \right) \tag{3-38}$$

$$LCE = 1 - \left( \frac{\sum_{l=1}^{N} |P_l - O_l|}{\sum_{l=1}^{N} |O_l - O_{av}|} \right) \tag{3-39}$$

$$O_l = \alpha + \beta(P_l) + \varepsilon \tag{3-40}$$

$$\beta = \frac{\sum_{l=1}^{N} (P_l - P_{av})(O_l - O_{av})}{\sum_{l=1}^{N} (P_l - P_{av})^2} \tag{3-41}$$

For a perfect association, the slope of the regression line would be equal to one and the intercept would be expected to be zero (Smith and Rose, 1995). Thus the slope was tested on a null hypothesis ($H_0$) that the slope is equal to one against the alternative hypothesis ($H_1$) that it is different from one whereas the intercept was tested to find out whether or not it was significantly different from zero. Testing the hypothesis that the intercept is not different from zero is not very useful if the slope is significantly different from one (Smith and Rose, 1995). The hypotheses for the t-tests can be summarised as follows:

For the intercept:

- $H_0$: Intercept ($\alpha$) = 0; $H_1$: Intercept ($\alpha$) ≠ 0

For the slope:

- $H_0$: Slope ($\beta$) = 1; $H_1$: Slope ($\beta$) ≠ 1.

The model results were compared with the observed FBS data by aggregating across farms as well as at the level of individual farms. The aggregate-level comparison was in two forms. The first aggregate level of comparison (referred to as AL-1) was conducted by comparing the model result obtained from running the models using farm average area and crop yields with average observed data. The AL-1 comparison was applied to crop area comparison. The second aggregate level comparison (referred to as AL-2) was conducted using the average of the model results obtained by running the models for each of the 281 farms and the average observed data. For example, to find the degrees of association between crops areas, the averages of the crops areas obtained from running the model for the 281 farms and the average crops areas from the FBS data for the 281 farms were used. For crop areas, this resulted in 10 data points, reflecting the nine crops and set-aside in the model.

Aggregate level comparisons were conducted for crop areas (representative of arable farm landscape), fertiliser amounts (representative of resource or input use) and gross margin, profit, fertiliser seed and fuel cost (representative of farm finances). The AL-1 comparison was done purposely to compare its results with the AL-2 results and also to be able to investigate changes in crop selection for the 'average' farm under all four models. The individual-level comparison was conducted by comparing the values of each individual farm with the FBS data using all the 281 observations. With the individual-level comparison, variables were compared one at a time. For example, predicted winter wheat areas were compared with observed winter wheat areas instead of comparing the area of all crops at the same time. Table 3-4 shows all the variables, which were predicted by the models and were compared to FBS data.

Table 3-4: Matrix of all the observed and model predicted variables compared.

| Model Type/Observed Data | Predicted/Observed Variables* | | | | | | |
|---|---|---|---|---|---|---|---|
| | Crop Areas | Gross Margin | Profit | Fixed Cost | Labour cost | Fertiliser, Seed and Fuel Cost | Fertiliser amounts |
| Pure Profit Model | + | + | + | + | + | + | + |
| Nitrate Leaching Model | + | + | + | + | + | + | + |
| Risk (MOTAD) Model | + | + | + | + | + | + | + |
| WGP Model | + | + | + | + | + | + | + |
| FBS Data | + | + | + | + | + | + | + |

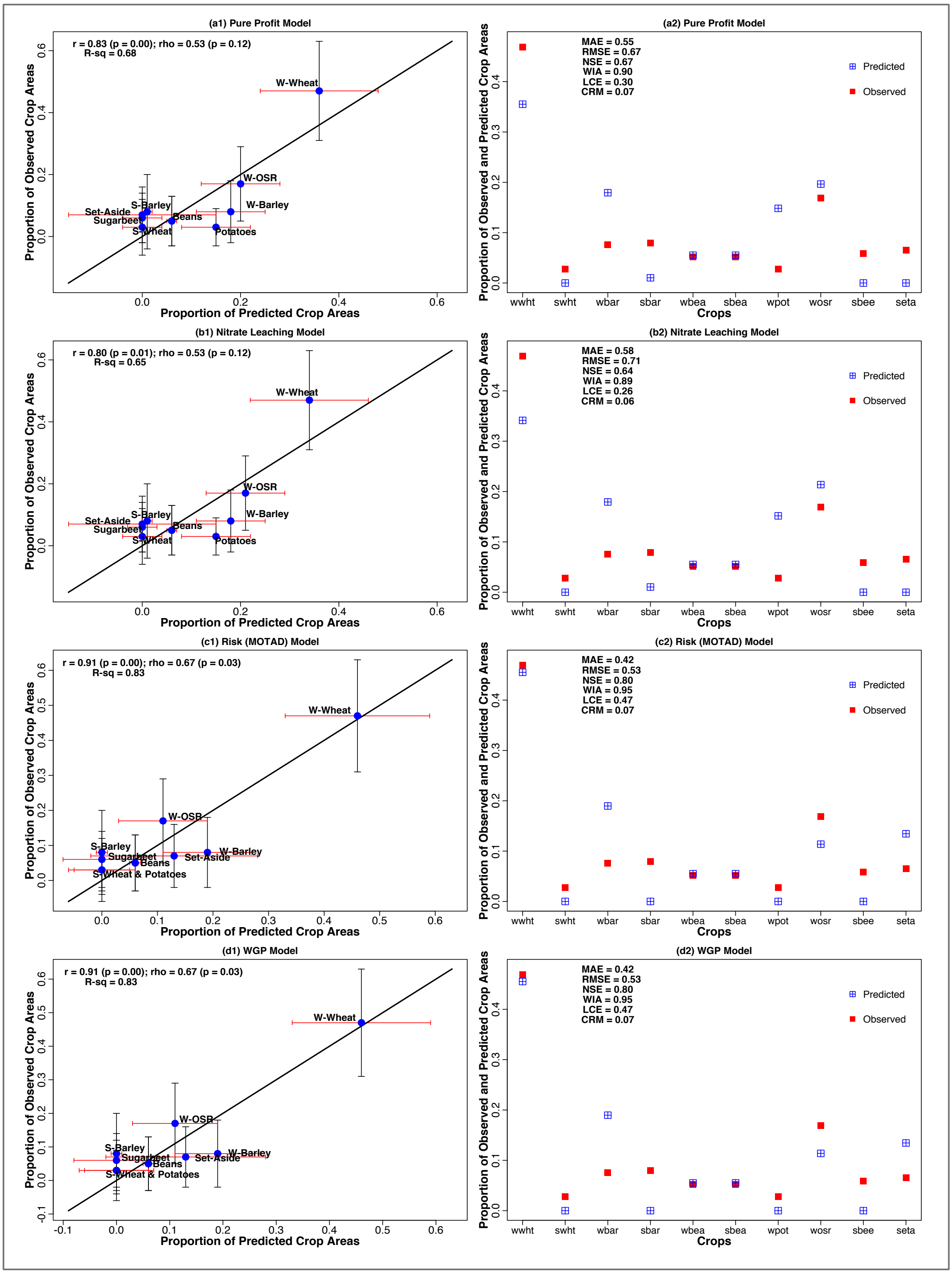
* The plus (+) indicates that the variable is part of set of variables considered for comparison.

## 3.11 Validation results

### 3.11.1 Aggregate-level comparisons between observed and predicted crop areas

The estimates of correlation and coefficient of determination for the aggregate-level comparison using average farm data (AL-1) showed positive association between predicted and observed crop areas especially under the risk (MOTAD) and WGP models ($r = 0.91$ (p-value = 0.00), $\rho = 0.67$ (p-value = 0.03), $R^2 = 0.83$) (see Figure 3-5 (c1) and (d1)). The model performance indicators also showed comparatively good model performance under MOTAD and WGP models (NSE = 0.80, WIA = 0.95, LCE = 0.47). However, RMSE, MAE and CRM estimates showed the existence of bias as well as under-predictions in the model predictions. The relatively high RMSE estimates than the MAE estimates can be attributed to the squaring of the errors (see Eq. (3-35)).

Although winter wheat was the dominant crop, it was under-predicted by all the four models especially the profit and nitrate leaching models (see Figure 3-5 (a2) to (d2)). Other crops such as winter OSR were also under-predicted however, crops such as winter barley and potatoes were over-predicted in the pure profit and nitrate leaching models. This may be due to the fact that in pure profit models, farmers are assumed to be indifferent to risk and hence the model mimics the behaviour of such farmers by selecting high profit generating crops without considerations to the associated risks. This also reflects in the results of the risk module application in Chapter 5 in which under risk neutral more land is allocated to high risk crops such as potatoes. Thus in the MOTAD and WGP models, which incorporated risk minimisation objectives, high-risk crops such as potatoes gave way to set-aside, which is considered risk-free in the crop plan. As a result, unlike the profit and nitrate leaching models, in the MOTAD and WGP models, potato area was under-predicted whereas set-aside was over-predicted. The positive CRM estimates (see Figure 3-4 (a2) to (d2)) suggest under-prediction of crop areas by all four models.




Note: For the Risk Model, MAD was set at £20,000, WGP Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). The solid line represents a perfect association. The error bars represent deviations in model predicted and observed crop areas.

Figure 3-5: Comparison between relative observed crop areas and crop areas predicted by the four different models (AL-1).

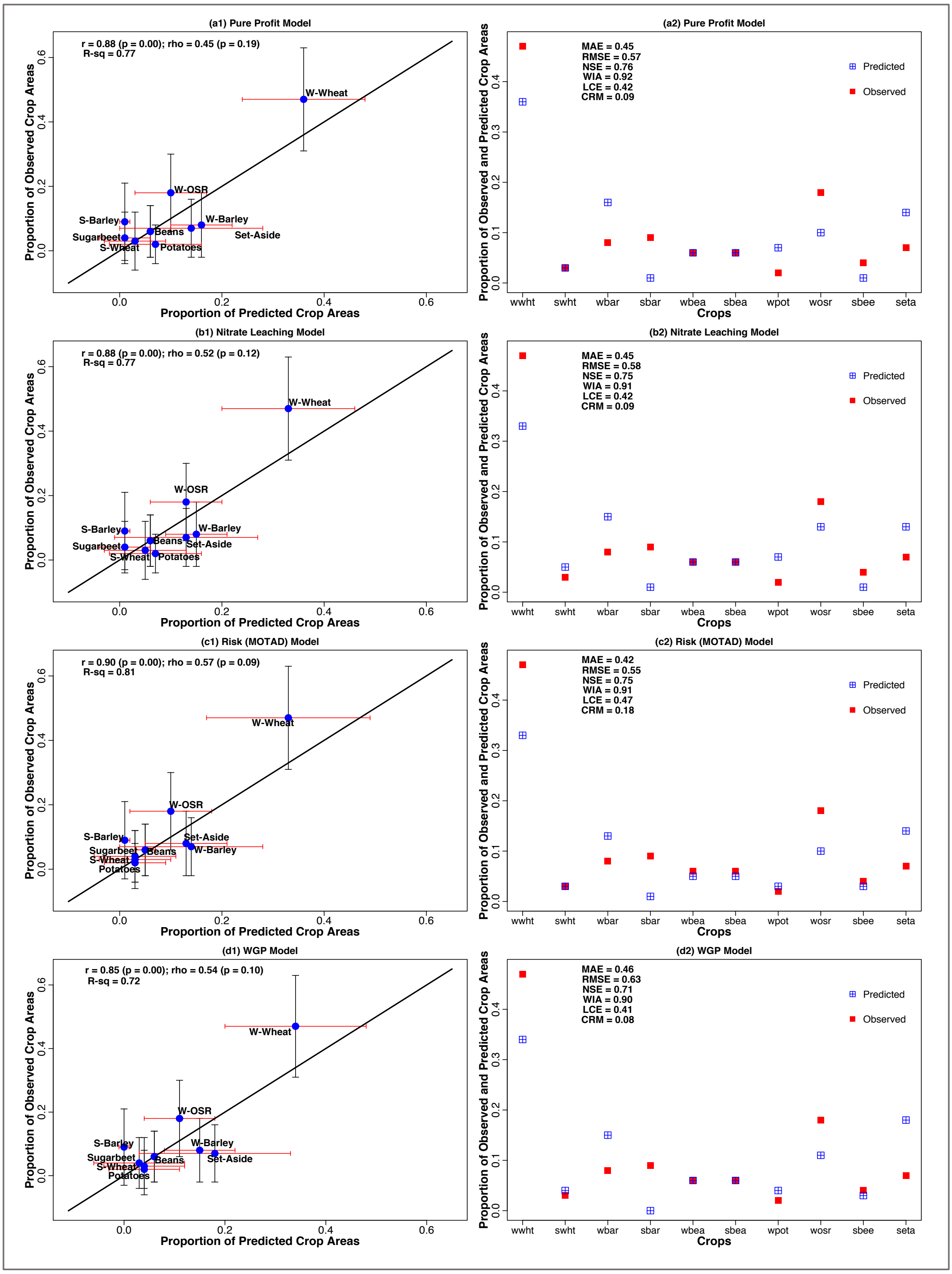
The non-zero and positive slopes values (see Table 3-5) are also an indication of positive associations between predicted and observed data. The results of the t-test (Table 3-5) under all models also showed that the intercepts and the slopes were respectively not significantly different from zero and one.

Table 3-5: Results of t-test on intercept and slope for regression of observed (FBS) data on model predicted data at the aggregate level.

| Model Output | Pure Profit Model | | Nitrate Leaching Model | | Risk (MOTAD) Model * | | WGP Model ** | |
|---|---|---|---|---|---|---|---|---|
| | α | β | α | β | α | β | α | β |
| Crop Areas (ha) (AL-1) | 4.22<br>(0.42)<br>{0.68} | 0.93<br>(-0.31)<br>{0.77} | 4.40<br>(0.42)<br>{0.68} | 0.92<br>(-0.342)<br>{0.742} | 6.30<br>(0.93)<br>{0.38} | 0.86<br>(-1.04)<br>{0.33} | 6.30<br>(0.93)<br>{0.38} | 0.86<br>(-1.04)<br>{0.33} |
| Crop Areas (ha)(AL-2) | -0.00<br>(-0.04)<br>{0.97} | 1.12<br>(0.57)<br>{0.58} | -0.01<br>(-0.46)<br>{0.65} | 1.25<br>(1.10)<br>{0.30} | -0.00<br>(-0.14)<br>{0.89} | 1.26<br>(1.23)<br>{0.25} | -0.00<br>(-0.06)<br>{0.95} | 1.12<br>(0.49)<br>{0.63} |
| Fertiliser Amounts (kg/ha) | -2.37<br>(-0.12)<br>{0.91} | 1.01<br>(0.06)<br>{0.95} | -2.37<br>(-0.12)<br>{0.91} | 1.01<br>(0.06)<br>{0.95} | -0.61<br>(-0.04)<br>{0.97} | 1.06<br>(0.68)<br>{0.53} | -1.73<br>(-0.09)<br>{0.93} | 1.09<br>(0.85)<br>{0.44} |
| Revenue/ Cost (£/ha) | 103.83<br>(0.63)<br>{0.54} | 1.03<br>(0.06)<br>{0.96} | 106.51<br>(0.65)<br>{0.54} | 1.01<br>(-0.03)<br>{0.98} | 102.35<br>(0.68)<br>{0.51} | 1.02<br>(0.05)<br>{0.96} | 138.24<br>(0.81)<br>{0.44} | 0.99<br>(-0.03)<br>{0.98} |

* MAD = £20,000, ** Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). Note: The values in parentheses are the t-values whereas the values in curly brackets are the corresponding p-values for both the intercept (α) and the slope (β).

The estimates of the Pearson correlation tests for the second aggregate level comparisons of observed and predicted crop areas using the average observed crop areas and averages of the crop areas predicted by the models for the 281 farms (AL-2), also showed positive relationship (see Figure 3-6). The estimates for the Pearson correlation tests were significant however, the estimates for the Spearman correlation tests were not significant under all four models apart from the estimate under the MOTAD model, which was near significant ($\rho$=0.57; p-value=0.09). This reflects the poor prediction of the rank order of crops apart from winter wheat (the dominant crop). The MOTAD model also gave relatively the best $R^2$ estimates ($R^2$=0.81).



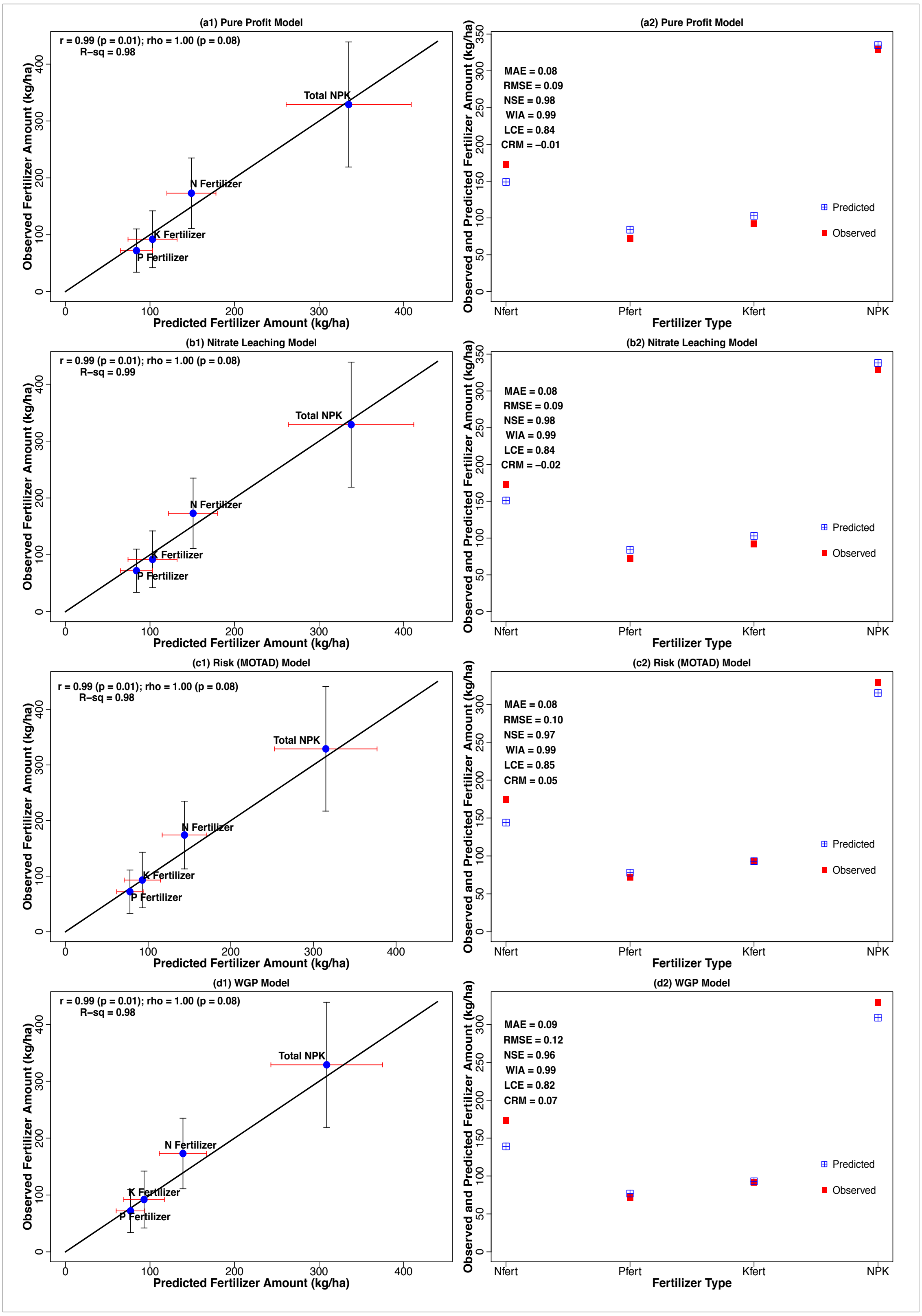

Note: For the Risk Model, MAD was set at £20,000, WGP Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). The solid line represents a perfect association. The error bars represent deviations in model predicted and observed crop areas.

Figure 3-6: Comparison between relative observed crop areas and crop areas predicted by the four different models (AL-2).

The AL-2 comparison also showed under-prediction of crops, with set-aside being over-predicted. This may be due to the fact that quite a reasonable number of farms in the FBS recorded crop yields far lower than the respective average yield and also the fact that the model was run for each individual farm using their time-averaged crop yields and area. Thus in a situation where yields for dominant crops such as winter wheat were very low, the model allocated more land to set-aside and hence set-aside being over-predicted. The results of the t-test showed the intercepts and slopes to be respectively not significantly different from zero and one. Also, model performance measures such as NSE and WIA were relatively high (NSE range: 0.71–0.76, WIA range: 0.90–0.92). The deviance measures (MAE and RMSE) (Figure 3-6 (a2) – (d2)) reflect the variability in model predicted farm areas, which were influenced by variability in crop yields of farms.

### 3.11.2 Aggregate-level comparisons between observed and predicted fertiliser amounts

The aggregate-level comparison of observed and predicted fertiliser amounts showed a positive association between predicted and observed fertiliser amounts. The estimates for the Pearson correlation tests under all four models were high and statistically significant ($r = 0.99$; p-value = 0.01, $R^2 = 0.98$) however, the estimates for the Spearman correlation test were near significant ($\rho = 1.00$; p-value =0.08). The results of the t-test (see Table 3-5) showed the intercepts to be not significantly different from zero and the slopes not significantly different from one. Model performance indicators also showed good model performance in terms of fertiliser prediction (NSE: range = 0.96–0.98, WIA = 0.99) (see Figure 3-6 (a2) to (d2)). The deviance measures (MAE and RMSE) were close to zero indicating the closeness of the predicted fertiliser amounts to observed amounts. In general, there was some over-prediction of fertiliser amounts by the profit and nitrate-leaching models (CRM < 0) however, nitrogen fertiliser amounts were under-predicted. The MOTAD and WPG models under-predicted fertiliser amounts (CRM > 0).

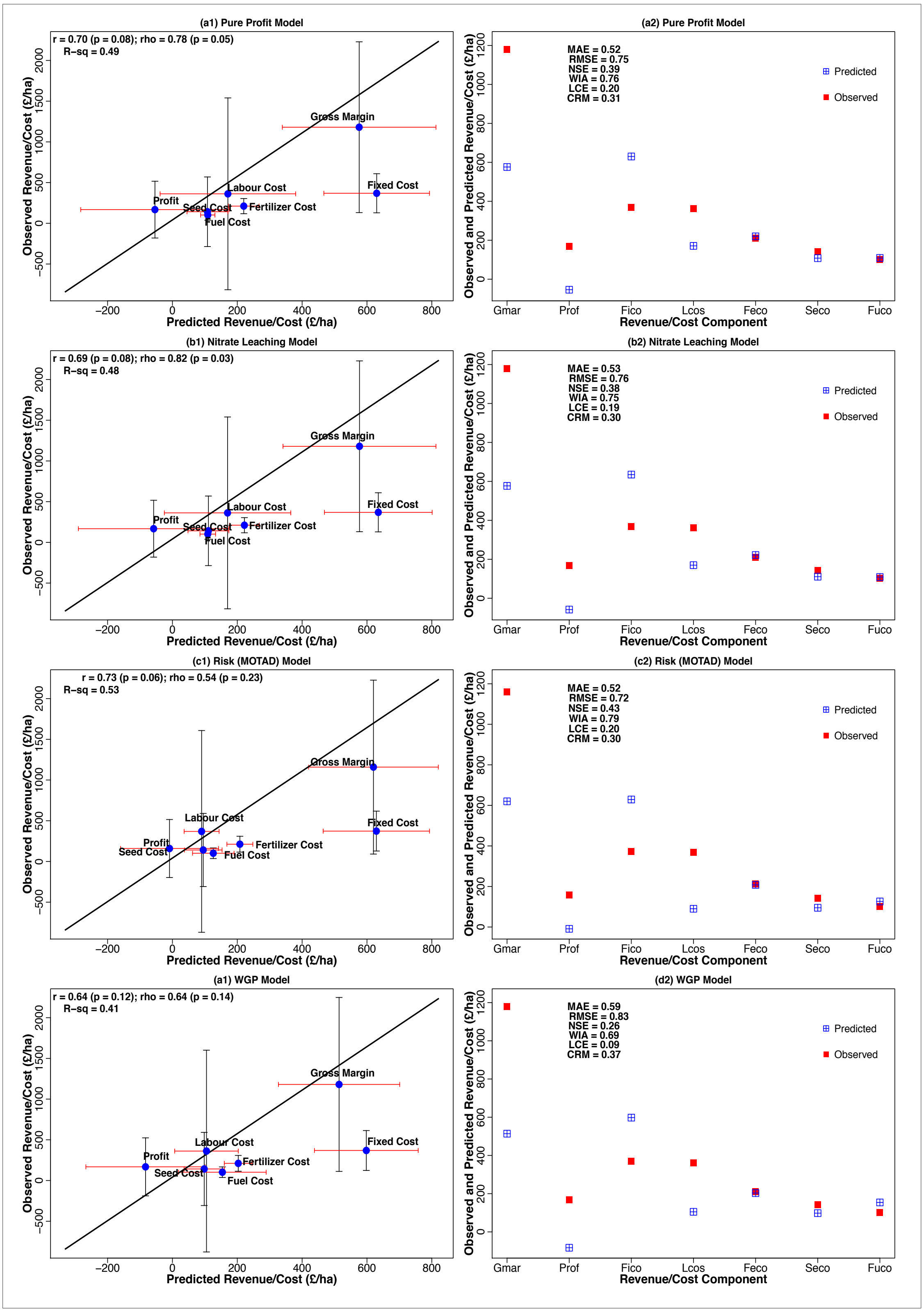



Note: For the Risk Model, MAD was set at £20,000, WGP Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). The solid line represents a perfect association. The error bars represent deviations in model predicted and observed crop areas.

Figure 3-7: Comparison between observed fertiliser amounts and fertiliser amounts predicted by the four different models (AL-2).

### 3.11.3 Aggregate-level comparisons between observed and predicted farm revenues and costs

The statistical measures of association based on the coefficient of determination showed some degree of association between predicted farm revenues/costs and observed farm revenues/costs ($R^2$ between 0.41 and 0.53). The estimates for the Pearson correlation test were not statistically significant (see Figure 3-8) with exception of estimates under the profit, nitrate leaching and MOTAD models, which were near significant (p-value between 0.06 and 0.08). Also estimates of the Spearman correlation test were not statistically significant with the exception of the estimate under the profit model ($\rho$ = 0.78; p-value = 0.05) and the nitrate-leaching model ($\rho$ = 0.82; p-value = 0.03). The deviance measures showed bias in model prediction of revenues/costs and the CRM estimates under all four models showed under-prediction. The positive model performance indicators (NSE, WIA and LCE), although low, are an indication of some degree of association between predicted and observed revenue/cost. The results of the t-test (see Table 3-5) with respect to revenues and costs showed that the slopes were not significantly different from one and the intercepts were not significantly different from zero.




Note: For the Risk Model, MAD was set at £20,000, WGP Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). The solid line represents a perfect association. The error bars represent deviations in model predicted and observed crop areas.

Figure 3-8: Comparison between observed farm revenue/cost and revenue/cost predicted by the four different models (AL-2).

### 3.11.4 Individual-level comparisons between predicted and observed crop areas

Comparisons between predicted and observed crop areas showed various degrees of association. These are reflected in the estimates for correlation and coefficient of determination under all models. Relatively good degrees of association were observed under crops/activities such as winter wheat, potatoes, winter OSR and set-aside (see Table 3-6). In general, the results of the t-test (Table 3-7) on the other hand showed that the slopes and intercept were different from one and zero respectively.

Table 3-6: Correlation and coefficient of determination estimates for comparing predicted crop areas to observed crop areas at the individual level.

| Crops | Pure Profit Model | | | Nitrate Leaching Model | | | Risk (MOTAD) Model * | | | WGP Model ** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | r | ρ | $R^2$ | r | ρ | $R^2$ | r | ρ | $R^2$ | r | ρ | $R^2$ |
| Winter wheat | 0.84 (0.00) | 0.66 (0.00) | 0.70 | 0.84 (0.00) | 0.65 (0.00) | 0.70 | 0.53 (0.00) | 0.55 (0.00) | 0.28 | 0.58 (0.00) | 0.54 (0.00) | 0.34 |
| Spring wheat | 0.10 (0.11) | -0.13 (0.04) | 0.01 | 0.08 (0.16) | -0.15 (0.01) | 0.01 | 0.01 (0.66) | -0.11 (0.08) | 0.00 | 0.11 (0.06) | 0.03 (0.67) | 0.01 |
| Winter barley | 0.29 (0.00) | 0.03 (0.85) | 0.08 | 0.28 (0.00) | -0.01 (0.85) | 0.08 | 0.06 (0.37) | 0.03 (0.67) | 0.00 | 0.21 (0.00) | 0.02 (0.70) | 0.05 |
| Spring barley | 0.18 (0.00) | 0.07 (0.26) | 0.03 | 0.19 (0.00) | 0.08 (0.18) | 0.04 | 0.05 (0.43) | 0.04 (0.55) | 0.00 | 0.12 (0.05) | 0.02 (0.77) | 0.01 |
| Winter beans | 0.15 (0.01) | 0.13 (0.03) | 0.02 | 0.16 (0.01) | 0.20 (0.00) | 0.03 | 0.31 (0.00) | 0.11 (0.00) | 0.11 | 0.19 (0.00) | 0.13 (0.00) | 0.04 |
| Spring beans | 0.22 (0.00) | 0.23 (0.00) | 0.05 | 0.22 (0.00) | 0.23 (0.00) | 0.05 | 0.39 (0.00) | 0.24 (0.00) | 0.15 | 0.22 (0.00) | 0.23 (0.00) | 0.05 |
| Ware potatoes | 0.59 (0.00) | 0.32 (0.00) | 0.35 | 0.59 (0.00) | 0.30 (0.00) | 0.34 | 0.38 (0.00) | 0.45 (0.00) | 0.14 | 0.22 (0.00) | 0.24 (0.00) | 0.05 |
| Winter OSR | 0.66 (0.00) | 0.51 (0.00) | 0.44 | 0.65 (0.00) | 0.50 (0.00) | 0.42 | 0.57 (0.00) | 0.44 (0.00) | 0.33 | 0.58 (0.00) | 0.51 (0.00) | 0.34 |
| Sugar beet | 0.37 (0.00) | 0.41 (0.00) | 0.14 | 0.37 (0.00) | 0.41 (0.00) | 0.13 | 0.30 (0.00) | 0.27 (0.00) | 0.09 | 0.70 (0.00) | 0.53 (0.00) | 0.49 |
| Set-aside | 0.41 (0.00) | 0.16 (0.01) | 0.17 | 0.41 (0.00) | 0.16 (0.01) | 0.17 | -0.02 (0.79) | 0.06 (0.36) | 0.00 | 0.33 (0.00) | 0.12 (0.04) | 0.11 |

* MAD = £20,000, ** Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). Note: Values in parenthesis represent the p-values.

Table 3-7: Results of the t-test on the intercept and slope of the regression of observed crop areas on predicted crop areas at the individual level.

| Crops | Pure Profit Model | | Nitrate Leaching Model | | Risk (MOTAD) Model * | | WGP Model ** | |
|---|---|---|---|---|---|---|---|---|
| | α | β | α | β | α | β | α | β |
| Winter wheat | **10.69** | 1.26 | 17.90 | 1.25 | 41.73 | 0.80 | 27.35 | 1.32 |
| | **(1.63)** | (5.58) | (2.82) | (5.19) | (5.93) | (-2.46) | (2.48) | (2.91) |
| | **{0.10}** | {0.00} | {0.01} | {0.00} | {0.00} | {0.01} | {0.01} | {0.00} |
| Spring wheat | 6.99 | 0.11 | 6.89 | 0.10 | 6.22 | 0.02 | 7.14 | 0.04 |
| | (4.54) | (-12.60) | (4.29) | (-13.42) | (-4.07) | (-17.68) | (4.86) | (-48.24) |
| | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} |
| Winter barley | 12.83 | 0.18 | 13.49 | 0.18 | 16.54 | 0.07 | 14.65 | 0.19 |
| | (5.12) | (-21.29) | (5.48) | (-21.76) | (6.10) | (-11.85) | (5.56) | (-15.17) |
| | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} |
| Spring barley | 19.83 | **1.11** | 19.94 | **1.20** | 17.77 | **0.54** | 21.33 | **1.73** |
| | (7.29) | **(0.31)** | (7.46) | **(0.55)** | (9.72) | **(-0.67)** | (7.96) | **(0.85)** |
| | {0.00} | **{0.75}** | {0.00} | **{0.58}** | {0.00} | **{0.50}** | {0.00} | **{0.40}** |
| Winter beans | 11.49 | 0.20 | 11.24 | 0.22 | **0.47** | **1.02** | 9.81 | 0.31 |
| | (6.06) | (-9.89) | (6.11) | (-9.74) | **(0.17)** | **(0.11)** | (4.91) | (-7.48) |
| | {0.00} | {0.00} | {0.00} | {0.00} | **{0.86}** | **{0.91}** | {0.00} | {0.00} |
| Spring beans | 9.51 | 0.34 | 9.52 | 0.34 | **-1.39** | **1.26** | 9.53 | 0.34 |
| | (4.98) | (-7.30) | (4.99) | (-7.30) | **(-0.55)** | **(1.35)** | (4.99) | (-7.31) |
| | {0.00} | {0.00} | {0.00} | {0.00} | **{0.58}** | **{0.18}** | {0.00} | {0.00} |
| Ware potatoes | **-1.75** | 0.37 | **-1.99** | 0.37 | 1.76 | 0.36 | 4.83 | 0.26 |
| | **(-1.10)** | (-20.47) | **(-1.25)** | (-20.35) | (2.25) | (-11.60) | (2.60) | (-10.82) |
| | **{0.27}** | {0.00} | **{0.21}** | {0.00} | {0.03} | {0.00} | {0.01} | {0.00} |
| Winter OSR | 24.07 | 0.78 | 20.13 | 0.79 | 21.43 | 0.74 | 27.21 | 0.62 |
| | (8.49) | (-4.12) | (6.5) | (-3.66) | (8.78) | (-3.89) | (8.79) | (-7.13) |
| | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} |
| Sugar beet | 13.34 | 0.58 | 13.34 | 0.58 | 5.80 | 0.14 | 6.27 | 0.43 |
| | (4.99) | (-4.89) | (4.99) | (-4.89) | (5.19) | (-29.56) | (2.94) | (-21.90) |
| | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} |
| Set-aside | 10.11 | 0.23 | 10.33 | 0.24 | 13.75 | -0.01 | 9.78 | 0.21 |
| | (4.50) | (-23.68) | (4.64) | (-23.30) | (8.43) | (-26.64) | (3.92) | (-22.20) |
| | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} |

* MAD = £20,000, ** Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). The values in parentheses are the t-values whereas the values in curly brackets are the corresponding p-values for both the intercept (α) and the slope (β). The values in bold represent t-test results which show that the slope and intercept were different from one and zero respectively.

