Adaptation to Climate Change: European Agriculture

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Adaptation to Climate Change: European Agriculture

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Abstract

Climate change is considered as one of the main environmental problems of the 21st century. Assessments of climate change impacts on European agriculture suggest that in northern Europe crop yields increase and possibilities for new crops and varieties emerge. In southern Europe, adverse effects are expected. Here, projected increases in water shortage reduce crop yields and the area for cropping, which directly affects the livelihood of Mediterranean farmers. However, the effect of adaptation is not well understood and therefore often highly simplified. Assessments mainly focus on potential impacts and not on the actual impacts.

The main objective of this study is to assess how adaptation influences the impact of climate change and climate variability on European agriculture. The aim is to improve insights into adaptation processes in order to include adaptation as a process in assessment models that aim to develop quantitative scenarios of climate change impacts at regional level.

We examined agricultural vulnerability and adaptation based on crop yields, farmers' income and agricultural biodiversity; the main ecosystem services provided by agriculture. We considered that farm performance concerning these ecosystem services is influenced by two groups of factors related to (1) farm characteristics and (2) regional conditions, such as biophysical, socio-economic and policy factors. The availability of extensive datasets for Europe, at regional and farm level, provided a unique opportunity to analyse farm performance in relation to climate and management, and hence, improve insights in adaptation.

Results demonstrate that farms that seem better adapted to prevailing conditions (i.e. higher crop yields and farmers' income) do not adapt better to climate change and climate variability. Regions and farm types that obtain higher crop yields and farmers' income have lower (relative) variability herein, but relationships between crop yield or income variability and climate variability are generally stronger than for regions or farm types with low crop yields and farmers' income. Impacts of climate variability on crop yields and farmers' income are generally more pronounced for temperate regions compared to Mediterranean regions.

These results suggest that, due to a larger adaptive capacity, actual impacts of climate change and associated climate variability will be less severe for Mediterranean regions than projected by earlier studies. Farmers adapt their management to prevailing climatic, socio-economic and policy conditions. This current management influences adaptation strategies that can be adopted in the future and hence on the climate impacts.

As actual impacts of climate change and climate variability on crop yields differ largely from potential impacts, which are based on simulations of potential and water limited crop yields, crop models need improvement to simulate actual crop yields. Although mechanistic modelling of all the processes determining crop yield and agricultural performance is not feasible, for reliable projections of the impacts of climate change on agriculture, models are needed that represent the actual situation and adaptation processes more accurately. Farmers continuously adapt to changes, which affects the current situation as well as future impacts. Therefore, adaptation should not be seen anymore as a last step in a vulnerability assessment, but as integrated part of the models used to simulate crop yields and other ecosystem services provided by agriculture.

Keywords: Climate change, climate variability, adaptation, agricultural vulnerability, farm management, crop yield, farmers' income

Preface

When I started to work on this PhD thesis, it was difficult to envisage how it would look like after four years. The proposal for the thesis was very broad, as well as my interests. But, during these four years the road became clearer and here it is, my thesis. From global level I ‘zoomed in’ to Europe; from land use including nature I focused on agriculture. And as little empirical studies had been performed, I concentrated on analysing actual adaptation and vulnerability to climate change and climate variability in the past decades. No future model projections are made in this thesis, but the insights obtained in this study can be used in impact assessment models to improve projections of future climate change impacts.

This thesis wouldn’t be here without the help of many people. Therefore, firstly, I would like to thank my supervisors for both the freedom and the supervision they gave me during these four years. In 2003 I started with one main supervisor, Rik Leemans. Rik, I am especially thankful for your positive attitude, the freedom you gave me and how you introduced me in the scientific community. Only two weeks after I started I was asked to come to Portugal for a project meeting. Lots of beer, wine and good dinners welcomed me in the world of science, and first collaborations started here. Also participating in and tutoring the summer school in the French Alps were very inspiring experiences.

The rest of my supervision team was shaped over the years. Rik’s interests were as broad as mine, and I needed someone who made me focus. The discussions I had with Frank Ewert became more and more frequent and after a year he became officially my co-promotor. Frank, thanks for your tips, our discussions, and your enthusiasm. Without you this thesis wouldn’t look the same.

After 2 ½ years my supervision team was completed. Economics became part of my thesis, but not yet of my supervision team. One discussion with Alfons Oude Lansink made us enthusiastic from both sides and also Alfons joined as a promotor. Alfons, thanks for the critical review of my work and your always quick responses. This helped me a lot in the last years.

Furthermore, I would like to thank Bas Eickhout and Tom Kram for the discussions we had at the Netherlands Environmental Assessment Agency (MNP) in Bilthoven, where I generally worked on Fridays. Although direct linkages between my work and the modelling work at the group KMD (Klimaat en Mondiale Duurzaamheid) has not yet been established, working at KMD once a week has been stimulating for me. I enjoyed the atmosphere and, therefore, I would also like to thank the other colleagues at KMD and especially Rineke Oostenrijk for always making me feel welcome.

As I spent most of my time at my office at the Haarweg, I would like to thank all the roommates that accompanied me in the peace palace (‘ladies palace’ most of the time) for a few days or several years and made working enjoyable: Marjolein Kruidhof, Mariana Rufino, Glaciela Kaschuk, Jessica Milgroom, Santiago Lopèz-Ridaura, Diedert Spijkerboer, Freddy Baijuka, Peter Frost and Argyris Kannellopou-los. Marjolein and Mariana, also thanks for being my paranymphs and always offering

me a place to sleep when I needed one. Living in Utrecht has many advantages, but it restricted me from having a drink with colleagues in Wageningen more often. Coffee breaks in the sun and 'gezellige' lunches are good for the atmosphere, but having a drink every once in a while also makes a difference. Next to my roommates, I thank Marc Metzger, Jochem Evers, Ilse Geijzendorffer, Myriam Adam, Pablo Tittonell, Tom van Mourik, Senthilkumar Kalimuthu, Nick den Hollander, Harm Smit, Sander Janssen, Lenny van Bussel, Rik Schuiling and all my other Haarweg colleagues and fellow PhD students for the good time I had at the Haarweg, at parties and at working trips. Ken Giller, also thanks to you, I enjoy working in your group. And lastly, thanks to Ria van Dijk and Charlotte Schilt for always providing assistance.

Contentwise there are more people that made this thesis possible. Much data is involved and thanks goes to Boudewijn Koole, Hendrik Boogaard, Marc Metzger and Erling Andersen for providing me these data. Thanks also to the EURURALIS project and SEAMLESS project for making this possible. My co-authors in some of the chapters, Hendrik Boogaard, Kees van Diepen, Tonnie Tekelenburg, Maurits van den Berg and Rob Alkemade; also thanks to you for your collaboration. Mariana Rufino thanks for painting the cover of this thesis, Gon van Laar for the tips for the lay out and Annemarieke Halfschepel for your help with the samenvatting.

Working is one thing, having a happy life another. Therefore I would also like to thank all my friends and family. My Frisian friends, the 'fryske famkes', Sanne, Jeltsje, Elise, Elbrich and Else, thanks for always being there for me to have fun, share my experiences and feelings whenever I needed some distraction. In Utrecht, there are many friends who were always in for a beer, to visit a concert or to have dinner: Hanneke, Lydia, Carla, Jans, Jouke, Stefan, Joop, Esther, Werchter festival vriendjes, de Stormtroopers and everybody else who receives this thesis. You made me wanting to stay living in Utrecht.

And of course, very important, I want to thank my parents, 'heit en mem' for always being there for me. Although I do not always make enough time to come over for a weekend, you know I love you and I am very happy with having you as my parents. This also applies to my sisters, Barber and Maayke. And last but not least, Hein, you've been a great support for me the last years of my PhD thesis and I hope we can support and enjoy each other a lot more in the coming years.

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Chapter 1

General introduction

1.1 Background

Climate change is considered as one of the main environmental problems of the 21st century. The recently released IPCC fourth assessment report states that global average surface temperature has increased by 0.74 ± 0.18 °C in the last century and is projected to increase by another 1.1–6.0 °C in this century (www.ipcc.ch; IPCC, 2007a). Eleven of the last twelve years from 1995 to 2006 belong to the twelve warmest years since systematic climate observations began in 1850. In Europe not only warmer conditions have been observed, but also changes in extreme weather events. For example, the European heatwave during the summer of 2003 is exceptional for the current climate and statistically very unlikely to occur (Schar et al., 2004). Only if one assumes that the present climate regime has already experienced a shift towards increased variability, the occurrence of this heatwave can be explained. It is projected that Europe will experience a pronounced increase in the incidence of such heatwaves and droughts.

The heatwave of 2003 had a considerable impact on crop productivity (Ciais et al., 2005). Assessments of climate change impacts on European agriculture suggest that in northern Europe, crop yields increase and possibilities for new crops and varieties emerge (Olesen and Bindi, 2002; Ewert et al., 2005). In southern Europe, adverse effects are expected. Here, projected increases in water shortage reduce crop yields and the area for cropping. This directly affects the livelihood of Mediterranean farmers (Metzger et al., 2006).

Until recently, most of the measures to reduce the impacts of climate change have been focussed on mitigation measures, such as reducing emissions or enhancing sinks of greenhouse gasses. Little emphasis was put on defining and assessing the possible role of adaptation. However, the world will likely continue to warm at a significant rate for many decades, whatever targets may be agreed for emission reductions. Adaptation is required if impacts are to be reduced (Hulme, 1997; Parry et al., 1998). As farmers continuously adapt to changes, they will also have some capacity to adapt to climate change. How, where and when adaptation can reduce impacts of climate change is explored in this thesis.

1.2 Climate change, impacts and adaptation

The extent to which systems are vulnerable to climate change depends on the actual exposure to climate change, their sensitivity and their adaptive capacity (IPCC, 2001). Exposure and sensitivity determine the potential impacts that occur given the projected climate change without considering adaptation. The actual impact is the impact that remains after accounting for adaptation. The adaptive capacity refers to the ability to cope with climate change, including climate variability and extremes, in order to (1) moderate potential damages, (2) take advantage of emerging opportunities, and/or (3) cope with its consequences. Most quantitative studies that address the vulnerability of agricultural systems have focused on exposure and sensitivity, while adaptive capacity is often highly simplified. Realistic adaptation processes are not well understood and therefore hard to quantify (Smit et al., 2001). Progress has been made (IPCC, 2007b), but the complexity of relationships and the resulting dynamic behavior remains difficult to unravel.

The impact of climate change on (agro-)ecosystems can be determined by assessing impacts on ecosystem services (Metzger, 2005; Reid et al., 2005). Ecosystem services are the direct or indirect benefits that people obtain from ecosystems. Ecosystem services thus form a direct link between (agro-)ecosystems and society and the concept is therefore especially useful for illustrating the need to employ mitigation or adaptation measures to prevent or alleviate impacts (Metzger, 2005). The main ecosystem services provided by the agricultural sector are food production, farmers' income (i.e. farmers' livelihood) and agricultural biodiversity.

Impacts of climate change on food production are generally assessed with crop models (Gitay et al., 2001). In crop modelling studies, farmers' responses to climate change are purely hypothetical and either no adaptation or optimal adaptation is assumed (e.g. Rosenzweig and Parry, 1994). Easterling et al. (2003) made a first attempt to model agronomic adaptation more realistically proposing a logistic growth function to describe the adaptation process over time. How agricultural adaptation varies spatially is not assessed to date, however. Mendelsohn and Dinar (1999) suggest that climatic conditions have a relatively smaller impact on farmers' income (i.e. net income/farm value) than on crop yields as simulated by crop models. Their cross-sectional analysis implicitly includes adaptation. As in different climates different crops provide the highest revenues, farmers can adapt by switching crops. By measuring farmers' income instead of crop yields this and other types of adaptation are accounted for.

The impact of climate change on agricultural biodiversity has received little attention, but is expected to be negative especially in colder regions like Scandinavia. Higher temperatures increase the risk of nitrate leaching and, simultaneously, the projected increase in crop yields is assumed to lead to intensification (Olesen and Bindi, 2002); this will threaten agricultural biodiversity. Results vary however and the uncertainty is large (Olesen et al., 2007).

Impact assessments focussing on one exposure (e.g. climate change) and one ecosystem service (e.g. crop yield) have provided important insights. However, ecosystem services are affected in different ways and interrelationships will influence vulnerability and adaptation. Multiple ecosystem services should thus be considered. Furthermore, climate change impacts should be analysed in the context of other changes (O'Brien and Leichenko, 2000). Adaptation to climate change will largely depend on the impact of other exposures. Ewert et al. (2005) showed that the impact of climate change on crop yields is relatively small compared to technological development. Farmers' income may be affected by climatic conditions, but the influence of markets and technology cannot be neglected. Socio-economic and policy conditions will determine where and how much adaptation is required.

First attempts to include adaptation in impact assessments aimed at developing regional scale indices of adaptive capacity to represent the regional context in which individuals adapt (Schröter et al., 2003; Brooks et al., 2005; Haddad, 2005). These indices were based on socio-economic indicators, such as GDP per capita, R&D expenditure and literacy rate, which can represent the regional context, but may not be representative for specific sectors or actors. More recently the focus has shifted from determining adaptive capacity to understanding the dynamics of adaptation (e.g Bharwani et al., 2005). So far, research has mainly focussed on conceptualizing adaptation; few quantitative studies have been performed.

Adaptations in agriculture vary depending on the climatic stimuli (to which adjustments are made), different farm types and locations, and the economic, political and institutional conditions (Bryant et al., 2000; Smit and Skinner, 2002). They include a wide range of forms (technical, financial, managerial), scales (global, regional, local) and actors (governments, industries, farmers). Adaptation options can be grouped into four main categories (Smit and Skinner, 2002): (1) technological developments, (2) government programs and insurance, (3) farm production practices, and (4) farm financial management. Theoretically, adaptation can be autonomous or planned. Autonomous adaptation occurs as a response without conscious decision by the agent (Reilly and Schimmelpfennig, 2000). Planned adaptation is the result of a deliberate decision of the farmer or a public agency, based on the awareness that conditions are about to change or have changed. In practice, distinctions are difficult to make. For example, more heat resistant cultivars can be the result of autonomous technological development, but also of crop breeding programs especially developed to adapt to climate change.

Theoretically, concepts of adaptive capacity and adaptation strategies are clearly defined. However, little empirical evidence of the validity of adaptive capacity indices or the adoption and effectiveness of adaptation strategies is available.