### 3.11.5 Individual-level comparisons between predicted and observed fertiliser amounts

Comparing predicted fertiliser amounts with FBS fertiliser amounts showed that the models predicted fertiliser amounts very well. The estimates for correlation and $R^2$ showed good association between observed and predicted fertiliser amounts under all four models ($r > 0.64$, $\rho > 0.46$; p-value = 0.00, $R^2$ between 0.40 and 0.80) (see Table 3-8). Also, the non-zero slopes from the regression of predicted fertiliser amounts versus observed fertiliser amounts showed the existence of a positive relationship (see Table 3-9) between predicted and observed fertiliser amounts. However, the results of the t-tests (Table 3-9) showed that the intercept and slope of the predicted and observed fertiliser amounts for each of the fertiliser types were different from zero and one respectively.

Table 3-8: Correlation and coefficient of determination estimates for comparing predicted fertiliser amounts to observed fertiliser amounts at the individual level.

| Fertiliser Type | Pure Profit Model | | | Nitrate Leaching Model | | | Risk (MOTAD) Model * | | | WGP Model ** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | r | ρ | $R^2$ | r | ρ | $R^2$ | r | ρ | $R^2$ | r | ρ | $R^2$ |
| N fertiliser | 0.83 (0.00) | 0.77 (0.00) | 0.70 | 0.83 (0.00) | 0.77 (0.00) | 0.70 | 0.74 (0.00) | 0.69 (0.00) | 0.55 | 0.85 (0.00) | 0.76 (0.00) | 0.72 |
| P fertiliser | 0.77 (0.00) | 0.61 (0.00) | 0.60 | 0.78 (0.00) | 0.61 (0.00) | 0.60 | 0.64 (0.00) | 0.48 (0.00) | 0.41 | 0.79 (0.00) | 0.62 (0.00) | 0.63 |
| K fertiliser | 0.78 (0.00) | 0.56 (0.00) | 0.61 | 0.78 (0.00) | 0.54 (0.00) | 0.61 | 0.64 (0.00) | 0.46 (0.00) | 0.40 | 0.79 (0.00) | 0.56 (0.00) | 0.63 |
| NPK fertiliser | 0.87 (0.00) | 0.78 (0.00) | 0.76 | 0.87 (0.00) | 0.78 (0.00) | 0.76 | 0.78 (0.00) | 0.69 (0.00) | 0.61 | 0.89 (0.00) | 0.78 (0.00) | 0.80 |

* MAD = £20,000, ** Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). Note: Values in parenthesis represent the p-values.

Table 3-9: Results of the t-test on the intercept and slope of the regression of observed fertiliser amounts on predicted fertiliser amounts at the individual level.

| Fertiliser Type | Pure Profit Model | | Nitrate Leaching Model | | Risk (MOTAD) Model * | | WGP Model ** | |
|---|---|---|---|---|---|---|---|---|
| | α | β | α | β | α | β | α | β |
| N fertiliser | 38.55<br>(5.44)<br>{0.00} | 0.84<br>(-460)<br>{0.00} | 36.93<br>(5.20)<br>{0.00} | 0.85<br>(-4.48)<br>{0.00} | 40.72<br>(4.83)<br>{0.00} | 0.90<br>(-1.97)<br>{0.05} | 30.20<br>(4.33)<br>{0.00} | **0.98**<br>**(-0.57)**<br>**{0.57}** |
| P fertiliser | 17.42<br>(4.83)<br>{0.00} | 0.59<br>(-14.10)<br>{0.00} | 17.02<br>(4.70)<br>{0.00} | 0.60<br>(-14.03)<br>{0.00} | 11.70<br>(2.29)<br>{0.02} | 0.75<br>(-4.30)<br>{0.00} | 13.08<br>(3.64)<br>{0.00} | 0.72<br>(-8.53)<br>{0.00} |
| K fertiliser | 22.93<br>(5.14)<br>{0.00} | 0.60<br>(-14.32)<br>{0.00} | 22.74<br>(5.07)<br>{0.00} | 0.60<br>(-14.27)<br>{0.00} | 22.47<br>(3.70)<br>{0.00} | 0.72<br>(-5.03)<br>{0.00} | 18.95<br>(4.22)<br>{0.00} | 0.72<br>(-8.59)<br>{0.00} |
| NPK fertiliser | 74.63<br>(6.49)<br>{0.00} | 0.70<br>(-12.72)<br>{0.00} | 72.38<br>(6.29)<br>{0.00} | 0.70<br>(-12.63)<br>{0.00} | 64.03<br>(4.24)<br>{0.00} | 0.82<br>(-4.24)<br>{0.00} | 56.13<br>(5.17)<br>{0.00} | 0.84<br>(-6.45)<br>{0.00} |

* MAD = £20,000, ** Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). The values in parentheses are the t-values whereas the values in curly brackets are the corresponding p-values for both the intercept (α) and the slope (β). The values in bold represent t-test results which show that the slope and intercept were different from one and zero respectively.

### 3.11.6 Individual-level comparisons between predicted and observed farm revenues and costs

Various degrees of association were found between predicted farm revenues/costs and FBS revenues/costs when they were compared at the farm individual level. The associations are reflected in the estimates for correlation and $R^2$ (see Table 3-10). Comparatively the r, ρ and $R^2$ estimates under the MOTAD model were relatively low however the estimates for Spearman correlation were relatively high especially for fertiliser cost, fuel cost, fixed cost and gross margin. The results of the t-test (see Table 3-11) showed that the intercepts and slopes were different from zero and one respectively, with the exception of a few (shown in bold in Table 3-11) which showed that the intercept and slope were not different from zero and one respectively.

Table 3-10: Correlation and coefficient of determination estimates for comparing predicted farm revenues/costs with observed farm revenue/cost at the individual level.

| Revenue/ Cost Type | Pure Profit Model | | | Nitrate Leaching Model | | | Risk (MOTAD) Model * | | | WGP Model ** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | r | ρ | $R^2$ | r | ρ | $R^2$ | r | ρ | $R^2$ | r | ρ | $R^2$ |
| Gross margin | 0.71 (0.00) | 0.70 (0.00) | 0.50 | 0.71 (0.00) | 0.70 (0.00) | 0.50 | 0.37 (0.00) | 0.59 (0.00) | 0.14 | 0.72 (0.00) | 0.71 (0.00) | 0.52 |
| Profit | 0.58 (0.00) | 0.43 (0.00) | 0.34 | 0.58 (0.00) | 0.43 (0.00) | 0.34 | 0.27 (0.00) | 0.35 (0.00) | 0.07 | 0.44 (0.00) | 0.43 (0.00) | 0.19 |
| Fixed cost | 0.71 (0.00) | 0.64 (0.00) | 0.51 | 0.71 (0.00) | 0.64 (0.00) | 0.51 | 0.48 (0.00) | 0.51 (0.00) | 0.23 | 0.74 (0.00) | 0.66 (0.00) | 0.55 |
| Labour cost | 0.29 (0.00) | 0.43 (0.00) | 0.08 | 0.32 (0.00) | 0.45 (0.00) | 0.10 | 0.03 (0.62) | 0.23 (0.00) | 0.00 | 0.33 (0.00) | 0.44 (0.00) | 0.11 |
| Fertiliser cost | 0.85 (0.00) | 0.80 (0.00) | 0.73 | 0.85 (0.00) | 0.80 (0.00) | 0.73 | 0.66 (0.00) | 0.71 (0.00) | 0.43 | 0.86 (0.00) | 0.79 (0.00) | 0.74 |
| Seed cost | 0.46 (0.00) | 0.73 (0.00) | 0.21 | 0.46 (0.00) | 0.72 (0.00) | 0.21 | 0.10 (0.10) | 0.63 (0.00) | 0.01 | 0.49 (0.00) | 0.74 (0.00) | 0.24 |
| Fuel cost | 0.80 (0.00) | 0.65 (0.00) | 0.64 | 0.81 (0.00) | 0.64 (0.00) | 0.65 | 0.43 (0.00) | 0.50 (0.00) | 0.18 | 0.76 (0.00) | 0.63 (0.00) | 0.58 |

* MAD = £20,000, ** Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). Note: Values in parenthesis represent the p-values.

Table 3-11: Results of the t-test on the intercept and slope of the regression of observed farm revenue/cost on predicted farm revenue/cost at individual level.

| Revenue/ Cost Type | Pure Profit Model | | Nitrate Leaching Model | | Risk (MOTAD) Model * | | WGP Model ** | |
|---|---|---|---|---|---|---|---|---|
| | α | β | α | β | α | β | α | β |
| Gross margin | **164.59** | 1.67 | **162.77** | 1.68 | **210.88** | 1.56 | **-151.21** | 2.63 |
| | **(1.66)** | (6.72) | **(1.64)** | (6.72) | **(1.30)** | (2.29) | **(-1.39)** | (10.70) |
| | **{0.10}** | {0.00} | **{0.10}** | {0.00} | **{0.20}** | {0.02} | **{0.17}** | {0.00} |
| Profit | 140.92 | 0.81 | 142.85 | 0.81 | 148.61 | 0.59 | 204.46 | 1.58 |
| | (5.56) | (-2.77) | (5.64) | (-2.81) | (6.91) | (-3.07) | (7.42) | (2.99) |
| | {0.00} | {0.01} | {0.00} | {0.01} | {0.00} | {0.00} | {0.00} | {0.00} |
| Fixed cost | **2.39** | 0.62 | **-0.23** | 0.62 | **-18.99** | 0.65 | **-18.28** | 0.69 |
| | **(0.09)** | (-10.54) | **(-0.01)** | (-10.47) | **(-0.41)** | (-4.61) | **(0.74)** | (-8.12) |
| | **{0.93}** | {0.00} | **{0.99}** | {0.00} | **{0.68}** | {0.00} | **{0.46}** | {0.00} |
| Labour cost | 239.31 | 0.25 | 225.80 | 0.30 | 297.17 | **0.29** | 206.15 | 0.62 |
| | (4.73) | (-15.38) | (4.48) | (-13.30) | (3.40) | **(-1.24)** | (4.02) | (-3.42) |
| | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | **{0.22}** | {0.00} | {0.00} |
| Fertiliser cost | 29.40 | 0.77 | 27.93 | 0.78 | 47.36 | 0.77 | 18.38 | 0.91 |
| | (3.23) | (-7.95) | (3.05) | (-7.86) | (3.56) | (-4.13) | (2.03) | (-2.85) |
| | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} | {0.04} | {0.01} |
| Seed cost | **18.33** | **0.96** | **16.77** | **0.97** | 100.45 | 0.31 | 33.55 | **0.85** |
| | **(0.80)** | **(-0.32)** | **(0.72)** | **(-0.31)** | (3.27) | (-3.53) | (1.59) | **(-1.65)** |
| | **{0.42}** | **{0.75}** | **{0.47}** | **{0.76}** | {0.00} | {0.00} | {0.11} | **{0.10}** |
| Fuel cost | **10.90** | 0.81 | **7.44** | 0.86 | 64.59 | 0.23 | 64.24 | 0.15 |
| | **(1.84)** | (-5.09) | **(1.26)** | (-3.84) | (10.28) | (-24.71) | (12.90) | (-115.0) |
| | **{0.07}** | {0.00} | **{0.21}** | {0.00} | {0.00} | {0.00} | {0.00} | {0.00} |

* MAD = £20,000, ** Weights: Profit maximisation = 0.8 (Target = £76,000), Nitrate leaching minimisation = 1 (Target = 10000 kg N), Risk minimisation = 0.05 (Target = £20,000). The values in parentheses are the t-values whereas the values in curly brackets are the corresponding p-values for both the intercept (α) and the slope (β). The values in bold represent t-test results which show that the slope and intercept were different from one and zero respectively.

## 3.12 Discussion and conclusion

In this chapter, four variants of arable farm models developed as part of the overall research aim have been described. These models were built combining mixed-integer, goal and risk programming approaches and using data such as farm management, soil and subsidy payments data. Also, using a different set of data, the Farm Business Survey (FBS) data from 281 lowland arable farms and a predictive validation approach, the models have been validated. We have conducted comparisons of the modelled results with the observed results at both aggregate and individual farm level. The aggregate-level comparison showed a positive relationship between predicted and observed crop areas with better fit observed under the MOTAD and WGP models, which explicitly incorporated farm risk. The individual level comparisons showed various degrees of association between predicted and observed crop areas.

Optimisation models based on linear programming and related approaches have been developed to investigate issues relating to agricultural land use (e.g. ten Berge *et al.*, 2002; Annetts and Audsley, 2002; Rounsevell *et al.*, 2003; Oglethorpe, 2010; Osgathorpe *et al.*, 2011; Cooke *et al.*, 2013). Although some of the approaches and/or formulations used by Annetts and Audsley (2002) and Cook et al. (2013) were adopted in developing the models presented in this thesis, there are some differences between our model and theirs, especially our multiple objective models (MOTAD and WGP). The models developed by Annetts and Audsley (2002) and Cooke *et al.*, (2013) were multiple objective linear/mixed-integer models, which may be prone to generating infeasible solutions due to the expression of other goals as inequality constraints which must be enforced. We developed the mixed-integer WGP model in which goals or objectives serve as constraints but are expressed as equations, and explicitly incorporate risk.

Unlike Cooke *et al.* (2013), in our MOTAD and WGP models the expected deviation in income acts as a model input to allow potential users to input their own deviation (risk) values as well as run the model at different income deviation (risk) levels to observe the effect on crop plan and the farming objectives. The machine numbers selected by our models are integers[16] and although integer machine numbers may lead to high fixed cost and lower profit estimates, the problem of infeasibility due to rounding up or down of optimal machine numbers is prevented. However, depending on the user's objective, the machine/labour numbers can be set as non-integers.

Again, unlike Annetts and Audsley (2002), the nitrate leaching estimates in our models were based on the N balance approach used by Wossink (1993) and uses data which are relatively not difficult to update. This approach was adopted due to the possibility of linking nitrate-leaching estimates (kg N/ha) to the recommended fertiliser amounts for crops in Defra (2010) using the soil type. Also, it makes it possible to convert nitrate estimates in kg N/ha to amounts (g/l),

[16] The model can still be solved to generate non-integer machine numbers if non-integer machine numbers are preferred.

which leach into ground water at a depth of one metre using the annual rainfall amount.

Validation of models has been conducted as part of model development process to increase the confidence level of potential model users (e.g. Abedingpour *et al.*, 2012; Cooke *et al.*, 2013; Gueymard, 2014). The models presented in this chapter were validated using predictive validation which is the most common form of validation (McCarl and Spreen, 1997) and the model results compared to observed data for 281 arable farms using statistical measures of association. A similar approach was used by Cooke *et al.* however, they used 150 farms and also no comparison was done between predicted and observed variables such as fertiliser quantities and farm costs and revenues. Also the main statistical measures of association they applied were primarily regression analysis and Spearman correlation.

In comparing our model results to the observed FBS data, statistical measures such as correlation coefficients, coefficient of determination and t-test in addition to mean absolute error (MAE) and root mean square error (RMSE) which measure dispersion of individual points (Gueymard, 2014) were applied. The Nash-Sutcliffe's model efficiency (NSE) proposed by Mayer and Butler (1993) as the best overall measure of model performance was also applied to measure model performance. In addition to the above measures was a graphical method (scatter plots with regression line) to observe biases and trends. Each of the statistical measures of association has its strengths and weaknesses. Thus the inclusion of more statistical measures was to draw on their strengths and present results that will give potential users of the models or proponents of the different measures of association better understanding of the accuracy or predictive power of our models. For example, correlation coefficients show the presence of relationships between predicted and observed data whereas NSE and the coefficient of residual mass (CRM) show the efficiency with which the models predict and whether the models over- or under-predict respectively. Thus combining these different measures can give different information about the model, which better informs potential users about the accuracy and predictive powers of the models.

The aggregate-level comparisons both gave better fits as far as crop area comparisons were concerned. The aggregate level comparisons based on the result for the 'average' farm (AL-1) made it possible to see better the changes in crop plan under each model. Pearson correlation shows the linear association between two values and according to Loague and Green (1991), part of the operational examination of models is the assessment of models' precision, which is the degree to which the model-predicted values approach a linear function of the observed data. Thus with relatively high linear correlation, it can be said that the models predict with relatively good precision. Winter wheat was the dominant crop and models predicted it more accurately than the other crops. Thus the poor correlation based on ranking of crops is because the rank order of the other crops is not predicted well. From a farmer behaviour perspective, it is likely that winter wheat may be chosen first and choice of the next crop may be context dependent. In terms of model comparison, the MOTAD model (and WGP under AL-1 comparison) gave better fits than pure profit and nitrate leaching models. Cooke *et al.* (2013) found a similar result when the farmR model was validated and attributed it to the inclusion of risk preferences of farmers.

The individual level comparison showed various degrees of association between predicted and observed crop areas reflecting how dominant some of the crops are in the arable landscape (e.g. winter wheat). Cooke *et al.* (2013) also found various degrees of association in their individual-level comparison when predicted crop areas were regressed on crop gross margins. The individual level comparison of farm revenues/costs also showed various degrees of association with a high degree of association for fertiliser costs. The good linear relationship between predicted and observed fertiliser amounts is an indication of the precision with which the models predict fertiliser amounts. This is because model precision indicates how model results approach a linear function of the observed data (Loague and Green, 1991).

The result for fertiliser cost is not surprising considering the good prediction of fertiliser amounts, which determine the fertiliser cost. The results for fixed and fuel costs may be due to the fact that there is some high degree of accuracy and precision associated with machine numbers selected by the models. The results for gross margin may be a reflection of the accuracy with which the models predicted crop areas, seed and fertiliser costs. The low estimates under the MOTAD model may be due to the fact that in a MOTAD model profit is maximised subject to the risk minimisation constraint, which may result in more crop diversification, which in turn has the potential to affect the estimation of farm revenues or costs.

In terms of the models' predictive powers, results showed that the models predicted crop areas and fertiliser amounts better than the farm revenues/costs. The better prediction of crop areas can be attributed to the fact that the models were developed to select optimal crop plans and that factors such as soil type and rainfall which influence efficient farm planning were captured and modelled, hence the better prediction of crop areas. The better prediction of fertiliser amounts by the models could also be due to the fact that the fertiliser amounts used in building the model were the recommended rates from Defra (2010), which are also the recommended rates guiding fertiliser application by arable farmers in the FBS and hence the small deviations between predicted and observed amounts.

The severe under-prediction of gross margin and profit may be due to the variability in crop prices due to factors which the farmers do not have control over. Again, in terms of the under-prediction of profit, it may also be due to high fixed cost estimates due to integer machine numbers selected by the models and the costs (prices) of machines selected to build the models. Comparatively, profit estimates by mixed-integer programming (MIP) models are normally lower than estimates by traditional linear programming models due to the extra constraints to force the models to select some activities as integers and with our models being MIP, profit estimates are likely to be low, hence the under-prediction. Labour costs were also under-predicted and again this reflects the variability in the labour requirements by different farms, which are influenced by factors that were not captured in the models as well as the integer labour numbers selected by the models. However, there was fairly good prediction of fertiliser cost, seed cost and fuel cost. In terms of individual-level comparison, there were positive correlations between the predicted and observed revenues/costs reflecting the predictive power of the models with respect to farm revenues and costs.

In general, the models predicted crop areas and fertiliser amount better than farm revenues/costs. The results of the validation reflect the strengths and weaknesses of the models in predicting crop areas, fertiliser amounts and farm revenues/costs however, some degrees of positive association or correlation were observed between model predictions and FBS data. This implies that based on the information/assumptions and data used and model specification, the models can make reasonably good predictions of crop areas as well as fertiliser amounts, which can provide insight into arable farming decision-making. However, with model calibration and validation seen as continuous processes in model development, continued calibration followed by validation and updating of models with detailed data could enhance their predictive powers and performance.

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# Appendix

Table 3-12: Crops and sequential operation matrix.

| Crop | Sequential Operations | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| Winter wheat | | + | + | | + | + | | + | + | + | | | |
| Spring wheat | | + | + | | + | + | | | + | + | | | |
| Winter barley | | + | + | | + | + | | + | + | + | | | |
| Spring barley | | + | + | | + | + | | | + | + | | | |
| Winter beans | | + | + | | + | + | | + | + | | | | |
| Spring barley | | + | + | | + | | | | + | | | | |
| Ware potatoes | | | + | + | + | | + | | | | + | | |
| Winter oilseed rape | | + | + | | + | | | | + | | | | |
| Sugar beet | | | + | + | + | | | | | | | + | |
| Set-aside | + | | + | | | | | | | | | | + |

1 = Start; 2 = P/K Fertiliser Spreading; 3 = Ploughing; 4 = Harrowing; 5 = Planting; 6 = Rolling; 7 = Ridging; 8 = Spraying; 9 = Combine harvesting; 10 = Baling; 11 = Potato harvesting; 12 = Sugar beet harvesting; 13 = End.
Note: The plus (+) means the operation is part of a set of operations for a crop.

Table 3-13: Model data and sources. Some data were obtained from the farmR model and in such instance data sources is listed as farmR model data

| Data | Unit | Source | Remarks |
|---|---|---|---|
| Annual labour cost | £/annum | Nix (2014)<br>farmR model data | |
| Crop rotation constraint due to disease | Number of years | Toosey (1988)<br>Jellings and Fuller (1995) | |
| Crop prices | £/t | Defra (2014b) | Agricultural Price Indices |
| Crop yields | t/ha | farmR model | Based on formulae used in the farmR model |
| Fertiliser amounts | kg/ha | Defra (2010) | Fertiliser Manual (RB209) |
| Fertiliser costs/prices | £/kg | ABC (2014) | Agro Business Consultants |
| Fuel price (Red Tractor Diesel) | £/l | ABC (2014) | Agro Business Consultants |
| Machinery depreciation rates | % | farmR model data | |
| Machinery repair/maintenance cost rates | % | farmR model data | |
| Machinery replacement rate | Years | farmR model data | |
| Penalties for suboptimal timing of operation | % | farmR model data | |
| Penalties due successive cropping | % | farmR model data | |
| Seed amounts | kg/ha | Toosey (1988) | |
| Seed cost/price | £/kg | ABC (2014) | Agro Business Consultants |
| Soil type indices | | farmR model data | |
| Rotational penalties | % | farmR model data | |
| Workable hours | hr | Tillett and Audsley (1987) | |
| Work rates for crop operations | hr/ha | Chamen and Audsley (1993) | |

Table 3-14: Data for gross margin and MOTAD (standard deviation) risk estimates

| Input/output Data* | Unit | Crops | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | WWHT | SWHT | WBAR | SBAR | WBEA | SBEA | WPOT | WOSR | SBEE | SETA |
| N fertiliser amount | kg/ha | 220 | 180 | 170 | 140 | 0 | 0 | 220 | 190 | 100 | -- |
| N fertiliser price | £/kg | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | -- |
| P fertiliser amount | kg/ha | 95 | 80 | 95 | 80 | 70 | 70 | 210 | 80 | 80 | -- |
| P fertiliser price | £/kg | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | -- |
| K fertiliser amount | kg/ha | 115 | 100 | 115 | 100 | 70 | 70 | 330 | 70 | 130 | -- |
| K fertiliser price | £/kg | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | -- |
| Seed amount | kg/ha | 185 | 195 | 175 | 175 | 200 | 225 | 2800 | 7 | 6 | -- |
| Seed price | £/kg | 0.4 | 0.38 | 0.37 | 0.38 | 0.41 | 0.43 | 0.25 | 7.37 | 91 | -- |
| Yield | t/ha | 10.56 | 6.76 | 8.1 | 6.28 | 5.75 | 4.82 | 39.53 | 3.22 | 65.27 | -- |
| Crop price | £/ha | 163 | 163 | 151 | 151 | 142 | 142 | 167 | 358 | 33 | -- |
| Subsidy SFP | £/ha | 207 | 207 | 207 | 207 | 207 | 207 | 207 | 207 | 207 | 207 |
| Sugar beet transport cost | £/t | -- | -- | -- | -- | -- | -- | -- | -- | 5 | -- |
| Sundry cost | £/ha | 211 | 140 | 154 | 108 | 98 | 92 | 2262 | 193 | 220 | 30 |
| Variable cost | £/ha | 574.9 | 455.5 | 468.7 | 383.9 | 257 | 265.8 | 3425.4 | 479.9 | 1283.9 | 30 |
| Output | £/ha | 1723.4 | 1103.2 | 1466 | 1136.8 | 818.8 | 686.2 | 6617.4 | 1152 | 2141 | 207 |
| Gross margin | £/ha | 1356 | 855 | 1204 | 960 | 769 | 627 | 3399 | 879 | 1064 | 177 |
| MOTAD Risk** | £/ha | 246 | 158 | 223 | 173 | 150 | 126 | 959 | 189 | 54 | 0 |

* Fertiliser amounts were based on recommended amounts for a heavy soil. ** MOTAD risk estimates are standard deviations estimates applied as representative of risk in the goal programming model. WWHT = Winter wheat; SWHT = Spring wheat; WBAR = Winter barley; SBAR = Spring barley; WBEA = Winter beans; SBEA = Spring beans; WPOT = Ware potatoes; WOSR = Winter oilseed rape; SBEE = Sugar beet; SETA = Set-aside.

Table 3-15: Deviations in gross margin for the MOTAD model

| Year | WWHT | SWHT | WBAR | SBAR | WBEA | SBEA | WPOT | WOSR | SBEE | SETA |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -371.9 | -238.5 | -315.65 | -244.9 | -192 | -160.75 | -608.4 | -92.89 | 13.15 | 0 |
| 2 | 92.1 | 59.5 | 97.35 | 75.1 | -54 | -44.75 | -450.4 | 220.11 | -51.85 | 0 |
| 3 | 124.1 | 79.5 | 235.35 | 182.1 | 26 | 23.25 | 260.6 | 139.11 | -51.85 | 0 |
| 4 | 261.1 | 167.5 | 122.35 | 94.1 | 222 | 186.25 | 1565.6 | -8.89 | 13.15 | 0 |
| 5 | -107.9 | -69.5 | -137.65 | -106.9 | -3 | -1.75 | -767.4 | -256.89 | 78.15 | 0 |

Table 3-16: Machine types and fixed/labour costs

| Machine | Capacity | Cost (Price) (£) | Depreciation Rate (%) | Replace Year | Depreciation (£) | Repair Cost Rate (£) | Repair Cost (£) | Annual Cost (£) |
|---|---|---|---|---|---|---|---|---|
| Tractor | 100kW | 50,000 | 22 | 5 | 7,972 | 12.05 | 6,025 | 13,997 |
| Power harrow | 3-4m | 16,000 | 14 | 4 | 3,492 | 5 | 800 | 4,292 |
| Sprayer | 1400 l | 21,000 | 18 | 7 | 2,533 | 6.8 | 1,428 | 3,961 |
| Combine harvester | 125kW | 95,000 | 18 | 7 | 11,459 | 5.8 | 5,510 | 16,969 |
| Baler | -- | 14,000 | 11 | 7 | 1,827 | 5.5 | 770 | 2,597 |
| Potato harvester | 2 row tailed | 80,000 | 18 | 7 | 9,650 | 6 | 4,800 | 14,450 |
| Sugar beet harvester | 2 row tailed | 70,000 | 18 | 7 | 8,443 | 5 | 3,500 | 11,943 |
| Annual labour cost | -- | -- | -- | -- | -- | -- | -- | 21,945 |

Note: Estimates were done taking into consideration an interest rate of 0.5%. Annual labour cost was obtained from Nix (2014). Prices/cost of machines were obtained from ABC (2014). In the context of mixed integer programing, the model selects integer machine numbers, for example the model may select 2 of the 100kW tractors whereas in reality a farmer with a smaller farm may need a smaller tractor say 50kW (0.5 of 100kW) or a farmer with a bigger farm size may need a 150kW tractor (1.5 of 100kW). Similar explanation cam be given to the other machine types as well as labour numbers. However, since the machine numbers generated by the model serve as a guide in farm planning, the machine numbers generated by the model can be said to be give good indication of machine selection.

***"A weed is a plant that has mastered every survival skill except for learning how to grow in rows."***

— Doug Larson

# 4 MODEL APPLICATION 1: GOAL-PROGRAMMING MODEL

*In Chapter 3, an arable farm level model informed by information from the first two chapters is described, verified and validated. Some of the factors and farm management practices identified and investigated in Chapters 1 and 2 were taken into consideration as constraints and parameters to build the model described in Chapter 3. The model was validated using predictive validation and Farm Business Survey (FBS) data for 281 lowland farms. The results of the validation through statistical measures of association showed good association between model predicted results and observed data. Modules in which risk was explicitly incorporated gave relatively better prediction than the ones in which risk was not explicitly modelled.*

*In this chapter, one of the modules in which risk was explicitly modelled, the mixed-integer weighted goal-programming model is applied to investigate the effect of using spring cropping to control black-grass, which is an important annual grass weed in UK arable farming. The study was primarily influenced by the need to make arable systems more sustainable with less or if possible no reliance on chemicals. With the potential of spring cropping reducing black-grass population or infestation, and hence reduce chemical input and cost, the incorporation of winter crop—spring crop rotation or sequence in crop plans is being encouraged. The study was also partly influenced by the Black-grass Resistance Initiative (BGRI) project. Again, in UK context, no study was found to have used the approach or the method adopted in this chapter as far as investigations on black-grass control strategies using optimisation or comparative static models are concerned.*

*Results show that at the aggregate level, spring cropping as black-grass control measure could cost the UK arable farming sector however, at the individual farm level, there could be cost (reduction in profit) or benefit (increase in profit) depending of the farm's characteristics such as soil type, rainfall pattern and area of land available to the farm. The policy implication of the results is that the estimates (on per hectare basis) give insight into possible farm payment to incentivise adoption of winter wheat—spring crop rotation as a black-grass control strategy and possibly reduce chemical input in arable farming systems.*

*A version of the study in this chapter was submitted to Agricultural Systems.*

**Sustainable weed control with rotational management: Estimating the aggregate cost of controlling black-grass (*Alopecurus myosuroides*) with spring cropping in UK arable farming**

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## Abstract

Black-grass is the most significant grass weed in UK arable farming and widespread herbicide resistance frequently renders chemical applications ineffective. High infestations of the weed can cause substantial yield losses and in the UK potential wheat yield losses from black-grass are estimated to lead to revenue losses ranging from around £57/ha to £422/ha. As a result, the use of non-chemical control measures such as rotation of winter wheat with spring crops is being promoted alongside chemical control in order to reduce black-grass infestation and herbicide cost. However, this strategy incurs a financial penalty because spring crops are also associated with lower yields. There is therefore a trade-off between reduced herbicide use and decreased yield penalties, and the reduced profit from spring crops. Here we investigate these costs of black-grass control using a farm level mixed-integer goal-programming model. We use Farm Business Survey data for 745 farms to parameterise the model to determine the optimal profit when spring cropping is used to control black-grass, compared with only chemical control. We find that in the short-term the loss of profit from spring cropping outweighs the benefits in terms of reduced herbicide usage and reduced yield penalties. Our results show that under a scenario of low black-grass infestation, controlling black-grass with a winter wheat—spring barley rotation could cost UK arable farming about £286 million (£82/ha) whereas controlling black-grass with winter wheat—spring beans rotation could cost UK arable farming about £650 million (£187/ha). Under a scenario of a very high black-grass infestation, controlling black-grass with winter wheat—spring barley rotation could cost UK arable farming about £35 million (£10/ha) whereas winter wheat—spring beans rotation could cost UK arable farming about £87 million (£25/ha). In a policy context, these cost estimates indicate possible policy payments needed to

incentivise adoption of spring cropping as a black-grass control measure depending on the level of infestation. Our results also suggest that if spring cropping is to be a successful strategy then the benefits to farmers will be in terms of long-term reductions in weed densities, but at the expense of short-term profitability.