1.3 Objectives

The main objective of this thesis is to assess how adaptation influences the impact of climate change and climate variability on European agriculture. The aim is to improve insights into adaptation processes in order to include adaptation as a process in assessment models that aim to develop quantitative scenarios of climate change impacts at regional level. Special reference is made to IMAGE (Integrated Model to Assess the Global Environment; MNP, 2006), a widely used model with global coverage to develop plausible scenarios for future developments and their environmental impacts, quantified for different regions.

To achieve these objectives, clarification is required on the scales at which impact and adaptation processes are observed, modelled and assessed. Changes in climatic conditions will affect crop yield at the field level through biophysical relationships and these impacts are commonly assessed with crop models. Site-specific crop models strongly emphasize biophysical factors, such as climate and soil. Validation for larger scale regional applications of these models remains unsatisfactory (Tubiello and

Ewert, 2002). The dynamic nature of climatic effects is well understood for potential, water and nitrogen limited growth and yield (e.g. van Ittersum et al., 2003, Figure 1.1). Actual farm yields, however, are also affected by other factors, such as pests and diseases, which depend on farm management and regional conditions. How these influence climate effects is less well understood.

Decisions regarding management and adaptation herein are made at the farm level. Potential impacts of climate change and variability on crop yields at field level can be assessed with crop models, but for projections of actual impacts at higher aggregation levels, the farm level should be considered to take farm management and adaptation into account (Figure 1.2).

Crop yields influence farmers' income and agricultural biodiversity, but goals of farmers related to the latter two will also affect crop yields. Crop yields and farmers' income comprise the main part of the analyses in this study, but agricultural biodiversity is also considered. Farm performance (at farm and regional level) is influenced by two groups of factors related to (1) farm characteristics and (2) regional conditions, such as biophysical, socio-economic, policy factors.

Climatic conditions (and other factors) do not only vary over time, they also vary spatially. Therefore, assessments of climate change impacts can be improved using insights from spatial (i.e. cross-sectional) analyses.

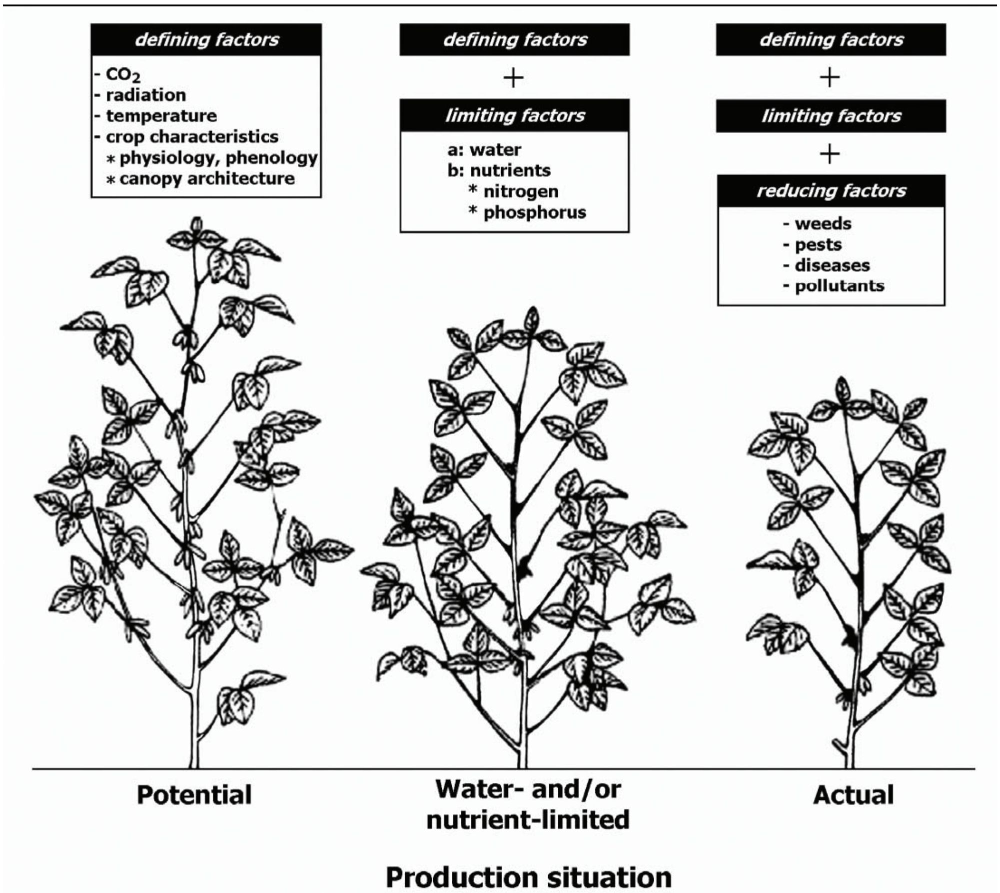

Figure 1.1. A hierarchy of growth factors, production situations and associated production levels (Source: Van Ittersum et al., 2003).

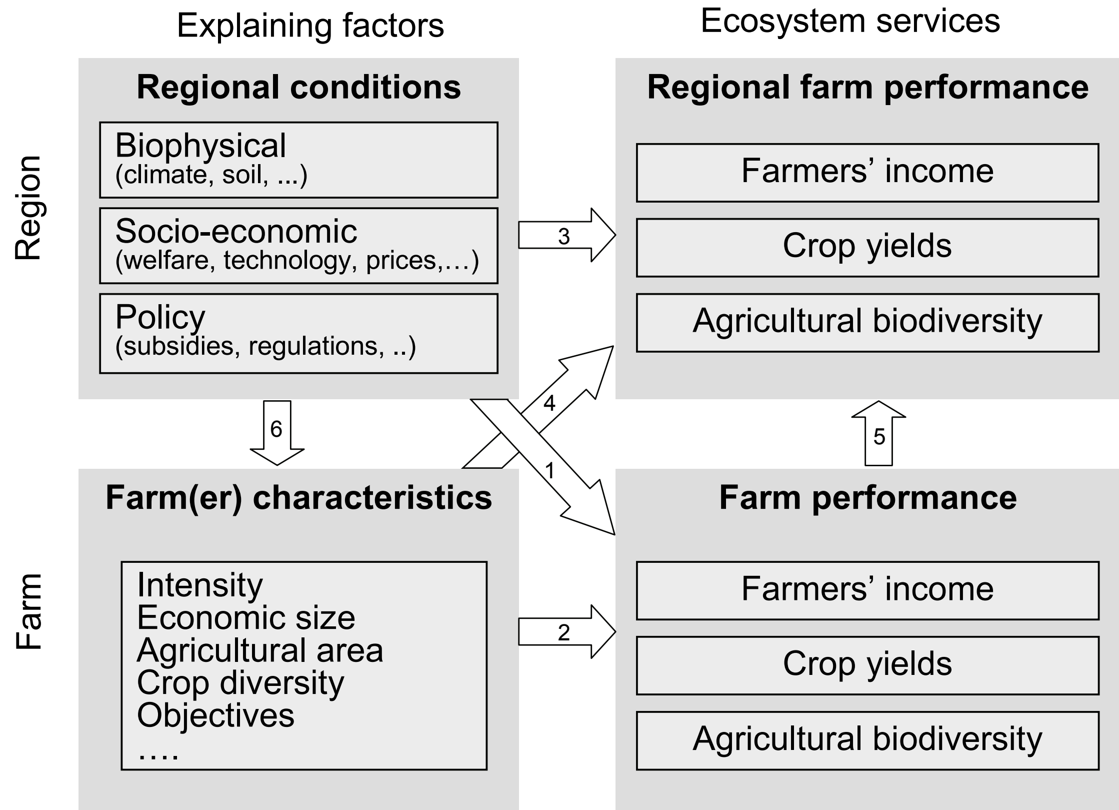

Figure 1.2. Summary overview of the investigated relationships (represented by the block arrows; numbers are referred to in Figure 1.3). Impacts of climate change on farm and regional agricultural performance are not only influenced by biophysical conditions, but also by other regional conditions and farm characteristics, which influence adaptation.

In order to improve insights in the role of adaptation in reducing impacts of climate change and variability, specific research questions related to Figure 1.2 are formulated:

I. What is the influence of regional conditions and farm characteristics on the impact of **spatial** climate **variability** on farm performance, in terms of crop yields and farmer's income?

II. What is the influence of regional conditions and farm characteristics on the impact of **trends and temporal variability** in climatic conditions on farm performance (i.e. trends and temporal variability in crop yields and farmer's income), at different aggregation levels?

III. Does regional **farm diversity** affect impacts of climate variability on regional crop yields?

IV. What is the impact of climatic conditions and subsidies on farm characteristics (i.e. **adaptation strategies,** such as change in crop choice, irrigation management) and on outputs in different European regions?

V. Which regional conditions and farm characteristics can explain the difference between simulated potential and water limited yields (representing potential impacts of climate variability) and actual yields (representing actual impacts) and how can inclusion of management and adaptation improve **crop model projections**?

VI. What are the impacts of farm characteristics and crop productivity on **agricultural biodiversity** and how will this evolve for different scenarios?

VII. How can we use the obtained insights on agricultural **adaptation** to climate change to improve **impact assessment models**?

1.4 Outline

Each Chapter in this thesis concentrates on one of the research questions (Figure 1.3). In Chapter 2 extensive data on farm characteristics of individual farms in the EU15 are combined with climatic and socio-economic data to analyse the influence of climate and management on crop yields and farmers' income and to identify factors that determine adaptive capacity. Assessments of climate change impacts can be improved using insights from such spatial (i.e. cross-sectional) analyses. Farm characteristics that are found to be important for farm performance are used to define a farm typology that is considered in the subsequent Chapters.

In Chapter 3, a temporal analysis is performed to assess whether relationships as found in Chapter 2 also apply when climatic conditions and other factors vary over time. The analysis considers different levels of organization (i.e. region and farm type). As the analysis suggests that diversity in farm types is important for regional vulnerability, this is further explored in Chapter 4 by analysing the relationship between farm diversity and the effects of climate variability on regional wheat yields.

Since farm characteristics influence farm performance, changes in farm characteristics influenced by changing climatic conditions can be considered as adaptation strategies. Interactions between climatic conditions and farm characteristics are explored in Chapter 5; adaptation strategies concern changes in fertilizer and crop protection use, irrigation management, crop choice, farm size and subsidies. Impacts of climate conditions and other factors on farm performance are also explored, but as impacts of temporal variability differ per region, for specific regions instead of EU15-wide as in Chapter 2 and 3.

In Chapter 6 the differences between simulated potential and water limited yields (representing potential impacts of climate variability) by a crop simulation model and actual yields (representing actual impacts of several factors) are explained by regional conditions and farm characteristics. This analysis reveals factors that are important next to biophysical conditions when simulating maize yields at regional level.

Besides crop yields and farmer's income, also agricultural biodiversity is important for European farmers when adapting to changing conditions. In Chapter 7 an adapted farm typology is used to assess agricultural biodiversity in the current situation and for future scenarios. The impact of climate change on agricultural biodiversity is not explicitly considered. The analysis is included to (1) demonstrate that there are trade offs between different ecosystem services and to (2) present how a farm typology can be used in impact assessments.

In Chapter 8 the results from all Chapters are discussed and synthesized. Recommendations on how to include adaptation in integrated assessment models, such as IMAGE, are presented.

	Research question	Ecosystem service	Relationships	Ch
I	Spatial variability	Crop yields (5) & farmers' income	1,2	2
II	Trends and temporal variability	Crop yields (5) & farmers' income	1,2,3,4	3
III	Farm diversity	Wheat yield	4,2,5	4
IV	Adaptation strategies	Output from agricultural activities (4)	6,1,2	5
V	Crop model projections	Maize yield	3,4	6
VI	Agricultural biodiversity	Agricultural biodiversity	2,5,1,4	7
VII	Adaptation in impact assessment models	Crop yields, farmers' income & agricultural biodiversity	All	8

Figure 1.3. Structure of the thesis in a methodological framework. Each research question is considered in a separate Chapter. Relationships refer to the block arrows in Figure 1.2.

Chapter 2

Analysis of farm performance in Europe under different climatic and management conditions to improve understanding of adaptive capacity

Abstract

The aim of this Chapter is to improve understanding of the adaptive capacity of European agriculture to climate change. Extensive data on farm characteristics of individual farms from the Farm Accountancy Data Network (FADN) have been combined with climatic and socio-economic data to analyse the influence of climate and management on crop yields and income and to identify factors that determine adaptive capacity.

A multilevel analysis was performed to account for regional differences in the studied relationships. Our results suggest that socio-economic conditions and farm characteristics should be considered when analysing effects of climate conditions on farm yields and income. Next to climate, input intensity, economic size and the type of land use were identified as important factors influencing spatial variability in crop yields and income. Generally, crop yields and income are increasing with farm size and farm intensity. However, effects differed among crops and high crop yields were not always related to high incomes, suggesting that impacts of climate and management differ by impact variable.

As farm characteristics influence climate impacts on crop yields and income, they are good indicators of adaptive capacity at farm level and should be considered in impact assessment models. Different farm types with different management strategies will adapt differently.

Keywords: Climate change, adaptive capacity, farm management, crop yield, farmers' income, multilevel modelling

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2.1 Introduction

Climate change is expected to affect agriculture very differently in different parts of the world (Parry et al., 2004). Many studies have analysed the influence of climate and climate change on agriculture, and the problem of agricultural vulnerability is increasingly recognized (e.g. Mendelsohn et al., 1994; Antle et al., 2004; Parry et al., 2004). The extent to which systems are vulnerable depends on the actual exposure to climate change, their sensitivity and their adaptive capacity (IPCC, 2001). Exposure and sensitivity determine the potential impacts, which include all impacts that occur given the projected climate change without considering adaptation. The actual impact is the impact that remains after allowing for adaptation. The adaptive capacity refers to the ability to cope with climate change including climate variability and extremes in order to (1) moderate potential damages, (2) take advantage of emerging opportunities, and/or (3) cope with its consequences. Most quantitative studies that address the vulnerability of agricultural systems have focussed on exposure and sensitivity, while adaptive capacity is often highly simplified. Realistic adaptation processes are not well understood and therefore hard to quantify (Smit et al., 2001).

The impact of climate change on society is frequently determined by assessing impacts on ecosystem services (Metzger, 2005; Reid et al., 2005). Because ecosystem services form a direct link between ecosystems and society, the concept is especially useful for illustrating the need to employ mitigation or adaptation measures to prevent or alleviate impacts (Metzger, 2005). The main ecosystem services provided by the agricultural sector are food production, farmers' income and environmental sustainability. Impacts of climate change on food production are generally assessed with crop models (Gitay et al., 2001). Studies have been performed on different levels of organization: crops (Tubiello and Ewert, 2002), cropping systems (e.g. Tubiello et al., 2000), regional (Iglesias et al., 2000; Saarikko, 2000; Trnka et al., 2004), continental (Harrison et al., 1995; Downing et al., 2000; Reilly, 2002) and global (IMAGE team, 2001; Parry et al., 2004).

In crop modelling studies, farmers' responses to climate change are purely hypothetical and either no adaptation or optimal adaptation is assumed. Easterling et al. (2003) made a first attempt to model agronomic adaptation more realistically proposing a logistic growth function to describe the adaptation process over time. How agricultural adaptive capacity varies spatially has not been assessed to date, however. Mendelsohn and Dinar (1999) suggest that climatic conditions have relatively smaller impact on farmers' income (net income / farm value) than on crop yields as simulated by crop models. Their cross-sectional analysis implicitly includes adaptive capacity. Adaptation strategies adopted could be agronomic strategies to increase crop yields as well as economic strategies such as changes in crops and inputs. Agro-economic models (Kaiser et al., 1993; Antle et al., 2004) can assess optimal economic adaptation strategies, but do not consider the capacity to adopt these. In addition, biophysical relationships are often underrepresented.

In Europe, concerns in agriculture are mainly related to farmer livelihood and the land available for farming (Schröter et al., 2005) and less to food production. A European vulnerability assessment showed that farmer livelihood is especially vulnerable in the Mediterranean region (Metzger et al., 2006). This projection was based on calculations suggesting that intensification of production will reduce the need for agricultural land in less favoured areas (Ewert et al., 2005; Rounsevell et al., 2005). Although the impact of climate change in Europe was projected to be small on average, regions with less favourable climatic conditions and hence lower crop yields would have difficulties to sustain farmer livelihood. Projected impacts on European agricultural land use were less severe when the global food market and regional land supply curves were included in the modelling framework (van Meijl et al., 2006). Assumptions related to different drivers have a large influence on climate change impact projections. Farm-level responses are usually not considered and spatial variability in farm performance and adaptive capacity is not well understood.

In this Chapter we analysed the impact of farm characteristics and climatic and socio-economic conditions on crop yields and farmers' income across the EU15. The influence of climate is assessed using a Ricardian approach, similar to that employed by Mendelsohn et al. (1994). By including farm-level information (e.g. farm size, intensity) and socio-economic conditions in the analysis, we captured factors that influence farm-level adaptive capacity. We investigated both crop yields and income variables and the relationships between these to understand farm performance and adaptation.

Emphasis is on spatial variability in farm performance considering data from three different years (1990, 1995 and 2000). Since data were available at different scales a multilevel statistical approach was used. Results of this study can improve the modelling of agricultural adaptation to climate change.

2.2 Methodology

2.2.1 Conceptual basis for analysing farm performance and adaptive capacity

Changes in climatic conditions will affect crop growth and yield at the field level through biophysical relationships and these impacts are commonly assessed with crop models. The dynamic nature of climate effects is well understood for potential, water and nitrogen limited growth and yield (e.g. van Ittersum et al., 2003). Actual yields, however, are also affected by other factors such as pests and diseases not considered in crop models and farm management will largely influence the obtained actual yield. Therefore, climate change impacts on crop yields also depend on factors determining farm performance. Potential impacts can be assessed with crop models, but for projections of actual impacts the adaptive capacity of farmers should be taken into account.

We found it important to distinguish between two groups of factors related to (1) farm characteristics and (2) regional conditions such as biophysical, socio-economic and policy factors (Figure 2.1). Both factor groups represent different levels of organization (farm and region). We account for possible interactions between farm characteristics and regional conditions on farm performance through a multilevel analysis (see section 2.2.3). Farm characteristics may also change as a result of regional impacts on farm performance, which, however, is not further addressed in this Chapter. As different crops respond differently to climatic conditions, yields of five important crops (wheat, grain maize, barley, potato and sugar beet), were analysed.

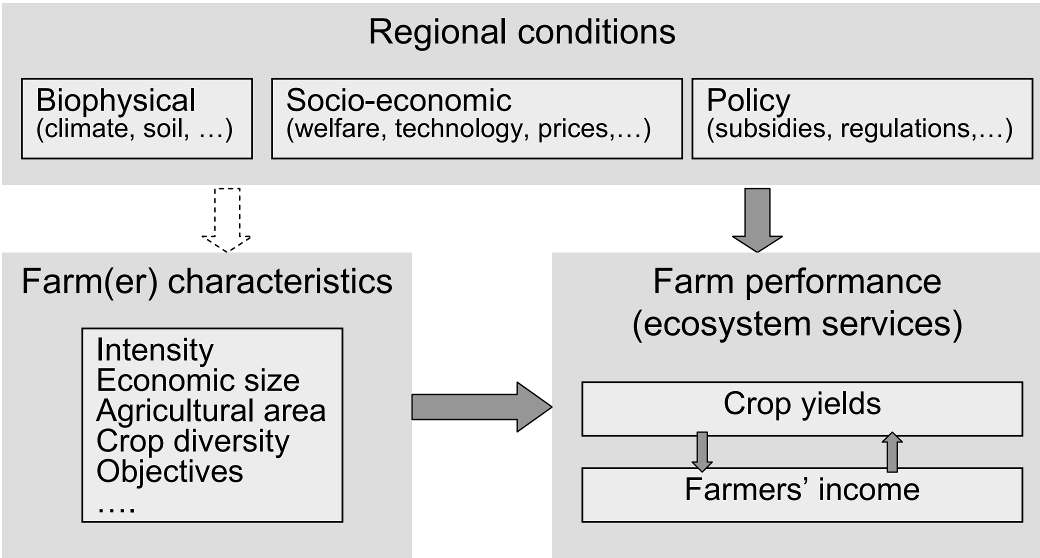

Figure 2.1. The investigated relationships (represented by the block arrows). Potential impacts of climate conditions are influenced by other regional conditions and farm characteristics, which determine adaptive capacity.

Farm management decisions have to be economically viable in order to ensure the farm's sustainability. We considered the economic performance of farms by including farmers' income in the analysis and explicitly studied relationships between income and crop yields. Farmers' income is represented by farm net value added per hectare (*fnv/ha*) and farm net value added/annual work unit (*fnv/awu*). *Fnv/ha* measures economic performance per unit of land and a relationship to crop yield can be expected. *Fnv/awu* is a measure that enables comparison of farmers' income directly to GDP per capita and can therefore relate farm performance to general socio-economic performance. By directly measuring revenues, we account for the direct impacts of climate on yields of different crops as well as the indirect substitution of different inputs, introduction of different activities, and other potential adaptations to different climates (Mendelsohn et al., 1994).

Farm characteristics that explain farm performance are related to determinants of adaptive capacity: awareness, technological ability and financial ability (Schröter et al., 2003; Metzger et al., 2006). Adaptive capacity is difficult to quantify explicitly from observations on farm performance however. Information about potential impacts, i.e. impact without adaptation, is not available as observed farm performance implicitly includes adaptation to present climatic and other conditions. We assume that adaptation is related to farm performance and farms that perform well are also well adapted.

2.2.2 Data sources and data processing

The Farm Accountancy Data Network (source: FADN-CCE-DG Agri and LEI) provides extensive data on farm characteristics of individual farms throughout the EU15[1]. Data have been collected annually since 1989. They have been used as an instrument to evaluate the income of agricultural holdings and the impacts of the Common Agricultural Policy. Information about the exact geographic location of the sample farms is not available for privacy reasons; only the region in which farms are located is known. In total, 100 HARM regions[2] are distinguished (see Figure 2.3) with 51,843 sample farms.

FADN considers the following land-using production types: specialist field crops, specialist permanent crops, specialist grazing livestock, mixed cropping and mixed crops/livestock. At approximately 40 percent of all farms, i.e. 20,936 farms, crop production is the main activity, i.e. when more than 66 percent of the total standard gross margin[3] (economic size) was obtained from the sale of field crop products and/or when the arable area was more than 66 percent of the total utilized agricultural area. Only these farms were included in the analysis of effects on farmers' income.

For each farm, data were available on outputs representing farm performance: crop yields and farm net valued added (Table 2.1). Crop yields of five important crops (wheat, grain maize, barley, potato and sugar beet) were calculated by dividing production (in tons fresh matter) by crop area (in ha). Farm characteristics considered to explain farm performance represent different determinants of adaptive capacity: awareness, technological ability and financial ability (Schröter et al., 2003; Metzger et al., 2006). Awareness is reflected in the land use (arable land, permanent cropping land, grassland, area of each crop grown). Arable farmers have more skills in crop production than livestock farmers and therefore obtain higher yields and probably less yield variability. A farmer growing a specific crop in a large area is expected to put more effort in obtaining a high crop yield. Technological ability is represented by the input intensity (irrigated area, input costs of fertilizer and crop protection products, whether the farm is conventional or organic). It is expected that farms with a high input intensity aim for a high output intensity. Financial ability is reflected by the economic size and/or the size of the farm in hectares. A larger farm is a priori expected to have more capital available for investments in new technologies. Altitude class and location in a less-favoured area (LFA) were used as proxies for the biophysical

[1] The EU15 comprises the 15 member countries of the European Union before the extension in 2004.
[2] HARM is the abbreviation for the harmonized division created by the Dutch Agricultural Economics Research Institute (LEI). It gives the opportunity to compare the different regional divisions of the EU15 used by Eurostat (NUTS2) and FADN.
[3] The standard Gross Margin (SGM) of a crop or livestock item is defined as the value of output from one hectare or from one animal less the cost of variable inputs required to produce that output.

characteristics of the land. More variables were available, but variables needed to be selected to reduce multicollinearity (see section 2.2.3 and 2.3.2). Data from three years (1990, 1995 and 2000) were considered but results presented refer mainly to the year 2000 as little or no differences were found among years.

Table 2.1. Data description and sources.

Variable	Definition	Source[a]	Mean[b]	S.D.[b]
Dependent				
Crop yield	Actual crop yield (tons/ha)	1	[c]	
Fnv/awu	Farm net value added[d] / annual work units (€)	1	26609	50478
Fnv/ha	Farm net value added / hectare (€)	1	906	1761
Farm characteristics				
Irr_perc*	Irrigated percentage of utilized agricultural area (%)	1	15	31
Fert/ha*	Costs of fertilizers and soil improvers per ha (€)	1	112	119
Prot/ha*	Costs of crop protection products per hectare (€)	1	97	113
Org*	1 = conventional, 2 = organic, 3 = converting/partially organic	1	1.01	0.17
Uaa	Utilized agricultural area (ha)	1	82	194
Ec_size*	Economic size[e] (ESU)	1	70	154
Labour	Annual work units (AWU[f])	1	1.9	4.1
Perm/uaa*	Permanent cropping area / utilized agricultural area (-)	1	0.038	0.092
Grass/uaa*	Grassland area / utilized agricultural area (-)	1	0.044	0.099
Crop_pr*	Crop area / total arable area (-)	1	[c]	
Biophysical conditions				
Alt*	Altitude: 1= < 300 m, 2 = 300-600 m, 3= > 600 m	1	1.5	0.8
Lfa*	1= not in lfa[g] , 2 = in lfa not mountain, 3 = in lfa mountain	1	1.6	0.8
Tmean*	Mean temperature (ºC) of first half year	2	9.1	2.5
Pmean*	Mean precipitation (mm) of first half year	2	64	17
Socio-economic conditions				
Ac*	Macro-scale adaptive capacity index (-)	2	0.54	0.12
Gdp/cap	Gross domestic product per capita (€)	3	14145	5181
Pop_dens	Population density (people per km^2)	3	158	151

* Independent variables included in multilevel models.

[a] 1: FADN, 2: ATEAM, 3: Eurostat (1 = farm level; 2,3 = HARM level).

[b] Statistics based on 2000 data, for cropping systems only.

[c] Differs per crop considered.

[d] Corresponds to the payment for fixed factors of production (land, labour and capital), whether they are external or family factors. As a result, holdings can be compared irrespective of the family/non-family nature of the factors of production employed. Fnv = total output − total intermediate consumption + balance current subsidies and taxes – depreciation.

[e] The economic size is determined on the basis of the overall standard gross margin of the holding. It is given in European Size Units (ESU); one ESU corresponds to a standard gross margin of €1200.

[f] One Annual Work Unit (AWU) is equivalent to one person working full-time on the holding.

[g] Lfa = Less-favoured area.

Climatic effects were analysed using data from the ATEAM project[4] based on New et al. (2002). Averages from the thirty-year period 1971–2000 are assumed to be representative for the climatic conditions that influence spatial variability in farm performance[5]. Mean temperature and precipitation of all months were obtained with a resolution of 10′×10′. As monthly climate variables are often correlated, average variables were created to not confound the results. Monthly mean temperatures of the first six months (January – June) have been averaged, resulting in the mean monthly temperature of the first half of the year. Also precipitation data was averaged to obtain the mean monthly precipitation for the first six months of the year that can be considered as the main growing period for Europe. All climatic data were averaged to HARM regions.

Data on regional socio-economic variables, such as GDP per capita and population density were obtained from Eurostat (2004). Population density can serve as a proxy for the pressure on the land. When land becomes scarce, rental rates increase, which is assumed to increase production intensity (van Meijl et al., 2006). Data were available at NUTS2[6] level and transformed to HARM regions.

A macro-scale adaptive capacity index has been developed at NUTS2 regional level for the EU15 (Schröter et al., 2003; Metzger et al., 2006). This adaptive capacity index serves as a proxy for the socio-economic conditions that influence farmers' decisions; it sets the regional context in which individuals adapt. The index is based on twelve indicators, which are aggregated by application of fuzzy set theory. The indicators comprise: female activity rate & income inequality (equality), literacy rate & enrolment ratio (knowledge), R&D expenditure & number of patents (technology), number of telephone lines & number of doctors (infrastructure), GDP per capita & age dependency ratio (flexibility), world trade share & budget surplus (economic power).