## 4.1 Introduction

The world's population has been projected to increase by 34% by 2050 (UN-DESA, 2013), meaning that demand for food will continue to increase. Agricultural production thus needs to be intensified in order to meet the growing food demand. However, such intensification can result in externalities to the environment such as pollution of water sources due to increased use of inputs such as pesticides to safeguard crop yields and hence productivity (Vasileiadis *et al.*, 2011; Skevas *et al.*, 2013; Skevas and Lansink, 2014). This has led to the need to make agricultural systems more sustainable (Pandey *et al.*, 1993). However, sustainability of agricultural systems such as arable systems cannot be achieved without the adoption of efficient or sustainable pest management or control strategies because pests affect the sustainability of farming systems (Gilioli *et al.*, 2016). Some pests compete with arable crops for soil nutrients, water and sunlight whereas others feed on crops as well as damage the crop physiology and thus serious pest infestations can reduce the yield potential of arable crops (Flint and van den Bosch, 1981; Mumford, 1981; Sells, 1995) and make arable systems unsustainable as well as threaten food security.

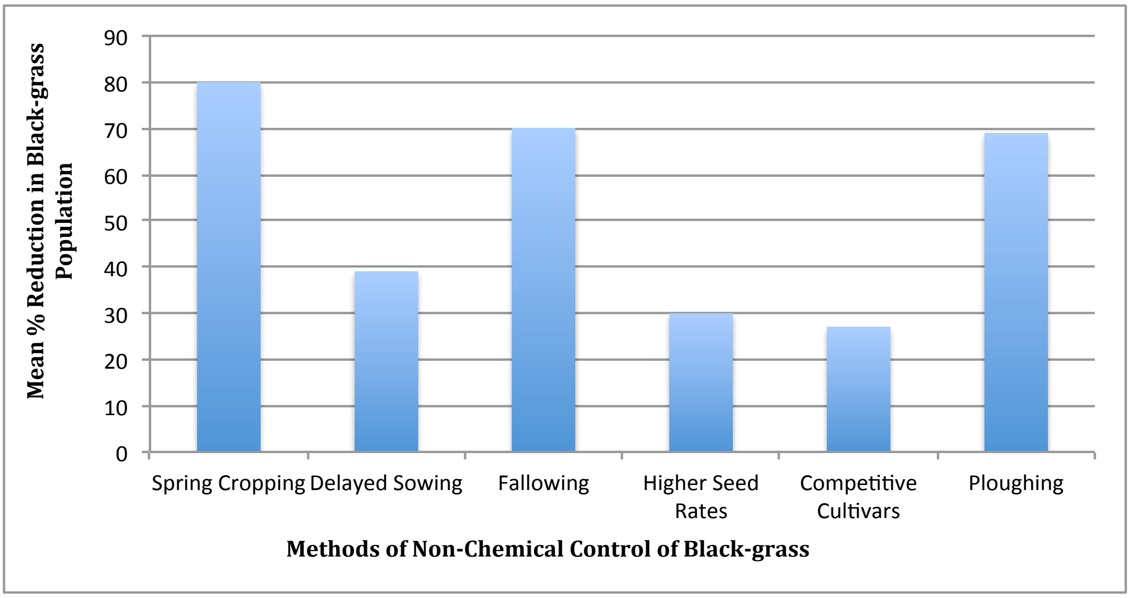
The common practice over the years has been the use of chemicals to control pests, resulting in pollution of water sources and the environment as well as impact on human health (Wijnands, 1997; Cuyno *et al.*, 2001; Carvalho, 2006; EC, 2007; Chalak *et al.*, 2008; Lodovichi *et al.*, 2013; Kouser and Qaim, 2015; Yaguana *et al.*, 2016). As a result, the European Commission's (EC, 2008) proposed a strategy to ensure safer use of pesticides. The strategy became mandatory in 2014 and it requires each member state to create the conditions necessary for implementing the Integrated Pest Management (IPM) system. The IPM system involves the use of multiple strategies for optimizing the control of all classes of pests in an ecologically and economically sound manner (Ehler, 2006). The IPM system promotes the use of pest management strategies that relies heavily on non-chemical pest management strategies or cultural practices and thus it prescribes minimum or sometimes no use of chemicals; prevents the use of chemicals with certain active ingredients or substances (Flint and van den Bosch, 1981; Wijnands, 1997; Sandler, 2010; Whitehouse, 2011; Hillocks, 2012; Ahuja *et al.*, 2015; Yaguana *et al.*, 2016). Examples of IPM practices are planned rotation, improving field margins, the cultivation of insect resistant crop varieties and adjustments in timing of operations (Bailey *et al.*, 2009).

As part of the IPM, the Integrated Weed Management (IWM) system has been created to promote a sustainable means of managing weeds (Chikowo *et al.*, 2009; Pardo *et al.*, 2010). Like the IPM, the IWM principles promote the use of cultural practices to control weeds, limits weed infestations with low or no reliance on herbicides and if possible without any side effects on the productivity and the total system economic performance (Chikowo *et al.*, 2009). Practices recommended under the IWM system include the use of tillage practices (e.g. ploughing), cultural practices (e.g. delayed sowing) and crop rotation (with spring cropping) (Moss and Hull, 2012; Lutman *et al.*, 2013; HGCA, 2014a; Bayer, 2015). Adoption of IWM strategies are associated with opportunity costs in terms of how much farm revenues may be lost due to reductions in yield. There can also be opportunity cost in terms of what costs may be saved or incurred due to changes in input use or the inclusion of a farm operation or a cultural practice and how much deviation in farmers' income (risk) may occur due to the risk associated with crop types. However, experimental investigations on the effectiveness of IWM strategies on weeds do not focus on such costs.

There are numerous weed species found on arable fields in the UK depending on the crop type and other factors such as soil type. Black-grass (*Alopecurus myosuroides* Huds.) is the most important annual grass weeds in the UK and Europe (Lutman *et al.*, 2013). It is a very competitive grass weed with the ability to produce large quantities of seeds to enhance its proliferation and can cause substantial yield reduction in arable crops especially in autumn (winter) sown crops (Gerowitt, 2003; Lutman *et al.*, 2013; Keshtkar *et al.*, 2015). The above traits of black-grass coupled with the frequency of growing autumn sown crops in the UK contribute to the increase in black-grass infestations, which require a high level of control (HGCA, 2008; Lutman *et al.*, 2013; Bayer, 2015; Keshtkar *et al.*, 2015). As with most pests, the control of black-grass in arable farming over the years has been primarily through the use of chemicals. However, it has developed resistance to a number of herbicidal active ingredients which has made control through herbicide application ineffective and unreliable, making black-grass the number one herbicide resistant weed in Europe (Moss *et al.*, 2007; Lutman *et al.*, 2013; Bajwa, 2014; Matzrafi *et al.*, 2014; Keshtkar *et al.*, 2015). Clearly, further (and potentially futile) application of herbicide adds to negative impacts on the environment (Wu, 2001; Chikowo *et al.*, 2009; Pardo *et al.*, 2010; Beltran *et al.*, 2012; Deytieux *et al.*, 2012; Bajwa, 2014) and the continued presence of black-grass has a significant impact on crop yields. Black-grass populations as low as 8-12 plants/m$^2$ has the potential to reduce winter wheat yield by 2-5% whereas populations of about 300 plants/m$^2$ can reduce yields by 37% (Bayer, 2015). For example, at an average yield level of 10.39 t/ha for winter wheat (AHDB control mean in 2015) and feed wheat price of £110/t, this could lead to costs to the sector of between £57/ha to £422/ha assuming 5% and 37% yield reduction respectively. We therefore have a major agricultural economic issue to deal with—the need for a response to alternative crop husbandry to mitigate black-grass and the need to re-balance the financial consequences of yield loss through black-grass infestation.

IWM strategies for black-grass control include tillage practices (e.g. ploughing), cultural practices (e.g. delayed sowing) and crop rotation (with spring cropping) (Moss and Hull, 2012; Lutman *et al.*, 2013; HGCA, 2014a; Bayer, 2015). However, this study focuses on the control of black-grass using crop rotation, specifically mandating spring cropping instead of winter cropping to control black-grass. The focus on crop rotation with spring cropping is primarily due to the fact that crop rotation with spring cropping is beneficial in several respects for the sustainability of agricultural systems (Schönhart *et al.*, 2011; HGCA, 2014a).

Also, the focus on spring cropping was made because the choice of crops in a rotation sets the basis for every weed management strategy (HGCA, 2014a). Again, among the set of non-chemical black-grass control strategies, crop rotation with spring cropping has been found to be more effective in reducing black-grass population or densities (Gerowitt, 2003; Bajwa, 2014). In some trials, sowing spring barley and spring wheat resulted in between 78% and 96% reductions in black-grass population relative to sowing winter crops whereas delayed sowing resulted in about 39% reduction (Moss and Hull, 2012; Lutman *et al.*, 2013) (see Figure 4-1 for the percentage reduction in black-grass population from the application of different methods of non-chemical control). This is because as black-grass germinates primarily in the autumn (and does not grow in spring-sown crops), winter-sown crops (mainly cereals) tend to favour the weed, as there is limited opportunity for weed control once the crop is established. In addition to the above, crop rotations with spring crops have been found to spread the workload on arable fields across the year, impact upon weed species and numbers and, in addition, can be beneficial for biodiversity (HGCA, 2014a). The inclusion of spring crops into the arable farm rotation is thus being encouraged since it allows for the autumn germination of black-grass to be killed off before establishment of spring-sown crops. Hence, the focus of spring cropping as a black-grass control strategy in the study is primarily due to its effectiveness in reducing black-grass population compared to other non-chemical weed strategies such as ploughing and delayed sowing, and also additional benefits such as benefit to biodiversity that the other management tools do not have.




Source: Bayer and Syngenta[17]. Note: The reduction in black-grass population under fallowing is on per year basis.

Figure 4-1: Reduction in black-grass population due to application of different methods of non-chemical control

However, spring crops also tend to be associated with lower yields and lower economic returns: winter wheat tends to dominate production in many areas because it is a more profitable crop. Thus, the adoption of such black-grass control measure could be associated with opportunity cost in terms of how much profit could be lost or how much savings could be made on chemical cost due to switching from a winter crop to a spring crop. This can be demonstrated using data from Nix (2014)—the gross margin for winter wheat and spring barley are £833/ha and £647/ha respectively whereas their respective herbicide costs are £70/ha and £48/ha. Switching from winter wheat to spring barley as part of measures to control black-grass reduces gross margin by £183/ha whereas herbicide cost reduces by £22/ha. Thus following a winter crop with a spring crop is likely to reduce herbicide input and cost but with a bigger reduction in revenue due to lower yields associated with spring crops (Pardo *et al.*, 2010; Moss and Hull,

[17] Bayer:
http://cropscience.bayer.co.uk/mediafile/261469/m27018_bgtf_cereals_brochure_a6_aw.pdf

Syngenta: https://www.syngenta.co.uk/black-grass/cultural

2012, Bayer, 2015). This means that each system will be associated with different levels of economic returns and hence risk. These need to be evaluated against the benefits of a reduction in black-grass infestation the system creates and the associated reduction in herbicide application costs. The following research questions are therefore asked:

1. What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring barley rotation?
2. What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring beans rotation?
3. Is there any effect of controlling black-grass with spring cropping on farm risk?
4. What is the effect of controlling black-grass with spring cropping on farm costs?
5. Is there any policy implication of the results?

Investigations on the effect of spring cropping on black-grass control are normally based on population monitoring in field experiments (e.g. Gerowitt, 2003; Chikowo *et al.*, 2009; Deytieux *et al.*, 2012; Moss and Hull, 2012; Keshtkar *et al.*, 2015). However, mathematical farm models based on linear programming and related approaches can serve as an alternative to field experiments, which may be expensive and time consuming. Such approaches have the capability to capture many of the complexities associated with arable farming weed management strategies through the imposition of winter crop—spring crop sequence or rotational constraints. Some studies (e.g. Pardo *et al.*, 2010; Beltran *et al.*, 2012) have used dynamic farm-modelling approaches to investigate non-chemical weed management strategies under the IWM however, none of these studies estimated the cost of black-grass control at the national scale using non-chemical means. Also, approaches like dynamic programming although suitable for handling multi-period problems, may be time consuming especially in situations where there are more stages or state variables under consideration (Kaiser and Messer, 2011) and unlike linear programming, in some instances dynamic programming approaches are likely to generate solutions for sub-problems, which may just be local optimums.

Although as profit maximisers farmers may be unwilling to adopt practices that might reduce farm profit or increase farm risk, it is well understood that farmer decision-making is more adequately represented by a utility maximising framework where income and risk (in the form of income variation) are traded off under the optimal farm plan (Pope and Just, 1991; Oglethorpe, 1995; Hennessy, 1998; Tiedemann and Latacz-Lohmann, 2013). This study uses a mixed-integer weighted goal-programming to model the economic/management consequences in terms of the opportunity cost of using spring crop rotations to manage black-grass at the farm scale. With the main focus of the study on comparing the economic outcomes of two cropping plans as part of black-grass management strategy, the use of the comparative static mixed-integer programming model can be said to be fit for purpose. The study also seeks to determine the consequences or opportunity costs of adopting spring crop rotation at the national scale through aggregate-level modelling and the consequence of this on the level of risk (measured by deviation in income) to which arable farmers will be exposed. The novelty of this study and the result presented lies in the approach adopted and the aggregation of the cost at the national level. Although similar approaches have been used to explicitly or implicitly model different weed management strategies, in terms of using a comparative static linear programming based approach to model black-grass control strategies, our results are novel because there has been no previous analysis of the economics of controlling black-grass using rotational management at farm or national scale.

## 4.2 Methods

### 4.2.1 Farming scenario

The study considers a scenario of an arable farm growing four crops: winter wheat (*Triticum aestivum* L.), spring barley (*Hordeum vulgare* L.), spring beans (*Vicia faba* L.) and winter oilseed rape (*Brassica napus* L.). Although crops such as winter barley and spring wheat are important in UK arable farming, the selection of the above four crops was primarily driven by Black-Grass Resistance Initiative (BGRI) project (http://bgri.info/) survey, which found the four crops to be common among the farms surveyed (Dr Helen Hicks *pers. comm.*). That is, the four crops selected encompasses the main crops grown in the UK and used as part of rotational management. The selection of the four crops was also partly due to the frequency of black-grass infestation on winter wheat fields and the need for winter wheat—spring crop sequences/rotations as part of the control strategies. Spring wheat was not selected due to the fact that winter wheat—spring wheat rotation or sequence was seen to be akin to continuous winter wheat cropping.

Each of the crops has a set of sequential and non-sequential farm operations carried out in the farm year. The farm season is divided into 26 two-week periods to allow for the consideration for timeliness penalties (see Figure 4-2 for the operation types). Also, the consideration of single year (with multiple within year periods) was made to focus on the comparison of two cropping plan scenarios within the farm season. With the primary aim of this chapter being to estimate or investigate the cost of black-grass control using spring crops in the rotation, other non-chemical control strategies such as non-inversion and zero tillage were not considered. The main focus is to investigate the effect of arable farmers switching from winter crops (specifically winter wheat) to spring crops (as part of black-grass control measures) on farm revenue.

The workable hours available to the farm to carry out each operation in each period depend on the soil type and rainfall pattern at the farm location. Also, the rate at which earth moving operations such as ploughing are carried out depends on the soil type whereas work rate of operations such as planting and combine harvesting depend on the seed amount and crop yield respectively. The work rates of both types of operations depend on the size of machines owned by the farm (see Table 3-16 in Chapter 3 Appendix). The dominant soil type at the farm determines the fertiliser amounts applied to each crop and this is done by linking the recommended fertiliser amounts in Defra (2010) to soil type and thus a change in soil type alter the fertiliser amounts to crops.

| PERIOD | WINTER WHEAT | FARM OPERATIONS | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | FE | FE (ns) | PO | PL | RO | SP | SP (ns) | CO |
| 01 JAN - 15 JAN | p1 | | | | | | 2 | | |
| 15 JAN - 29 JAN | p2 | | | | | | 2 | | |
| 29 JAN - 11 FEB | p3 | | | | | | 2 | | |
| 12 FEB - 25 FEB | p4 | | | | | | 2 | | |
| 26 FEB - 11 MAR | p5 | | | | | | 2 | 2 | |
| 12 MAR - 25 MAR | p6 | | | | | | 2 | 2 | |
| 26 MAR - 08 APR | p7 | | 2 | | | | | 2 | |
| 09 APR - 22 APR | p8 | | 2 | | | | | 2 | |
| 23 APR - 06 MAY | p9 | | | | | | | 2 | |
| 07 MAY - 20 MAY | p10 | | | | | | | 2 | |
| 21 MAY - 03 JUN | p11 | | | | | | | | |
| 04 JUN - 18 JUN | p12 | | | | | | | | |
| 18 JUN - 01 JUL | p13 | | | | | | | | |
| 01 JUL - 16 JUL | p14 | | | | | | | | |
| 16 JUL - 29 JUL | p15 | | | | | | | | |
| 30 JUL - 12 AUG | p16 | 1 | | 1 | | | | | |
| 13 AUG - 26 AUG | p17 | 1 | | 1 | | | | | 2 |
| 27 AUG - 09 SEP | p18 | 1 | | 1 | | | | | 2 |
| 10 SEP - 23 SEP | p19 | 1 | | 1 | 1 | 1 | | | |
| 24 SEP - 08 OCT | p20 | 1 | | 1 | 1 | 1 | | | |
| 08 OCT - 21 OCT | p21 | 1 | | 1 | 1 | 1 | | | |
| 22 OCT - 04 NOV | p22 | 1 | | 1 | 1 | 1 | 1 | | |
| 05 NOV - 18 NOV | p23 | 1 | | 1 | 1 | 1 | 1 | | |
| 19 NOV - 02 DEC | p24 | | | 1 | 1 | 1 | 1 | | |
| 03 DEC - 16 DEC | p25 | | | 1 | 1 | 1 | 1 | | |
| 16 DEC - 31 DEC | p26 | | | 1 | 1 | 1 | 1 | | |

| PERIOD | SPRING BARLEY | FARM OPERATIONS | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | FE | FE (ns) | PO | PL | RO | SP (ns) | CO | BA |
| 01 JAN - 15 JAN | p1 | | | 2 | 2 | | | | |
| 15 JAN - 29 JAN | p2 | | | 2 | 2 | | | | |
| 29 JAN - 11 FEB | p3 | | | 2 | 2 | | | | |
| 12 FEB - 25 FEB | p4 | | | 2 | 2 | | | | |
| 26 FEB - 11 MAR | p5 | | | 2 | 2 | 2 | | | |
| 12 MAR - 25 MAR | p6 | | | 2 | 2 | 2 | | | |
| 26 MAR - 08 APR | p7 | | 2 | | 2 | 2 | 2 | | |
| 09 APR - 22 APR | p8 | | 2 | | | 2 | 2 | | |
| 23 APR - 06 MAY | p9 | | | | | 2 | 2 | | |
| 07 MAY - 20 MAY | p10 | | | | | | 2 | | |
| 21 MAY - 03 JUN | p11 | | | | | | | | |
| 04 JUN - 18 JUN | p12 | | | | | | | | |
| 18 JUN - 01 JUL | p13 | | | | | | | | |
| 01 JUL - 16 JUL | p14 | | | | | | | | |
| 16 JUL - 29 JUL | p15 | | | | | | | | |
| 30 JUL - 12 AUG | p16 | 1 | | | | | | | |
| 13 AUG - 26 AUG | p17 | 1 | | | | | | 2 | 2 |
| 27 AUG - 09 SEP | p18 | 1 | | | | | | 2 | 2 |
| 10 SEP - 23 SEP | p19 | 1 | | | | | | | 2 |
| 24 SEP - 08 OCT | p20 | 1 | | 1 | | | | | |
| 08 OCT - 21 OCT | p21 | 1 | | 1 | | | | | |
| 22 OCT - 04 NOV | p22 | 1 | | 1 | | | | | |
| 05 NOV - 18 NOV | p23 | 1 | | 1 | | | | | |
| 19 NOV - 02 DEC | p24 | | | 1 | | | | | |
| 03 DEC - 16 DEC | p25 | | | 1 | | | | | |
| 16 DEC - 31 DEC | p26 | | | 1 | | | | | |

| PERIOD | SPRING BEANS | FARM OPERATIONS | | | | |
|---|---|---|---|---|---|---|
| | | FE | PO | PL | SP (ns) | CO |
| 01 JAN - 15 JAN | p1 | | 2 | | | |
| 15 JAN - 29 JAN | p2 | | 2 | | | |
| 29 JAN - 11 FEB | p3 | | 2 | | | |
| 12 FEB - 25 FEB | p4 | | 2 | 2 | | |
| 26 FEB - 11 MAR | p5 | | 2 | 2 | | |
| 12 MAR - 25 MAR | p6 | | 2 | 2 | | |
| 26 MAR - 08 APR | p7 | | | 2 | | |
| 09 APR - 22 APR | p8 | | | | | |
| 23 APR - 06 MAY | p9 | | | | 2 | |
| 07 MAY - 20 MAY | p10 | | | | 2 | |
| 21 MAY - 03 JUN | p11 | | | | | |
| 04 JUN - 18 JUN | p12 | | | | 2 | |
| 18 JUN - 01 JUL | p13 | | | | 2 | |
| 01 JUL - 16 JUL | p14 | | | | | |
| 16 JUL - 29 JUL | p15 | | | | | |
| 30 JUL - 12 AUG | p16 | 1 | | | | |
| 13 AUG - 26 AUG | p17 | 1 | | | | |
| 27 AUG - 09 SEP | p18 | 1 | | | | 2 |
| 10 SEP - 23 SEP | p19 | 1 | | | | 2 |
| 24 SEP - 08 OCT | p20 | 1 | 1 | | | |
| 08 OCT - 21 OCT | p21 | 1 | 1 | | | |
| 22 OCT - 04 NOV | p22 | 1 | 1 | | | |
| 05 NOV - 18 NOV | p23 | 1 | 1 | | | |
| 19 NOV - 02 DEC | p24 | | 1 | | | |
| 03 DEC - 16 DEC | p25 | | 1 | | | |
| 16 DEC - 31 DEC | p26 | | 1 | | | |

| PERIOD | WINTER OILSEED RAPE | FARM OPERATIONS | | | | | |
|---|---|---|---|---|---|---|---|
| | | FE | FE (ns) | PO | PL | SP (ns) | CO |
| 01 JAN - 15 JAN | p1 | | | | | | |
| 15 JAN - 29 JAN | p2 | | | | | | |
| 29 JAN - 11 FEB | p3 | | | | | | |
| 12 FEB - 25 FEB | p4 | | 2 | | | | |
| 26 FEB - 11 MAR | p5 | | 2 | | | 2 | |
| 12 MAR - 25 MAR | p6 | | 2 | | | 2 | |
| 26 MAR - 08 APR | p7 | | | | | 2 | |
| 09 APR - 22 APR | p8 | | 2 | | | 2 | |
| 23 APR - 06 MAY | p9 | | 2 | | | | |
| 07 MAY - 20 MAY | p10 | | | | | | |
| 21 MAY - 03 JUN | p11 | | | | | | |
| 04 JUN - 18 JUN | p12 | | | | | | |
| 18 JUN - 01 JUL | p13 | | | | | | |
| 01 JUL - 16 JUL | p14 | | | | | | |
| 16 JUL - 29 JUL | p15 | | | | | | 2 |
| 30 JUL - 12 AUG | p16 | 1 | | 1 | 1 | | 2 |
| 13 AUG - 26 AUG | p17 | 1 | | 1 | 1 | | |
| 27 AUG - 09 SEP | p18 | 1 | | 1 | 1 | | |
| 10 SEP - 23 SEP | p19 | 1 | | 1 | 1 | | |
| 24 SEP - 08 OCT | p20 | 1 | | 1 | | | |
| 08 OCT - 21 OCT | p21 | 1 | | 1 | | 1 | |
| 22 OCT - 04 NOV | p22 | 1 | | 1 | | 1 | |
| 05 NOV - 18 NOV | p23 | 1 | | 1 | | 1 | |
| 19 NOV - 02 DEC | p24 | | | 1 | | 1 | |
| 03 DEC - 16 DEC | p25 | | | 1 | | | |
| 16 DEC - 31 DEC | p26 | | | 1 | | | |

Note: The operations with (ns) are non-sequential operations. The shaded squares with 1's means operations carried out in year 1 of the crop season and the squares with 2's means operations carried in year 2 of the crop season. The squares with circles represent the optimal periods in which the operations can be carried out without yield, rotational or timeliness penalties. FE = Spreading of phosphorous/potassium fertiliser, PO = Ploughing, PL = Planting, RO = Rolling, SP = Spraying, CO = Combine harvesting, BA = Baling, FE (ns) = Nitrogen fertiliser application (non-sequential), SP = Spraying (non-sequential).

Figure 4-2: Sequential and non-sequential farm operations of winter wheat, spring barley, spring beans and winter oilseed rape

Crop rotation is characterised by a crop cycle whereas crop sequence is about the order of appearance of crops on the same hector of land during a fixed period (Dury *et al.*, 2012). With respect to the four crops being considered in this study, the crop rotation can be described to be a 4-year crop cycle, which can be repeated by the farmer at the end of the cycle. In this study we focus on the crop sequence in the rotation by looking at mandatory winter wheat-spring barley or spring beans sequence as part of the black-grass control strategies. Farms practising crop rotation normally decide the hectare of land (a field) allocated to a crop as well as the deciding the crop successions. For example, after harvesting winter wheat on a field a farmer will decide the next crop to grow—this could be another wheat, a winter or a spring crop depending on the objective of the farmer or consideration of other factors such as soil types, expected revenue, weather and risk (Dury *et al.*, 2012). With the possibility of farmers repeating the crop cycle or rotation plans over a long period, this study is not focused on long term rotation plans or the length of the rotation but on rotation plans in which every hectare of winter wheat harvested must be followed by a spring crop (in the context of this study spring barley or spring beans).

Two cropping plan options are thus considered and compared in this study. Option 1 is a scenario of a farm growing four crops on four different fields: winter wheat (WWHT), spring barley (SBAR), spring beans (SBEA) and winter oilseed rape (WOSR). With winter wheat being the dominant arable crop in the UK, it is assumed that farmers are likely to allocate bigger proportion or more fields of the total farm land to winter wheat and the rest allocated to the other crops. In terms of crop sequence or succession it is assumed that each crop can be grown on any of the fields A, B, C and D (as shown by the arrows in Figure 4-3 (a)) after harvesting any of the crops without necessarily following winter wheat with a spring crop or allocating the same or more hectares of land to a spring crop than winter wheat. However, WOSR—SBEA or SBEA—WOSR sequences are not encouraged since such sequences could encourage possible disease build up and subsequently yield loss.

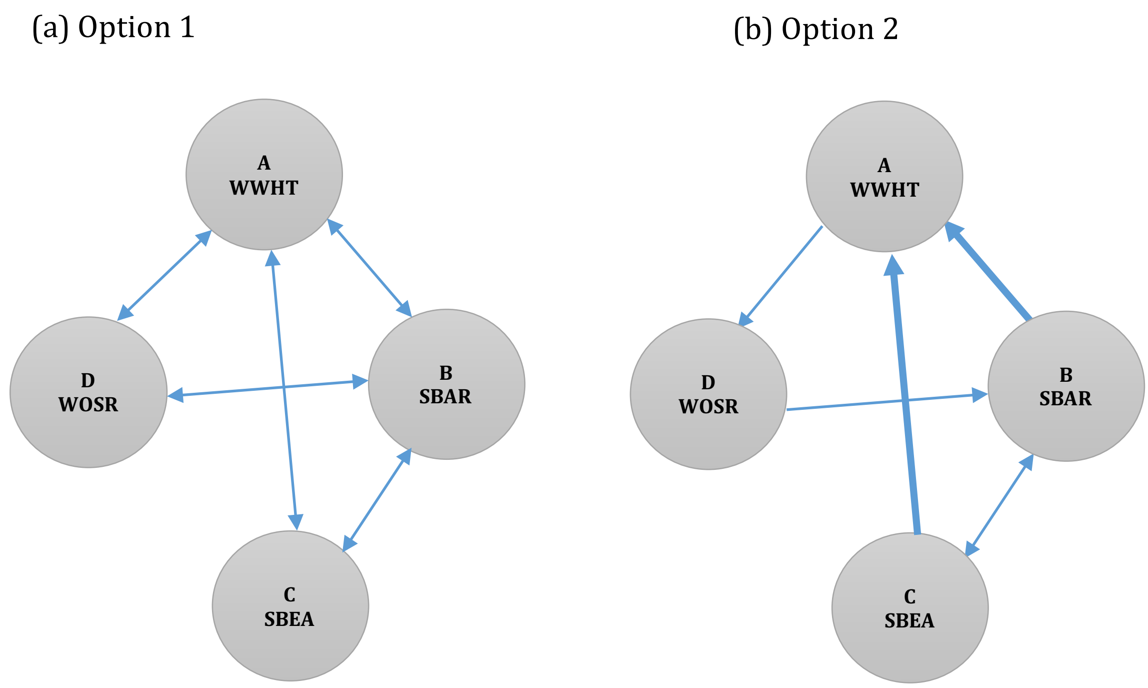



Figure 4-3: Cropping plan scenarios. Under Option 2 every winter wheat harvested is followed by either SBAR or SBEA (shown by thick arrow lines).

Winter wheat—spring crop sequence has been found to reduce black-grass infestation and as a result it is being promoted as a non-chemical black-grass control strategy. To capture this, the farmer adopts Option 2 (as shown in Figure 4-3 (b)) in which a mandatory winter wheat—spring barley or spring beans sequence is assumed. Using Figure 4-3, the main difference between Option 1 and 2 is that for example, under Option 1, a farmer may not use all the area of field A allocated to WWHT to grow spring barley or spring beans whereas under Option 2, the farmer has to use all the area of field A or more (use of parts of other fields) to grow either spring barley or spring beans after harvesting WWHT.

How the adoption of Option 2 as a black-grass control measure by a farmer impact on farm revenue and farm costs as well as risk is the focus of this study. Thus the focus is not on the length of the rotation or long term rotation predictions or on black-grass population dynamics but on the adoption of a cropping plan, which involves mandatory winter wheat—spring barley or spring beans sequence as black-grass control measure. As a result, the comparative static optimisation model, which is applied in this chapter is set up to generate annual cropping plans with implicit rotations, which if adopted, crops can be rotated or sequenced on field basis either by following Option 1 or Option 2. This approach was adopted to make it possible to compare profit margins of two cropping plans—profit margin of Option 2 (chosen as a black-grass control measure) and the profit margins of Option 1.

#### 4.2.1.1 Modelling black-grass infestation

Although it is acknowledged that the issues concerning black-grass infestation is of dynamic nature and that the benefit of a control measure applied in one year may reflect in subsequent years, with the focus of the study on the comparison of the economic outcomes of two cropping plans that can be adopted as part of black-grass control strategies, black-grass population dynamics or infestation is therefore not explicitly modelled and hence the use of static single year model. The effect of black-grass infestation is modelled through scenarios of winter wheat yield reductions under different levels of infestation (see Table 4-3 for yield penalties under different levels of black-grass infestation on winter wheat fields). This was done to make it possible to observe the level of infestation after which it will be more beneficial to switch to spring cropping, considering low profitability associated with spring cropping.

### 4.2.2 The mixed-integer weighted goal programming model

Linear programming models can serve as an alternative to field experiments when it comes quantifying the cost of adopting a rotation plan through the estimation of the differences in optimum profits for alternative crop or rotation plans. Many of the weed management strategies can be captured in linear programming (LP) models to investigate the amount of profit lost through the adoption of strategies such as winter crop—spring crop sequences. Also, some dynamics can be introduced into mixed-integer and goal programming models by dividing the cropping season into multi-periods and incorporating them into the model (McCarl and Spreen, 1997).

Linear or mixed-integer programming models can be formulated as multi-objective models (e.g. Annetts and Audsley, 2002; Cooke *et al.*, 2013) by maximizing or minimizing one objective whiles the other objectives are expressed as inequality constraints. However, such formulations may have a limitation in the sense that each goal expressed as inequality constraint must be enforced, otherwise will result in infeasible solution (Hazell and Norton, 1986; Zgajnar and Kavcic, 2011). To overcome this limitation, a weighted goal-programming model was applied to optimise goals simultaneously.

A typical goal programming (GP) minimises the deviations from goal targets (Barnett *et al.*, 1982; Romero and Rehman, 1984) and can generally be expressed mathematically as:

$$\text{Minimise } D = \sum_{g=1}^{h} (u_g d_g^- + v_g\, d_g^+) \tag{4-1}$$

subject to $G_g(\mathbf{a}) + d_g^- - d_g^+ = T_g, \quad \mathbf{a} \in Cons$

$d_g^-, d_g^+, \mathbf{a} \geq 0$

Where $D$ represents total deviation to be minimised, $G_g(\mathbf{a})$ is a linear function or objective (goal) of $\mathbf{a}$ (see Eq. (4-3) and (4-4)) which is a vector of decision variables $T_g$ is the target set for the $g$th objective or goal, $d_g^-$ and $d_g^+$ represent the negative (under-achievement) and positive (over-achievement) deviations from goal targets whereas $u_g$ and $v_g$ are the relative weights attached to the deviation variables respectively and *Cons* is a set of constraints (e.g. constraints under Section 4.2.3). For maximisation goals, the minimisation of the deviation is focused on the negative deviations whereas for minimisation goals positive deviations are the focus of the minimisation in the GP objective function.