2.2.3 Statistical analysis

Multilevel modelling

The effect of climate and management on farm performance is analysed by fitting a multilevel (or generalized linear mixed model; GLMM) model to the data. A multilevel model expands the general linear model (GLM) so that the data are permitted to exhibit correlated and non-constant variability (e.g. Snijders and Bosker, 1999; McCulloch and Searle, 2001). Multilevel modelling originates from the social sciences and has more recently also been applied to geographic studies (e.g. Polsky and Easterling, 2001; Pan et al., 2004). A multilevel model can handle complex situations in which experimental units are nested in a hierarchy. In a multilevel model, responses from a subject are thought to be the sum of the so-called fixed and random

[4] ATEAM (Advanced Terrestrial Ecosystem Analysis and Modelling), www.pik-potsdam.de/ateam/ateam.html.

[5] Spatial variability in crop yields and income is mainly determined by long-term climate variability. Temporally, variability in crop yields and income is relatively smaller than climate variability (results not shown). Using yearly climate data disturbs the impact of long-term spatial variability in climatic conditions.

[6] Nomenclature des Units Territoriales Statistiques 2: regions or provinces within a country as distinguished by Eurostat.

effects. If a variable, such as fertilizer use, affects wheat yield, it is fixed. Random effects contribute only to the covariance of the data. Intercepts and slopes of variables may vary per region and this covariance is modelled using random effects. Hence, multi-level modelling accounts for regional differences when analysing within region effects of farm characteristics on yields and income. In Figure 2.2 this is depicted graphically.

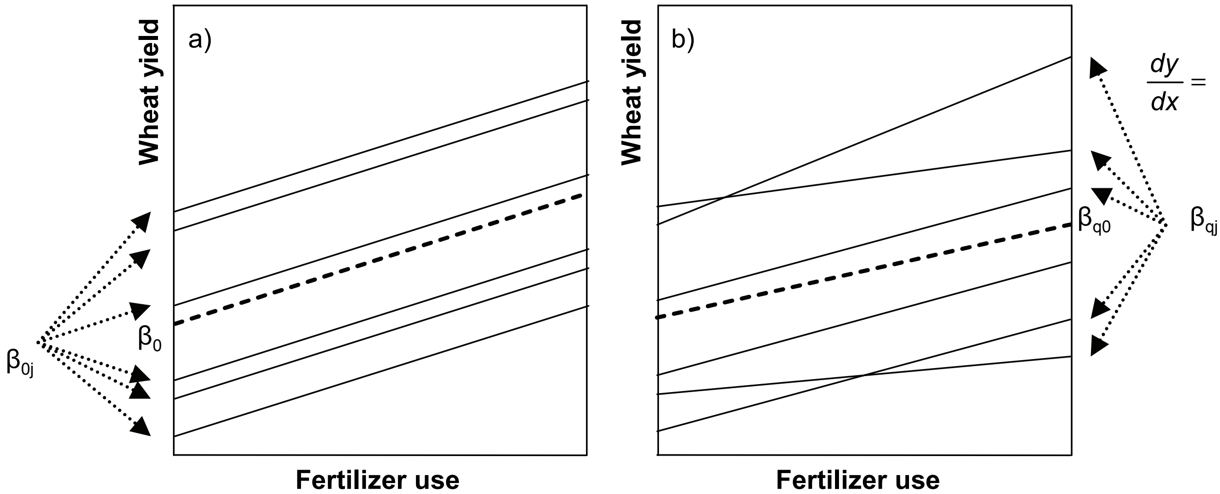

Figure 2.2. Graphical example of a multilevel model with (a) random intercept β_{0j} and (b) random intercept β_{0j} and slopes β_{qj}. Each solid line represents the effect of fertilizer use on wheat yield in a specific region j, whilst the dotted line represents the mean (fixed) relationship across all regions (β_{q0}). In a simple regression model, the mean relationship is a line through all the data points, while in a multilevel model it is the average of the relationships per region.

Fitting a multilevel model to the data comprises a few steps. Firstly, the model is formulated with fixed effects only as in a GLM, to compare against models including different forms of HARM-level variation.

$$y_{ij} = \beta_{0j} + \sum_{q=1...Q} \beta_{qj} x_{qij} + r_{ij} \tag{1}$$

In equation 1, y_{ij} is the dependent variable, β_{0j} is the intercept estimate, β_{qj} is the coefficient estimate of the variable x_{qij}, i indexes the farm, j indexes the HARM region and the residual $r_{ij} \sim N(0, \sigma^2)$. In this model, β_{0j} and β_{qj} are the same for all HARM regions. The model gives similar results as a GLM. The goodness of fit is measured in different ways though. A multilevel model is based on (restricted) maximum likelihood methods, versus the minimization of squared error in GLM. The preferred GLM is the model with the highest R^2, while the preferred multilevel model is selected using likelihood ratio tests. The preferred multilevel model is the model with the lowest information criteria, such as –2 log likelihood (deviance) or Aikaike's Information Criterion (AIC). A single deviance or AIC has no useful interpretation, it is only the difference between the values of different models that matters.

In a second model, the proposition that the average of the dependent variable varies between regions is being tested by including a random intercept. This model combines equation 1 and 2.

$$\beta_{0j} = \beta_0 + \mu_j \qquad (2)$$

where μ_j is the regional level residual from the average intercept estimate. To test whether the overall model fit is improved, two models can be compared by subtracting the deviances. This is the χ^2, and the associated d.f. is the difference in the number of parameters. A random intercept model allows for a better representation of the influence of farm-level variables on the dependent variables, as regional differences are being captured in the random intercept. Since the focus is on the explanation of variables within regions, regional differences in climatic or socio-economic conditions which are not captured by the selected variables, do not confound the results. The influence of variables can also differ between regions. We therefore tested the random coefficients model, in which also the slopes vary between regions. This model combines equation 1−3.

$$\beta_{qj} = \beta_{q0} + u_{qj} \qquad (3)$$

where u_{qj} is the regional level residual from the average coefficient estimate. All statistical analyses were performed with the data of the years 1990, 1995 and 2000 separately. Since results were consistent across years only results from 2000 are presented (see section 2.3).

Selection of variables

Crop yields (wheat, grain maize, barley, potato and sugar beet) and income variables (farm net value added/annual work unit, farm net value added/ha) were the dependent variables in different models. These and the independent variables are presented in Table 2.1. For the climate variables, linear and quadratic terms were included to capture their potential nonlinear effects on crop yields and income variables. For crop yield models all sample farms in the database were analysed, for income models only farms where crop production was dominating were considered (see section 2.2.2).

The two-way relationship between the dependent variables and fertilizer and crop protection use violates a basic assumption of independence and therefore can lead to endogeneity. Farmers' decisions about the rate of fertilizer and crop protection applications depend on its marginal effects on the net value added, which is determined by the marginal effect on crop yields, the prices of crops, and the prices of fertilizers and crop protection products. Non-linearity of the relationship between these input costs and dependent variables has been tested by curve estimation in SPSS 11. To test for the impact of erroneously treating endogenous variables as exogenous, we used instrumental variables (IV) to estimate the effect of *fert/ha* and *prot/ha* on the dependent variables. Using instrumental variables allows for removing the error terms in *fert/ha* and *prot/ha* that confound with the errors in the equations of crop yields and farm income. All variables in the database that could possibly influence application of *fert/ha* and *prot/ha* were included as instrumental variables in the IV regression (e.g. land improvement costs, costs on machinery and equipment, percentages of various crops, annual working units). The IV regression was performed with a multilevel model. Endogeneity of *fert/ha* and *prot/ha* was tested by the Hausman test (Hausman, 1978). The test statistic is

$$M = (\tilde{\beta} - \hat{\beta})'(\tilde{V} - \hat{V})(\tilde{\beta} - \hat{\beta}) \quad (4)$$

where $\tilde{\beta}$ is the parameter vector resulting from the model based on IV estimates for the possible endogenous variables and $\hat{\beta}$ is the parameter vector of the model with the observed values. $\tilde{V}$ and $\hat{V}$ are the variance-covariance matrices of $\tilde{\beta}$ and $\hat{\beta}$, respectively. This test has a χ^2 distribution with N degrees of freedom (N is the number of parameters). The null hypothesis is that the two estimators do not differ. If the null hypothesis is rejected, exogeneity of the variables under investigation is rejected. The Hausman test can result in negative test values. One way to deal with this is to apply the test on the parameters tested for endogeneity only (Ooms and Peerlings, 2005).

Before fitting a multilevel model, the possible influence of multicollinearity must be examined. Climate, socio-economic and management variables all have, to some extent, a north-south gradient in the European Union. A high multicollinearity causes coefficient estimates to be unreliable and confounding in interpreting the model results. An advantage of a full multilevel model in comparison with GLMs is that multicollinearity only needs to be examined per level. As the influence of management variables is analysed per region (as random effects account for regional differences), a possible correlation of input use (at individual farm level) with climatic variables (at regional level) won’t influence the results.

The linear mixed model procedure in SPSS 11 does not include collinearity diagnostics. We therefore applied a linear regression model to the data to examine these. We based the selection of variables on the partial correlation matrix and on the linear regression model with wheat yield as dependent variable. Firstly insignificant variables were removed; secondly variables with a variance inflation factor (VIF) of 10 or higher were removed from the analysis (Allison, 1999). The process of excluding variables was continued until all condition indices (CI) were below 30 and all variables contributed to the output. CI greater than 30 indicate that multicollinearity is a serious concern; multicollinearity is not present when all condition indices equal one.

2.3 Results

2.3.1 Spatial variability in yield and income variables

In Figure 2.3 the spatial variability of wheat yield, maize yield, farm net value added/annual work unit (*fnv/awu)* and farm net value added/hectare (*fnv/ha)* between and within HARM regions in 2000 is presented. The coefficient of variation (CV)

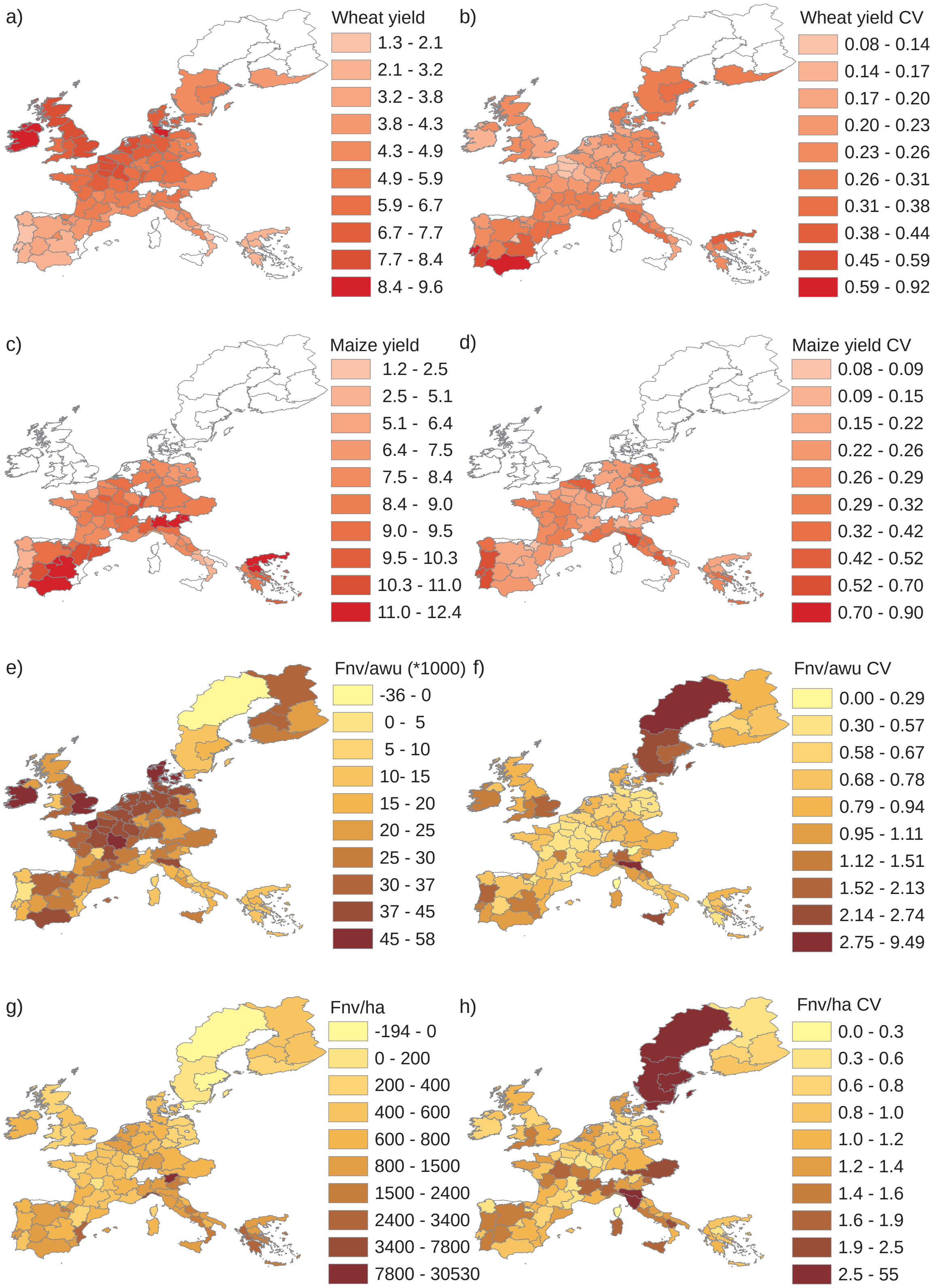

Figure 2.3 (in colour on p.176). Spatial variability of crop yields (tons/ha) and income variables (€) in 2000 between and within HARM regions for (a) average wheat yield, (b) CV of wheat yield, (c) average maize yield, (d) CV of maize yield, (e) average of farm net value added/annual work unit (fnv/awu), (f) CV of fnv/awu, (g) average of farm net value added/hectare (fnv/awu) and (h) CV of fnv/ha. Only values for regions where more than 15 farms grow the crop considered are presented.

gives an indication of the spatial variability within a region due to management and/or biophysical factors. Spatial distributions of yields were different for wheat and maize. Wheat yields were generally highest in north-west Europe, while the highest maize yields were obtained in Spain and Greece. Spatial variability within regions was generally higher in regions with lower yields. The variability among regions of *fnv/awu* was similar to that of wheat yields, but different to the spatial variability of *fnv/ha* which was especially high for some Mediterranean regions.