In this chapter the mixed-integer weighted goal-programming (MIWGP) module of the SAFMOD was applied to investigate the effect of the adoption of winter wheat—spring crop sequence on farm revenues and costs. The model allows weights and goal targets to be set to optimize three arable farming goals by selecting optimum crop plan and machines/labour numbers (see Figure 4-4 for the flow chart showing the outline of the MIGWP model and associated assumptions). Model codes can also be found via the following link: https://github.com/kwadjoahodo/SAFMOD

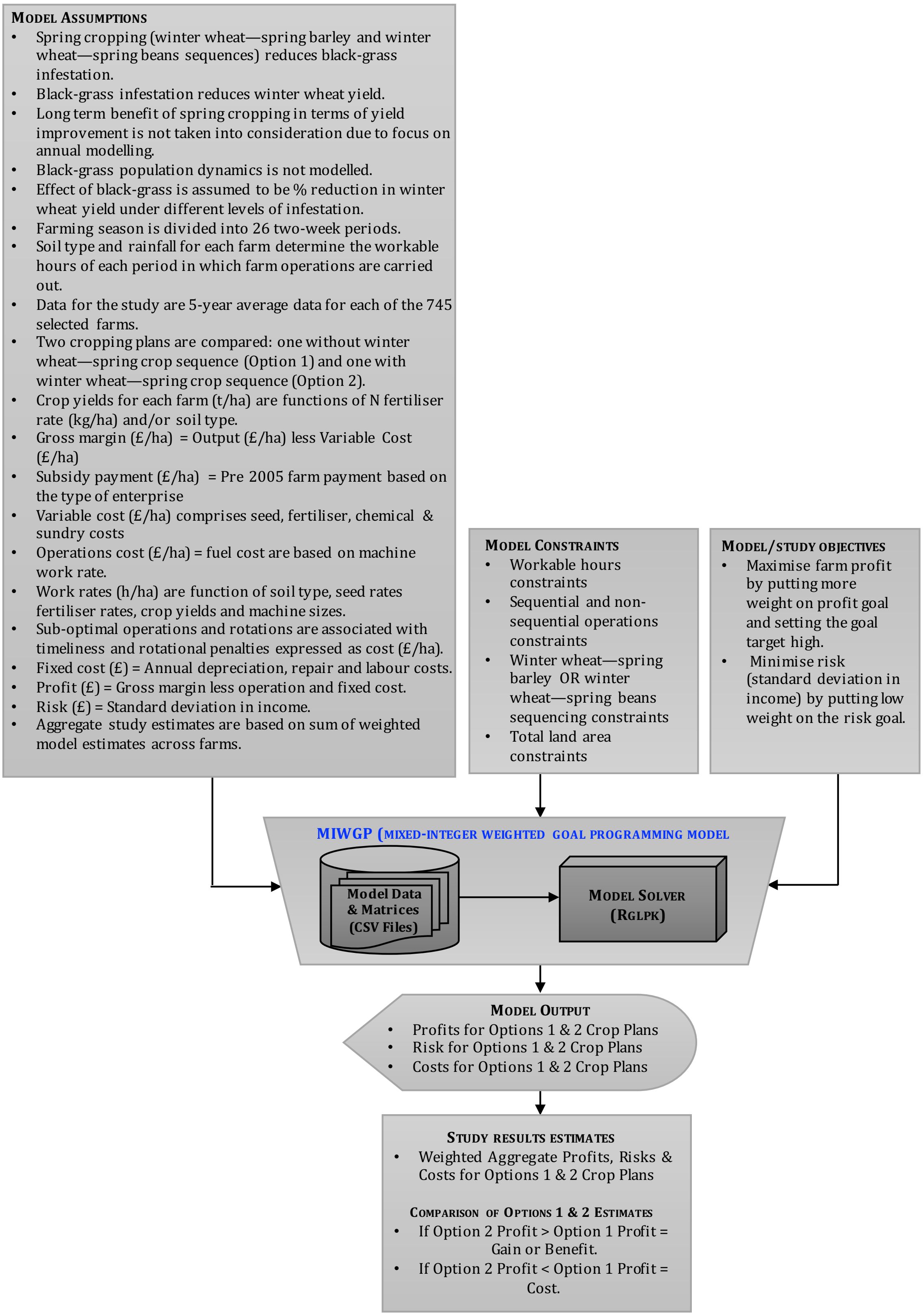



Figure 4-4: Flowchart showing the outline of the MIWGP model.

The choice of the MIWGP model which considers a single year planning horizon but with discrete within year periods was driven by the fact that the focus of the study was not on black-grass population dynamics but on the analysis of the annual economic (short term) benefit/cost of cropping plans that can be adopted to control black-grass although it is acknowledged that the adoption of such cropping plans in one year may have long term benefit in subsequent year(s). Also, with the costs and benefits of a crop plan normally incurred within the cropping season (normally a year), comparative economic analysis of different cropping plans or enterprises (e.g. gross margin analysis or farm budget) are normally carried out on annual basis and thus the application of the MIWGP model in this chapter was found to be fit for purpose.

The MIWGP model has 10 activities (9 crops[18] and set-aside) (see Chapter 3 Appendix for list of crops) but was set up to select four crops: winter wheat, spring barley, spring beans and winter oilseed rape. These crops were found to be common among farmers when a black-grass survey was conducted in England as part of a BGRI project as crop set use by farmers for black-grass management. The model assumes that there is always one farmer (integer) in addition to the labour numbers selected by the model and thus basically makes the model a mixed-integer. Also, the model can be set up to select integer machine and labour numbers. The decision variables are the crop types (cropping plan). The model originally optimises three arable farming goals: maximise profit, minimise nitrate leaching and minimise risk however, the results on nitrate-leaching goal were not presented in this study. This was due to the fact the focus was on profit maximisation and to some extent risk since they both depend on crop yields and prices. The risk minimisation goal was based on the minimisation of total absolute deviation (MOTAD) approach developed by Hazell (1971). The overall model thus combines mixed-integer, goal programming and MOTAD approaches. Although, a MOTAD model could have been applied, with the primary focus on profit maximisation and some consideration to risk, the MIWGP model serves the same purpose as a typical MOTAD model in which the mean absolute deviation is set

[18] The crops/activities are: winter and spring wheat (*Triticum aestivum* L.), winter and spring barley (*Hordeum vulgare* L.), winter and spring beans (*Vicia faba* L.), ware potatoes (*Solanum tuberosum* L.), winter oilseed rape (*Brassica napus* L.) and sugar beet (*Beta vulgaris* L.).

high, hence fit for purpose. The model was programmed using the R programming language (R Core Team, 2015).

The MIWGP model can be expressed mathematically as shown by Eq. (4-2) subject to Eq. (4-3) and (4-4) and a set of constraints under Section 4.2.3. The algebraic expressions shown by Eq. (4-2) to (4-6) were adapted versions of expressions used by Annetts and Audsley (2002), Rounsevell *et al.* (2003) and Cooke *et al.* (2013).

$$\text{Minimise } D = u_1 d_1^- + v_2 d_2^+ \tag{4-2}$$

Subject to:

**Goal 1:** Profit maximisation

$$G_{profit} = \sum_i \bar{E}_i a_i - \sum_i \sum_j \sum_k C_{ijk} y_{ijk} - \sum_m C_m n_m + u_1 d_1^- = T_1 \tag{4-3}$$

Where $\bar{E}_i$ is the expected gross margin for the $i$th crop, $a_i$ is the area of crop $i$ and it is equal to sum of the area of first or last operation carried on a crop $i$, $C_{ijk}$ is the cost of the $j$th operation on the $i$th crop in period $k$ and $y_{ijk}$ is the area of $j$th operation on the $i$th crop in period k. $C_m$ is the cost of machinery and labour required to perform field operations and $n_m$ is the number of machines of types $m$ required to perform the field operations.

**Goal 2:** Risk minimisation

$$G_{risk} = \sum_i a_i \sigma_i - v_2 d_2^+ = T_2 \tag{4-4}$$

Where $\sigma_i$ is the standard deviation in income for the $i$th crop.

### 4.2.3 Model constraints

#### 4.2.3.1 Resource constraints

This constraint ensures that the amount of a resource needed to carry out an operation on a crop does not exceed the amount of the resource available. Thus this constraint ensures efficiency in resource use. The resource type considered is the number of workable hours available in a period and it is determined using the farm's soil type and rainfall.

$$\sum_{i}\sum_{j} S_{ijkm}y_{ijk} \leq L_{mkw}n_m \qquad \forall m,k,w \tag{4-5}$$

Where, $S_{ijkm}$ is the work rate of operation $j$ carried on crop $i$ using a machine of type $m$ in period $k$ and $y_{ijk}$ area of operation $j$ carried on a crop $i$ period $k$. $L_{mkw}$ is the amount of resource (workable hours) available in period $k$ to carry out an operation with workability type $w$ using machine type $m$ and $n_m$ the number of machine type $m$ calculated by the model.

#### 4.2.3.2 Sequential and non-sequential operation constraints

The sequential operation constraint ensures that an operation is not performed before its preceding operation and that the area of the successor operation cannot exceed the area of the preceding operation. For example, before a crop is harvested it has to be planted or sown first and the area harvested cannot exceed the area planted. The constraint can be expressed as follows:

$$\sum_{k\leq K} y_{ijk} \leq \sum_{k\leq K} y_{i(j-1)k} \qquad \forall\, i,j > 1,k \tag{4-6}$$

Where, $K$ belongs to a set of periods in which an operation can be carried out on a crop. Under Eq. (4-6), $y_{ijk}$ is the area of successor operation $j$ carried on the $i$th crop in period $k$, $y_{i(j\text{-}1)k}$ is the area of the preceding operation $j$-1 carried out on the $i$th crop in period $k$. For non-sequential operations, total area of each operation is equal to the total crop area.

#### 4.2.3.3 Winter wheat—spring crop sequence constraint

To achieve the aim of this chapter, this new constraint was imposed. The constraint was enforced to ensure either a mandatory winter wheat—spring barley or winter wheat—spring beans sequences. Supposing the area of winter wheat = $a_1$, area of spring barley = $a_2$ and area of spring beans = $a_3$, the new winter wheat—spring crop sequence constraints can be stated as shown below (Eq. (4-7)) and under a scenario of ensuring winter wheat—spring beans sequence, $a_2$ is replaced with $a_3$. For example, when the model is run under a scenario of winter wheat—spring barley rotation, the winter wheat—spring beans sequence or rotation constraint is not enforced and vice versa). This means that the winter wheat—spring barley and winter wheat—spring beans sequence constraints were not enforced simultaneously.

$$a_1 - a_2 \leq 0 \tag{4-7}$$

#### 4.2.3.4 Total cropping area constraint

The total cropping area constraint ensures the sum of areas of all crops is equal to the total area cropped. The total area can be considered as land use constraint in the sense that it ensures that the area of land occupied by a crop or between crops at any time must be no more than the area of land available for crops. The constraint can be expressed as:

$$\sum_i a_i = \text{Total cropping area} \tag{4-8}$$

### 4.2.4 Modelling sub-optimal operations and rotations

In arable farming, the timing of farm operations such as ploughing, planting, spraying and harvesting are crucial in weed management. To incorporate efficient timing of farm operation in the MIWGP model, the farming season was divided into 26 two-week periods. Although in a strategic farm planning this fine detail may not be considered or needed, the two-week periods make it possible to take into consideration the analysis or the inclusion of timeliness penalties with respect to optimal and sub-optimal periods in which farm operations of each crop are carried out. Also, it has to be noted that the time horizon considered is assumed to be infinity with the length of the crop cycle dependent on the model solution (number of crops selected by the model). Sub-optimal operations and rotations can encourage black-grass emergence or infestation as well as result in crop yield reductions. To capture this in the model, penalties were imposed on sub-optimal operations (mainly planting and harvesting) and rotations (e.g. wheat-barley sequence). To take into consideration the influence of variation in weather on workable hours, which in turn influence the periods in which operations are carried out and the possibility of operation being carried out in a sub-optimal period, the model was run for each of the farms selected using their respective annual rainfall figures. Thus depending on the annual rainfall value at which maximisation model is run, it is possible some of the periods in which operation are carried out could be sub-optimal. The yield penalty (yield loss) with respect to sub-optimal operations could range from zero to over 20% whereas the yield loss with respect to sub-optimal rotation could range from zero to 100% (forbidden crop sequence). For example, the optimum time for sowing winter wheat is between late September and early October however, if sown in early or late December could attract a yield penalty of about 15% whereas spring barley following winter wheat could attract a penalty of about 11%. For sub-optimal operations, the yield penalties were expressed as cost per hectare (yield penalty × crop yield × crop price) and added to the cost of operation in the respective periods in the objective function.

### 4.2.5 Model validation

The model described above was validated using prediction validation (McCarl and Spreen, 1997) and 2009-2013 Farm Business Survey (FBS) data for 281 lowland arable farms in England and Wales with crop yields, farm area, soil types and rainfall as data inputs. The soil type was used to determine the fertiliser amounts for each crop, and both the annual rainfall and soil data were used to determine the workable hours using land indicator type function under Section 3.4.5 in Chapter 3. After model runs, aggregate level comparison of model results (e.g. crop areas, fertiliser amounts and farm revenues/costs) and observed FBS data was carried out using statistical measures of association (see examples in Gaiser *et al.* (2010); Pulvento *et al.* (2013) and Gueymard (2014)). The nine crops and set-aside (including the crops used in this study) originally used to develop the model were compared to observed data (see Chapter 3 for more information on model validation). The results of the aggregate-level comparison are presented in Table 4-1. Measures of association such as the root mean square error (*RMSE*) and mean absolute error (*MAE*) showed some level of bias in the model predictions. However, under the comparison of crop areas (and fertiliser amounts) estimates such as the Pearson correlation ($r$), Spearman correlation ($\rho$), coefficient of determination ($R^2$) showed positive association. Nash-Sutcliffe's model efficiency ($NSE$), Willmott's index of agreement ($WIA$) and Legates's coefficient of efficiency ($LCE$) showed positive association between model generated results and observed data. Also, the results of the t-test on the intercept and slope of regressing the observed data on predicted results showed that the intercept and slope were not different from zero and one respectively. The Coefficient of residual mass ($CRM$) showed some under-prediction by the model. Comparatively the model predicted crop areas and fertiliser amounts better than farm revenues/costs and this may be due to the variability in labour and fixed cost which may be due to factors that may not have been explicitly captured. On individual crop basis, based on Pearson correlation coefficient estimates, relatively better positive relationships were observed between model predicted winter wheat and winter oilseed rape areas compared to that of spring barley and spring beans. Thus at the aggregate level, the model predicts crop areas better than at the individual crop level.

Table 4-1: Model validation results of the comparison between predicted and observed crop areas, fertiliser amounts and farm revenues/costs.

| Measures of Association | Measures of Association Estimates | | |
|---|---|---|---|
| | Crop areas | Fertiliser amounts | Farm revenues/costs |
| $r$ | 0.91*** | 0.99*** | 0.64 |
| $\rho$ | 0.67** | 1.00 | 0.54 |
| $R^2$ | 0.83 | 0.98 | 0.41 |
| $MAE$ | 0.42 | 0.09 | 0.59 |
| $RMSE$ | 0.53 | 0.12 | 0.83 |
| $NSE$ | 0.80 | 0.96 | 0.26 |
| $WIA$ | 0.95 | 0.99 | 0.69 |
| $LCE$ | 0.47 | 0.82 | 0.09 |
| $CRM$ | 0.07 | 0.07 | 0.37 |
| Intercept | 0.02 (0.99) {0.34} | -1.73 (0.09) {0.93} | 138.24 (0.81){0.44} |
| Slope | 0.85 (-1.08) {0.30} | 1.09 (0.85){0.44} | 0.99 (-0.03){0.98} |

*** Significant at 1%; ** Significant at 5%; For LCE the values are normally low compared to NSE and WIA due to the higher magnitude of the denominator. For the t-test on the intercept and slope the values in parentheses are the t-estimates and the values curly brackets are the p-values. Farm revenues/costs consist of gross margin profit, seed, fertiliser, fuel, labour and fixed costs. Fertiliser types are N, P, K and NPK.

### 4.2.6 Economic evaluation components

The economic evaluation was based on gross margin estimates, which were defined as output plus subsidy less fertiliser, seed, black-grass herbicide and sundry costs. The output estimates were based on crop yields and prices whereas the subsidy was based on Single Farm Payments values and the sundry costs were obtained from Nix (2014). The descriptive statistics of the yield and price data are presented in Table 4-7 in the Chapter Appendix. The fertiliser cost estimates were based on recommended amounts in Defra (2010) and were determined through a sub-model, which uses soil type to select fertiliser amount for crops. The seed amounts were based of seed rates obtained from Toosey (1988). The black-grass control costs for each of the crops were chemical costs only (shown in Table 4-2) estimated using 2015 prices (Dr Helen Hicks[19] *pers. comm.*). The costs were average estimates based on all fields of a typical 240ha arable farm with a five-year rotation.

Table 4-2: Black-grass chemical control cost (£/ha)

| Crop | Black-grass Control Cost (£/ha) |
|---|---|
| Winter wheat | 178 |
| Spring barley | 84 |
| Spring beans | 96 |
| Winter oilseed rape | 112 |

Source: Black-Grass Resistance Initiative (BGRI) Project (http://bgri.info/)

Farm profit optimised by the model was defined as the gross margin less operations cost and cost of machinery and labour. The operations costs were functions of work rates for machines, which in turn were functions of machine sizes, fertiliser amounts, seed rates, crop yields and soil type as well as fuel price. For example, work rate for spraying was a function of spraying tank capacity whereas work rate for combine harvesting was determined by crop yield and size of combine harvester. The functions for estimating the work rates were obtained from the farmR model (Cooke *et al.*, 2103) and Chamen and Audsley (1993). It

[19] The data were obtained from a farmer through a farm survey as part of the Black-Grass Resistance Initiative (BGRI) Project (http://bgri.info/)

should be noted that the operations cost took into consideration yield penalties for sub-optimal operations. The fixed cost estimates were based on annual machinery cost (consist of annual depreciation and repair cost) and annual labour cost (see Table 3-16 in Chapter 3 Appendix for machine types selected for the study and annual fixed cost estimates). Due to lack of data on machine numbers for each of the farms selected and used for the study, the total fixed cost estimate for each farm was based on the optimal machine/labour numbers selected by the model, which in turn depended on the optimal crop plan for the farm (also selected by the model).

### 4.2.7 Model data, calibration and model runs

To be able to estimate the aggregate cost of controlling black-grass with spring crops, crop yield, price and arable area data as well as soil type and rainfall of 745 farms in the 2013/14 Farm Business Survey (FBS) were used as model inputs. That is the data used were 2013 FBS data for the selected 745 based on which the model was run. The farms consisted of farms at altitudes <300m, 300mm—600m and >600m with arable area of greater than or equal to 40ha (minimum area = 40ha and maximum area = 1931ha). Based on the criteria used in selecting the farms, it is possible that this sample may include some of the farms used in validating the model. The soil type[20] data were based on dominant soil types obtained for FBS defined counties in which farms are located whereas the rainfall data were based on average rainfall[21] for FBS defined regions in which farms are located.

With the focus of the chapter on effect of spring cropping as black-grass control measure on farm revenue, highest weight (weight = 1) was put on the profit maximisation goal. Also since a goal-programming model minimises the deviation from a goal target, the profit goal target was set very high (£800,000). This was done based on the assumption that arable farmers are profit maximisers but are also concerned about income deviation (risk) levels. Thus the weight for the risk minimisation goals was set relatively very small (weight = 0.1 and the risk

[20] Soil data were obtained from Soilscapes: http://www.landis.org.uk/soilscapes/
[21] Rainfall data obtained from Met Office: http://www.metoffice.gov.uk/climate/uk/summaries/datasets

target was set at £22,000 with possible over-achievement of goal target). The weights on both goals were normalised by dividing by their respective targets. The model was set up again to use the crop yields and prices, farm area, soil type and rainfall as model inputs.

The crop yields and prices for each farm were used to estimate farm outputs, out of which the gross margins for each of the farms were estimated. It should be noted that the data for each farm were the 2013 FBS data and thus not average estimates. For example, the yield values used in estimating the gross margin for farms were actual yield data for farm for the year 2013. The Table 4-7 shows the descriptive statistics of the individual farm data used as model inputs. The soil types and rainfall figures for each farm were used to estimate the workable hours in each of the 26 two-week period using the land indicator type function in Tillett and Audsley (1987) (see Section 3.4.5). Also, the soil types determined the fertiliser amount of each crop and thus linked to the estimation of fertiliser cost and hence variable costs for each crop.

To take into consideration the impact of black-grass on winter wheat yield, yield losses under for different black-grass infestation levels were considered (see Table 4-3). The yield loss estimates were averages across 10 fields based 2014 and 2015 winter wheat harvests based on a black-grass survey carried out on farms in England[22] (Dr Helen Hicks, *pers. comm.*). For each field, yield maps were overlaid with 20m×20m weed survey grid to relate wheat yield to weed density. For each field, mean yield across grid squares in each density state was estimated. To control for variation in yield between fields, the maximum mean yield loss from the five density states was selected as 100%, and percentage yield calculated for each density state relative to this. The data on yield loss shown in Table 4-3 were adopted due to inability to obtain a UK level data.

[22] The 10 fields were from farms in four counties in England: Northamptonshire, Oxfordshire, Warwickshire and Yorkshire.

Table 4-3: Yield reduction of winter wheat at different four levels of black-grass infestation

| Level of Infestation | Black-grass Density (Plants per 400 (20×20) m$^2$) | Reduction in Winter Wheat Yield (%) |
|---|---:|---:|
| No/low | 1-160 | 0 |
| Medium | 161-450 | 3 |
| High | 451-1450 | 12 |
| Very high | >1450 | 24 |

Source: BGRI Project (http://bgri.info/)

The model was then run for each of the 745 farms to generate crop plans similar to Option 1, without enforcing constraint under Eq. (4-8). The model run was done under all levels of black-grass infestation (one level of infestation at a time) to take into consideration reductions in winter wheat yields due to black-grass. This means that to generate result for Option1, the model was run without imposing mandatory winter wheat—spring barley or winter wheat—spring beans rotation (sequence) constraints. The model was run again for each farm by first imposing only the mandatory winter wheat—spring barley sequence constraint (Option 2). The process was repeated by imposing only the winter wheat—spring beans constraint (also Option 2) without imposing the winter wheat—spring barley sequence constraint.

### 4.2.8 Aggregation of model results

To the achieve the aim of aggregating the cost of adopting spring cropping as a black-grass control strategy in the UK, the model generated results were aggregated across farms. It is acknowledged that they may be biases associated with aggregation with respect to linear programming approaches and also due to variability is farm classes (see for example Buckwell and Hazell, 1972; Önal and McCarl, 1989). However, the current approach gives an indication of the impact of spring cropping as a black-grass control strategy on farm revenue in the UK arable farming sector. Although running the model for each farm using the farm's own data and aggregating results post optimally and weighting the aggregate estimates to bring them as close as possible to UK national level (as is the case in this chapter) could to reduce aggregation bias, it is also acknowledged that the choice of the four crops may affect the accuracy of aggregated estimates. Notwithstanding, in the context of the four crops, which are essentially the crops grown in the UK and used as part of rotational management, the aggregate estimates give an indication of the potential effect of spring cropping as a black-grass management tool on farm revenue at the national level.

To estimate the aggregate cost/benefit, the differences in optimum profits for Options 1 and 2 were estimated and aggregated as either the cost (loss of profit) or benefit (increase in profit) of black-grass control with either spring barley or spring beans. For example, to estimate the aggregate cost with respect to winter wheat-spring barley rotation under a level of infestation, the differences between Option 1 and Option 2 were estimated for each farm after which they were summed (aggregated) across farms (745 farms). In order to reduce possible aggregation bias and bring the aggregate cost estimate as close as possible to the UK level, each farm estimate was weighted using the sample weight assigned to each farm in the FBS. For each spring cropping sequence and under each level of infestation, the aggregate cost can be estimated as shown in Eq. (4-9) (see illustration of calculation in Box 4-1 under Chapter Appendix), where $OP1_z$ and $OP2_z$ are the profits generated by the *i*th farm for choosing Option 1 and Option 2 crop plans respectively, $wt_z$ is sampling weight assigned to the *i*th farm in the FBS data and $F$ is the number of farms. Also, other model estimates presented under Section 4.3 were weighted.

$$Aggregate\ Cost = \sum_{z=1}^{F} OP2_z wt_z - \sum_{z=1}^{F} OP1_z\, wt_z \tag{4-9}$$

## 4.3 Results

Although the model was run for four levels of black-grass infestations, the results presented here focus primarily on zero/low and very high levels of black-grass infestations. Descriptive statistics of model estimates under the different levels of infestation and under Options 1 and 2 are shown in Table 4-8 to Table 4-10 in the chapter Appendix.

### 4.3.1 The cost of black-grass control with spring barley

Table 4-4 shows the aggregate cost estimates of controlling black-grass with spring barley. Our headline estimates are that controlling black-grass with a crop plan (based on the selected four crops) including a mandatory winter wheat—spring barley rotation under a scenario of low black-grass infestation could cost UK arable farming about £286 million whereas under a scenario of very high black-grass infestation, adoption of winter wheat—spring barley rotation as a black-grass control strategy could cost UK arable farming about £35 million. These equate to per hectare costs of approximately £82/ha and £10/ha respectively. Implementing a winter wheat—spring barley rotation after a low black-grass infestation reduced profit by 25.30% (from £1,129,791,000 to £843,920,000 (£326/ha to £243/ha)) and under very high infestation, profit reduced by 7.49% (from £461,931,000 to £427,349,000 (£116/ha to £107/ha)) (see Table 4-4).

The MOTAD estimated risk also reduced by 5.17% (from £687,162,000 to £685,583,000 (£225/ha to £213/ha) whereas under very high infestation risk reduced by 0.23% (from £687,162,000 to £685,583,000 (£198/ha to £197/ha). The reduction was mainly due to lower income deviation estimates associated with spring barley as well as winter OSR, which was selected in addition to the winter wheat—spring barley rotation. The results also show that controlling black-grass with spring cropping could reduce farm risk. However, under a scenario of very high infestation the reduction may be negligible due to the fact that spring cropping did not result in a bigger reduction in profit. The lower levels of profit observed were mainly due to yield reductions in winter wheat yield due to black-grass infestation.

In terms of costs, all variable cost components reduced. For example, under low black-grass infestation, N fertiliser and black-grass chemical (herbicide) costs reduced by 9.63% (from £651,062,000 to £588,350,000 (£188/ha to £170/ha)) and 15.63% (from £614,135,000 to £518,173,000 (£177/ha to £149/ha)) respectively. Under very high infestation, N fertiliser and black-grass control costs reduced by 3.73% (from £584,409,000 to £562,588,000 (£169/ha to £162/ha)) whereas black-grass control (herbicide) cost reduced by 6.45% (from £509,732,000 to £479,853,000 (£147/ha to £138/ha)). The reduction in N fertiliser and herbicide costs was due to lower N fertiliser and chemical control cost associated with spring barley. These have obvious environmental benefits. The relatively lower reduction in herbicide cost under very high infestation was due to the fact that there was not much change in the crop plan (under Option 1) when winter wheat—spring barley was imposed. Operations and fixed costs on the other hand increased by 7.10% (from £1,160,147,000 to £1,242,547,000 (£335/ha to £358/ha)) and 1.79% (£1,538,744,000 to £1,566,280,000 (£444/ha to £452/ha) respectively under low infestation. Under very high infestation, operations cost increased by 2.61% (from £1,282,282,000 to £1,315,802,000 (£370/ha to £380/ha)) and fixed cost increased by 1.15% (from £1,554,583,000 to £1,572,475,000 (£448/ha to £454/ha)) respectively. The increase in operations cost was due to the fact that with the implementation of the winter wheat—spring barley rotation, some land was allocated to winter OSR and for some farms, spring beans. Both spring beans and winter OSR have slower work rate with respect to combine harvesting and as a result relatively more time is spent on the field harvesting, leading to increase in operations cost. Also the harvesting periods of winter wheat and spring barley overlap, meaning that more machines/labour are needed in order to perform harvesting within the optimal periods and as a result lead to increase in fixed cost.

Table 4-4: Aggregate revenues/costs estimates of controlling black-grass with winter wheat—spring barley rotation under four levels of black-grass infestations.

| Revenue/Cost Components (and Risk) | Row No. | Explanation | Weighted Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Zero/Low Infestation | | Medium Infestation | | High Infestation | | Very High Infestation | |
| | | | Option_1(a) (£'000) | Option_2(b) (£'000) | Option_1(a) (£'000) | Option_2(b) (£'000) | Option_1(a) (£'000) | Option_2(b) (£'000) | Option_1(a) (£'000) | Option_2(b) (£'000) |
| Output | R1 | Yield × Price | 5,410,305 | 4,974,317 | 5,278,981 | 4,908,165 | 4,937,771 | 4,723,395 | 4,596,412 | 4,523,713 |
| Output + Subsidy | R2 | R1+Subsidy | 6,277,119 | 5,841,131 | 6,145,780 | 5,774,964 | 5,804,581 | 5,590,198 | 5,463,216 | 5,390,535 |
| N Fertiliser Cost | R3 | | 651,062 | 588,350 | 643,804 | 585,884 | 619,968 | 577,652 | 584,409 | 562,588 |
| P Fertiliser Cost | R4 | | 236,200 | 225,999 | 234,922 | 225,544 | 230,938 | 224,005 | 224,733 | 221,187 |
| K Fertiliser Cost | R5 | | 209,882 | 199,823 | 208,373 | 199,163 | 204,058 | 197,090 | 197,011 | 193,374 |
| Seed Cost | R6 | | 293,145 | 282,980 | 291,634 | 282,421 | 287,412 | 280,444 | 280,343 | 276,850 |
| Black-grass Herbicide Cost | R7 | | 614,135 | 518,173 | 602,654 | 514,487 | 566,123 | 501,283 | 509,732 | 476,853 |
| Sundry Cost | R8 | | 443,991 | 373,064 | 435,727 | 370,513 | 409,054 | 361,238 | 368,202 | 344,002 |
| Variable Cost | R9 | R3+R4+R5+ R6+R7+R8 | 2,448,415 | 2,188,387 | 2,417,111 | 2,178,011 | 2,317,552 | 2,141,711 | 2,164,430 | 2,074,855 |
| Gross Margin | R10 | R2-R9 | 3,828,704 | 3,652,746 | 3,728,670 | 3,596,952 | 3,487,029 | 3,448,487 | 3,298,786 | 3,315,681 |
| Cost of Farm Operations | R11 | | 1,160,147 | 1,242,547 | 1,173,065 | 1,249,123 | 1,212,628 | 1,272,019 | 1,282,282 | 1,315,802 |
| Gross Profit | R12 | R10-R11 | 2,668,534 | 2,410,199 | 2,555,636 | 2,347,882 | 2,274,380 | 2,176,486 | 2,016,515 | 1,999,824 |
| Fixed Cost | R13 | | 1,538,744 | 1,566,280 | 1,533,824 | 1,565,004 | 1,535,590 | 1,565,123 | 1,554,583 | 1,572,475 |
| Profit | R14 | R12-R13 | 1,129,791 | 843,920 **(-285,870)** | 1,021,814 | 782,878 **(-238,936)** | 738,790 | 611,364 **(-127,426)** | 461,931 | 427,349 **(-34,583)** |
| MOTAD Risk | R15 | Deviation in income | 780,359 | 740,026 | 764,178 | 731,499 | 723,165 | 708,088 | 687,162 | 685,583 |

Note: The values in parentheses are the differences in profits (b-a). Option 1 represents a crop plan in which the farmer can allocate a bigger proportion of farm land to any of the four crops (winter wheat, spring barley, spring beans and winter oilseed rape) whereas Option 2 represents a crop plan with mandatory winter wheat—spring barley rotation.

### 4.3.2 The cost of black-grass control with spring beans

Table 4-5 shows the aggregate cost estimates of controlling black-grass with spring beans. Our headline estimates (based on the selected four crops) in this instance are that adopting a winter wheat—spring beans rotation as a black-grass control measure under a scenario of low black-grass infestation could cost UK arable farming about £650 million (£187/ha) whereas under a scenario of very high infestation, the strategy could cost UK arable farming about £87 million (£25/ha). These results show that it will cost UK arable farming more by adopting winter wheat—spring beans rotation than adopting winter wheat—spring barley rotation however under a scenario of very high infestation, winter wheat—spring beans rotation could result in lower profit loss than under low black-grass infestation. Implementing winter wheat—spring beans rotation resulted in 57.51% reduction in profit (from £1,129,791,000 to £480,078,000 (£326/ha to £138/ha)) under low black-grass infestation (see Table 5). Under very high infestation, profit reduced by 18.94% (from £461,931,000 to £374,462,000 (£133/ha to £108/ha)).

Under a scenario of low black-grass infestation, MOTAD estimated risk also reduced by 6.81% (from £780,359,000 to £727,217,000 (£225/ha to £210/ha)) but increased by 2.92% (from £687,162,000 to £707,201,000 (£198/ha to £204/ha)) under very high infestation. The increase in risk under very high infestation was due to the crop combinations selected by the model after the winter wheat—spring beans rotation constraint was imposed. The gross margin estimate associated with spring beans was relatively lower than that of spring barley and as a result, with imposition of winter wheat-spring beans sequence, more land was allocated to spring barley which is associated with relatively high risk and hence the increase in the MOTAD risk.

In terms of costs, variable cost components reduced. For example, under low infestation, N fertiliser cost reduced by 25.61% (from £651,062,000 to £484,341,000 (£188/ha to £140/ha)) whereas black-grass herbicide cost reduced by 32.02% (from £614,135,000 to £417,504,000 (£177/ha to £120/ha)). Under very high infestation, N fertiliser reduced by 15.29% (from £584,409,000 to £495,054,000 (£169/ha to £143/ha) and chemical control cost reduced by 21.42%

(from £509,732,000 to £400,534,000 (£147/ha to £116/ha)). Again, these have obvious environmental benefits. The bigger reduction in N fertiliser and black-grass herbicide costs can be attributed to the fact that spring beans has no N fertiliser requirement and also the other crops (spring barley and winter OSR) selected in addition to the winter wheat—spring beans rotation have lower N fertiliser requirements and black-grass chemical cost than winter wheat, hence the reduction. Again, the relatively lower reduction in herbicide cost under very high infestation was due to the fact that there was not much change in the crop plan (under Option 1) when winter wheat—spring beans was imposed. Farm operations and fixed costs increased by 25.16% (from £1,160,147,000 to £1,452,088,000 (£335/ha to £419/ha)) and 5.55% (from £1,538,744,000 to £1,624,074,000 (£444/ha to £468/ha)) respectively under low infestation. Under very high infestation, operations cost increased by 14.01% (from £1,282,282,000 to £1,461,879,000 (£370/ha to £422/ha)) and fixed cost increased by 6.38% (from £1,554,583,000 to £1,653,802,000 (£448/ha to £477/ha)). Comparatively, the bigger increases in operations and fixed costs (than under spring barley) were due to the selection of some amount of winter OSR in addition to the winter wheat—spring beans rotation. In terms of harvesting work rate, spring beans and winter OSR have slower work rate, leading to higher operations costs. Also, the harvesting periods of winter wheat, spring beans and spring barley overlap meaning that more machines/labour are needed to perform the operations, leading to higher fixed cost and hence bigger reduction in profit.

Table 4-5: Aggregate revenues/costs estimates of controlling black-grass with winter wheat—spring beans rotation under four levels of black-grass infestations.

| Revenue/Cost Components (and Risk) | Row No. | Explanation | Weighted Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Zero/Low Infestation | | Medium Infestation | | High Infestation | | Very High Infestation | |
| | | | Option_1(a) (£'000) | Option_2(b) (£'000) | Option_1(a) (£'000) | Option_2(b) (£'000) | Option_1(a) (£'000) | Option_2(b) (£'000) | Option_1(a) (£'000) | Option_2(b) (£'000) |
| Output | R1 | Yield × Price | 5,410,305 | 4,565,631 | 5,278,981 | 4,545,237 | 4,937,771 | 4,507,318 | 4,596,412 | 4,472,760 |
| Output + Subsidy | R2 | R1+Subsidy | 6,277,119 | 5,432,456 | 6,145,780 | 5,412,049 | 5,804,581 | 5,374,117 | 5,463,216 | 5,339,571 |
| N Fertiliser Cost | R3 | | 651,062 | 484,341 | 643,804 | 485,963 | 619,968 | 490,508 | 584,409 | 495,054 |
| P Fertiliser Cost | R4 | | 236,200 | 212,246 | 234,922 | 212,164 | 230,938 | 211,870 | 224,733 | 211,600 |
| K Fertiliser Cost | R5 | | 209,882 | 181,441 | 208,373 | 181,445 | 204,058 | 181,543 | 197,011 | 181,453 |
| Seed Cost | R6 | | 293,145 | 279,647 | 291,634 | 278,542 | 287,412 | 275,153 | 280,343 | 271,911 |
| Black-grass Herbicide Cost | R7 | | 614,135 | 417,504 | 602,654 | 415,209 | 566,123 | 407,355 | 509,732 | 400,534 |
| Sundry Cost | R8 | | 443,991 | 300,972 | 435,727 | 299,347 | 409,054 | 293,655 | 368,202 | 288,873 |
| Variable Cost | R9 | R3+R4+R5+R6+R7+R8 | 2,448,415 | 1,876,150 | 2,417,111 | 1,872,668 | 2,317,552 | 1,860,082 | 2,164,430 | 1,849,422 |
| Gross Margin | R10 | R2-R9 | 3,828,704 | 3,556,308 | 3,728,670 | 3,539,383 | 3,487,029 | 3,514,036 | 3,298,786 | 3,490,150 |
| Cost of Farm Operations | R11 | | 1,160,147 | 1,452,088 | 1,173,065 | 1,453,900 | 1,212,628 | 1,457,446 | 1,282,282 | 1,461,879 |
| Gross Profit | R12 | R10-R11 | 2,668,534 | 2,104,146 | 2,555,636 | 2,085,461 | 2,274,380 | 2,056,633 | 2,016,515 | 2,028,264 |
| Fixed Cost | R13 | | 1,538,744 | 1,624,074 | 1,533,824 | 1,624,067 | 1,535,590 | 1,640,454 | 1,554,583 | 1,653,802 |
| Profit | R14 | R12-R13 | 1,129,791 | 480,074 **(-649,717)** | 1,021,814 | 461,396 **(-560,418)** | 738,790 | 416,179 **(-322,610)** | 461,931 | 374,462 **(-87,469)** |
| MOTAD Risk | R15 | Deviation in income | 780,359 | 727,217 | 764,178 | 723,510 | 723,165 | 714,712 | 687,162 | 707,201 |

Note: The values in parentheses are the differences in profits (b-a). Option 1 represents a crop plan in which the farmer can allocate a bigger proportion of farm land to any of the four crops (winter wheat, spring barley, spring beans and winter oilseed rape) whereas Option 2 represents a crop plan with mandatory winter wheat—spring beans rotation.

### 4.3.3 The cost/benefit of black-grass control at individual farm level

The aim of this section is to show the cost (benefit) of controlling black-grass at individual farm level. The results of two farms labelled Farm 1 and Farm2 are used for the illustration (see Table 4-6). The results show that, although at the aggregate level, using winter wheat—spring crop rotation as a black-grass control measure could cost the arable sector, at the individual farm level, there could be either reductions (costs) or increase (benefits or gains) in farm revenue depending on the location of the farm and the hectares of land available to the farm.

The dominant soil type for Farm 1 is a light soil whereas that of Farm 2 is a heavy soil. In terms of rainfall, Farm 1 is located at an area of moderate rainfall and Farm 2 is located at an area of high rainfall. Thus in terms of workable hours, Farm 1 will have relatively more time available to perform farm operations whereas Farm 2 may be restricted. The area of Farm1 is smaller than that of Farm 2 and with profit maximisation objective, Farm 1 may be restricted in terms of allocating land to all crops. This is reflected in the cropping pattern of Farms 1 and 2 (see Table 4-6). Under Option 1 for Farm 1, about 97% (127ha) of the land (131ha) was allocated to winter wheat, which is the most profitable crop whereas under Farm 2 (with bigger farm area) land is allocated to all the four crops in order to maximise profit, with about 45% (119ha) of farm area (267ha) allocated to winter wheat.

Under Option 2 for Farm 1, to be able to adopt a winter wheat—spring barley sequence as black-grass control measure and maximise profit, 57ha of winter wheat must be cropped (70ha or 55% less of 127ha) however, under Farm 2, 104 ha (15 ha or 13% less of 119 ha) has to be cropped. Thus there is no drastic reduction in in the area of winter wheat, which is the most profitable crop and this coupled with the selection of all the other crops, associated with lower variable costs resulted in the increase in gross margin (profit) instead of reduction observed under Farm 1.

Table 4-6: Revenues/costs estimates of controlling black-grass with winter wheat—spring barley rotation under low level of black-grass infestations

| Revenue/ Cost Components (and Risk) | Row | Explanation | Unit | Farm 1 | | Farm 2 | |
|---|---|---|---|---|---|---|---|
| | | | | Option 1 | Option 2 | Option 1 | Option 2 |
| Output | R1 | Yield × Price | £ | 154,957 | 138,320 | 290,531 | 289,899 |
| Output + Subsidy | R2 | R1+Subsidy | £ | 182,074 | 165,416 | 345,800 | 345,168 |
| N Fertiliser Cost | R3 | | £ | 13,250 | 9,610 | 37,733 | 36,162 |
| P Fertiliser Cost | R4 | | £ | 7,784 | 7,034 | 14,499 | 14,329 |
| K Fertiliser Cost | R5 | | £ | 7,004 | 6,323 | 12,627 | 12,464 |
| Seed Cost | R6 | | £ | 9,776 | 9,633 | 18,416 | 18,488 |
| Black-grass Herbicide Cost | R7 | | £ | 23,023 | 16,570 | 34,901 | 33,582 |
| Sundry Cost | R8 | | £ | 16,640 | 11,747 | 25,281 | 24,269 |
| Variable Cost | R9 | R3+R4+R5+ R6+R7+R8 | £ | 77,476 | 60,917 | 143,457 | 139,295 |
| Gross Margin | R10 | R2-R9 | £ | 104,597 | 104,499 | 202,343 | 205,873 |
| Cost of Farm Operations | R11 | | £ | 33,140 | 32,560 | 82,226 | 83,683 |
| Gross Profit | R12 | R10-R11 | £ | 71,455 | 72,023 | 120,109 | 122,182 |
| Fixed Cost | R13 | | £ | 31,426 | 39,577 | 108,151 | 109,440 |
| Profit | R14 | R12-R13 | £ | 40,029 | 32,446 **(-7,583)** | 11,958 | 12,742 **(783)** |
| MOTAD Risk | R15 | Deviation in income | £ | 22,000 | 21,759 | 45,713 | 46,018 |
| **Cropping** | | | ha | | | | |
| Winter wheat | | | | 127 | 57 | 119 | 104 |
| Spring barley | | | | 0 | 57 | 94 | 104 |
| Spring beans | | | | 4 | 17 | 13 | 18 |
| Winter OSR | | | | 0 | 0 | 41 | 40 |
| **Farm Information** | | | | | | | |
| Farm area | | | ha | 131 | | 267 | |
| Soil type | | | | Light soil | | Heavy soil | |
| Rainfall | | | mm | 769 | | 1294 | |

Under Farm 1, using winter wheat—spring barley rotation as a black-grass control reduced profit by £7,583 (a cost) whereas under Farm 2 profit was increased by £783 (a gain or benefit) however, risk increased under Farm 2. The increase in risk may be due to the fact that the estimate of risk is linked to gross margin estimates and hence increase in gross margin is likely to be associated with increase in risk. The increase in risk may also imply that the bigger farm area available for a farmer to work on, the more risk the farmer is exposed to. A farmer whose primary aim is to maximise profit with little consideration to risk is likely to accommodate high risk so as to maximise profit (this is also reflected in the results presented in Chapter 5). In terms of herbicide cost, for Farm1, it reduced by 28% (from £23,023 to £16,570) whereas under Farm 2, it reduced by about 4% (from £34,901 to £33,582). This was as a result of the allocation of land to all four crops under Farm 2 and hence contributed to the smaller reduction in black-grass control cost. The reductions in herbicide cost shows the possibility of gains in terms of cost savings by controlling black-grass with spring cropping however, in the case of Farm 1, the reduction was not big enough to offset the reduction in profit.

The above results show that on individual farm basis, the effect (in terms of profit loss or gain) of using winter-wheat spring crops rotation or sequence to control black-grass may be different across farms depending on the farm characteristics such as soil type, rainfall and total area of land or cropping area available to the farm.

## 4.4 Discussion and conclusion

In this chapter, we have used a farm level mixed-integer goal programming model and Farm Business Survey data for 745 farms to investigate the aggregate cost (loss of profit) of controlling black-grass with spring cropping in UK arable farming. Results showed that in the short term, controlling black-grass with a winter wheat—spring barley rotation under a low black-grass infestation scenario could cost UK arable farming about £286 million (£82/ha) whereas controlling black-grass with winter wheat—spring beans could cost UK arable about £650 million (£187/ha). Under a scenario of very high black-grass infestation, adopting winter wheat—spring barley rotation as a black-grass control strategy could cost UK arable farming about £35 million (£10/ha) whereas adopting a winter wheat—spring beans rotation could cost about £87 million (£25/ha). The results show that after a very high black-grass infestation on a winter wheat field, switching to spring cropping could be relatively 'beneficial' in the sense that loss of profit due to mandatory winter wheat—spring crop rotation was lower. Also, although the overall effect showed as a reduction in profit, there could be reductions in variable costs and in some cases reduction in farm risk, and on individual farm basis, there could be gains depending on the location of farm and the land available to the farm. Again, since spring cropping has the potential to reduce black-grass infestation, it possible that there can be improvements in yield due to reductions in black-grass population in the long run and that it is possible that spring cropping can be beneficial to UK arable farming in the long run.

Investigating the effect of spring cropping on black-grass has normally been based on field experiments (e.g. Chauvel *et al.*, 2001; Moss and Hull, 2012; Keshtkar *et al.*, 2015). However, such experiments could be expensive and time consuming thus making mathematical models the best alternative. Although some studies were found to have applied mathematical models to investigate weed management strategies with respect to the IWM (e.g. Pandey and Medd, 1991; Swinton and King, 1994; Wu, 2001; Pannell *et al.*, 2004; Pardo *et al.*, 2010; Beltran *et al.*, 2012), the models found were based on dynamic programming approaches which although may be more appropriate especially in the context of modelling population dynamics, may be associated with a limitation of generating complicated model with solutions for sub-problems that may just be local optimum but not global optimum. Also, none of the studies cited estimated the cost of adopting a non-chemical black-grass control measure at the national scale. In this study we developed a farm level model combining mixed-integer, goal and risk programming approaches, incorporating some of the weed management strategies through the modelling of optimal and sub-optimal operations and winter wheat—spring barley or spring beans rotations or sequences. In linear programming based models, dynamics can be incorporated through the modelling of multi-periods in which activities or operations are carried out (McCarl and Spreen, 1997). Thus in our model, the crop season was divided into 26 two-week periods to incorporate some within year dynamics, which are important in annual farm planning and cropping and to allow for timeliness penalties but without dividing the main objective (problem) into sub-problems (which was not required due to focus of the study). In this study, four crops and some specific farm (tillage) operations and assumptions were adopted. As with models, the accuracy of results is normally influenced by the model formulation and the quality of data used in building the model. Although these may serve as a limitation of the model and by extension the study in the case of the aggregation, the results presented give insight into the effect of the adoption of farm management strategies on farming objective, specifically profit maximisation and to some extent risk minimisation objectives in arable farming.

The results of the aggregate cost of black-grass control with spring cropping showed that in the short term, UK arable farming can lose profit by adopting winter wheat—spring barley or spring beans rotation, although under a scenario of very high black-grass infestation in winter wheat fields, loss of profit due to switching to spring cropping could be lower. The overall effect of controlling black-grass with spring cropping resulted in profit reduction due to lower yields or profitability associated with spring crops as well as winter OSR (Nix, 2014). The lower profitability associated with spring crops makes arable farmers reluctant to adopt such a non-chemical weed management strategy under the IWM system (Chikowo *et al.*, 2009). Also, the reduction in profit was partly due to the increase in operations and fixed cost due to the crop combination and the implication is that the crops selected by farmers could have a great influence on the profitability of their farm enterprise through associated labour and machinery costs (Barnard and Nix, 1973; Kay, 1981). For example, with the implementation of mandatory winter wheat—spring beans rotation, some amount of spring barley and winter OSR were also selected. However, winter wheat and spring barley have overlapping harvesting periods (mid-August to early-September) with overlapping optimal harvesting period (mid-August to late-August). Also the optimal harvesting period of spring beans (late-August to early-September) overlap with the harvesting periods of winter wheat and spring barley. Thus to be able to perform harvesting operations within these periods in order not to incur yield penalties and also perform some ploughing to start the establishment of a new crop, more machines/labour are required leading to higher operations and fixed costs. To improve the profitability, there is the need to choose a cropping plan or system aimed at reducing labour and machinery costs through efficient labour and machinery planning but promotes profitability (Barnard and Nix, 1973). The implication is that if arable farmers were to adopt spring cropping to control black-grass, the strategy needs to be combined with efficient timing or planning of operations and machinery/labour use especially in periods in which labour requirements are high and this can be very effective and improve farm profits.

Comparison of the spring barley and spring beans results shows that in terms of black-grass control, spring barley can be said to be better than spring beans with respect to the relatively lower aggregate cost estimates associated with the winter wheat—spring barley rotation. This is a reflection of the fact that the choice of crop in the rotation is very significant in weed management (HGCA, 2014a). The severity and distribution of black-grass in Europe are determined mainly by soil types and cropping systems (Moss, 2013). Thus selecting the right spring crop with consideration to the farm's situation (HGCA, 2014b) can be biologically and economically viable as far as reductions in black-grass population and profit maximisation are concerned.

The increase in profit observed at the individual farm level implies that depending on the farm's situation based on factors such as soil type and prevailing rainfall pattern and the hectares of land available to the farm, controlling black-grass with spring cropping can be economically beneficial and in some cases reduce farm risk in terms reduction in deviations in income. To some arable farmers, controlling black-grass with spring crops has the potential to be profitable due to the associated lower variable costs and the increasing cost of chemical control associated with winter crops (Bayer, 2016). With the inability of black-grass developing resistance to non-chemical control, drawing on the benefits of other non-chemical control measures such as ploughing and delayed sowing in addition to rotation plans such as the ones shown by Option 2 could make black-grass control with spring cropping very effective (Moss and Lutman, 2013; HGCA, 2014b) and reduce chemical inputs which in turn could improve profitability and benefit the environment. Thus depending on a farm's situation and with the help of agronomist, winter wheat—spring barley or spring beans sequences could be adopted as part of a package of black-grass management strategies especially farm which normally grow the four crops adopted for the study.

It is important to view the impact of this modelling in a policy context. The eradication or mitigation of black-grass is a major challenge and in terms of food security and environmental protection, its management provides positive public goods. The provision of positive externalities from agriculture have generally been encouraged through the adoption of the provider gets principle (Hanley and Oglethorpe, 1997; Hanley *et al.*, 1998) and so the aggregate per hectare costs of black-grass management provide us with an estimate of possible policy payments needed to incentivise adoption of the system needed to generate those positive externalities. Although it is acknowledged that spring cropping reduces black-grass population and that reduction in infestation in one year can lead to improvement in yield in subsequent years, the £82/ha estimate based on the four crops selected for the study suggests a cost to UK arable farming for the adoption of winter wheat—spring barley sequence or rotation and thus would represent such a possible payment level if farmers were to adopt spring cropping after incidence of zero or low black-grass infestation. However, with relatively lower loss of profit under a scenario of very high black-grass infestations on winter crop fields, farmers may be better of switching to spring cropping and such payments to incentivise adoption may not be required.

The overall effect of controlling black-grass with spring crops resulted in a reduction in profit in the short term, which could affect the adoption of such non-chemical strategy by arable farmers. However, with EU Sustainable Use of Pesticides Directive requiring arable farmers to give priority to non-chemical methods of plant protection (HGCA, 2014b), continuous research using linear programming based optimisation approaches to come up with optimal profit estimates of different spring cropping strategies to control black-grass could encourage farmers to adopt such non-chemical black grass control measure as part of a package of weed control strategies. Also, future research with a combined linear or goal programming and dynamic programming (focusing on black-grass population dynamics) approaches in addition to the inclusion of more crops could also lead to more robust estimates to better inform policy to incentivise farmers to adopt spring cropping, particularly winter wheat—spring barley or spring beans rotation as a black-grass control measure.

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## Appendix

Table 4-7: Summary rainfall, farm area, crop yield and price data for farms used in the study

| Variable | Unit | Mean | Standard deviation |
|---|---|---:|---:|
| Annual Rainfall | mm | 856.3 | 236.7 |
| Area | ha | 186.5 | 219.7 |
| Winter wheat yield | t/ha | 7.8 | 1.6 |
| Spring barley yield | t/ha | 5.7 | 1.0 |
| Spring beans yield | t/ha | 3.7 | 0.8 |
| Winter OSR yield | t/ha | 3.1 | 0.7 |
| Winter wheat price | £/t | 163.1 | 22.4 |
| Spring barley price | £/t | 150.7 | 16.3 |
| Spring beans price | £/t | 220.8 | 17.2 |
| Winter OSR price | £/t | 342.1 | 26.2 |

Box 4-1: Illustration of aggregate cost estimates

The estimation of aggregate cost is illustrated below with results for 10 farms under low infestation
The Option 2 is winter wheat-spring barley sequence

| Farms | Profit Option 1 | Profit Option 2 | Weight | Weighted Profit Option 1 | Weighted Profit Option 2 | Difference |
|---|---|---|---|---|---|---|
| | **A** | **B** | **C** | **D** | **F** | **E** |
| | | | | **A × C** | **B × C** | **F − D** |
| Farm 1 | 40,029 | 32,446 | 23.12 | 925,379 | 750,074 | -175,305 |
| Farm 2 | 46,180 | 25,738 | 23.71 | 1,094,937 | 610,241 | -484,696 |
| Farm 3 | 24,063 | 7,285 | 2.33 | 56,054 | 16,970 | -39,084 |
| Farm 4 | 20,575 | 12,856 | 15.78 | 324,739 | 202,902 | -121,838 |
| Farm 5 | 126,009 | 57,938 | 40.51 | 5,104,061 | 2,346,790 | -2,757,271 |
| Farm 6 | 43,758 | 41,530 | 32.85 | 1,437,606 | 1,364,417 | -73,188 |
| Farm 7 | 87,580 | 70,613 | 13.27 | 1,162,357 | 937,174 | -225,183 |
| Farm 8 | 57,913 | 58,019 | 13.66 | 791,116 | 792,567 | 1,451 |
| Farm 9 | -10,827 | -10,827 | 31.64 | -342,558 | -342,558 | 0 |
| Farm 10 | 27,569 | 27,569 | 10.71 | 295,329 | 295,329 | 0 |
| **Aggregate Cost (Sum of Column E values for Farms 1 to 10)** | | | | | | **-3,875,115** |

Table 4-8: Weighted mean and standard deviation estimates of model results for 745 under Option 1 crop plan

| Model Estimates | Low infestation | | Medium infestation | | High infestation | | Very high infestation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Sd | Mean | Sd | Mean | Sd | Mean | Sd |
| Output | 240,167 | 280,177 | 234,338 | 273,287 | 219,191 | 257,799 | 204,038 | 240,398 |
| Output + Subsidy | 278,646 | 322,910 | 272,815 | 316,064 | 257,669 | 300,685 | 242,516 | 283,355 |
| N Fertiliser Cost | 28,901 | 32,744 | 28,579 | 32,418 | 27,521 | 31,340 | 25,942 | 30,103 |
| P Fertiliser Cost | 10,485 | 11,828 | 10,428 | 11,768 | 10,251 | 11,588 | 9,976 | 11,375 |
| K Fertiliser Cost | 9,317 | 10,557 | 9,250 | 10,491 | 9,058 | 10,323 | 8,745 | 10,087 |
| Seed Cost | 13,013 | 14,687 | 12,946 | 14,614 | 12,758 | 14,438 | 12,445 | 14,195 |
| Black-grass Herbicide Cost | 27,262 | 30,913 | 26,752 | 30,392 | 25,131 | 28,835 | 22,627 | 26,870 |
| Sundry Cost | 19,709 | 22,329 | 19,342 | 21,955 | 18,158 | 20,815 | 16,345 | 19,381 |
| Variable Cost | 108,687 | 122,745 | 107,297 | 121,299 | 102,878 | 116,860 | 96,081 | 111,541 |
| Gross Margin | 169,959 | 202,687 | 165,518 | 197,549 | 154,792 | 187,617 | 146,435 | 176,316 |
| Cost of Farm Operations | 51,500 | 57,996 | 52,073 | 58,712 | 53,829 | 60,828 | 56,921 | 63,448 |
| Gross Profit | 118,458 | 148,178 | 113,446 | 142,223 | 100,961 | 129,863 | 89,514 | 115,997 |
| Fixed Cost | 68,306 | 77,640 | 68,087 | 77,376 | 68,166 | 78,696 | 69,009 | 78,916 |
| Profit | 50,152 | 79,556 | 45,359 | 74,002 | 32,795 | 61,463 | 20,505 | 49,098 |
| MOTAD Risk | 34,641 | 39,457 | 33,922 | 38,531 | 32,102 | 36,471 | 30,504 | 34,508 |

Sd = Standard deviation. The unit for all estimates are £.

Table 4-9: Weighted mean and standard deviation estimates of model results for 745 under Option 2 crop plan with mandatory winter wheat-spring barley rotation

| Model Estimates | Low infestation | | Medium infestation | | High infestation | | Very high infestation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Sd | Mean | Sd | Mean | Sd | Mean | Sd |
| Output | 220,813 | 259,998 | 217,877 | 256,381 | 209,675 | 246,977 | 200,811 | 236,222 |
| Output + Subsidy | 259,292 | 302,981 | 256,355 | 299,371 | 248,153 | 289,967 | 239,290 | 279,177 |
| N Fertiliser Cost | 26,117 | 29,945 | 26,008 | 29,878 | 25,642 | 29,215 | 24,974 | 28,700 |
| P Fertiliser Cost | 10,032 | 11,397 | 10,012 | 11,384 | 9,944 | 11,268 | 9,819 | 11,158 |
| K Fertiliser Cost | 8,870 | 10,146 | 8,841 | 10,132 | 8,749 | 10,017 | 8,584 | 9,853 |
| Seed Cost | 12,562 | 14,272 | 12,537 | 14,257 | 12,449 | 14,136 | 12,290 | 13,965 |
| Black-grass Herbicide Cost | 23,002 | 26,452 | 22,838 | 26,353 | 22,252 | 25,384 | 21,168 | 24,479 |
| Sundry Cost | 16,561 | 19,009 | 16,447 | 18,940 | 16,036 | 18,243 | 15,270 | 17,625 |
| Variable Cost | 97,144 | 111,117 | 96,683 | 110,821 | 95,072 | 108,031 | 92,104 | 105,528 |
| Gross Margin | 162,148 | 193,788 | 159,671 | 190,681 | 153,081 | 184,938 | 147,185 | 177,122 |
| Cost of Farm Operations | 55,157 | 61,325 | 55,449 | 61,475 | 56,466 | 63,134 | 58,409 | 65,089 |
| Gross Profit | 106,990 | 134,955 | 104,224 | 131,678 | 96,616 | 124,363 | 88,774 | 115,040 |
| Fixed Cost | 69,528 | 78,815 | 69,472 | 78,870 | 69,477 | 80,190 | 69,803 | 79,663 |
| Profit | 37,462 | 64,387 | 34,752 | 61,346 | 27,139 | 54,212 | 18,970 | 47,949 |
| MOTAD Risk | 32,850 | 37,569 | 32,472 | 37,065 | 31,433 | 35,735 | 30,433 | 34,486 |

Sd = Standard deviation. The unit for all estimates are £.

Table 4-10: Weighted mean and standard deviation estimates of model results for 745 under Option 2 crop plan with mandatory winter wheat-spring beans rotation

| Model Estimates | Low infestation | | Medium infestation | | High infestation | | Very high infestation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Sd | Mean | Sd | Mean | Sd | Mean | Sd |
| Output | 202,671 | 237,825 | 201,766 | 236,150 | 200,083 | 235,185 | 198,549 | 233,625 |
| Output + Subsidy | 241,150 | 280,741 | 240,245 | 279,086 | 238,561 | 278,093 | 237,027 | 276,491 |
| N Fertiliser Cost | 21,500 | 24,315 | 21,572 | 24,399 | 21,774 | 24,773 | 21,976 | 24,915 |
| P Fertiliser Cost | 9,422 | 10,652 | 9,418 | 10,648 | 9,405 | 10,628 | 9,393 | 10,623 |
| K Fertiliser Cost | 8,054 | 9,175 | 8,054 | 9,177 | 8,059 | 9,206 | 8,055 | 9,206 |
| Seed Cost | 12,414 | 14,091 | 12,365 | 14,032 | 12,214 | 13,759 | 12,070 | 13,671 |
| Black-grass Herbicide Cost | 18,533 | 20,856 | 18,431 | 20,723 | 18,083 | 20,080 | 17,780 | 19,900 |
| Sundry Cost | 13,360 | 14,990 | 13,288 | 14,893 | 13,036 | 14,422 | 12,823 | 14,294 |
| Variable Cost | 83,284 | 93,898 | 83,129 | 93,708 | 82,570 | 92,692 | 82,097 | 92,448 |
| Gross Margin | 157,867 | 188,566 | 157,116 | 187,109 | 155,990 | 187,413 | 154,930 | 186,208 |
| Cost of Farm Operations | 64,459 | 72,633 | 64,540 | 72,802 | 64,697 | 72,854 | 64,894 | 72,910 |
| Gross Profit | 93,404 | 119,178 | 92,575 | 117,461 | 91,295 | 118,049 | 90,036 | 117,052 |
| Fixed Cost | 72,094 | 80,847 | 72,093 | 80,672 | 72,821 | 83,640 | 73,413 | 84,108 |
| Profit | 21,311 | 50,629 | 20,482 | 49,336 | 18,474 | 47,649 | 16,623 | 47,311 |
| MOTAD Risk | 32,282 | 36,805 | 32,117 | 36,505 | 31,727 | 35,930 | 31,393 | 35,626 |

Sd = Standard deviation. The unit for all estimates are £.

***"Only those who will risk going too far can possibly find out how far it is possible to go."***

— T.S. Eliot

# 5 MODEL APPLICATION 2: RISK MODEL

*In the preceding chapter, the mixed-integer weighted goal-programming model was applied to investigate spring cropping as a black-grass control measure. The model was parameterised using data for 745 farms selected from the FBS to investigate the cost (or gain) of controlling black-grass with spring cropping, particularly winter wheat—spring crop sequence or rotation. The results show that at the aggregate (national) level, the strategy could cost the UK arable sector between £35 and £286 million for adopting winter wheat—spring barley sequence to control black-grass whereas adopting winter wheat—spring beans sequence could cost between £87 and £650 million depending on the level of infestation. However, on individual farm basis, there could be benefits (increase in profit) as well as cost (loss of profit) depending on the farm's soil type, rainfall level, and area of land available to the farm. The policy implication is that the aggregate level results on per hectare bases give indication of possible farm payment to incentivise the adoption of the strategy as part of the black-grass control package.*

*Risk aversion behaviour of arable farmers also influence farmers decision-making. For example, a farmer's level of risk aversion can influence their adoption of new technologies, innovation or sustainable farm management strategies such crop rotation with winter crop—spring crop sequence to control black-grass. Thus risk is very significant in sustainable arable farming. In this chapter, a mixed-integer MOTAD model and a randomly generated risk aversion parameter method are applied to investigate and evaluate absolute risk aversion coefficient and cropping decision. Also, the model is applied to investigate a scenario of how farmers would react to policy change depending on their level of risk aversion. Although different approaches have been applied to investigate farmers risk aversion, no study was found in UK context to have applied the methodology adopted in this study. The results show levels of risk aversion across regions in England. The policy implication of the results is that arable farm policies can be regionalised, tailored to farmers' risk aversion.*

*A version of the study presented was submitted to the American Journal of Agricultural Economics for publication.*

**Risk in agriculture: Modelling spatially-referenced farmer risk behaviour using an evolved mixed-integer MOTAD approach**

*Kwadjo Ahodo, David Oglethorpe, Robert P. Freckleton*

## Abstract

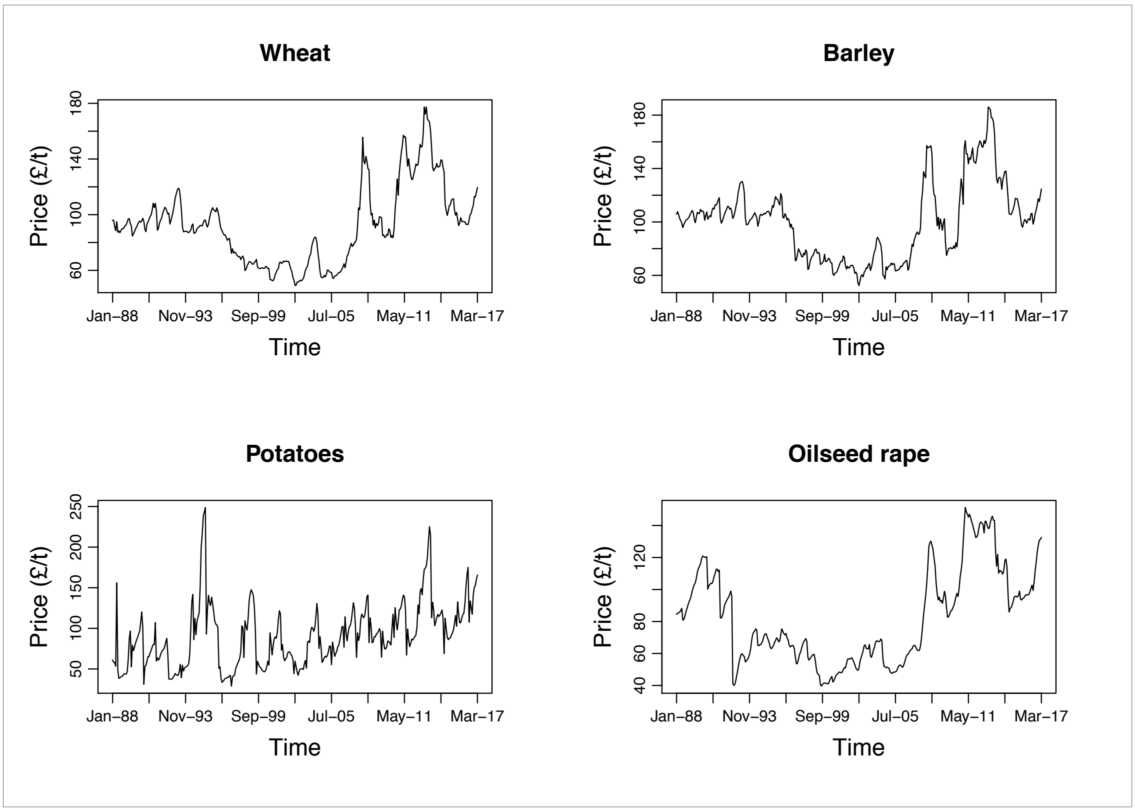
Incorporation of risk into farm models has become accepted as vital in terms of approximating more closely to real-world farm decision-making and improving the predictive power of models. In terms of policy, sustainability goals associated with direct farm or subsidy payments to replace risk-reducing inputs such as fertiliser affect the balance of income-variance relationships and create awareness of the risks associated with alternative farm plans. Farm models need to be able to estimate where risk exists and incorporate how decisions might be taken in the context of that risk. A conceptual, methodological and empirical framework is developed to achieve this and fill a gap in the literature. A mathematical mixed-integer MOTAD model, which allows the generation of a portfolio of alternative farm plans and an efficient expected income-variance (E-V) frontier using randomly generated risk aversion parameters is built and validated. Model-predicted farm plans were compared with real-world observed farm-level land use to estimate spatial differences in risk-attitude. Results showed risk-aversion among arable farmers across regions in England. An analysis of a shift in market prices to illustrate policy relevance shows how the model provides a means of estimating spatially referenced risk farmer typologies, which could be valuable in promoting regional agricultural policy.