2.3.2 Selection of variables affecting crop yields and farmers' income

The instrumental variables regression model could account for 81.2% of the variation in *fert/ha* and 83.1% of *prot/ha*. Results of the Hausman test indicated that fertilizer use and crop protection use were exogenous to crop yields ($p>0.05$), but endogenous to *fnv/ha* and *fnv/awu* ($p<0.001$). Hence the observed values were used in the crop yield models, while the estimates based on the IV model were used in the income models.

In a partial correlation matrix (Table 2.2) we identified variables that were correlated, and variables that were correlated to the dependent variables in which we were interested. The correlation between crop protection use *(prot/ha)* and wheat yield for example was significantly positive with an $r = 0.467$, suggesting that *prot/ha* may be a good predictor of wheat yield and should be included in the multilevel model.

For each model it was tested whether including quadratic terms improved model performance. Models that include mean temperature (*tmean),* as well as the macro-scale adaptive capacity (*ac)* showed Variance Inflation Factors of nearly 2 and Condition Indices higher than 30, which indicates that coefficient estimates were not reliable. For each model either climate variables or the *ac* have been included. *Gdp/cap* was highly correlated with *ac* and was excluded from further analysis. Both variables can represent the socio-economic conditions influencing farmers' decision making; however, *ac* is more comprehensive and a better indicator of the regional context in which individuals adapt. Although population density (*pop_dens)* had a significant positive effect on wheat and maize yields and *fnv/awu*, its effect was not significant in multilevel models and was excluded from further analysis.

On the individual farm level, the size of the farm in hectares (*uaa*) and labour units (*labour*) were highly correlated with the economic size of the farm (*ec_size*). Only *ec_size* was included in the multilevel models. As the share of arable land (*ar/uaa*), permanent cropping land (*perm/uaa*) and grassland (*grass/uaa*) in total *uaa* almost add up to one, they can not all be included in the model. Consequently, *ar/uaa* is excluded from the model. Thus, a negative effect of the other land use types implies a positive effect of *ar/uaa.*

Table 2.2. Partial correlation matrix of selected variables for the year 2000 for farms with crop production as the main farming activity. Pearson's correlation coefficients (r) in bold are significant. Names of crops refer to actual yields. Other variables are described in section 2.2.2 and Table 2.1.

	wheat	maize	potato	sugar beet	barley	fnv/awu	fnv/ha	irr_perc	fert/ha	prot/ha	perm/uaa	grass/uaa	uaa	ec_size	labour	tmean	pmean	ac	gdp/cap
maize	**0.261**																		
potato	**0.397**	**0.411**																	
sugar beet	**0.211**	**0.173**	**0.242**																
barley	**0.688**	**0.197**	**0.277**	**0.190**															
fnv/awu	**0.138**	**0.033**	**0.221**	**0.034**	**0.264**														
fnv/ha	-0.012	**0.101**	**0.086**	**0.069**	**0.020**	**0.267**													
irr_perc	**-0.097**	**0.152**	0.016	**0.209**	-0.003	**-0.028**	**0.170**												
fert/ha	**0.249**	**0.259**	**0.128**	**0.108**	**0.355**	**-0.033**	**0.356**	**0.280**											
prot/ha	**0.467**	**0.136**	**0.286**	**0.125**	**0.539**	**0.015**	**0.378**	**0.276**	**0.522**										
perm/uaa	**-0.183**	**-0.064**	**-0.142**	**-0.110**	**-0.183**	**-0.066**	**0.160**	**0.018**	**0.057**	**0.104**									
grass/uaa	**0.031**	**-0.131**	**-0.137**	0.004	**0.018**	**-0.027**	**-0.105**	**-0.117**	**-0.106**	**-0.125**	**-0.117**								
uaa	0.006	**-0.048**	0.009	**-0.094**	**0.024**	**0.106**	**-0.081**	**-0.070**	**-0.074**	**-0.040**	**-0.094**	**0.097**							
ec_size	**0.076**	**-0.033**	**0.088**	**-0.091**	**0.081**	**0.134**	**-0.041**	**-0.038**	**-0.033**	**0.046**	**-0.076**	**0.050**	**0.928**						
labour	**-0.043**	**-0.038**	-0.005	**-0.084**	-0.013	0.008	**0.023**	-0.004	-0.001	**0.029**	-0.001	**0.057**	**0.817**	**0.866**					
tmean	**-0.196**	**-0.076**	-0.012	**0.040**	**-0.133**	**-0.080**	**0.128**	**0.272**	**0.064**	0.001	**0.231**	**-0.145**	**-0.144**	**-0.160**	**-0.079**				
pmean	**-0.122**	-0.013	**-0.260**	0.018	-0.008	**-0.041**	**0.021**	**-0.112**	**0.056**	0.012	**0.053**	**0.082**	**-0.129**	**-0.103**	**-0.062**	**-0.104**			
ac	**0.396**	**-0.065**	**0.104**	**-0.238**	**0.285**	**0.105**	**-0.150**	**-0.422**	**-0.112**	**-0.021**	**-0.183**	**0.170**	**0.134**	**0.164**	**0.060**	**-0.687**	**0.120**		
gdp/cap	**0.287**	0.006	**0.095**	-0.018	**0.183**	**0.099**	**-0.097**	**-0.334**	**-0.067**	0.006	**-0.129**	**0.068**	**-0.035**	0.009	**-0.081**	**-0.621**	**0.203**	**0.764**	
pop_dens	**0.211**	**0.064**	**0.167**	**-0.029**	**0.153**	**0.027**	**0.032**	**-0.130**	**0.032**	**0.114**	-0.007	**0.070**	**-0.030**	**0.026**	-0.010	**-0.025**	**0.123**	**0.270**	**0.272**

2.3.3 The influence of climate and management on crop yields

The multilevel model with wheat yield as dependent variable clearly improved when random intercepts and slopes were introduced. The deviance decreased from 61744 for a model with fixed effects only, to 57104 ($p<0.001$) when a random intercept was included, to 55735 ($p<0.001$) when random slopes were included. The covariance parameters of the random effects were significant for all variables, indicating significance of between-region variation. Thus, for estimating parameters of fixed effects it is better to use the model with random intercept and slopes; this also holds for all other crop yield models.

Table 2.3 presents the fixed effects of multilevel models with random intercept and slopes. The coefficient estimates refer to models with climate variables included. However, since we were also interested in the effects of *ac*, coefficient estimates for *ac* (i.e. without climate variables) are shown.

Wheat yield was significantly related to all variables included in the model, except for irrigated percentage (*irr_perc)*. The parameter estimates of the linear and quadratic terms of mean temperature (*tmean)* and precipitation (*pmean)* suggest that relationships with wheat yield were concave in these variables. Variables representing input intensity (fertilizer use, *fert/ha*; crop protection use, *prot/ha*; conventional/organic farming, *org*) and financial ability (economic size, *ec_size*) all influenced wheat yields significantly positive. The type of land use also influenced wheat yield significantly: the percentage of wheat area (*crop_pr*) had a positive effect and the percentage of permanent cropping area (*perm/uaa)* and grassland area (*grass/uaa*) had a negative effect, indicating a positive effect for the percentage of arable land (*ar/uaa*). The influence of *irr_perc* was not significant, which was probably due to the fact that wheat is usually not irrigated. Effects of factors representing growing conditions were highly significant. Farms on higher altitudes (*alt*) and farms in less favoured areas (*lfa*) had, ceteris paribus, lower wheat yields compared to farms under more favourable conditions. These results suggest that climatic conditions influence wheat yields, but that farm characteristics can increase or diminish this influence.

Relationships for maize yields were less clear than for wheat. Effects of *tmean* were only significant at $p<0.10$, while the effect of *pmean* was not significant. Variation in *pmean* across Europe was relatively small and availability of water depends also on other factors such as soil water holding capacity and depth and potential evapo-transpiration. In regions with a low water availability irrigation is applied to maize.

Including quadratic terms of climate variables didn't improve model performance (in terms of AIC). For some farm characteristics such as *irr_perc, fert/ha* and *perm/uaa* significant effects were evident. The maize growing area (*crop_pr)* was significant at $p<0.10$, but highly significant in models with fixed effects only, suggesting that maize yields were, ceteris paribus, higher in regions were more maize was grown. Effects on yield were also observed for *ec_size* but were only significantly positive in a model without random slopes. This means that within regions, farms with

Table 2.3. Fixed effects of multilevel models for the year 2000 with random intercept and slopes, with crop yields and income variables as dependent variables.

Variables y_{ij} β_{q0}	Wheat yield	Maize yield	Potato yield	Sugar beet yield	Barley yield	Fnv/awu	Fnv/ha
Intercept (β_0)	0.50^{a}	9.75***	21.76***	-30.64^{a}	3.76***	33728^{ab}	-755^{a}
Fert/ha	0.0020***	0.0037***	0.0105**	0.0113*	0.0025***	-52.02***	2.72***
Prot/ha	0.0043***	0.0002	0.0098**	0.0129***	0.0043***	-17.18$^{ab(+)}$	7.02*
Irr_perc	-0.0008^{a}	0.0098**	0.0132	0.0418$^{a(+)b(-)}$	-0.0039†	2285$^{a(-)}$	0.96
Org=2	-1.52***	-1.42^{ab}	-4.96**	-15.07*	-1.02***	-5482	622***
Org=3	-0.79**	-1.36	-3.75†	-4.49	-0.73***	-1391	282^{ab}
Ec_size	0.0014***	0.0011$^{a(-)b(+)}$	0.0240***	0.0011$^{a(-)}$	0.0014***	247***	-0.016^{a}
Perm/uaa	-2.58***	-1.95***	-6.07***	-13.97†	-1.92***	-15055***	713†
Grass/uaa	-0.59***	-0.25^{a}	-1.57^{ab}	-4.99*	-0.24**	-27936***	30.3$^{a(-)}$
Crop_pr^{c}	0.26**	0.38†	2.28*	-1.25^{a}	-0.31***		
Alt=2	-0.15*	-0.18^{a}	1.16*	0.33^{a}	0.03^{ab}	-2425*	39.3
Alt=3	-0.30**	-0.55*	0.27^{a}	-0.09$^{ab(+)}$	-0.11^{a}	-1786$^{a(+)}$	161*
Lfa=2	-0.32***	-0.38**	-1.95*	-3.08**	-0.22***	-2298*	-0.72$^{ab(+)}$
Lfa=3	-0.47***	-0.77***	-3.82***	-2.41^{ab}	-0.22**	-2150†	399***
Tmean	0.43***	-0.18†	1.45*	6.15*	0.37***	2515†	43.1$^{ab(-)}$
Pmean	0.13**	-0.0022^{a}	-0.056^{a}	2.21†	0.006^{a}	-94.6^{a}	-35.3$^{a(+)}$
Tmean^2	-0.0449***		-0.105*	-0.435**	-0.037***	-273**	-0.68$^{ab(+)}$
Pmean^2	-0.0008**			-0.017†			0.22$^{a(-)}$
Ac^{d}	8.33***	2.16^{a}	3.98^{ab}	8.46^{a}	6.65***	44729**	-797^{a}

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$.

[a] Significant ($p < 0.05$) in models with fixed effects only. If the sign changes, this is indicated between brackets.

[b] Significant ($p < 0.05$) in models with fixed effects and random intercept. If the sign changes, this is indicated between brackets.

[c] 'Crop' is the crop concerned in the column.

[d] The models presented exclude the the adaptive capacity index *ac*. When the *ac* is included instead of the climate variables, these are the coefficient estimates and significance levels. Coefficient estimates of other variables are similar.

large economic size generally obtain higher maize yields. In models with random slopes other variables can account for this however. The negative effect in the fixed effects model suggests higher yields in regions with mainly smaller farms. The correlation between *prot/ha* and maize yield (Table 2.2) was not confirmed in the multilevel model. Maize yields were lower on organic farms (*org)*, at higher altitudes (*alt*) and in less favoured areas (*lfa*).

Results for barley were similar to the ones for wheat for most variables which was also true for potato and sugar beet. Although these root crops are often irrigated, there was no significant relationship between *irr_perc* and yield. This result is explained by the fact that in regions with insufficient precipitation these crops are always irrigated, whereas in regions with sufficient precipitation no irrigation takes place. Hence, variation among farms is insufficient to identify a significant effect. *Tmean* had a non-linear influence on barley, potato and sugar beet yields, whereas the influence of *pmean* was not significant. The effect of *ac* on crop yield was positive for all crops, although not always significant in models with random effects. This suggests some influence of the regional context for farm-level adaptation.

2.3.4 The influence of climate and management on income variables

Variability in farmers' income

Multilevel models with farm net value added/annual work unit (*fnv/awu*) and farm net value added/hectare (*fnv/ha*) as dependent variable, clearly improved with random intercept and slopes. Applying a random coefficients model to the data can thus give better insight in the effect of specific variables on farmers' income. *Fnv/awu* was significantly positive related to *ec_size* and *ac* and negative to *fert/ha*, *perm/uaa* and *grass/uaa.* The relation with *tmean* was concave; there was no significant relation with *pmean.* For *fnv/ha*, effects of *fert/ha* and *prot/ha* were significantly positive. Although not always significant, organic farming, altitude and a less favoured area location generally had a positive effect on *fnv/ha*, whereas they had a negative effect on *fnv/awu.*

The positive effect of variables representing input intensity on *fnv/ha* was not evident for *fnv/awu.* On the other hand, variables that did not influence *fnv/ha,* like *ec_size* and *ac,* had an effect on *fnv/awu.* Results show that intensification leads to higher *fnv/ha*, but also that *fnv/awu* is, ceteris paribus, higher on larger farms and on farms with a lower intensity. Enlargement thus seems to be a better adaptation strategy than intensification. However, it is evident that farmers' income is influenced by most farm characteristics considered.

Fnv/ha was not related to climate variables, whereas *tmean* had a non-linear concave effect and *pmean* a negative effect on *fnv/awu*. This was surprising, as especially *fnv/ha,* which should reflect the productivity of the land, was expected to be influenced by climatic variables. Apparently, the relationship between crop productivity and farmers' income is not straightforward, as also evident from the change in signs in models without random effects and the (non-significant) negative effect of *ac* on *fnv/ha*, which was positive for crop yields and *fnv/awu.*

Relationship between crop yields and farmers' income

There was a highly significant relationship at the regional level between yields of most crops and *fnv/awu* [wheat, $r^2 = 0.685$; barley, $r^2 = 0.638$; sugar beet, $r^2 = 0.407$; potato, $r^2 = 0.348$; maize, $r^2 = 0.209$ (only significant at the $p<0.10$ level)]. These correlations were also significant at the farm level, but less pronounced (Table 2.2). Although a causal relation can be assumed, this relation seems to be confounded by other factors. Income was highly distorted by government support programs; the highest subsidies were received in the same regions where the highest wheat yields were observed (e.g. northern France, England, East Germany). *Fnv* represents the sum of revenues from outputs (O) – variable input costs (I) + subsidies – taxes. The average O – I was negative in these regions, but due to subsidies the average *fnv* became positive. Although average *fnv/ha* was still low, the large farm sizes resulted in high *fnv/awu*.

Thus, *fnv/ha* was not related to crop yields and was especially high in many Mediterranean countries with typically lower crop yields and smaller farms (note, however, that Table 2.2 shows a small positive within region correlation between *fnv/ha* and yields of some crops). This suggests that maximizing crop yields is not always an efficient economic strategy. Clearly, differences in *fnv/awu* in Europe were mainly determined by farm size and subsidies, while climatic conditions played a minor role.

2.3.5 Separating between climatic and management effects

Results from a multilevel analysis cannot directly differentiate between climate and management effects. However, the influence of farm characteristics can be identified by comparing the influence of *tmean* estimated by a multilevel model including climatic conditions and farm characteristics with the influence estimated by a model only including climatic conditions (Kaufmann and Snell, 1997). An example is provided for wheat yield (Figure 2.4a). Omitted-variable bias in the model only including climatic variables causes overestimation of the direct effect of *tmean,* as the effect of farm characteristics is forced into the parameter estimates of the climatic variables. As a result, the reduction in yield when climate conditions move away from the optimum are much more severe in the model including only climate variables compared to the model with all variables included. This suggests that current wheat management in relation to the variables included in the model amplifies the effect of climatic conditions in less favourable areas. The exacerbated climate effect in less favourable areas can be explained by (1) less- favourable socio-economic conditions (lower *ac*) influencing management and/or (2) planned adaptation as the reduction in marginal product lowers the optimal use of purchased inputs for wheat production (Kaufmann and Snell, 1997). Adaptation is not focused on wheat production, but on income, and hence inputs are reduced.

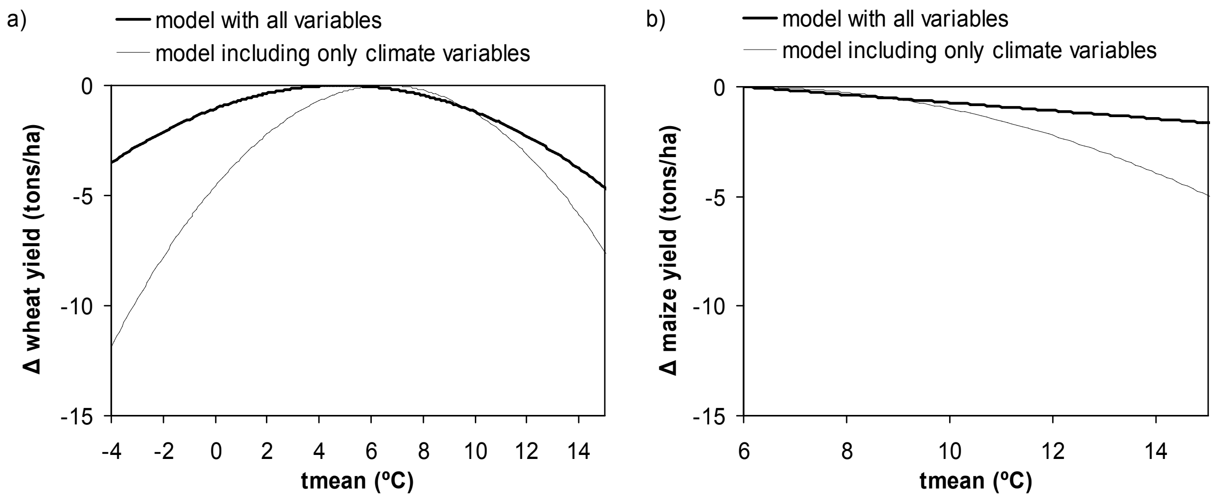

Figure 2.4. The effect of tmean (°C) on (a) wheat yield (tons/ha) and (b) maize yield (tons/ha), based on the full multilevel model, including climate variables and farm characteristics (thick line) and a model only including climate variables. A value of zero represents no reduction in yield and is the physiological optimum for that variable. The model only including climate variables indicates the total impact of tmean, while the full multilevel model indicates the impact that can directly be attributed to tmean. The difference between both lines indicates the amplifying effect of farm characteristics on the impact of tmean on crop yields.

For maize, the effects of climatic conditions were not significant (Table 2.3). Nevertheless, we can also draw the relationship between *tmean* (including the quadratic term) and maize yield. Figure 2.4b shows that effects of climatic conditions were smaller than for wheat yield, especially when farm characteristics were considered. Average maize yields were relatively similar all over the EU15; only in Portugal and southern Italy yields were much lower (where *tmean* was around 13ºC and farms were generally smaller and less intensive). As there is (almost) no reduction in marginal product, the use of inputs is close to optimal. Only in regions where *ac* is specifically low, sub-optimal management decreases maize yields.

2.4 Discussion

2.4.1 Methodology of analysis

The FADN database provides information on a range of farm characteristics for individual farms across the EU15. Extent and detail of this database is unique and a good basis for analysis of relationships determining adaptive capacity of farms in Europe.

No data are provided on absolute amounts of inputs and we used economic variables on production costs as proxy indicators for input intensity. The amount of money spent on inputs is not necessarily directly related to the quantities used on the farm. However, prices of fertilizers and crop protection products are very similar throughout the EU15, and costs can, therefore, serve as a proxy for quantities.

Moreover, our methodology of multilevel modelling with random effects reduced the potential disturbing effect of regional differences in prices of fertilizers and pesticides. Andersen et al. (2004a) showed input costs to be clearly related with nitrogen surplus. To correct for endogeneity between input costs and outputs, we used instrumental variables to estimate fertilizer and crop protection use.

FADN data refer to individual farms, but information about the exact location of the farms is not accessible for privacy reasons. Farms are located within a HARM region, and only few variables are provided to characterize their specific location. The altitude class (*alt)* and whether or not a farm belongs to a Less Favoured Area (*lfa)* give some information on the biophysical conditions. Other factors such as soil characteristics that are known to influence crop yields were not included in the analysis. However, recent studies suggest that soil characteristics explained only little of the spatial variability in wheat yields across Europe (Bakker et al., 2005) and significant effects on farmers' income were not observed in other regions (Liu et al., 2004). It can be assumed that farms are randomly distributed throughout each region, minimizing the influence of local conditions. The exogeneity of fertilizer and crop protection use in relation to crop yields and the many significant variables that were found to explain variability in yields and income support this assumption.

Climatic conditions can be represented in different ways. Temperature and precipitation are often represented by several variables including various months or seasons. Although climate variability may have different effects for different months, multicollinearity can inflate the standard errors, which complicates the identification of significant effects on individual variables. Polsky and Easterling (2001) accounted for this and excluded variables to minimize multicollinearity. We prevented this problem by including a minimum set of representative variables, i.e. one for temperature and one for precipitation.

2.4.2 Factors determining farm performance and adaptive capacity

Spatial variability of both crop yields and farmers' income across Europe was high and largely explained by a set of selected climatic and socio-economic including management factors. This is consistent with recent investigations in which more than 80% of the variability in regional wheat yields across Europe could be explained by climatic and socio-economic factors (Bakker et al., 2005). However, our results also indicate that spatial yield variability across Europe and the importance of factors explaining this variability differs among crops. Maize yields are expected to decrease in southern Europe due to climate change (Wolf and van Diepen, 1995), but the present results indicate that climate has only a small influence on maize yields. Management can decrease but also increase the effect of climatic conditions (as presented in Figure 2.4), suggesting that farm management will be important for adaptation to climate change.

Variability in farmers' income (*fnv/awu* and *fnv/ha*) was mainly related to farm characteristics and less to climatic conditions suggesting that farmers in Europe have largely adapted to the local climate. This contrasts with other studies in which, also based on Ricardian analysis, significant influences of climate variability on farmers' income have been reported, as for the United States (Mendelsohn et al., 1994; Polsky and Easterling, 2001), India and Brazil (Mendelsohn and Dinar, 1999), China (Liu et al., 2004) and Cameroon (Molua, 2002). The relationship between climate variables and farmers' income can be highly distorted by government support programs, as in the European Union and the United States. However, our data also suggest that farmers have adapted in other ways and not only through subsidies. In regions with relatively low crop yields, farmers seem to grow more profitable crops to increase *fnv/ha*. This is supported by the fact that *fnv/ha* is, ceteris paribus, higher in less favourable areas and on higher altitudes. Also, revenues from output per ha and revenues from output – input costs per ha, excluding subsidies from *fnv/ha,* were higher on organic farms, on higher altitudes and in less favoured areas. Although subsidies comprised a large part of *fnv* on many European farms, they were higher in more favourable areas, which implies they should amplify the climate effect instead of decreasing it. In more favourable areas, farm size has been increased to profit from the high crop yields of relatively unprofitable crops, which increased *fnv/awu.*

Few recent attempts have been made for integrated assessment of climate effects on agriculture considering both biophysical and socio-economic factors (e.g. Parry et al., 2004). We know of no studies that explicitly analysed factors that influence agricultural adaptive capacity to climate change. Characteristics like farm size, area sown with a specific crop, access to technology, education, tenancy status, attitude towards risk and contact with extension agents are the main factors that affect technology adoption (Caswell et al., 2001; Sheikh et al., 2003). The first three characteristics have also been identified in this research, while the others represent farmers' characteristics that can only be identified by detailed surveys.

Optimization models that assess the vulnerability of agriculture (e.g. Kaiser et al., 1993; Antle et al., 2004) might be useful for identifying efficient adaptation strategies. But more insight in farmers' behaviour is needed to be able to predict how climate change will influence economic vulnerability. In this study we showed factors that influence the adaptive capacity of farmers. We assume that adaptation is related to farm performance and farms that perform well are also well adapted. It should be noted however that responses to spatial variability in climate conditions indicate long-term adaptation to climate conditions; see Chapter 3 for analysis of temporal variability. As mentioned in section 2.3.5, maximizing crop yields is not the only objective of farmers and adaptation may be focused on other objectives. Sterk et al. (2006) showed that farmers do not search for optimal strategies; rather they adapt their management gradually over the years. Models should describe what individuals do rather than asserting how individuals should make decisions. Even with extensive datasets the complexity remains difficult to unravel however. Factors related to farmers' objectives and perceptions require detailed surveys, which are difficult to be performed across Europe. Results from the present study provide helpful information about factors determining adaptive capacity in agriculture at an aggregated level which may be further substantiated as more detailed information about farmers behaviour becomes available.

2.5 Conclusion

From our analysis of farm performance in Europe under different climatic and management conditions we conclude that next to climate, input intensity, economic size and the land use type are important factors influencing spatial variability in crop yields and income. In general, crop yields and income are increasing with farm size and farm intensity. Nevertheless, effects differed among crops and high crop yields were not always related to high incomes. This suggests that impacts of climate and management also differ by impact variable. Climate influences crop yields, but has no direct influence on farmers' income.

As farm characteristics influence the impact of climate variability on crop yields and income, they are good indicators of adaptive capacity at farm level. Therefore, they should be considered in models attempting to assess climate change impacts on agriculture.

Chapter 3

Vulnerability and adaptation of European farmers. A multi-level analysis of yield and income responses to climate variability

Abstract

Climate change affects potential crop yields that can be well assessed with mechanistic crop models at the field level. Actual yields, however, largely depend on crop management practices, determined by many factors and interactions at regional and farm level. For future projections quantitative understanding of these relationships is essential and subject of this study. We analyse impacts of climate change and variability on trends and variability in yields of five crops and farmers' income at regional and farm type level in Europe. Climate effects on trends and variability of yields and income are observed at both levels but the effects depend on management factors and differ between yields and income. Often, Mediterranean regions are characterized as most vulnerable to climate change. Our data, however, show that although yield variability is generally highest in Mediterranean regions, this is only partly due to climate variability. The variability in farmers' income per hectare (*fnv/ha*) decreases when temperatures increase, while the trend in *fnv/ha* increases with higher temperatures. The results suggest effective adaptation to climatic conditions in Mediterranean regions. For regional projections of climate change impacts on agriculture, we recommend to (1) include climate, socio-economic conditions and farm characteristics, and (2) consider relationships between farmers' income and crop yields, as these influence the ability to adapt.

Keywords: Climate change, climate variability, adaptive capacity, farm management, agricultural vulnerability

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3.1 Introduction

Global average surface temperature has increased with 0.74 ± 0.18 °C in the last century and is projected to increase by another 1.1–6.0 °C in this century (IPCC, 2007a). Associated effects on agriculture have frequently been reported. Assessments for European agriculture suggest that in northern Europe crop yields increase and possibilities for new crops and varieties emerge (Olesen and Bindi, 2002; Ewert et al., 2005). In southern Europe, adverse effects are expected. Here, projected increases in water shortage reduce crop yields and the area for cropping which directly affects the livelihood of Mediterranean farmers (Metzger et al., 2006).

Impacts of climate change on agriculture are generally assessed with mechanistic crop models (Gitay et al., 2001). Studies have been performed at different levels of organization: crops (see review of Tubiello and Ewert, 2002), cropping systems (e.g. Tubiello et al., 2000), regional (Iglesias et al., 2000; Saarikko, 2000; Trnka et al., 2004), continental (Harrison et al., 1995; Downing et al., 2000; Reilly, 2002) and global (IMAGE team, 2001; Parry et al., 2004). Although crop models are based on sound physiological mechanisms, they also comprise empirical relationships. This limits their applicability to conditions for which they were developed and tested (Passioura, 1996). Applying these models across scales is difficult and can endanger the conclusions (Marshall et al., 1997).