## 5.1 Introduction

Risk is inevitable in agriculture and the call to make conventional arable systems to more sustainable even exposes farmers to more risk (Lien *et al.*, 2007; Berentsen and van Asseldonk, 2016). This is because sustainable arable farming systems are underpinned by sustainable farming principles, which promotes efficient use of, and sometimes reductions in the amounts of vital inputs such as fertilizers and pesticides normally used by farmers to safeguard crop yields and farm productivity (Berentsen and van Asseldonk, 2016). Although reductions in such inputs could be beneficial to the environment through reductions in nitrate leaching and pollution of water sources, it can also impact negatively on crop yields and hence farm productivity. Also, the adoption of sustainable principles may mean adopting new farm management strategies and technologies, which may or may not be driven by regulations (policy) in order to achieve the desired results but may be associated with unproven benefits on farm productivity, exposing farmers to risk. The implication is that sustainable arable systems, although seen as beneficial to the environment, could increase the risk and uncertainties in the arable farming business.

Hardaker *et al.* (2015) grouped the types and sources of risk in farming under the following main headings: institutional, personal, production and price or market risks. Institutional risk concerns the type of policy guiding or guarding agricultural practices can present farmers with institutional risks. For example, the nitrate directive prescribes maximum N fertiliser amounts to be applied in Nitrate Vulnerable Zones (NVZs) (Defra, 2013) and this can impact on crop yields. However, subsidy payments (another policy) such as single farm payments may also serve as a payment for the opportunity cost for not applying above the maximum N fertiliser limits. Also, the banning of certain herbicidal active ingredients can constrain the weed management efforts of arable farmers. Personal risks are concerned with the farmer or the farm workers—for example, incorrect application of an input (e.g. fertiliser) by a farmer can cause losses in production. Again, the adoption of an improved but untested technology by an arable farmer as part of efforts to make the farm more sustainable may be associated with risk (Hardaker, *et al.*, 2015).

Arable farmers are also exposed to production risks through variability in weather and incidence of pests and diseases (Hardaker, *et al.*, 2015; Berentsen and van Asseldonk, 2016). For example, high infestation of black-grass can cause substantial yield reduction in winter wheat yield and hence farm productivity (Bayer, 2015). The variability or volatility in crop prices (as reflected in Figure 5-1) as well as input prices, coupled with the fact that farmers are price takers, exposes them to price or market risk. With the other types of risks such as weather, pest and diseases or risk associated with inputs translating into production risk through variability in crop yield, the study presented in this chapter primarily focus on production (yield) and price risk.




Source: Based on data from the Defra's Agricultural Price Indices (https://www.gov.uk/government/statistics/agricultural-price-indices).

Figure 5-1: Prices of wheat, barley, potatoes and oilseed rape from January 1998 to March 2017.

The inevitability of risk in agriculture means the consideration of risk in farm planning or farm planning analysis is crucial. Incorporation of risk into farm simulation modelling has become accepted as crucial to approximate more closely to real-world farm decision-making (Charness *et al.*, 2013; Hazell *et al.*, 1983; Hardaker *et al.*, 2015). Ignoring risk-averse behaviour of farmers in farm planning models can lead to biased model estimates (Hazell *et al.*, 1983; Hardaker, 2000; Hardaker *et al.*, 2015). Incorporating risk aversion or preference of farmers in farm planning models has been found to improve predictive power of models (Hazell *et al.*, 1983; Oglethorpe, 1995; Cooke *et al.*, 2013). In a policy context, the increasing pressure to combine productivity goals with sustainability goals in farming systems exacerbates the problem of risk when pressure mounts to replace risk-reducing inputs, such as pesticides and fertilisers, with more sustainable but economically riskier husbandry options such as organic, rotationally-restricted or simply lower-input systems (Lien *et al.*, 2007; Berentsen and van Asseldonk, 2016). It is thus important that the discipline continues to advance our ability to understand, represent and simulate agricultural risk and do so whilst also improving model transferability and applicability to spatially-specific problems.

A crucial component of usefully understanding risk for any kind of policy application is to know the extent to which farmers are affected by their exposure to risk. Knowing where risk exists and incorporating those risks into a modelling framework is one thing, appreciating how decisions might be taken in the context of that risk is another. Ideally, as well as being able to model alternative risky farm plans we need to know farmers' attitude to risk and elicit their risk preferences since this will influence how farm decisions are taken and decisions relating to the overall strategy of the farm business in general (Kingwell, 1994; Charness *et al.*, 2013; Hardaker *et al.*, 2015, Saqib *et al.*, 2016).

Much attention has been paid in literature to farmers' risk aversion, attitudes toward risk or farm risk in general through the use of farm planning models and other approaches (e.g. Hazell, 1971; Hazell *et al.*, 1983; Elamin and Rogers, 1992; Oglethorpe, 1995; Adesina and Ouattara, 2000; Lien, 2002, Gardebroek, 2006; Lien *et al.*, 2007; Acs *et al.*, 2009; Brick *et al.*, 2012; Cooke *et al.*, 2013; Saqib *et al.*, 2016). Also, the incorporation of farmers' risk aversion or attitude towards risk into risk models has normally been through either direct elicitation (e.g. Dillon and Scandizzo, 1978; Binswanger, 1980; Oglethorpe, 1995; Harrison *et al.*, 2007; Brick *et al.*, 2012; Charness *et al.*, 2013) or through indirect approaches (listed in McCarl and Spreen, 1997) which can be used to identify or approximate farmers' risk aversion. However, in terms of the indirect approaches not many have been applied in conjunction with risk models where a robust predictive decision framework is thus created (Hazell *et al.*, 1983; Elamin and Rogers, 1992).

In this chapter a conceptual, methodological and empirical framework is developed to bridge this gap in the literature by combining and advancing approaches used by Hazell *et al.* (1983), Elamin and Rogers (1992) through the application of a mathematical mixed-integer MOTAD model (hereafter MIMOTAD) which allows the generation of a portfolio of alternative farm plans which offer alternative risky options. From this set an efficient expected income-variance (E-V) frontier is generated using randomly generated non-deterministic risk aversion parameters and by comparing estimated farm plans with real-world observed farm-level land use and identify spatial differences in risk-attitude. Although the model utilises data from the UK, the principles of its construction, testing and use are entirely transferable, unlike many existing risk elicitation examples. The method is highly policy relevant in that it suggests, and provides a means to create, the existence of spatially-referenced risk farmer typologies, which could be valuable in the promotion of regional agricultural policy.

Although other risk programming approaches such as quadratic and stochastic programming exist and may have some advantages over MOTAD, which is a linear approximation of the quadratic programming (QR), MOTAD continued to be used for modelling risk in farming systems (e.g. Adesina and Ouattara, 2000; Ogurtsov *et al.*, 2008; Cooke *et al.*, 2013) and thus fit for purpose as far as the aim of this chapter is concerned. Quadratic programming (QR) assumes farmer's utility function to be quadratic, an assumption regarded as unacceptable in that quadratic are not increasing at all points and also quadratic utility function implies increasing absolute risk aversion (Hardaker *et al.*, 2015). Another assumption to validate QR, which is seen as a drawback for QR is that the distribution of net revenues is normal in that the distribution of farm revenues is unlikely to be normal due to variability in revenues (Hardaker *et al.*, 2015). With the distribution of farm revenues normally skewed, it has been found that in such instance, the mean absolute deviation used as a measure of risk in MOTAD may outperform the sample variance used as a measure of risk in QR (Hazell and Norton, 1986). Thus QR can be said to be weak under the normality assumption (Barnard and Nix, 1973) thus making MOTAD fit for purpose especially in situations where the measurement of risk is based on deviations in income, which in turn is based on historical data of income data, which are likely to be skewed. Stochastic programming has been found to have advantages over QR and MOTAD in that it can better handle random variation (Barnard and Nix, 1973). However, stochastic programming can be complicated due to estimation of probability distribution for all items in the model matrix likely to be associated with random variation and as a result making it to complicated and time consuming (Barnard and Nix, 1973; Kall and Wallace, 1994). Thus with the focus of this chapter on production and price risk, which are based on historical farm income data likely to be skewed, coupled with the fact the construction of MOTAD model is relatively less time consuming but offer a better alternative to other risk modelling approaches, the MOTAD approach is found to be fit for purpose in terms of farm level risk modelling.

## 5.2 Utility theory and income-risk trade-offs

Assuming all feasible farm plans produce or yield the same expected income over time, a risk-averse farmer will seek to adopt the farm plan that minimises variance (risk) given the expected income (Hazell, 1971). The utility function of a risk-averse decision-maker has a negative rate of change of marginal utility with respect to wealth whereas for a risk-neutral decision-maker, the rate of change of marginal utility is zero (Arrow, 1965; Hardaker *et al.*, 2015). This implies that for a risk-averse farmer, expected utility will decrease as the level of payoff increases (Hardaker *et al.*, 2015).

Variance (V) level can be parameterised to generate associated expected income (E) levels with associated V's to derive efficient set of E-V farm plans for the risk-averse farmer. The part of the derived E-V frontier at which the highest level of income is attained represents the farm plan at which the maximum profit exists and only one farm plan can generate that expected income. Different levels of E can be generated by different farm plans with associated V levels. Parameterisation of E-V pairs is considered as a more appropriate approach to estimate the possible impacts of risk-free environmental policies with respect to shifts in the efficient E-V set (Hope and Lingard, 1992). However, the application of this approach to analyse potential policy impacts critically depends on knowledge of where on that portfolio of E-V efficient farm plans the farmer is currently producing. Estimating this point on the E-V frontier can lead to more convincing decisions regarding the success of such policies. Again, knowledge of the farm plan which maximises the utility derived from varying E-V pairs allows a better assessment of risk minimising techniques within farm-level planning problems, through comparison with observed farm plans (Lin *et al.*, 1974; Oglethorpe, 1995; Kreitler *et al.*, 2014).

Agri-environmental policies associated with sustainable agriculture normally involve direct payments to farmers for the generation of positive externalities derived through the adoption of less intensive farm plans (based on the 'provider gets policy', Hanley *et al.*, 1999). Farmers receiving direct income payments mean that a certain proportion of their income is generated effectively 'risk-free' and introduction of this would adjust the shape of the E-V frontier. The implication would be the policy having different impacts for different farmers depending on where they positioned on the E-V frontier based to their level of risk-aversion. This is illustrated in Figure 5-2where the inclusion of a 'risk-free' option available for less intensive, profit-suboptimal farm plans 'tilted out' the E-V efficient farm plans from 0P to EsP.

The risk-averse farmer will rationally produce at the point where her/his utility for an E-V pair is maximised. This represents the point at which the E-V frontier lies tangent to their highest attainable iso-utility curve, which in turn depends on the level of the farmer's risk aversion. If the producer displayed an iso-utility curve as described by $I_{21\text{-}23}$ then the shift in the E-V frontier would have little or no effect on the farm plan adopted by the farmer, implying that the risk-free agri-environment option would not be adopted. However, if the producer displayed an iso-utility curve as described by $I_{11\text{-}13}$ then the shift in the E-V frontier from 0P to EsP would cause a change in the farm plan and at least part of the agri-environment option would be adopted.

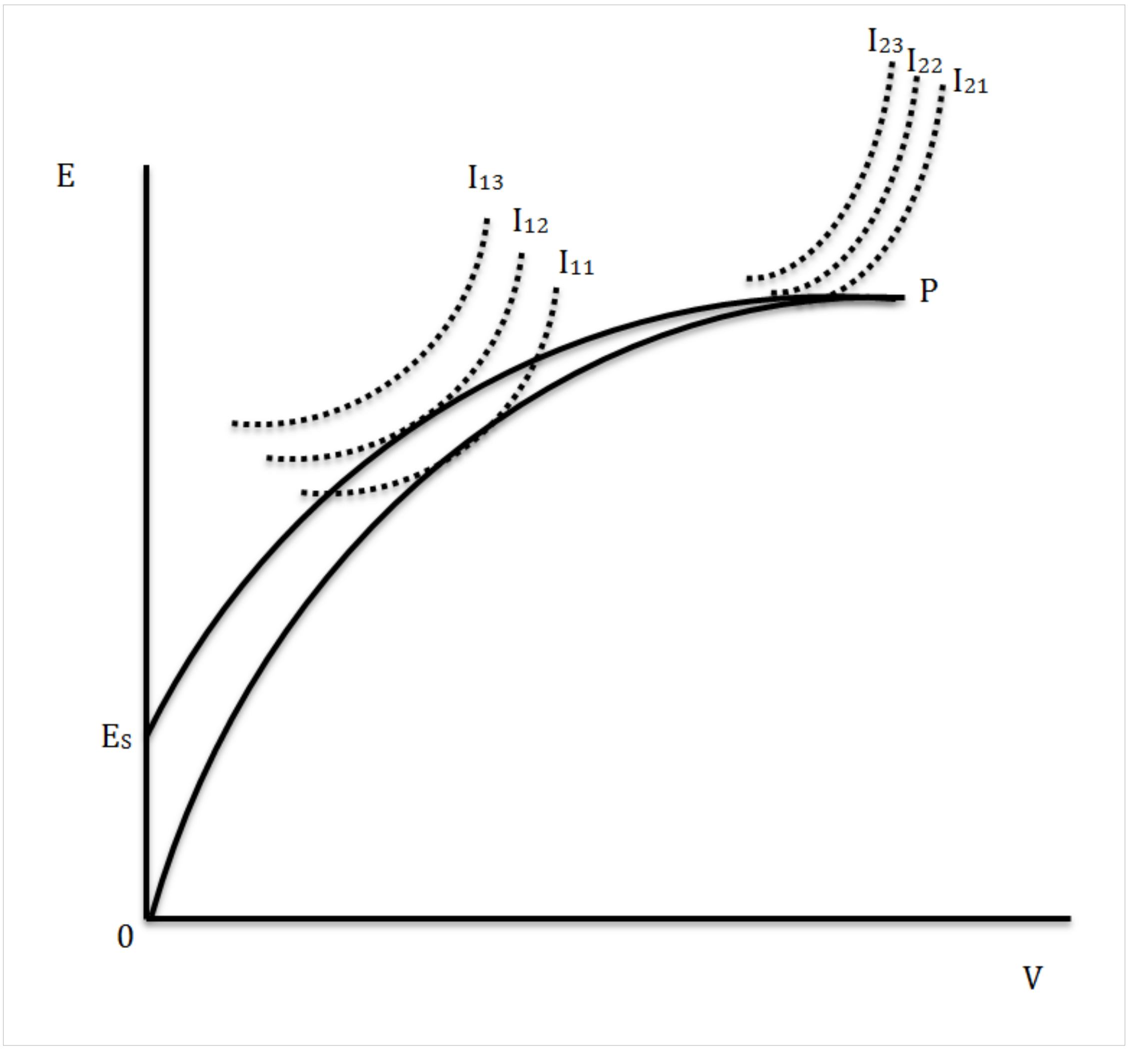



Figure 5-2: Shift in an E-V frontier by incorporation of a risk-free enterprise

In order to simulate this phenomenon of maximised utility, there is the need to recreate the risky portfolio of farm plans facing a farmer and simultaneously establish how the farmer will select from those plans according to her/his risk preference or risk aversion level. This requires the estimation of farm-specific E-V frontiers and subsequently the estimation of risk-aversion points on those E-V frontiers. The estimation of risk-aversion points on E-V frontiers can be achieved by either the direct and primary elicitation of farmer-specific utility functions (e.g. Oglethorpe, 1995) or through indirect modelling approaches (e.g. Hazell *et al.*, 1983; Elamin and Rogers, 1992). In the indirect approaches, a model capable of generating efficient E-V pairs is calibrated to represent a particular situation and identify which risk-aversion parameter best enables the model to most accurately match observed land use. The risk aversion parameter is essentially estimated by making inferences from observed economic behaviour (Lien, 2002). This indirect approach is thus adopted in this chapter. Although the 'parent' model (SAFMOD) is described in Chapter 3, Section 5.3 explains the development of the mixed-integer MOTAD model as a stand-alone model capable of generating efficient E-V pairs to represent different representative farm situation. Using data from the UK Farm Business Survey, the model is applied to generate results, based on which the coefficients of absolute risk aversion are estimated and demonstrate how risk aversion affects farm choice. Finally, an example and analysis of an induced shift in the E-V frontier are presented to show the spatial differences in land use in response to variation in crop prices caused by policy change. The research questions of this study can therefore be summarised as follows:

1. Are arable farmers in England risk averse?
2. Are there any differences in risk aversion across regions in England?
3. Do the levels of risk aversion influence cropping decisions?
4. What is the effect of policy change on farmers with different levels of risk aversion?

## 5.3 Methods

### 5.3.1 Minimisation of total absolute deviation (MOTAD) model

The incorporation of risk into agricultural land-use mathematical programming models have normally been through the use of risk programming approaches, mainly quadratic risk programming (QRP) (e.g. Markowitz, 1952; Freund, 1956; Lien, 2002) and its linear approximation version, the minimisation of total absolute deviation (MOTAD) (Hazell, 1971; Adesina and Ouattara, 2000; Stott *et al.*, 2003; Börner, 2006; Cooke *et al.*, 2013; Osaki and Batalha, 2014) as well as stochastic programming (Acs *et al.*, 2009; Hazell *et al.*, 2015). In QRP, expected income is maximised subject to the constraint on income variance through the use of a variance-covariance matrix and assumes a quadratic utility function of the decision maker. However, in MOTAD the variance is replaced with mean absolute deviation ($M_n$) or in some formulations, the standard deviation. Another assumption to validate QRP is that the distribution of total income is normal (Ogurtsov *et al.*, 2008) however, in agriculture the distribution of income is normally skewed (Hardaker *et al.*, 2004). Although QRP models are said to generate more efficient solutions than MOTAD, MOTAD is still relevant and continued to be used in farm risk modelling (e.g. Cooke *et al.*, 2013; Osaki and Batalha, 2014) and in instances where the enterprise income distributions are skewed, the mean absolute deviation in MOTAD may outperform sample variance in QRP (Hazell and Norton, 1986; Adesina and Ouattara, 2000) and thus makes application of MOTAD in model farm risk (deviation in income) also fit for purpose.

In this study, a mixed-integer MOTAD model[23] (hereafter MIMOTAD) developed using the R programming software (R Core Team, 2015) (see for the flowchart summarising the model outline and associated assumption) is applied to investigate farmers' risk version and cropping decisions and subsequently used to estimate (approximate) coefficient of absolute risk aversion for arable farmers in the England under the expected value-variance (E-V) framework. This is done based on the assumption that the farmer (the decision maker) wants to maximise her or his expected utility based on the linear utility function shown by Eq. (5-1), which is the expected income ($E$) (defined by Eq. (5-2)) less half of the coefficient of absolute aversion ($R_a$) multiplied by the variance ($V$) in income. Eq. (5-1) basically estimates the certainty equivalent from the expected income ($E$) discounted by the risk premium ($0.5R_aV$). The magnitude of $R_a$ determines the importance the farmer attaches to risk and hence the farmer's level of risk aversion. That is, it reflects how much $E$ the farmer is willing to forgo in order to reduce $V$. Also, the use of Eq. (5-1) means a linear utility function is assumed for the farmer or decision maker.

$$U = E - \frac{1}{2} R_a V \tag{5-1}$$

[23] Model codes can be found via the following link: https://github.com/kwadjoahodo/SAFMOD

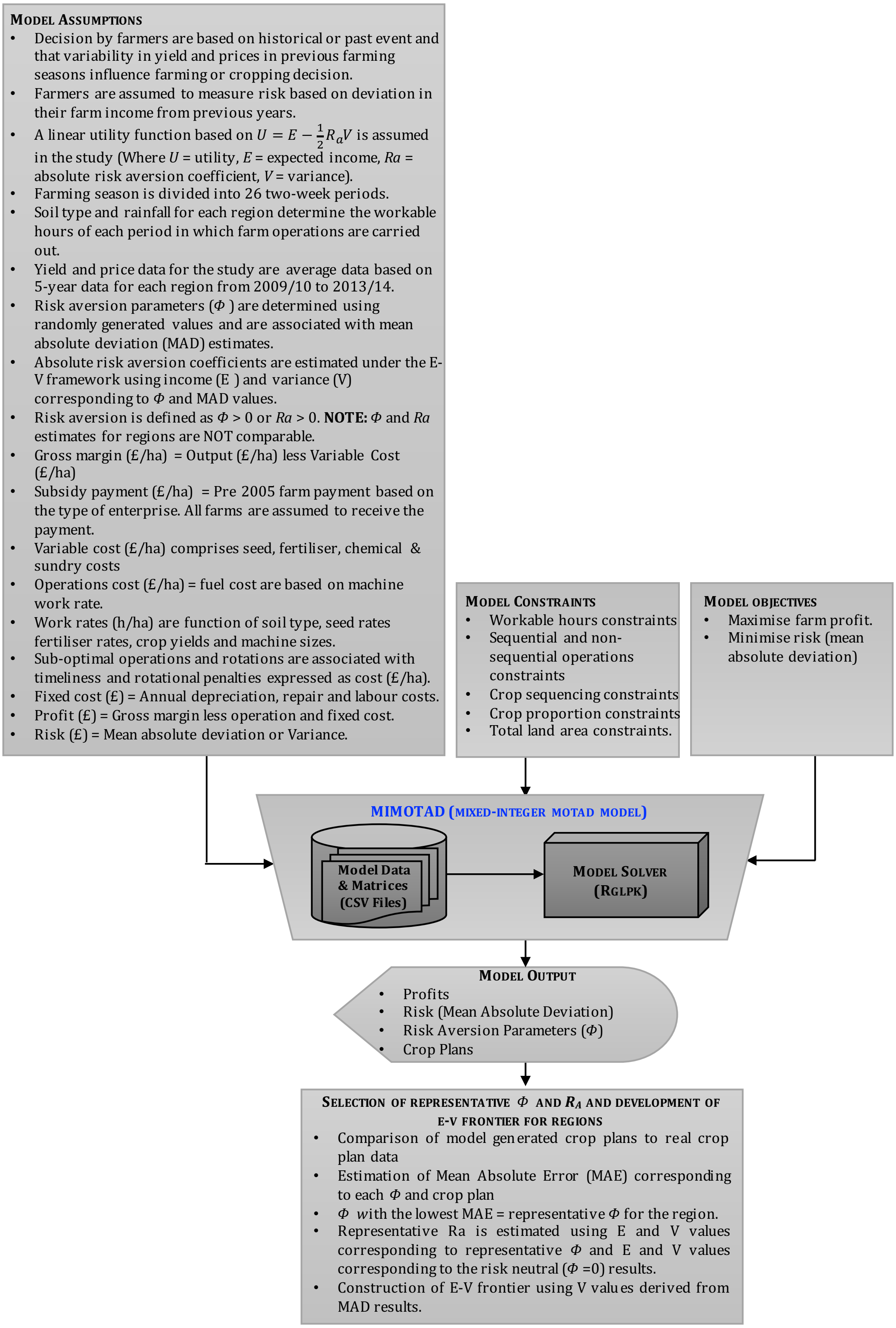



Figure 5-3: Flowchart showing the outline of the MIMOTAD model and associated assumption.

Although MOTAD is a linear approximation of expected value-variance (E-V) (Hazell, 1971) and generates income-mean absolute deviation (E-M) frontier, the $M_n$ in MOTAD can be converted to $V$ (Kaiser and Messer, 2010) to generate an E-V frontier based on which an approximated absolute risk aversion coefficient can be estimated from the ratio of the income ($E$) and variance ($V$). The MIMOTAD model maximises expected income (farm profit) subject to deviation in income (measured by $M_n$) (Eq. (5-3) and (5-4)) and a set of constraints under Section 5.3.2. The model formulation is an adapted formulation from Hardaker (1997) (based on the linear approximation of Freund (1956) formulation) and can be stated as follows:

$$OBJ_{profit} = \sum_i \bar{E}_i a_i - \sum_i \sum_j \sum_k C_{ijk} y_{ijk} - \sum_m C_m n_m - \sum_q p_q d_q \tag{5-2}$$

$$\sum_i \left(E_{iq} - \bar{E}_i\right) a_i + d_q \geq 0 \quad for\ all\ q \tag{5-3}$$

$$\sum_q p_q d_q \leq M_n,\ M_n \text{ varied} \tag{5-4}$$

Where $\bar{E}_i$ is the mean expected gross margin, $a_i$ is the area of crop $i$ and it is equal to sum of the area of first or last operation carried on a crop $i$, $C_{ijk}$ is the cost of the $j$th operation on the $i$th crop in period $k$ and $y_{ijk}$ is the area of $j$th operation on the $i$th crop in period $k$. $C_m$ is the cost of machinery and labour required to perform field operations and $n_m$ is the number of machines of types $m$ required to perform the field operations. $E_{iq}$ is the gross margin of the $i$th crop under $q$th state of nature and, $d_q$ is an $s$ by 1 vector of activity levels measuring negative income deviations under $q$th state of nature, $p_q$ is a 1 by $s$ vector of probabilities of the $q$th state of nature and $M_n$ is a measure of mean absolute deviation (MAD) or risk, which can be parametrically varied.

In the MIMOTAD model, $M_n$ is parametrically varied and the magnitude reflects the level of risk aversion. When $M_n$ is set at its highest possible value, MIMOTAD is solved as a pure profit maximisation model (representing the income for the risk-neutral farmer). However, to be able to parameterise $M_n$ using weights (represented by $\Phi$) to serve as risk aversion parameter, Eq. (5-4) was modified to get Eq. (5-5).

$$pd \leq M_n - \Phi M_n, \tag{5-5}$$
$$M_n \; fixed \; at \; highest \; value, \Phi \; varied \; from \; its \; maximum \; value \; to \; 0$$

The risk aversion parameter ($\Phi$) is then parameterised until no solution of interest can be generated (Hardaker *et al.*, 2015). When $\Phi$ is zero (reflecting no risk aversion or risk neutral), the highest values for both $M_n$ and expected income are obtained and the model is solved as a pure profit maximisation model (Hazell *et al.*, 1983). When $\Phi$ is at its highest possible value (reflecting extreme risk aversion), the lowest possible values are obtained for both $M_n$ and expected income.

### 5.3.2 Model constraints

The constraints considered in MIMOTAD are resource, sequential/non-sequential operations and crop sequencing or rotational constraints. Other constraints considered are total cropping area and crop area or proportion constraints.

The resource (workable hours) constraint (Eq. (5-6)) ensures that the amount of a resource needed to carry out an operation on a crop does not exceed the amount of the resource available. Thus this constraint ensures resource use efficiency.

$$\sum_i \sum_j S_{ijkm} y_{ijk} \leq L_{mkw} n_m \qquad \forall m, k, w \tag{5-6}$$

Where, $S_{ijkm}$ is the work rate of operation *j* carried on crop *i* using a machine of type *m* in period *k* and $y_{ijk}$ area of operation *j* carried on a crop *i* period *k*. $L_{mkw}$ is the amount of resource (workable hours) available in period *k* to carry out an operation with workability type *w* using machine type *m and* $n_m$ the number of machine type m calculated by the model.

The sequential operation constraint (Eq. (5-7)) ensures that a successor operation is not carried out until its preceding operation has been carried out and that the area of the successor operation must be equal to the area of the preceding operation. For example, a crop cannot be harvested until it has been planted (sown) and the area harvested must be equal to the area planted. The constraint can be expressed as follows:

$$\sum_{k \le K} y_{ijk} \le \sum_{k \le K} y_{i(j-1)k} \qquad \forall\, i, j > 1, k \tag{5-7}$$

Where, $K$ belongs to a set of periods in which an operation can be carried out on a crop. For non-sequential operations, which are carried out based on the stages of crop development,

$$a_i = \sum_{k} y_{ijk} \tag{5-8}$$

The crop sequencing/rotational constraint (Eq. (5-9)) ensures that the total area of a successor crop is equal to the area of the last operation of the predecessor crop. This can be expressed as follows:

$$\sum_{c} r_{ick} = \sum y_{iJk} \tag{5-9}$$

$$\sum_{k \le K} y_{c1k} \le \sum_{c} r_{ick} \tag{5-10}$$

Where, $r_{ick}$ is the area of crop $c$ taking over from (following) crop $i$ in period $k$ whereas $y_{iJk}$ is the area of last or final operation $J$ carried out on crop $i$ in period $k$. The constraint represented by Eq. (5-10) ensures that the area of the first operation of crop $c$ in period $k$ ($y_{c1k}$) does not exceed $r_{ick}$.

In the MIMOTAD model, limitations/constraints are put on the areas of crops such as potatoes, winter oilseed rape and/or legumes (field beans), however there is more flexibility in the rotation plan selected by the model. The crop proportions were formulated in such a manner to reflect some of the pest management principles of breaking disease cycles using crop rotation. For example, the proportion of winter oilseed rape is less than or equal to 1/3 of the total land area to appear 1 in 3 years in the rotation. Again, the crop proportions were formulated to capture the 'greening' rules of the Common Agricultural Policy (Defra, 2014), which ensures that no one crop can take more than 75% of the crop area. The total area constraint ensures the sum of areas of all crops is equal to the total cropping area available to the farmer.

### 5.3.3 Validation of the MIMOTAD model

The MIMOTAD model was verified and validated validation by results through predictive validation (McCarl and Spreen, 1997). The verification was done by solving the model with two different solvers to check consistency on the results generated by the model. The predictive validation was carried out using UK Farm Business Survey (FBS) data from 2009 to 2013 for 281 lowland arable farms in England and Wales with crop yields, farm area, soil types and rainfall as data inputs (see Section 3.7 of Chapter 3 for more information on model validation). Aggregate level comparison of model results (crop areas) and observed FBS data was carried out using statistical measures of association (see examples in Gaiser *et al.* (2010); Pulvento *et al.* (2013) and Gueymard (2014)) and results are presented in Table 5-1.

Table 5-1: Model validation comparison between predicted and observed crop areas

| Measures of association | Estimates |
|---|---|
| r | 0.91{0.01} |
| ρ | 0.67 {0.05} |
| $R^2$ | 0.83 |
| MAE | 0.42 |
| RMSE | 0.53 |
| NSE | 0.80 |
| WIA | 0.95 |
| LCE | 0.47 |
| CRM | 0.07 |
| Intercept | 0.02 (0.99) {0.34} |
| Slope | 0.85 (-1.08) {0.30} |

Sample size for all estimates = 10 based on the number of activities (9 crops plus set-aside) in the model. LCE values are normally low compared to NSE and WIA due to the higher magnitude of the denominator. Values in parentheses: in brackets are t-statistics and in braces are p-values.

Although measures of association such as the root mean square error (RMSE) and mean absolute error (MAE) showed some level of bias in the model predictions, estimates such as the Pearson correlation (r), Spearman correlation (ρ), coefficient of determination ($R^2$), Nash-Sutcliffe's model efficiency (NSE), Willmott's index of agreement (WIA) and Legates's coefficient of efficiency (LCE) showed positive association between predicted crop areas and observed crop areas. The results of t-test on the intercept and slope of regressing the observed crop areas on predicted crop areas showed that the intercept and slope were not different from zero and one respectively.

### 5.3.4 Identification of risk aversion parameters

There are different approaches or methods of eliciting risk aversion coefficient or parameter from farmers. McCarl and Spreen (1997) listed six different approaches for specifying the risk aversion parameter. These involve developing the efficient frontier by solving for many risk aversion parameters. Also, an efficient frontier can be developed and presented to farmers to pick acceptable points. Again, an approach in which some sort of gambling game is played with farmers by asking them to choose between two options, after which a coin is tossed to determine whether or not the outcome is bad or good and the results used to estimate risk aversion coefficients for farmers (e.g. Dillon and Scandizzo, 1978; Binswanger, 1980). However, such direct elicitation approach can be time consuming and expensive.