Site-specific crop models strongly emphasize biophysical factors, such as climate and soil. Validation for regional applications of these models remains unsatisfactory (Tubiello and Ewert, 2002). The potential impacts of climate change and variability are well understood for potential, water and nitrogen limited yields (e.g. van Ittersum et al., 2003). Actual yields, however, are also affected by other factors, such as pests and diseases which depend on management (e.g. Landau et al., 1998) and regional socio-economic conditions (e.g. Chapter 2). Such factors are often not considered in available crop models but can largely modify the considered climate change effects (Ewert et al., 2007). Statistical analyses have reported climate change impacts on yields (Lobell and Asner, 2003; Chen et al., 2004; Tao et al., 2006), but climate effects can also be confounded by these other factors. The risk of confounding factors and relationships is larger at higher aggregation levels (Bakker et al., 2005).

At the county level in the United States, Kaufmann and Snell (1997) showed that the relationship between maize yield and climate is influenced by input intensity, size and land use characteristics. Similar factors explain farm level responses to spatial climate variability in Europe (Chapter 2). Responses to spatial variability in climatic conditions provide some indication for the long-term adaptation to prevailing conditions. It is not clear to which extent these relationships also apply when climatic conditions vary over time.

In this Chapter we combine agricultural statistics at regional and farm type level with climate data to assess the impact of climate change and variability on crop yields and farmers' income in the EU15. Regression models are applied with three purposes (Table 3.1).

Table 3.1. Matrix demonstrating insights to be obtained in the analyses.

Effects of regional conditions and farm characteristics	Effects on crop yields and income	
	Trend	Variability
Trend	Long-term adaptation	-
Variability	-	Short-term adaptation
Average	Adaptation to prevailing conditions	

Firstly, we investigate the relationship between trends in climatic conditions and trends in farm performance represented by crop yields and income in combination with farm and regional characteristics (section 3.3.1). This provides insight into the long-term adaptation to climate change. Secondly, we analyse the relationship between temporal variability in climatic conditions and variability in farm performance in combination with other factors (section 3.3.2). These results will indicate what determines short-term adaptation to climate variability. Thirdly, we analyse the impact of prevailing climatic conditions, farm and regional characteristics on both trends and variability of farm performance (section 3.3.1 and 3.3.2). This is done by relating calculated averages to trends and variability to supplement the assessment with insight in the adaptation of farmers to prevailing conditions. The overall aim of the study is to improve understanding of the relative importance of climate and socio-economic factors and farm characteristics for explaining crop yield and income at two levels of organization. We hypothesize that adaptation is determined by the same factors independent of the aggregation level, but that the importance of these factors varies.

3.2 Methodology

3.2.1 Framework for empirical analysis of climate impacts

In our analysis we assume that vulnerability to climate change may differ depending on the level of organization (O'Brien et al., 2004; Adger et al., 2005). For instance, at the regional level the agricultural sector as a whole may be able to adapt. However, some farm types may still be more vulnerable than others. Thus, apart from climate change impacts on crop yields and farmers' income possible effects of farm characteristics and regional conditions, such as policy factors are also considered in this analysis (Figure 3.1).

An analysis of crop yields can indicate the vulnerability of food production, an analysis of farmers' income of farmers' livelihood; two major ecosystem services of agriculture (Costanza et al., 1997; Reid et al., 2005; Metzger et al., 2006). As different crops respond differently to climatic conditions, yields of five crops (wheat, grain maize, barley, potato and sugar beet) are analysed. Farmers' income is considered because it accounts for the direct impacts of climate on yields of different crops as well as the indirect substitution of inputs, introduction of different activities, and other potential adaptations to different climates (Mendelsohn et al., 1994). Farmers' income is represented by farm net value added per hectare (*fnv/ha*) and farm net value

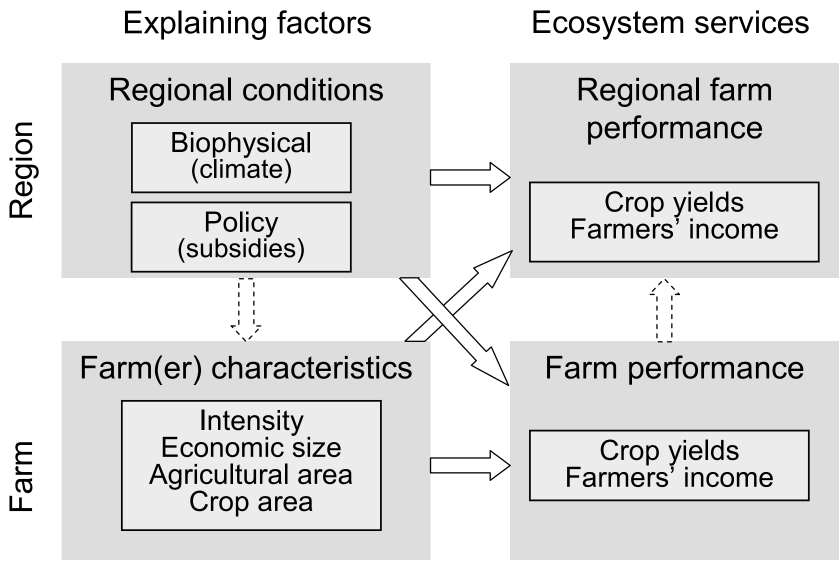

Figure 3.1. Conceptual model of investigated relationships (straight arrows). Potential impacts of climate change and variability on crop yields and farmers' income (ecosystem services) are influenced by other regional conditions and farm characteristics, as adaptation takes place.

added/annual work unit (*fnv/awu*). *Fnv/ha* measures economic performance per unit of land. *Fnv/awu* is a measure that enables comparison of farmers' income directly to gross domestic product per capita (*gdp/cap*) and can therefore relate farm performance to general socio-economic performance.

The main aim of this study is to understand the relative importance of climate and socio-economic factors and farm characteristics for explaining crop yield and income, in order to improve understanding of adaptive capacity. Standard panel data techniques such as fixed effects models (Deschenes and Greenstone, 2006) do no suffice for our purposes. Such models can indicate the average impact of inter-annual changes in temperature and precipitation. With further specification it is possible to obtain regional or farm type specific impacts, but factors that influence climate impacts cannot be assessed. Factors that influence inter-annual variability in crop yields and farmers' income can only be assessed per region, as potential impacts of climate change vary per region (e.g. Gitay et al., 2001).

In this study we apply an approach that is more appropriate to obtain generic insights into the relative importance of climatic and socio-economic conditions and farm characteristics for explaining farm performance. For each region or farm type, the trend and variability in dependent (e.g. wheat yield) and independent (e.g. temperature) variables are calculated. Subsequently, we compare trends (and variability) among regions (or farm types), instead of analysing changes within regions. Such an approach has previously been applied (e.g. Lobell and Asner, 2003; Lobell et al., 2005) and allows to assess larger datasets coherently and, with inclusion of other factors, to distinguish the impact of e.g. climate change from other factors. In section 3.2.3 we will elaborate on this in more detail.

3.2.2 Data sources

Regional and farm type data are obtained from the Farm Accountancy Data Network (source: FADN-CCE-DG Agri and LEI) from 1990–2003. The FADN provides extensive data on farm characteristics of individual farms throughout the EU15 (Chapter 2). Data have been collected annually since 1989; for East Germany, Finland and Sweden since 1995. They have been used to evaluate the income of farmers and the consequences of the Common Agricultural Policy. In total, 100 HARM regions are distinguished with more than 50,000 sample farms. At the regional level, farm characteristics are represented by variables representing land use, farm size and intensity (Table 3.2). Farm types are distinguished based on these variables (Table 3.3). Such a typology proved to be suitable for impact assessment studies (Andersen et al., 2006; Andersen et al., 2007).

Table 3.2. Data description and averages in the EU15 from 1990−2003.

Variable	Description	Average
Dependent variables		
Crop yield	Yield of specific crop (tons/ha)	Varies per crop [c]
Fnv/ha	Farm net value added per hectare[a] (€)	582 [c]
Fnv/awu	Farm net value added per annual working unit (€)	10883 [c]
Climatic conditions		
Tmean	Mean temperature (ºC) of first half year	9.8 [d]
Pmean	Mean precipitation (mm) of first half year	51.5 [d]
Policy factors		
Subs/ha	Total subsidies / utilized agricultural area (€)	268 [c]
Land use		
Ar/uaa	Arable area / utilized agricultural area (-)	0.53 [c]
Perm/uaa	Permanent cropping area / utilized agricultural area (-)	0.11 [c]
Grass/uaa	Grassland area / utilized agricultural area (-)	0.32 [c]
Crop_pr	Crop area / total arable area (%)	Varies per crop[c]
Size		
Ec_size	Economic size[b] (ESU)	51.4 [c]
Uaa	Utilized agricultural area (ha)	70.0 [c]
Intensity		
Fert/ha	Costs of fertilizers and soil improvers per hectare (€)	92.6 [c]
Prot/ha	Costs of crop protection products per hectare (€)	67.3 [c]
Irr_perc	Irrigated percentage of utilized agricultural area (%)	7.2 [c]

[a] Corresponds to the payment for fixed factors of production (land, labour, capital), whether they are external or family factors. As a result, holdings can be compared irrespective of the family/non-family nature of the factors of production employed. Fnv = total output – total intermediate consumption + balance current subsidies and taxes – depreciation.

[b] The economic size is determined on the basis of the overall standard gross margin of the holding. It is given in European Size Units (ESU); one ESU corresponds to a standard gross margin of €1200.

[c] Source: FADN.

[d] Source: MARS.

Table 3.3. Farm typology. Each farm type is characterized by a land use, size and intensity dimension.

	Dimension and type	Definition
Land use		*(Specialization), Land use type rule*[a]
1	Arable/cereal	(1+6), < 12.5% fallow and >= 50% cereals
2	Arable/fallow	(1+6), >= 12.5% fallow
3	Arable/specialized crops	(1+6), >= 25% of arable land in specialized crops
4	Arable/others	(1+6), other arable
5	Dairy cattle/permanent grass	(4.1), >= 50% grass and < 50% temporary grass
6	Dairy cattle/temporary grass	(4.1), >= 50% grass and >= 50% temporary grass
7	Dairy cattle/land independent	(4.1), UAA = 0 or LU/ha => 5
8	Dairy cattle/others	(4.1), other dairy cattle
9	Beef and mixed cattle/permanent grass	(4.2 and 4.3), as 5
10	Beef and mixed cattle/temporary grass	(4.2 and 4.3), as 6
11	Beef and mixed cattle/land independent	(4.2 and 4.3), as 7
12	Beef and mixed cattle/others	(4.2 and 4.3), other beef and mixed cattle
13	Sheep and goats/land independent	(4.4), as 7
14	Sheep and goats/others	(4.4), other sheep and goats
15	Pigs/land independent	(5.1), as 7
16	Pigs/others	(5.1), other pigs
17	Poultry and mixed pigs/poultry	(5.2)
18	Mixed farms	(7)
19	Mixed livestock	(8)
20	Horticulture	(3)
21	Permanent crops	(2)
Size		
1	Small scale	< 16 ESU
2	Medium scale	>= 16 ESU and < 40 ESU
3	Large scale	>= 40 ESU
Intensity		
1	Low intensity	Total output per ha < €500 euro
2	Medium intensity	Total output per ha >= €500 and < €3000
3	High intensity	Total output per ha >= €3000

[a] The specialization dimension is based on the EU/FADN farm typology (http://ec.europa.eu/comm/agriculture/rica/diffusion_en.cfm). Only the most important land use type rules are described here; the % of area relates to the utilized agricultural area (uaa). A full description is given in Andersen et al. (2006).

Policy is represented by total subsidies per hectare (*subs/ha*). Other socio-economic conditions are not explicitly considered. Data on *gdp/cap* at regional level are only directly available from 1995 onward and Bakker et al. (2005) showed that impacts of *gdp/cap* on crop yields in this period were small.

Monthly temperature and precipitation data are obtained from the MARS project (www.marsop.info). Temperatures and precipitation of the first six months are averaged to provide an indication of the temperature (*tmean*) and precipitation (*pmean*) conditions in the main growing period. MARS data are available per grid cell of 50 x 50 km and are averaged per HARM region.

3.2.3 Statistical techniques

Estimation of trends

Trends in crop yields and income are estimated using the General Linear Model (GLM)

$$y_{mit} = \beta_{0mi} + \delta_{mi} \cdot t + r_{mit} \quad (1)$$

where y_{mit} is the dependent variable, *m* relates to crop yield or income, β_{0mi} is the intercept per region/farm type *i*, and δ_{mi} is the coefficient of the trend (*t*=1,2,..,N) per region/farm type and the residual $r_{mit} \sim N(0, \sigma^2)$. Trends are assumed to be linear as was earlier observed for this period (Calderini and Slafer, 1998; Ewert et al., 2005). The curve estimation procedure in SPSS 12 confirmed that this model performed best. For climate, socio-economic and management variables x_{nit} the trend δ_{ni} is estimated similarly.

We test for stationarity along the linear trend δ_{mi} by estimating serial correlations among residuals using $r_{mit} - r_{mi,t-1} = \alpha_{mi} + \gamma_{mi} \cdot r_{mi,t-1} + \varepsilon_{mit}$. Stationarity exists if the mean and variance of the error term is constant. The test shows that for a few *m* in several *i*, γ_{mi} is significant, which implies that there is serial correlation among residuals r_{mit}. Hence, not all models have a constant variance. This implies that our parameter estimates are consistent, but not necessarily all efficient. However, this does not invalidate our approach since we explain differences in trends requiring consistent estimates rather than efficient parameter estimates.