Charness *et al.* (2013) also reviewed other elicitation approaches and although such approaches and the others mentioned above may have their associated advantages, the approach applied in this study is relatively not complicated and not associated with any financial constraints. The approach adopted in this chapter is similar to the one suggested in McCarl and Spreen (1997) and applied by Simmons and Pomareda (1975), Brink and McCarl (1978) and Hazell *et al*. (1983) however, their estimated representative risk aversion parameters were not randomly generated. Also, as part of our approach, the arable farming system is modelled in detail to reflect the real decision environment which farmers face. The adopted approach was primarily due to time and financial constraints for direct elicitation through Binswanger's approach or generating efficient frontier and presenting to farmers to pick acceptable points. The model is solved for different randomly generated risk aversion parameters ($\Phi$) after which the cropping at $\Phi$ points representing change of basis are selected and compared with observed cropping. The level of deviation or association is then measured using statistical estimates such as the mean absolute deviation or error ($MAE$). Also, the means and standard deviations of model results (cropping) at the selected points and observed cropping were compared. However, the determination of the representative $\Phi$ was based on the minimum $MAE$ value.

### 5.3.5 Data, evaluation of model components and model runs

The two main objectives in the MIMOTAD model are expected farm profit maximisation, which is gross margin less farm operation and machinery and labour costs, and risk (deviation) in income measured by mean absolute deviation. Crop yield and price data were obtained from 2009/10 to 2013/14 Farm Business Survey (FBS) for three FBS defined regions in England (North England, East England and West England) to estimate output (yield × price) (see chapter Appendix for price and yield data). The crop prices were adjusted for inflation to 2016 prices using HM Treasury (2016) deflator series. The gross margin is defined as output (plus Single Farm Payment, SFP) less fertiliser, seed and sundry costs including chemical costs. The SFP value and the sundry costs were obtained from Nix (2014). The fertiliser costs are based on Defra (2010) recommended fertiliser amount, determined by soil type, whereas seed costs were based on seed rates from Toosey (1988). Gross margins under $q$th state of nature were generated for the three regions. The mean gross margins and subsequently the deviations in income were estimated.

The operations costs were functions of work rates for machines, which in turn were functions of machine sizes, fertiliser amounts, seed rates, crop yields, soil type and fuel price. The operations cost took into consideration yield penalties for sub-optimal operations and rotations. The fixed cost (annual machinery and labour cost) estimates were based on annual depreciation, repair/maintenance and annual labour costs.

Following Hazell *et al*. (1983), each of the three regions (North England, East England and West England) was treated as a single farm and the model was run for each region by using the representative soil type, rainfall amount and average total cropping area. The crop areas are average crops areas for farms with arable areas greater or equal to 40ha from 2009/10 to 2013/14 crop years. Table 5-2 shows the observed average crop areas, representative soil types and rainfall amounts for the three regions selected.

Table 5-2: Observed average crop areas, representative soil types and annual rainfall for the selected regions.

| Crops | Average Regional Crop Areas (ha) | | |
|---|---|---|---|
| | North England | East England | West England |
| Winter wheat | 67.0 | 118.6 | 69.8 |
| Spring wheat | 25.1 | 28.0 | 19.9 |
| Winter barley | 34.6 | 37.1 | 27.0 |
| Spring barley | 34.1 | 42.0 | 34.7 |
| Beans* | 21.6 | 31.2 | 26.4 |
| Ware potatoes | 22.5 | 49.3 | 28.6 |
| Winter oilseed rape | 33.2 | 60.5 | 49.4 |
| Sugar beet | 15.7 | 53.9 | -- |
| Total area | 254 | 421 | 256 |
| | | | |
| Soil type | Heavy soil (Index = 2) | Heavy soil (Index = 2) | Medium soil (Index = 1.5) |
| Rainfall (mm) | 944 | 613 | 1223 |

* Beans consist of winter and spring beans

The model was run in a non-deterministic manner, essentially run 10000 times for each of the three regions using entirely randomly[24] generated $\Phi$ values from zero (reflecting risk neutral) to its possible highest value (reflecting extreme risk aversion). The resultant MAD's were then converted to standard deviation ($\sigma$) using the Fisher constant in Eq. (5-11) (Hazell and Norton, 1986) and squaring $\sigma$ to obtain the variance ($V$) (Kaiser and Messer, 2010). The number of states of nature, $s$ is equal to 5.

[24] The $\Phi$ values were randomly generated using the uniform distribution random number generator function in the R programming language.

$$\sigma = MAD \times \left[\frac{s\pi}{2(s-1)}\right]^{0.5}, \qquad V = \sigma^2 \tag{5-11}$$

The model generated cropping at each $\Phi$ value was compared with observed cropping applying the statistical approaches shown below, where $O_i$ is the observed area for the *i*th crop, $P_i$ is the model generated area for the *i*th crop, $O_{av}$ and $P_{av}$ are the means of the observed and model data respectively and $N$ is the number of observations. $MAE$ = mean absolute error (deviation), $RMSE$ = root mean square error, $_{m}WIA$ = modified Willmott's index of agreement (Willmott *et al.*, 2012). The $\Phi$ values at which the lowest $MAE$ estimate was obtained were chosen as representative risk aversion parameter for each region.

$$MAE = \frac{1}{O_{av}}\left(\frac{\sum_{i=1}^{N}|P_i - O_i|}{N}\right) \tag{5-12}$$

$$RMSE = \frac{1}{O_{av}}\sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{N}} \tag{5-13}$$

$$mWIA = 1 - \frac{\sum_{i=1}^{N}|P_i - O_i|}{2\sum_{i=1}^{N}|O_i - O_{av}|} \tag{5-14}$$

### 5.3.6 Estimation of the coefficient of absolute risk aversion under the E-V framework

The approximate coefficients of absolute risk aversion ($R_a$) were estimated for each of the points on the generated E-V frontier corresponding to the representative $\Phi$ values, which gave the lowest $MAE$ estimates using Eq. (5-15), (adapted from Lien, 2002). With MIMOTAD formulated to set the measure of risk at its possible highest value and then progressively reduced until no further solutions of interest are found (Hardaker, 1997; 2004; 2015) and as a result in estimating $R_a$, $E_{rn}$ and $V_{rn}$ are the highest expected income ($E$) and variance ($V$) respectively corresponding to the risk neutral solution were used. Thus Eq. (5-15) was fit for purpose. $E_l$ and $V_l$ are the *l*th $E$ and $V$ respectively on the E-V frontier.

The certainty equivalent (*CE*), risk premium (*RP*) and proportional risk premium (*PRP*) (Eq. (5-16)-(5-18)) were estimated to help in the analysis of risk attitudes across the regions. The *PRP* is the proportion of the expected payoff of a risky prospect that the decision maker (farmer) would be willing to pay to trade away all the risk for a sure thing (Hardaker, 2000). To determine whether or not farmers in a particular region are risk averse, a simple rule was developed. For a risk neutral farmer, $R_a = 0$; and for a risk averse farmer, $R_a > 0$. Thus, regions with estimated $R_a$ values (as well as identified $\Phi$ values) greater than zero were described as risk averse.

$$R_a = \frac{2\times(E_{rn} - E_i)}{V_{rn} - V_i} \tag{5-15}$$

$$CE = U = E - \frac{1}{2}R_a V \tag{5-16}$$

$$RP = \frac{1}{2}R_a V \tag{5-17}$$

$$PRP = \frac{RP}{E} = \frac{1}{2}R_a \frac{V_{rn}}{E_{rn}} \tag{5-18}$$

Where $R_a$ is the measure of absolute risk aversion, $E_{rn}$ and $V_{rn}$ are the expected income and variance respectively corresponding to the risk neutral solution, $E_i$ and $V_i$ respectively are the expected income and variance corresponding to the ith risk aversion parameter ($\Phi$), $E$ and $V$ are respectively the expected income and variance for the selected or representative risk aversion parameter or $R_a$. RP is the risk premium, *CE* is the certainty equivalent which is also a measure of utility (*U*).

## 5.4 Results

### 5.4.1 Estimated risk aversion parameters and cropping decisions

The risk aversion coefficients show that arable farmers in North, East and West England are risk averse ($\Phi$ and $R_a$ >0). The results of the three regions are shown in Table 5-3. The representative risk aversion parameter ($\Phi$) at which the comparison of the model generated crop areas and observed crop areas gave the best-fit were $\Phi$=0.30 ($R_a$ = 0.000012, $MAE$ = 0.29), $\Phi$=0.54 ($R_a$ = 0.0000064, $MAE$ = 0.12) and $\Phi$=0.14 ($R_a$ = 0.0000090, $MAE$ = 0.27) respectively for North, East and West England. It should be noted that the risk aversion parameters and the absolute risk aversion coefficients for the three regions presented in Table 5-3 and are not comparable. For each region, *RP* was lowest at the highest level of risk aversion meaning risk premium decreases with increase in risk. Also, the *PRP* estimates were highest at the highest level of risk-aversion implying that for a more risk-averse arable farmer, a bigger proportion of her/his income will be absorbed by their risk premiums to achieve the *CE*.

In terms of cropping, the results of all regions show risk aversion ($\Phi$ or $R_a$) influenced cropping patterns. In the case of North England, the areas of spring wheat and sugar beet increased from 0.0ha ($\Phi$=0) to 51.8ha and 63.5ha respectively at $\Phi$=0.67 ($R_a$=0.000031). The lowest coefficient of variation estimates (CV=0.05) for spring wheat is also a reflection that it was associated with low risk The area of spring barley and ware potatoes reduced to 0.0ha at $\Phi$=0.67, indicating possible large variances associated with their revenues. Thus such crops may be considered high-risk crops and it is possible that not many farms in North England will grow them especially potatoes.

For East England, areas of crops such as spring wheat and sugar beet increased from 0.0ha ($\Phi$=0) to 188.4ha and 105.2ha respectively ($\Phi$=0.81 and $R_a$=0.000019). The results suggest that these crops may be associated with low risk. Thus it is possible that in a situation where the areas of dominant or profitable crops such winter wheat and ware potatoes drastically reduce at higher risk aversion levels, land may be allocated to spring wheat or sugar beet. Areas of spring barley and ware potatoes however, reduced to 0.0ha at $\Phi$=0.81 ($R_a$=0.000019) reflecting the possibility of large variances associated with their revenues. As with Northern England, area of beans remained unchanged. Some hectares of land (22.0ha) were not cropped or utilised under extreme risk aversion ($\Phi$=0.81).

Under West England, the biggest spring wheat area (45.8ha) was obtained under the highest $\Phi$ value ($\Phi$=0.48; $R_a$=0.000042). It was found that spring wheat revenues correlated negatively with revenues of all the other crops, meaning that as the areas of most of the other crops (e.g. ware potatoes, winter oilseed rape) reduce under high levels of risk aversion, it is likely land will be allocated to spring wheat. Unlike the other regions, the area of winter barley increased from 55.6ha to 83.4ha as risk aversion increased. This may be due to the fact that in West England, no farm was found to grow sugar beet and as a result crops such as winter barley may become the alternative less risky crop. The area of beans, although remained unchanged under lower risk aversion levels, increased to 25.2ha the highest level of risk aversion ($\Phi$=0.48).

Table 5-3: Result of the comparison of model generated crop areas with observed crops areas in North, East and West England under different risk aversion coefficients.

| Results | Risk Aversion Parameter | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | North England | | | | East England | | | | West England | | | |
| | $\Phi$ = 0 | **$\Phi$ = 0.303** | $\Phi$ = 0.669 | Observed Cropping (ha) | $\Phi$ = 0 | **$\Phi$ = 0.540** | $\Phi$ = 0.814* | Observed Cropping (ha) | $\Phi$ = 0 | **$\Phi$ = 0.144** | $\Phi$ = 0.482 | Observed Cropping (ha) |
| Farm Income, *E* (£) | 62,049 | **50,351** | 7,241 | -- | 204,984 | **153,447** | 19,247 | -- | 90,871 | **86,970** | 26,653 | -- |
| *MAD* (£) | 44,956 | **32,069** | 15,232 | -- | 102,756 | **47,890** | 19,331 | -- | 46,923 | **41,943** | 25,376 | -- |
| $\sigma$ (£) | 62,995 | **44,936** | 21,344 | -- | 143,986 | **67,106** | 27,087 | -- | 65,751 | **58,772** | 35,558 | -- |
| $V$ (£$^{2}$' $10^{6}$) | 3,968.37 | **2,019.24** | 455.57 | -- | 20,731.97 | **4,503.22** | 733.71 | -- | 4,323.19 | **3,454.15** | 1,264.37 | -- |
| *CV* | 1.02 | **0.89** | 2.95 | -- | 0.70 | **0.44** | 1.41 | -- | 0.72 | **0.68** | 1.33 | -- |
| $R_a$ | 0.00 | **0.0000120** | 0.0000312 | -- | 0.00 | **0.0000064** | 0.0000186 | -- | 0.00 | **0.0000090** | 0.0000420 | -- |
| *CE* (£) | 62,049 | **38,232** | 133 | -- | 204,984 | **139,146** | 12,433 | -- | 90,871 | **71,465** | 108 | -- |
| *RP* | 0.00 | **12,119** | 7,108 | -- | 0.00 | **14,301** | 6,814 | -- | 0.00 | **15,505** | 26,545 | -- |
| *PRP* | 0.00 | **0.24** | 0.98 | -- | 0.00 | **0.09** | 0.35 | -- | 0.00 | **0.18** | 1.00 | -- |
| Cropping (ha) | | | | | | | | | | | | |
| Winter wheat | 65.5 | **59.5** | 74.0 | 67.0 | 92.6 | **119.1** | 11.0 | 118.6 | 55.6 | **74.9** | 62.8 | 69.8 |
| Spring wheat | 0.0 | **16.8** | 51.8 | 25.1 | 0.0 | **45.9** | 188.4 | 28.0 | 0.0 | **0.0** | 45.8 | 19.9 |
| Winter barley | 38.3 | **60.4** | 22.3 | 34.6 | 66.3 | **40.7** | 34.5 | 37.1 | 55.6 | **45.0** | 83.4 | 27.0 |
| Spring barley | 42.3 | **21.3** | 0.0 | 34.1 | 88.5 | **28.9** | 0.0 | 42.0 | 45.8 | **34.8** | 0.0 | 34.7 |
| Beans | 15.8 | **15.8** | 15.8 | 21.6 | 26.4 | **26.4** | 26.4 | 31.2 | 16.0 | **16.0** | 25.2 | 26.4 |
| Ware potatoes | 44.4 | **30.2** | 0.0 | 22.5 | 105.2 | **50.7** | 17.1 | 49.3 | 45.8 | **40.3** | 11.9 | 28.6 |
| Winter OSR | 47.6 | **36.5** | 26.6 | 33.2 | 42.0 | **62.1** | 16.3 | 60.5 | 37.3 | **45.0** | 26.8 | 49.4 |
| Sugar beet | 0.0 | **13.4** | 63.5 | 15.7 | 0.0 | **47.3** | 105.2 | 53.9 | -- | **--** | -- | -- |
| Measure of Dispersion/Association | | | | | | | | | | | | |
| Mean | 31.73 | **31.73** | 31.73 | 31.73 | 52.57 | **52.57** | 49.86 | 52.57 | 36.54 | **36.54** | 36.54 | 36.54 |
| Standard deviation | 23.83 | **19.05** | 28.24 | 15.81 | 41.71 | **29.20** | 64.63 | 28.90 | 21.04 | **23.77** | 29.26 | 17.36 |
| *MAE* | 0.38 | **0.29** | 0.64 | | 0.62 | **0.12** | 1.06 | | 0.44 | **0.27** | 0.64 | |
| *RMSE* | 0.46 | **0.36** | 0.78 | | 0.70 | **0.16** | 1.42 | | 0.47 | **0.33** | 0.79 | |
| $_{m}WIA$ | 0.43 | **0.56** | 0.03 | | 0.13 | **0.84** | -0.32 | | 0.38 | **0.62** | 0.11 | |

* For East of England, 22.0ha of farm area was unused. The column in bold represents the risk aversion parameter value at which the comparison of model generated cropping and observed cropping gave the best-fit and minimum deviation (error). *V* = variance, *CV* = Coefficient of variation, *CE* = Certainty equivalent, *RP* = Risk premium, *PRP* = Proportional risk premium, *MAE* = Mean absolute error, *RMSE* = Root mean square error, $_{m}WIA$ = Modified Willmott's index of agreement.

### 5.4.2 Risk aversion behaviour across regions

The risk aversion parameters ($\Phi$) identified based on the risk optimal solutions ranged from 0.14 to 0.54. The corresponding $R_a$ estimates based of Eq. (5-15) ranged from 0.0000064 to 0.0000140. Although the $R_a$ estimates ($R_a$>0) show risk-aversion of arable farmers in all regions, the differences in the shapes of the E-V frontier as well as the positioning of the points showing the $R_a$ estimates (see Figure 5-4), reflect the differences in the risk aversion levels across the regions[25].

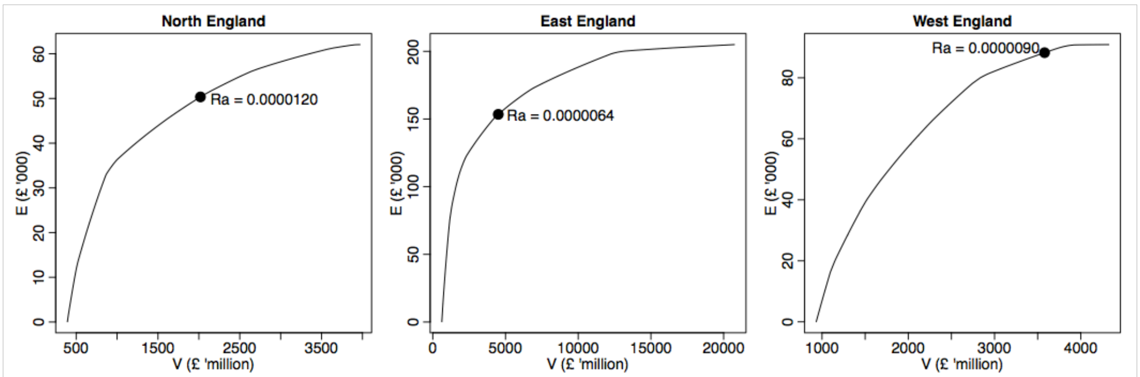



Figure 5-4: E-V frontier showing the absolute risk aversion estimates for North England, East England and West England.

Table 5-4 shows a summary of the risk optimal solutions with the $\Phi$, $R_a$ and other estimates. The estimates of the *PRP* show that for arable farmers in East England, a relatively smaller proportion of their income would be absorbed in their risk premium in order to achieve the *CE*. This is reflected in the lowest *PRP* estimate (*PRP*=0.09). The smaller estimates of the *PRP* also reflect how risk efficient arable farmers in East England may be and this is because a lower *PRP* means *CE* forms the biggest proportion of the expected income (about 91% or 0.91, which is 1-*PRP*).

[25] Due to differences in exposure to risk in different regions, it should be noted that risk aversion parameters or absolute risk aversion estimates across region are not comparable and the presentation under Section 5.4.2 is mainly based on convenience as farm far observing the differences in the shape of E-V and discussion of the results are concerned.

Table 5-4: Summary of regional results showing estimated absolute risk aversion coefficients

| Risk Aversion Estimates | Regions | | |
|---|---|---|---|
| | North England | East England | West England |
| ***Φ*** | **0.303** | **0.540** | **0.144** |
| Farm Income, *E* (£) | 50,351 | 153,447 | 86,970 |
| *MAD* (£) | 32,069 | 47,890 | 41,943 |
| *σ* (£) | 44,936 | 67,106 | 58,772 |
| *V* (£²’ 10⁶) | 2,019.24 | 4,503.22 | 3,454.15 |
| *CV* | 0.89 | 0.44 | 0.68 |
| $\boldsymbol{R_a}$ | **0.0000120** | **0.0000064** | **0.0000090** |
| *CE* (£) | 38,232 | 139,146 | 71,465 |
| *RP* | 12,119 | 14,301 | 15,505 |
| *PRP* | 0.24 | 0.09 | 0.18 |

Note: The risk aversion parameters and absolute risk aversion coefficients estimates presented in the Table for the three regions are not comparable.

### 5.4.3 Use of the model to illustrate policy application

Of interest under this section is the relative difference in the extent a market or policy shift might have on farm situations displaying different levels of risk aversion. In this analysis, the model calibrations for East and West England are exposed to an external market shock by reducing crop prices by 20%. This scenario is picked to represent a different kind of shift in the E-V frontier from the one illustrated in Section 5.2. The scenario is intended to represent a situation not dissimilar to the immediate effect of Brexit (i.e. the decision made in June 2016 for Britain to exit the European Union) on the sterling exchange rate. Crops sold in the UK (i.e. crops not exported) effectively took an approximate 20% reduction in real value when compared to world prices in the immediate economic aftermath.

The effect of the reduction in the prices of all crops, other things being equal, is to shift the E-V frontier to the right and this results in all feasible farm plans suddenly making less expected income with relative variance or risk staying the same. This is shown in Figure 5-5 where the maximum attainable profit falls from $P_1$ to $P_2$ with the iso-utility curves for the East of England represented by $I_{E1}$ and $I_{E2}$ and the iso-utility curves for the West of England represented by $I_{W1}$ and $I_{W2}$.

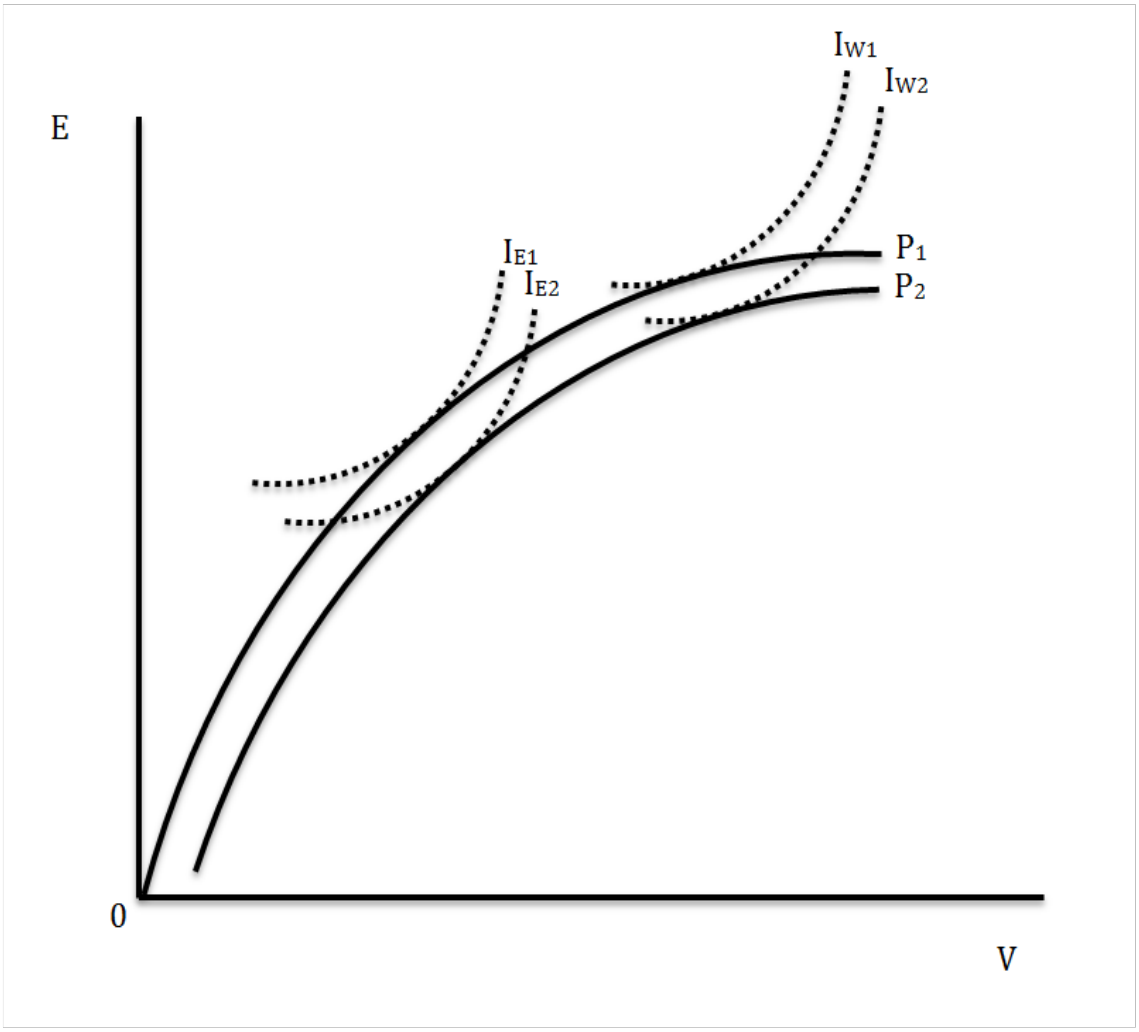



Figure 5-5: Shift in an E-V Frontier through a blanket crop price reduction

With the relative curvature of the E-V frontier different at each iso-utility curve, the uniform shift in the E-V frontier has different consequences for each farmer because different ratios of expected income are traded for variance. The farm plans associated with these shifts estimated by the model are shown in Table 5-5.

The results are intuitive in that the reduction in prices, other things being equal, means that per dollar, each farmer is exposed to more risk. The more risk-averse farmer would therefore be expected to have a more dramatic response to the market change. The East of England model predicts a reduction in the areas of spring wheat and sugar beet with increase in the area of barley production. This is interesting in that this shift is accompanied by an intensification of NPK fertiliser use, which is a bad outcome for agri-environmental objectives and is caused by attempts to secure similar levels of expected income through farm plans with relatively greater risk. In the case of West of England, the changes are less dramatic, but follow a similar pattern with reduction in areas of winter wheat and increase in area of spring barley. However, the intensity of NPK fertiliser use does not change. This shows, however, the beneficial use of the model in market or policy analysis—the same policy will have different outcomes dependent on the level of risk aversion. The formulation of the model means with the availability of data to calibrate it to represent different farm situations, it can be applied to estimate the risk preference and utility maximising farm plans for any farmer representative group and test the impact of a change in market or policy on that group.

Table 5-5: Farm plans associated with crop price reductions

| Land Use (ha) | East of England | | | West of England | | |
|---|---|---|---|---|---|---|
| | Change in Crop Prices | | | Change in Crop Prices | | |
| | -20% | **0%** | % Change | -20% | **0%** | % Change |
| Winter wheat | 138.9 | **119.1** | 17% | 62.4 | **74.9** | -17% |
| Spring wheat | 0 | **45.9** | -100% | 0 | **0** | - |
| Winter barley | 61.2 | **40.7** | 50% | 46.4 | **45** | 3% |
| Spring barley | 51.1 | **28.9** | 77% | 42.9 | **34.8** | 23% |
| Beans | 27.8 | **26.4** | 5% | 16 | **16** | 0% |
| Ware potatoes | 58.6 | **50.7** | 16% | 42.9 | **40.3** | 6% |
| Winter OSR | 61.2 | **62.1** | -1% | 45.3 | **45** | 1% |
| Sugar beet | 22.1 | **47.3** | -53% | 0 | **0** | - |
| NPK intensity (kg/ha) | 416.7 | **404.9** | 3% | 423.6 | **424.3** | 0% |

## 5.5 Discussion and conclusion

In this chapter, we have applied a mixed-integer MOTAD model and data from the UK Farm Business Survey (FBS) to investigate and estimate farmer risk aversion in England. The results show that arable farmers in England are risk-averse. The representative absolute risk aversion coefficient estimates were 0.000012, 0.0000064 and 0.0000090 respectively for North, East and West England. In each region, variations in risk aversion influenced cropping patterns and hence cropping decisions. Also, results show that in a situation of a possible change in policy, farmers may react to or be affected differently depending on their levels of risk-aversion.

MOTAD models have been used extensively to model risk at the farm (e.g. Hazell, 1971; Adesina and Ouattara, 2000; Cooke *et al.*, 2013, Osaki and Batalha, 2014). MOTAD has been criticised as not being able to generate efficient solutions as QRP, stochastic programming (SP) or the direct maximisation of expected utility (DMEU) approaches (Hardaker *et al.*, 2015) however, despite the limitation, it continues to be used in farm planning model to explicitly model risk. This is due to the drawback associated with QRP, SP and DMEU approaches. The QRP approach assumes quadratic utility function, an assumption regarded as unacceptable; it also assumes normal distribution of farm revenues, which are normally skewed (Hardaker *et al.*, 2015). Stochastic programming although is found to be superior to QRP and MOTAD is complicated in that probability distribution of all model items associated with random variation needs to be estimated (Barnard and Nix, 1973). The DMEU approach (Lambert and McCarl, 1985) is also considered to be superior to the aforementioned approaches however, it can be applied only when an individual decision-maker's utility function is available (Hardaker *et al.*, 2015).

Another reason for the suitability and continuous attractiveness of MOTAD to farm risk modellers is the possibility of solving MOTAD problems using linear programming (LP) algorithms, which is the most commonly used and best-known mathematical programming approach (Stott *et al.*, 2003) or computational convenience (Hardaker *et al.*, 2015) and in a situation where it may be impossible or difficult to obtain a suitable solver for a QRP or solvers for QRP may not be readily available, MOTAD will be a very good alternative. Also, the mean absolute deviation in MOTAD performs better than the sample variance in QRP in instances where enterprise income distributions are skewed (Hazell and Norton, 1986), and with the distribution of agriculture incomes normally skewed, the use of MOTAD in farm risk modelling can be said to be still relevant and fit for purpose. Again, production and price risks are common with arable farming systems and with MOTAD being one of the most widely used methods for analysing such risks (Börner, 2006), the application of MOTAD in this study can be said to be relevant.

Drawing on the strengths or advantages of MOTAD, a mixed-integer MOTAD model was developed and applied to estimate absolute risk aversion coefficients for different typologies of farmer and cropping decision. The adopted approach is an advancement of the approaches used by Hazell *et al.* (1983), Elamin and Rogers (1992) in that the risk aversion parameters based on which absolute risk aversion coefficients are estimated and efficient E-V frontier developed are randomly generated. Although direct elicitation approaches to deriving risk aversion parameters may have their advantages, they may be expensive, time consuming and associated with biases. They also may fail to achieve intended purpose and in such instances the derivation of risk aversion parameters may have to be through parameterisation of the model as was the case for Börner (2006). Thus, in this study the model parameterisation approach was adopted but through randomly generated risk aversion parameters to investigate risk behaviour and cropping decisions of arable farmers. This approach was found to be less time consuming and not associated with financial constraint or burdens, biases (normally associated with direct methods) and thus fit for purpose in this study.

The absolute risk aversion coefficient estimates imply that arable farmers in England can be said to be risk-averse. The estimates of the proportional risk premium suggest that for arable farmers in England, not a bigger proportion of their income would be sacrificed in risk premium in order to achieve risk efficiency. This is a reflection of risk aversion (Hardaker, 2000; Hardaker *et al.*, 2015). In terms of cropping, the areas of crops such as spring wheat and sugar beet were found to increase when the level of risk-aversion increased, indicating that such crops may be associated with low risk (Hazell, *et al.*, 1983). This suggests that a risk neutral arable farmer may not select sugar beet as part of her/his crop plan. The areas of crops such as spring barley and potatoes were however found to reduce as risk-aversion increased meaning that their revenues may be associated with large variances (Hazell *et al.*, 1983). The revenues of crops such as winter wheat, winter barley, ware potatoes and winter oilseed rape correlated positively with most other crops and according to Hazell *et al.* (1983), such crops tend to have lower outputs under risk-averse behaviour. At extreme risk aversion levels some hectares of land were not utilised under East England, which had comparatively bigger average farm areas. The implication is, it is possible depending on the prevailing crop prices that an extremely risk-averse farmer with bigger farm area may not utilise all her/his farmland.

The approach we adopted in this study thus presents a framework, which can estimate the different risk preferences of different typologies of farmers relying on the best fit of model results to their existing or observed land use. The representative farmers are classified by region although, typologies of farm type, size, or income group could have similarly been used as done by (Kehkha *et al.*, 2005). What is crucial is that there is now a system whereby the impact on farm plans of any market or policy shifts can be estimated across those typologies through the use of MOTAD methodology, which is based on LP approach (the best-known mathematical programming approach). It has been shown that if, for example, there was a reduction in wholesale prices for all crops caused by a currency devaluation, the impact of this on the different types of farms with different risk aversion characteristics could be examined. This is a valuable feature for any model, which may need to consider either the impacts of regionalised agricultural policy or the impacts of national or international policy on different regions.

Although it is acknowledged that the accuracy of the results may be affected by the limitations of the approach adopted in this study through model specification and the limitations of MOTAD, the results do give insight into whether or not arable farmers in different regions exhibit different risk-averse behaviours. In a policy formulation context, the policy maker or planner gaining such insight into the risk aversion behaviour of arable farmers will be able to devise increasingly effective policies—ones which avoid creating more risk (Hardaker *et al.*, 2015) or mitigating risk so as to not create unintended consequences such as input-use intensification. Policies which introduce forms of direct (risk-free) payment may improve sustainability outcomes, however those policies may be more enhanced if farmers with greater risk aversion are targeted. As shown in the analysis, such a policy might have greater effect if implemented in the East rather than the West of England. The model which has been developed as part of this study is entirely transferable and given available data for calibration, it provides a conceptual, methodological and empirical framework, which bridges an important gap in the literature and advances modelling capability.

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# Appendix

Table 5-6: Price data for North, East and West England from 2009 to 2013

| Year | Crops | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Winter wheat | Spring wheat | Winter barley | Spring barley | Beans | Ware potatoes | Winter OSR | Sugar beet |
| 2009 | 124 | 213 | 116 | 116 | 164 | 127 | 274 | 36 |
| 2010 | 168 | 271 | 141 | 167 | 224 | 178 | 318 | 33 |
| 2011 | 175 | 242 | 165 | 194 | 233 | 129 | 386 | 33 |
| 2012 | 197 | 264 | 187 | 207 | 305 | 246 | 389 | 32 |
| 2013 | 174 | 204 | 157 | 158 | 185 | 163 | 316 | 32 |
| Mean | 168 | 239 | 153 | 168 | 222 | 169 | 337 | 33 |
| Standard deviation | 27 | 30 | 27 | 35 | 54 | 48 | 50 | 2 |

Table 5-7: Yield data for North England from 2009 to 2013

| Year | Crops | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Winter wheat | Spring wheat | Winter barley | Spring barley | Bea ns | Ware potatoes | Winter OSR | Sugar beet |
| 2009 | 8.0 | 5.4 | 6.9 | 5.6 | 4.1 | 36.4 | 3.4 | 57.3 |
| 2010 | 8.3 | 4.0 | 7.1 | 5.2 | 3.4 | 34.3 | 3.7 | 56.8 |
| 2011 | 8.2 | 4.8 | 7.1 | 5.4 | 4.4 | 42.2 | 4.3 | 61.0 |
| 2012 | 6.6 | 4.1 | 6.5 | 4.7 | 3.5 | 25.2 | 3.2 | 55.1 |
| 2013 | 7.4 | 5.7 | 6.7 | 5.8 | 3.7 | 37.4 | 2.8 | 72.9 |
| Mean | 7.7 | 4.8 | 6.9 | 5.3 | 3.8 | 35.1 | 3.5 | 60.6 |
| Standard deviation | 0.71 | 0.76 | 0.26 | 0.42 | 0.42 | 6.25 | 0.56 | 7.19 |

Table 5-8: Yield data for East England from 2009 to 2013

| Year | Crops | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Winter wheat | Spring wheat | Winter barley | Spring barley | Bea ns | Ware potatoes | Winter OSR | Sugar beet |
| 2009 | 8.4 | 4.7 | 6.7 | 6.0 | 3.7 | 38.5 | 3.6 | 64.6 |
| 2010 | 8.0 | 3.9 | 6.8 | 5.0 | 2.9 | 38.2 | 3.6 | 56.1 |
| 2011 | 8.0 | 3.9 | 6.0 | 4.9 | 3.5 | 38.1 | 3.9 | 68.7 |
| 2012 | 6.9 | 5.0 | 6.7 | 5.1 | 3.8 | 34.1 | 3.5 | 61.4 |
| 2013 | 7.8 | 5.3 | 6.8 | 5.8 | 3.7 | 37.8 | 3.1 | 66.5 |
| Mean | 7.8 | 4.6 | 6.6 | 5.4 | 3.5 | 37.3 | 3.5 | 63.5 |
| Standard deviation | 0.56 | 0.64 | 0.34 | 0.50 | 0.36 | 1.83 | 0.29 | 4.91 |

Table 5-9: Yield data for West England from 2009 to 2013

| Year | Crops | | | | | | |
|---|---|---|---|---|---|---|---|
| | Winter wheat | Spring wheat | Winter barley | Spring barley | Bean s | Ware potatoes | Winter OSR |
| 2009 | 7.8 | 5.0 | 6.6 | 5.9 | 2.8 | 40.1 | 3.5 |
| 2010 | 7.7 | 3.5 | 6.9 | 5.1 | 2.7 | 42.7 | 4.0 |
| 2011 | 8.5 | 3.8 | 7.1 | 5.8 | 3.4 | 41.6 | 4.3 |
| 2012 | 5.9 | 3.0 | 6.1 | 4.4 | 3.3 | 27.9 | 3.3 |
| 2013 | 7.2 | 4.5 | 6.6 | 5.9 | 3.5 | 38.7 | 3.1 |
| Mean | 7.4 | 4.0 | 6.7 | 5.4 | 3.1 | 38.2 | 3.6 |
| Standard deviation | 0.97 | 0.80 | 0.38 | 0.66 | 0.36 | 5.95 | 0.50 |

***"It's clear that agriculture, done right, is the best means the world has today to simultaneously tackle food security, poverty and environmental degradation."***

— Irene Rosenfeld

# 6 GENERAL DISCUSSION

## 6.1 Introduction

Complexities exist in sustainable arable farming systems due to the associated conflicting farming objectives and constraints. To able to increase agriculture productivity to ensure food security whilst minimising impact on the environment, it is imperative to investigate agricultural systems underpinned by sustainable principles to identify efficient and sustainable farming strategies. With mathematical models, many of the complexities can be captured and investigated and results used to inform farm management and policy decisions. Thus the main aim of the research was to develop a farm level mathematical model that can be used for evaluating economic as well as environmental viability and riskiness of alternative cropping systems that may be adopted to deal with increased pressure on input use. To begin the model development, a review of literature was conducted (Chapter 1). The literature review identified some of the farm management and cultural practices, farm inputs and policies as well as farming objectives, which are normally modelled or parameterised in farm models. The review of mathematical modelling approaches identified gaps in models and modelling approaches capabilities to inform the development of a robust model.

Chapter 2 builds on the review of literature by investigating the impact of some of the farm inputs/outputs and policies on arable farming objectives (profit maximisation and risk minimisation) identified through literature review. The results showed the effect of variation in farm inputs/outputs and policy on arable farming objectives and for farm located in the Nitrate Vulnerable Zones, the single farm payment serves as a payment for the opportunity cost for farmers not being able to apply nitrogen fertiliser above the prescribed amount. The results obtained from Chapter 2 and the information gathered through the literature review informed the development of an arable farm level model which combined mixed-integer, goal and risk programming approaches to optimise farm profit, risk and nitrate leaching. The model is described and validated with data from the Farm Business Survey in Chapter 3. The model was then applied to investigate two issues considered to be significant in arable farming systems: black-grass (weed) control and farmers risk aversion or risk behaviour of arable farmers.

The model was first applied to investigate the impact of the adoption of a non-chemical control of black-grass using spring cropping on farm profit and to some extent risk (Chapter 4). This study is a novel contribution to literature in terms of using linear programming based (comparative static) model to investigate the effect of spring cropping, particularly winter wheat—spring barley or spring beans rotation as a black-grass control measure on farm revenues. The results show a reduction in farm revenue in the short term but with potential reductions in black-grass infestation in the long term. The implication is that adoption of some sustainable farming strategies (such as weed management strategies) and change in policy can make arable farming a risky business through reductions in farm revenue.

Thus the model (risk (MOTAD) programming module) was applied again to investigate risk behaviour of arable farmers in England (Chapter 5). Again, this study is a novel contribution to literature in terms of using a randomly generated risk aversion parameters method and a MOTAD model to estimate absolute risk aversion coefficient under the E-V framework as well as investigating cropping under risk. The results show that arable farmers in England are risk averse and that farmers would react to changes in policy as well as input use differently due to differences in their levels of risk aversion. The application of the model also shows its policy analysis relevance. Model applications to answer specific research questions have been summarised in Table 6-1 below.

Table 6-1: Model applications and specific research questions addressed

| Aims/Objective and Specific Research Questions | Inputs Applied | Tools Applied | Outputs |
|---|---|---|---|
| ***A. Investigation of factors affecting arable farming profit, crop complexity and risk under the single farm payment policy.***<br><br>**<u>Specific research questions:</u>**<br>1. How do changes in rainfall at a farm location and moving from one soil type to the other affect farming objectives?<br>2. How do changes in N fertiliser under different soil types and rainfall affect the arable farming objectives?<br>3. Can increase in crop prices influence farmers to apply N above N max and forgo the Single Farm Payment (SFP) if farmers have the right to do so?<br>4. Is there any difference in the objectives of farms applying the N max and receiving the SFP and those who may apply above the N max and forgo the SFP? | 1. Farm inputs (e.g. fertiliser, seed, chemical, machinery and labour)<br><br>2. Farm/environmental factors (e.g. soil type, rainfall)<br><br>3. Economic and policy factors (e.g. input and crop prices, subsidies) | Modified farmR model (farmR model was modified to include apply the single farm payment (SFP) not explicitly modelled. | Variations in:<br>1. Farm Profit<br>2. Risk (standard deviation in income)<br>3. Crop complexity |
| ***B. Description, verification and validation of an arable farm models for optimising farm profit, nitrate leaching and risk.***<br><br>**<u>Specific research questions:</u>**<br>1. What is the degree of association between model predicted crop areas and observed crop areas (land use)?<br>2. What is the degree of association between model predicted fertiliser amounts and observed fertiliser amounts (input use)?<br>3. What is the degree of association between model predicted revenues/costs and observed revenues/cost? | 1. Farm inputs (e.g. fertiliser, seed, chemical, machinery and labour)<br><br>2. Farm/environmental factors (e.g. soil type, rainfall)<br><br>3. Economic and policy factors (e.g. input and crop prices, subsidies) | SAFMOD Model consisting of:<br>1. Mixed-integer profit model<br>2. Mixed-integer nitrate leaching model<br>3. Mixed-integer risk (MOTAD) model<br>4. Mixed-integer weighted goal-programming model | Estimation of:<br>1. Farm profit<br>2. Risk (mean absolute deviation & standard deviation in income)<br>3. Nitrate leaching<br>4. Crop plan (crop areas)<br>5. Farm Costs |

Table 6-1 Continued

| Aims/Objective and Specific Research Questions | Inputs Applied | Tools Applied | Outputs |
|---|---|---|---|
| ***C. Estimating the aggregate cost of controlling black-grass (Alopecurus myosuroides) with spring cropping in UK arable farming.***<br><br>**<u>Specific research questions:</u>**<br>1. What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring barley rotation?<br>2. What is the aggregate cost of black-grass control to the UK arable farming sector using winter wheat—spring beans rotation?<br>3. Is there any effect of controlling black-grass with spring cropping on farm risk?<br>4. What are the effects of controlling black-grass with spring cropping on farm costs? | 1. Farm inputs (e.g. fertiliser, seed, chemical, machinery and labour)<br><br>2. Farm/environmental factors (e.g. soil type, rainfall)<br><br>3. Economic and policy factors (e.g. input and crop prices, subsidies) | SAFMOD module 4:<br><br>Mixed-integer weighted goal-programming model | Estimation and comparison of aggregate:<br>1. Farm profits<br>2. Risks (standard deviations in income)<br>3. Crop areas<br>4. Fertiliser costs<br>5. Seed costs<br>6. Herbicide costs<br>7. Fixed costs |
| ***D. Model spatially-referenced farmer risk behaviour using an evolved mixed-integer MOTAD approach.***<br><br>**<u>Specific research questions:</u>**<br>1. Are arable farmers in England risk averse?<br>2. Are there any differences in risk aversion across regions in England?<br>3. Do the levels of risk aversion influence cropping decisions?<br>4. What is the effect of policy change on farmers with different levels of risk aversion? | 1. Farm inputs (e.g. fertiliser, seed, chemical, machinery and labour)<br><br>2. Farm/environmental factors (e.g. soil type, rainfall)<br><br>3. Economic and policy factors (e.g. input and crop prices, subsidies) | SAFMOD module 3:<br><br>Mixed-integer risk (MOTAD) Programming model | Estimation of:<br>1. Farm profits<br>2. Risk (mean absolute deviation and variance)<br>3. Crop plans<br>4. Risk aversion parameters/absolute risk aversion<br><br>Development of an E-V frontier |

## 6.2 Comparison of SAFMOD and models identified in UK

The model described, validated and applied in this study, was developed drawing on the strength of different mathematical programming approaches and existing models so as the fill the gaps identified on model capabilities (Section 1.4.6). The model consists of four modules (see Section 3.2.1) and draws on the strengths of mixed-integer, risk and goal-programming approaches to optimise farm profit, nitrate-leaching and risk employing data from existing models, farm management and related literature. Each module has been validated using data of 281 lowland arable farms from the Farm Business Survey (FBS) and statistical measures of association to test the degree of association between model results and observed farm data (Chapter 3). The validation showed good association between model-generated crop areas and observed crop areas, and between model-estimated fertiliser amounts and observed fertiliser amounts. Better predictions were observed under modules in which risk was explicitly incorporated or modelled. Hazell *et al.* (1983) and Cooke *et al.* (2013) found the incorporation of farmers' risk preference to improve the predictive power of models.

Different mathematical modelling approaches have been applied extensively to model agricultural systems and land use (e.g. Brink and McCarl, 1978; Annetts and Audsley, 2002; Rounsevell *et al.*, 2003; Cooke *et al.*, 2013). However, in the UK not many arable farm mathematical programming models based on optimisation approaches were identified. Two main models were identified: The Silsoe farm model (SFARMOD) (Annetts and Audsley, 2002) and the farmR model (Cooke *et al.*, 2013), which is itself a mixed-integer programming (MIP) implementation of the SFARMOD but explicitly incorporate risk. Again, in UK context, no arable farm level mathematical programming model was found to consist of four modules, which can be applied as stand-alone models as has been demonstrated in Chapters 4 and 5. Thus the SAFMOD adds to the few models (not modular) identified in the UK. Although some of the formulations and data from the above two models (especially farmR) were adopted in developing the SAFMOD, there are some differences. The SFARMOD is a multiple objective linear programming (not mixed-integer) model, which optimises profit and environmental outcomes (nitrate-leaching and pesticide use). The farmR is a mixed-integer programming implementation of

SFARMOD however, it explicitly incorporate risk and does not optimise any environmental outcome.

Unlike the SFARMOD and the farmR models, SAFMOD consists of four different modules. The first module is a mixed-integer model, which maximises farm profit by selecting optimal crop sequences and machine/labour numbers. The module can be more applicable is a situation where the focus is only on profit maximisation as a single objective without consideration to other objectives. Module two is a mixed-integer nitrate-leaching minimisation model. Although it is designed as a pure nitrate-leaching minimisation model, profit target can be set as a constraint and the model can be solved optimising nitrate-leaching subject to the profit target to carry out trade-off analysis of economic and environmental outcomes. Again, unlike the SFARMOD, the nitrate-leaching estimates in SAFMOD were based on the nitrogen (N) balance approach adopted from Wossink (1993). This approach is based on N fertiliser requirement of crops, soil N supply and atmospheric deposited N, and thus makes it relatively easy to update through changes in total N input determined by the soil type. However, due to lack of data on changes in nitrate-leaching amounts with respect to farm operation and rotation types, SAFMOD only optimises nitrate-leaching using base nitrate-leaching estimates per crop. This is seen as a limitation of the model in estimating nitrate leaching, however, with availability of the data on changes in nitrate-leaching amounts due to operation and rotation types, the model can be easily updated.

The third module is a mixed-integer risk model based on the MOTAD approach. It is similar to the farmR model however, farmR was formulated as a multiple objective mixed-integer model. The risk model in SAFMOD is formulated as a typical MOTAD model to parameterise the risk level (Hardaker *et al.*, 1997) and weight can be attached to the risk level to serve as a measure of risk aversion. Such a formulation generates typical expected mean income-mean absolute deviation (E-M) frontier or expected mean-variance (E-V) (as shown in Chapter 5). Again, unlike farmR, the MOTAD model in SAFMOD incorporate income deviation matrix as constraint, which is an original feature of a MOTAD model. The MOTAD model incorporates a nitrate-leaching minimisation objective (not included in farmR) as a constraint and the model can be solved to maximise profit, minimise risk and nitrate leaching. The nitrate-leaching objective can be set to zero and the model solved as a pure MOTAD model. To overcome the single objective limitation of LP approach as well as some of the limitations linear programming based models and hence the models above, a weighted goal-programming model (fourth module) (applied in Chapter 4) was developed to optimise the three objectives simultaneously by setting goal targets and attaching weight. This model is different from both SFARMOD and farmR in that it is a goal-programming model.

The comparison of the SAFMOD to the farmR and SFARMOD are summarised in the Table 6-2 below and it can be observed that apart from some of the differences highlighted above the SAFMOD offers other options that farmR and SFARMOD are unable offer in their current state. In terms of machine and labour numbers, SAFMOD is able to select integer machine and labour number, which farmR and SFARMOD are unable to. Thus the continuity assumption in LP is much relaxed in SAFMOD than in the other models. With the type of soil significant in arable farming systems, unlike the other models, in SAFMOD the soil type is linked to the recommended fertiliser rates of crops by Defra. In terms of incorporation of policy, the SAFMOD incorporates the subsidy payment based on the single farm payment scheme and thus makes it easy for future updating of SAFMOD to capture the newly introduced basic farm payment. Also, the crop proportion modelling in SAFMOD unlike the other models capture the CAP's 'greening' rule for crop diversification, which ensures that at least there must be two crops in rotation and that no one crop can take more than 70% of the cropping area. The approach to modelling crop rotation can be based on absolute crop areas or proportion (see Barnard and Nix, 1973) and the SAFMOD offers the options to choose between approaches.

Thus through the SAFMOD different assumptions are applied and several mathematical programming approaches are combined to create a robust arable farm level model, which offers four variants of arable farm level mathematical programming models, which are capable of being applied to achieve thorough and deep assessment more than any one of the few arable farm level models, based on mathematical programming identified in the UK. Thus the gap identified with respect to model capability under Section 1.4.6 can be said to have been filled or partly filled with development of the SAFMOD.

Table 6-2: Comparison of the SAFMOD and SFARMOD and farmR models

| Criteria for Comparison | Models | | |
|---|---|---|---|
| | **SAFMOD** | farmR | SFARMOD |
| A. Modelling Approaches | | | |
| *1. Mixed-integer programming* | + | + | - |
| *2. Risk (MOTAD) programming* | + | + | - |
| *3. Weighted goal-programming* | + | - | - |
| B. Modules | | | |
| *1. Standalone pure profit model* | + | - | - |
| *2. Standalone pure nitrate leaching model* | + | - | - |
| *3. Standalone MOTAD model with income deviation matrix as constraint* | + | - | - |
| *4. Standalone weighted goal programming model* | + | - | - |
| C. Objectives optimised | | | |
| *1. Farm profit* | + | + | + |
| *2. Risk (Deviation in income)* | + | + | - |
| *3. Nitrate leaching* | + | - | + |
| D. Selection of integer machine and labour numbers | + | - | - |
| E. Determination of fertiliser rates of crops by soil type | + | - | - |
| F. Modelling of single farm payment (SFP) | + | - | - |
| G. Modelling of crop proportions to reflect CAP's Greening rule. | + | - | - |
| H. Option for running model for mono-cropping scenario | + | - | - |
| I. Different options for modelling crop rotation | + | - | - |
| J. Option for setting risk target in risk model | + | - | - |
| K. Nitrate leaching model based on N balance approach | + | - | - |
| L. Inclusion of nitrate leaching minimisation objective (constraint) in risk model | + | - | - |

Plus (+) sign means the model uses the mathematical modelling approach, optimise an object or has the capability to perform such function whereas minus (-) sign means otherwise.

## 6.3 Assessment of levels of interaction of SAFMOD

Assessing the SAFMOD under levels of interaction, it can be said to fall under three of the levels of interaction shown under Section 1.4 and in Table 6-3.

Table 6-3: Levels of interaction of the SAFMOD

| Model | Type | Levels of Interaction | | |
|---|---|---|---|---|
| | | Policy—Agricultural Land Use Level (P-L) | Land use—Environment Level (L-E) | Climate—Agricultural Land Use Level (C-L) |
| SAFMOD | Comparative static (Dynamics is introduced into the model through discrete within year periods) | + | + | + |

Note: The plus (+) means the model falls under that level of interaction.

Under the policy—agricultural land use interaction level, the model can predict or simulate changes in agricultural land use due to changes in policy. In terms of farm payment policy, the model captured the single farm payment policy (Nix, 2014) and the proportion or the limitations put on crop areas reflect the 'greening' rules (Defra, 2014) as part of the farm payment policy. Changes in farm payments (policy) can be simulated or parameterised to observe changes in crop plans or land use. The results generated through model application (Chapter 4) also provide indication of possible farm payment to incentivise adoption of spring cropping as a black-grass control measure. Again, in Chapter 5 the MOTAD module was applied to illustrate policy application (Section 5.4.3) by looking at the effect Brexit on the sterling and it subsequent effect on farmers' decision, attitude towards risk and land use. Thus SAFMOD can be used to simulate changes in cropping (land use) due to changes in policy.

In terms of land use—environment interaction level, the SAFMOD can simulate how changes in land use affect the environment. For example, parameterising the N fertiliser amounts influences cropping, which in turn can determine the level of nitrate-leaching into underground water. Under climate—agricultural land use interaction level, SAFMOD can show how variability in climate affect land use. SAFMOD incorporates rainfall to estimate workable hours. Variation in rainfall can be simulated to observe changes in crop plans selected by the model (land use), meaning that SAFMOD is capable of simulating changes in land use due to changes in climate. Although there are some differences, SAFMOD shares similar levels of interaction with models such as MODAM (Zander and Kächele, 1999), SFARMOD (Annetts and Audsley, 2002), SWAP (Howitt *et al.*, 2010) and FSSIM (Louhichi *et al.*, 2010). Again in UK context, SAFMOD adds to the few models, which can be applied to carry out scenario modelling with respect to the levels of interactions above.

## 6.4 Factors influencing UK arable farming

Arable farming systems are affected by a variety of factors—input and output, farm specific and environmental factors and policy (Harwood *et al.*, 1999; Olesen and Bindi, 2002; Bojnec and Lattruffe, 2013; Brown *et al.*, 2013; Jannoura *et al.*, 2014). These factors need to be investigated to assess their impact. In Chapter 2, sensitivity analysis (Pannell, 1997) was conducted to investigate impact of some of these factors on profit, risk and management complexity arable farms operating in Nitrate Vulnerable Zones (NVZs) and receiving the Single Farm Payment (SFP). This was done under the assumption that farmers have been given the option of forfeiting the SFP and applying N fertiliser above the prescribed amounts (Nmax). Results showed that farmers could obtain higher yields by applying above Nmax however, forfeiting the SFP would result in reductions in farm income and increase in risk. The SFP was found to act as payment for the opportunity cost to farmers for being constrained by the Nitrate Directive (ND) (EU, 2016) through the NVZ rules to apply Nmax. The implication is that the ND influence fertiliser input use, which in turn influences crop selection, whereas the SFP pays for the opportunity cost due to the constraint. Thus both ND and SFP (policies) can be said to influence how and what to produce (Angus *et al.*, 2009). With respect to the approach adopted, the farming objectives, the SFP and NVZs, no study was found have used similar approach. For example, with respect to the SFP, studies that link it to the interactions and variations in factors such as rainfall and soil type was found to be lacking. This gap is thus filled through the approach adopted and hence contribution to knowledge.

## 6.5 Implications of SAFMOD results on farming and policy decisions

Farm models are essentially developed to mimic real farming systems (Robertson *et al.*, 2012) and some models are developed to inform farming decisions and others, policy decisions (Janssen and van Ittersum, 2007; Robertson *et al.*, 2012). For a model to perform its intended function, keys aspects of the real systems are captured and modelled. The two modules of SAFMOD were thus applied to answer research questions in Chapters 4 and 5.

### 6.5.1 Sustainable weed management strategies in arable farming

Weeds compete with crops for nutrients and sunlight and reduce yield potential of crops (Baligar *et al.*, 2001). The weed control measure which has been used over the years is the use of herbicides however, weeds such as black-grass continue to develop resistance to these chemicals which impact negatively on the environment. There is thus the need for non-chemical control measures to help reduce chemical input use (Bond and Grundy, 2001; Rask and Kristoffersen, 2007). One of such non-chemical strategies was investigated in Chapter 4. The weighted goal-programming module was applied to estimate aggregate cost of controlling black-grass with spring crop rotation. The results can inform farming decision in terms of effect of the strategy on farming costs and benefits in terms of reductions in black-grass infestation in the long run. The aggregate cost estimates on per hectare basis give indication of possible farm payment to incentivise the adoption of spring cropping (particularly spring barley) to manage black-grass in UK arable farming. This study is a novel contribution to literature in terms of using linear programming based (comparative static) model to investigate the effect of spring cropping, specifically winter wheat—spring barley or spring beans rotation as a black-grass control measure on farm revenues. Although it is acknowledged that there may be some biases in the model estimates influenced by model formulation and the farm data used, the results of the study provide insight into potential short and long term benefits of spring cropping as a black-grass control measure.

### 6.5.2 Risk aversion in arable farming

Risk consideration is significant in arable farming in that information on farmers' risk-aversion has been found to influence land use and thus vital for both farm and policy planning (Hardaker *et al.*, 2015). Also, incorporating risk in farm model has been found to improve predictive power of model (Cooke *et al.*, 2013). In Chapter 5, the effect of farmer risk-aversion on cropping patterns (Hazell *et al.*, 1983) and hence the intensity of input use, are shown. Certain crops are selected based on the farmer's level of risk-aversion and the 'riskiness' associated with the crops due to the variability their yields and prices (Hazell *et al.*, 1983, Adesina and Ouattara, 2000). Illustration of policy application of the risk module showed how arable farmers would react to policy change depending on their level of risk-aversion or where they are 'sat' on the efficient E-V frontier. These findings can inform farming decisions as far as crop selection is concerned. In terms of policy, the results showed policy analysis relevance of the model and the need for regionalised policy since farmers are likely to react to changes in policy differently depending on their level of risk-aversion, influenced by where they are located. Many approaches have been applied in eliciting farmers absolute risk aversion, however, no study was found to have used randomly generated risk aversion parameters and MOTAD to develop and E-V frontier as well as estimate absolute risk aversion coefficients for different regions in England. This study thus filled this gap and the novel contribution to knowledge lies in the methodology.

## 6.6 Limitations identified in the study

As part of the main research aim, an arable farm level has been created, which offer four variants of whole arable farm models capable of being applied to carry out thorough assessment as far as farm systems analysis is concerned. Although results generated through the model application based on assumptions set, mathematical programming and data used can serve as guides in decision-making in arable farming, as with all mathematical programming models, they cannot be devoid of limitations or drawbacks. It is acknowledged that mathematical programming models based on comparative static approach may fail to capture the dynamic nature of some aspects of the arable farming systems. In such instances dynamic/recursive or stochastic programming approaches be more suitable. However, with farming decision normally taken within year, farming analysis based on an LP model for a single year with discrete within year periods (as in the case of SAFMOD) can generate reasonable or satisfactory results fit for purpose in farm systems analysis.

In Chapter 4, the weighted goal-programming model is applied to carry out an economic assessment of spring cropping as black-grass management strategy. Although the study results provide indication about the possible economic outcome of adopting the strategy, some limitations are acknowledged. Firstly, with spring cropping capable of reducing black-grass population, the implication is that there can be benefits in terms of long terms of improvement or increase in yield (and hence farm revenue) in subsequent years(s). The consideration of such long term benefit, although is out of the scope of the study due to focus on comparison of the cost/benefits of two cropping plans, elimination of such long term benefit is acknowledged as a limitation in the analysis and hence a limitation of the study. Secondly, in black-grass management, the decision taken in one year may influence decision-making in another year. This means the incorporation of black-grass population dynamics through dynamic programming approaches can be very vital and thus ignoring such dynamic nature of the problem could affect the robustness of the results and hence acknowledged as another limitation. Thirdly, four crops were selected for the study (winter wheat, spring barley, spring beans and winter oilseed rape) meaning that other crops of economic importance such as winter barley are eliminated and thus could affect the accuracy of the aggregate estimates. Finally, aggregate bias is one of the problems in LP approach (Buckwell and Hazell, 1972) due to differences in characteristics among farmers. Thus with use of data of farms of different sizes, although the model was run for each farm based on its own data, there can still be existence of possible aggregation error and this can be seen as another limitation of the aggregation approach and hence limitation of the study.

In Chapter 5, a mixed-integer MOTAD model was applied to evaluate risk aversion parameters of arable farmers under the E-V framework. Limitation of the study is acknowledged through the limitations associated with the MOTAD approach (Hardaker *et al*., 2015) although MOTAD deals with the single objective limitation of linear programming. One of the well-known approaches in risk programming is quadratic programming (QR) with some advances in risk programming approaches through the use of stochastic and the maximisation of direct utility programming approaches (Hardaker *et al*., 2015). Although there are similarities between these approaches and MOTAD in terms of the structure of the technical constraints and are also associated with limitations, they have been found to generate more risk efficient crop plans than MOTAD (Hardaker *et al*., 2015). The mean absolute deviation in MOTAD has been found to outperform the sample variance in QR in instances where the distribution of farm income is skewed (Hazell and Norton, 1986) however, choosing MOTAD over approaches such as stochastic simulation programming means ignoring the random variation in so many factors which influence the arable and are associated with random variation. Thus this limitation of the MOTAD approach may translate into the limitation of the study.

## 6.7 Future work in sustainable arable farming systems modelling

### 6.7.1 Pesticide minimisation and further nitrate leaching modelling

Negative externalities are associated with arable farming due to the intensive use of risk-reducing inputs such as fertiliser and pesticides (Skevas and Lansink, 2014). Although the SAFMOD optimises nitrate-leaching using base estimates for crops, with the availability of data, future updating of the model to take into consideration nitrate-leaching with respect to farm operation and rotation sequences (Annetts and Audsley, 2002) could lead to more robust nitrate leaching estimates. Also, with the effect of pest on arable farming productivity (Sinden *et al.*, 2004; Popp *et al.*, 2013), coupled with arable farmers being identified as risk-averse (Chapter 5) and are likely to apply pesticide to safeguard yield, it will be imperative in future to update the model to incorporate pesticide minimisation objective especially with respect to black-grass population dynamics and management. This could aid in the prediction of robust optimal crop/farm plans for weed management.

### 6.7.2 Further validation with regional or county level data

The validation (Chapter 3) and model application (Chapter 5) show the effect of incorporating risk in the predictive power of models (Hazell *et al.*, 1983). Going forward, model can be calibrated for different counties in the UK to predict optimal crops plans as well as investigate the effect of policy change on farms in different regions or counties depending on their risk-aversion levels.

### 6.7.3 Environmental and economic goals trade-off modelling

The trade-off in sustainable arable farming systems is primarily between environmental and economic objectives (Tilman *et al.*, 2002). Thus the goal-programming model can be calibrated to generate trade-offs between these objectives under different environmental and economic scenarios to select optimal farm plans to inform farming decisions. Also, sensitivity analysis of all farm inputs and outputs, policy, farm and environmental parameters to investigate their effect on crop selection in order to better inform farming decision.

### 6.7.4 Livestock system modelling

The livestock sector contributes immensely to total agricultural output in the UK (Thornton, 2010; Defra, 2015). Also, the livestock sector contributes to the negative externalities from agriculture (McMichael *et al.*, 2007; Garnett, 2009; Gill *et al.*, 2010) to the environment. Thus, going forward, it will be imperative to extend the SAFMOD to include livestock farm level modelling. With this, a better assessment of wholly livestock farming or mixed farming systems can be conducted to effectively inform farming and policy decisions. Through the inclusion of livestock systems, farm manure analysis can be incorporated into the SAFMOD.

### 6.7.5 Dynamic/stochastic modelling

With dynamic nature of some aspect of arable farming systems as well as random variation associated the factors such as weather, price, which influence decision making in arable farming, future updating of the SAFMOD to capture such dynamics can be vital in the model's predictive power. Also, combining SAFMOD with black-grass population dynamics can go a long way in generating robust results, which can effectively inform black-grass management decisions in arable farming. In terms of risk modelling, stochastic programming although complicated, can be applied to develop a risk model more capable of capturing random variation associated with arable farming factors better.

## 6.8 Conclusion

Mathematical programming models have the capabilities to capture many of the complexities in arable farming systems. In this research, an arable farm level model, which consists of four modules, has been developed and validated. The model adds four variants of arable farm models to the few farm models identified in the UK by drawing on the strengths of different mathematical modelling approaches. The model thus offers an ensemble of arable farm level mathematical programming modelling tools, which can be used to carry out thorough assessment in arable farming system than any one of the model identified could do especially in the UK context. Through this model, the aggregate cost of black-grass control with spring cropping has been investigated and estimated for the UK arable farming sector. The per hectare estimates give indication of possible farm payments to incentivise adoption of spring cropping as a black-grass management strategy. Again through the model, a randomly generated risk-aversion parameter method has been applied to estimate absolute risk-aversion coefficient under the E-V framework for arable farmers in England. Policy application illustration of the model shows the relevance of the model in policy analysis and the need for regional policies tailored to risk aversion. In this thesis, it has been demonstrated that mathematical modelling approach can be applied to analyse different aspects of, as well as innovations in arable farming systems. Although effectiveness of a model lies in its specification and the quality of data used, with availability of data and continuous validation of the model, results generated by the model can effectively inform farming and policy decisions to enhance the development of robust and sustainable arable farming systems for multiple benefits to ensure food security and safeguard the environment.

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