Analysis of trends

A second group of GLMs are used to identify the extent to which the independent variables combined in one model can explain trends in yields and income determined by Eq. 1. The general set up of this GLM is

$$\delta_{mi} = b_{0m} + b_{mn} \cdot x_{ni} + e_{mi} \quad (2)$$

where δ_{mi} is the estimated trend parameter obtained from estimation of Eq. 1, x_{ni} is a vector of *n* explanatory variables (trend δ_{ni} or average of x_{nit}; Figure 3.2) and e_{mi} is an error term. At the farm type level, multilevel models (or General Linear Mixed Model (GLMM)) are used with the farm type dimensions as explaining factors x_{ni} (Chapter 2, Snijders and Bosker, 1999). A multilevel model controls for regional effects, when analysing data from farm types in different (HARM) regions. This allows analysing the difference among farm types within regions. At the regional level, all regions with less than 5 years of data and arable land < 10,000 ha are excluded from the analysis. Little data occurs mainly in less favoured regions where crops are cultivated on a very small area. At the farm type level all farm types with less than 3 years of data are

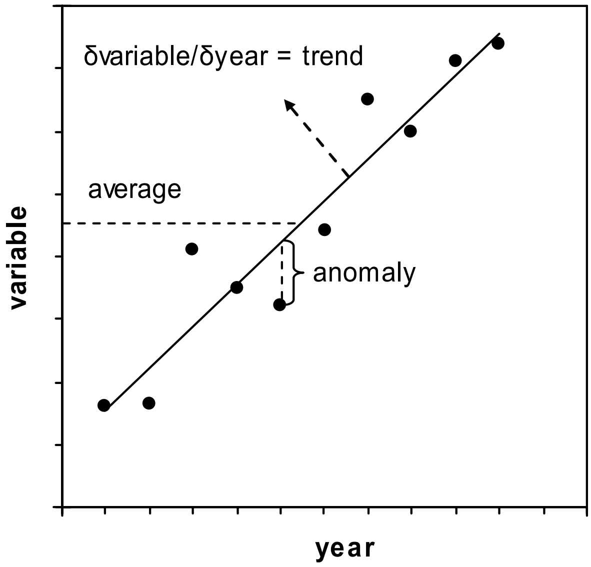

Figure 3.2. Measures used in the statistical analysis. Trends of dependent variables are related to trends and averages of independent variables (section 3.3.1). Variability is measured by the average of relative anomalies. Variability in dependent variables are related to variability and averages of independent variables (section 3.3.2).

excluded; to analyse the sensitivity also models requiring more years of data per farm type are applied.

A consideration when applying Eq. 2 is the possible heteroskedasticity in the model. Estimates of δ_{mi} from Eq. 1 may be more precise in regions with large agricultural areas than in regions with smaller agricultural areas (e.g. Deschenes and Greenstone, 2006). As we have data at farm type level we can asses the relationship between heteroskedasticity and precision at regional level. An analysis of variances shows that the variance in farm type level trends r_{mit} per HARM region is not dependent on agricultural area or other variables used in our regression, so heteroskedasticity of this form is not present. A second form of heteroskedasticity can occur when e_{mi} from Eq. 2 is dependent on the values of the independent variables. This is tested with the Breusch-Pagan test, which shows that there is no relationship between e_{mi} and the independent variables.

Although the tests indicate that heteroskedasticity is not a problem, we use weighted least squares (WLS) instead of ordinary least squares (OLS) to provide optimal estimates. Agricultural areas vary largely per region and regions with small agricultural areas have a relatively large influence with OLS. Therefore, the crop area is used as the weight for crop yields (specific per crop) and the utilized agricultural area for farmers' income.

The impact of x_{ni} on δ_{mi} is determined by the parameter estimates b_{mn}. In order to assess the relative impact of different variables on the trends, we calculate the elasticity at the mean for each parameter estimate b_{mn} as

$$\varepsilon(b_{mn}) = b_{mn} \cdot \left(\frac{\bar{x}_{ni}}{\bar{\delta}_{\text{mi}}} \right) \quad (3)$$

Analysis of variability

Variability in crop yields and income is based on the relative anomaly from the expected yields or income variables. At the regional level, expected yields and income are derived from the trend in Eq. 1. The absolute anomaly is given by its error term, i.e. = r_{mit}. The relative anomaly is computed as the ratio of the absolute anomaly and expected income or yield, i.e. $r_{mit} / (\beta_{0mi} + \delta_{mi} \cdot t)$. Complete time series are not always available at the farm type level, which results in less reliable trend estimates. As only few trends are significant, we use the average crop yield or income between 1990 and 2003 per farm type as indicator of the expected yield or income when computing the absolute and relative anomaly.

The same approach as for the analysis of trends is used. Per *i,* variability v_{mi} is measured as the average relative anomaly without considering positive or negative signs [as $r_{mit} \sim N(0, \sigma^2)$]. Variability v_{ni} in explanatory factors x_{nit} is similarly measured. Subsequently, at the regional level GLMs are used to identify the combined effect of the explanatory variables x_{ni} (variability v_{ni} or average of x_{nit}). At the farm level, multilevel models (Chapter 2; Snijders and Bosker, 1999) are used to analyse the effects of farm type characteristics on yield and income variability.

3.3 Results

3.3.1 Trends in crop yields and income variables

Regional level

Both positive and negative trends are observed in crop yields, but as time series are short, only around 25% of the trends are significant (Figure 3.3). Generally, crop yield trends are positive and higher in temperate regions (e.g. France, Germany), but high trends are also observed in Spain, while trends in Italy are mainly negative. The spatial pattern is different for farmers' income, as significantly positive trends in *fnv/ha* are found in Greece, Portugal, Italy and Ireland and some regions in Spain, while trends are mainly negative in temperate and Nordic regions. The trend in *fnv/awu* is positive in almost all regions and is significant in around half of the regions, mainly in the Mediterranean.

These differences in trends can be partly explained by trends in climatic conditions and management (Table 3.4, first column per crop). Results of the GLMs indicate a large negative effect of the trend in *tmean* on crop yield trends; the elasticity is large and negative for all crop yield trends. Where temperature increases faster, crop yield trends are lower. Also the effect of the trend in *pmean* is mainly negative, implying that a decreasing *pmean* has not reduced yield trends. When assessing the effect of

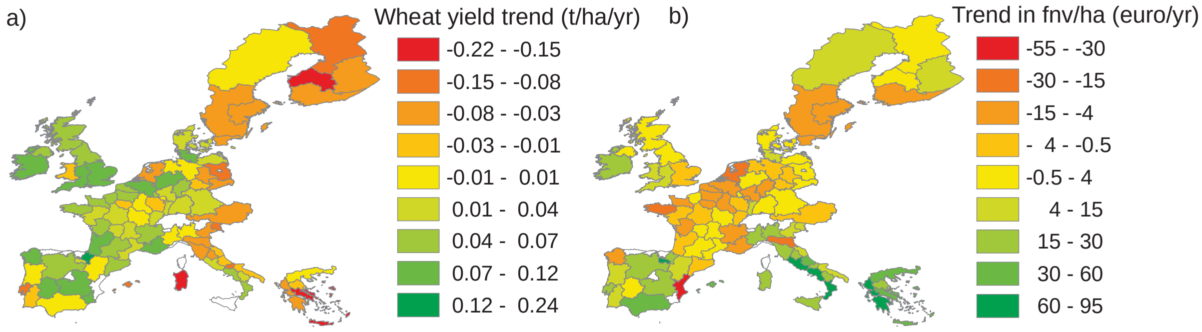

Figure 3.3 (in colour on p.177). Selected examples of trends from 1990−2003 in (a) wheat yield (t/ha/yr) and (b) fnv/ha (farm net value added per hectare in euro/yr).

changes in climatic conditions, effects of changes in management cannot be ignored. The impact of trends in management variables is similar for all crops. Effects on yield trends are generally positive for trends in *ec_size* and *fert_ha* suggesting that changes in size and intensity can influence climate impacts on crop yields.

Differences in trends may also be explained by differences in prevailing conditions (Table 3.4, second column). Consideration of averages in the analysis indicates whether prevailing conditions are of importance. Results of the GLMs show that the elasticity of average *tmean* is large, but the effect differs per crop. The effect of average *pmean* is also not coherent, but significantly concave for barley and negative for maize. Hence, spatial variability in the calculated averages of climatic conditions does not have the same effect as temporal change (i.e. trends) in climatic conditions. Considering management factors, the trends in wheat and barley yields are larger where the average crop area (*crop_pr*) is higher; for sugar beet and potato the opposite is the case. Similar results were obtained for the effects of trends in *crop_pr,* suggesting that effects of *crop_pr* on yield trends are of more general nature. In contrast, the effect of average *ec_size* is negative for the wheat yield trend, while the effect of the trend in *ec_size* was positive. This suggests that smaller farms that grow fast have highest wheat yield trends. Policies also influence trend yields as high subsidies (*subs/ha*) have a negative impact on most crop yield trends.

Trends in *fnv/ha* and *fnv/awu* are not significantly influenced by trends in climatic conditions. Trends in other factors have more impact; trends in *subs/ha, fert/ha, gr/uaa* and *perm/uaa* have a significant positive impact on the trend in *fnv/ha.* Subsidies have a direct effect on income, an increasing input intensity (*fert/ha*) can indirectly increase output intensity and increasing other land uses can lead to a more profitable use of the land. When prevailing conditions are considered, it is clear that trends in *fnv/ha* and *fnv/awu* increase with average *tmean* which was not for the case for yields of most crops. This suggests that in Mediterranean regions, with generally a less favourable climate, more adaptations took place (related to trends as mentioned above) compared to temperate regions. Apparent is that regions with a large average *ec_size* and large trends herein (e.g. France, Germany), have lower trends in both *fnv/ha* and *fnv/awu.*

Table 3.4. Combined effects of trends and averages of explaining variables on trends in crop yields and income variables from 1990 to 2003 at regional level. Presented are the elasticity at the mean of the parameter estimates ε(b) per variable (bold: $p<0.05$; italic: $p<0.10$) and the R^2 of each model.

	Wheat		Barley		Maize		Sugar beet		Potato		Fnv/ha		Fnv/awu	
	Trend	Average	Trend	Average	Trend	Average	Trend	Average	Trend	Average	Trend	Average	Trend	Average
Ec_size	**1.984**	**-1.998**	**2.122**	0.176	*0.358*	0.169	0.272	0.293	**0.604**	0.101	**-0.576**	0.016	-0.212	**-0.248**
Fert/ha	*0.950*	4.000	**0.944**	*7.773*	0.074	0.732	**0.272**	-1.239	0.015	-1.389	**0.459**	1.292	0.078	0.327
Prot/ha	-0.431	-2.331	-0.011	-0.587	-0.178	0.015	-0.027	-0.183	0.120	-0.025	-0.016	**-2.098**	-0.124	**-0.779**
Irr_perc	*-0.750*	0.245	*-0.870*	-0.255	0.064	-0.025	0.072	0.010	0.141	0.058	0.093	0.179	0.037	0.089
Gr/uaa	-0.120	2.245	0.019	0.276	0.002	*0.520*	**0.147**	-0.376	0.081	0.259	**0.067**	-0.115	0.007	0.040
Perm/uaa	-0.234	-0.329	0.030	-1.684	**-0.146**	-0.105	*0.226*	*-0.679*	0.161	**-0.824**	**0.138**	**0.453**	-0.006	-0.181
Crop_pr	0.197	**6.317**	**0.045**	**5.539**	-0.033	-0.059	**-0.001**	**-0.490**	**-0.032**	-0.039				
Tmean (25)	-0.876	**8.417**	-0.896	14.971	*-1.323*	-0.116	-0.414	2.292	-0.579	*5.122*	-0.151	**2.410**	-0.132	*0.693*
Pmean(25)	-0.466	-8.340	**-0.941**	**17.393**	-0.032	*-3.542*	-0.105	2.336	**-0.280**	-0.408	-0.108	-0.378	-0.054	-0.530
Tmean (75)	**-13.561**	*-4.137*	**-11.440**	24.292	-2.267	0.523	-1.951	6.693	-1.968	7.493	0.518	1.646	-0.164	0.049
Pmean (75)	-0.533	-1.534	**-1.062**	**-1.647**	0.023	-1.345	-0.148	1.583	-0.463	-2.491	-0.099	-0.837	-0.105	-1.709
Subs/ha	-0.321	*-4.362*	1.383	-0.677	-0.259	**-1.311**	-0.662	-0.254	0.158	**1.156**	**1.565**	**1.262**	*0.461*	0.270
R^2	0.510	0.471	0.456	0.540	0.370	0.418	0.637	0.488	0.552	0.416	0.532	0.527	0.219	0.368

Note: As for *tmean* and *pmean* quadratic terms are included, the elasticity at the 25th percentile and 75th percentile are more indicative than the elasticity at the mean. The p-levels refer to the linear and the quadratic variable. The mean values of the trends in *fert/ha*, *gr/uaa*, *perm/uaa, wheat_pr, barley_pr* and *sugarbeet_pr* and the 25th percentile of *pmean* are negative, so – ε(b) is presented to indicate the direction of the observed effects. The values of the trends of almost all variables (dependent and independent) have a large variation (CV>2), implying that effects may be different at other values than around the mean. Caution should therefore be taken when comparing models.

An increase in the average farm size is thus positively related to trends in crop yield, but negatively to the trend in farmers' income. Hence, although farms in these regions do not seem to be particularly vulnerable to changes in climatic conditions, there is some indication for increasing vulnerability related to farmers' income.

Farm type level

Inter-annual variability is generally large and for most farm types time series are shorter than 14 years. There are also some temporal changes in the farm types. While the number of small scale, low intensive farm types declines, the number of large scale, intensive farm types tends to increase. The trend models estimating δ_{mi} per farm type within each region result in few significant trends in crop yields and income variables (not shown). Despite these results, we analyse whether the differences in trends can be attributed to differences in farm types. Results however differ depending on how farm types are selected for the analysis. When only farms with more than 3 years of data are included, few significant differences are observed. When only farms with more than 10 years of data are included, we see that small scale farms have significantly higher trends for most crop yields and *fnv/ha* compared to large scale farms, while the opposite is observed for *fnv/awu* (not shown). With respect to farm intensity and land use, few significant estimates are found. More significant differences among farm types are observed in region-specific models, but the effects of farm type dimensions do not point into the same direction. Hence, trends differ among regions in relation to climate and management conditions, but the effect of management cannot be generalized across regions.

3.3.2 Variability in crop yields and income variables

Regional level

Relative anomalies in regional crop yields from 1990−2003 range between 5–15% for most crops and are somewhat larger in Mediterranean and Scandinavian regions, where yields are lower (Figure 3.4). Maize yield anomalies are smaller in Greece and Spain, where maize yields are higher. The spatial pattern in variability of *fnv/ha* and *fnv/awu* is similar to most crop yields, but the average anomalies are larger.

The models show that a high variability in *pmean* increases variability in wheat and barley yield, but decreases variability in maize, sugar beet and potato yields (Table 3.5, first column per crop). The impact of a high variability in *tmean* is negative for all crops, but only significant for wheat. A negative relationship suggests that regions with a high temperature variability have adapted better. A management factor that significantly contributes to lower yield variability is a low variability in *crop_pr*.

Variability in yields and income can also be related to prevailing climatic and management conditions (Table 3.5, second column per dependent variable). Yield variability of all crops increases with average *tmean* [ε(*tmean)* is higher at the 75th percentile compared to the 25th percentile]. Effects of *pmean* are mainly convex, implying lowest variability at average levels of precipitation. The impact of

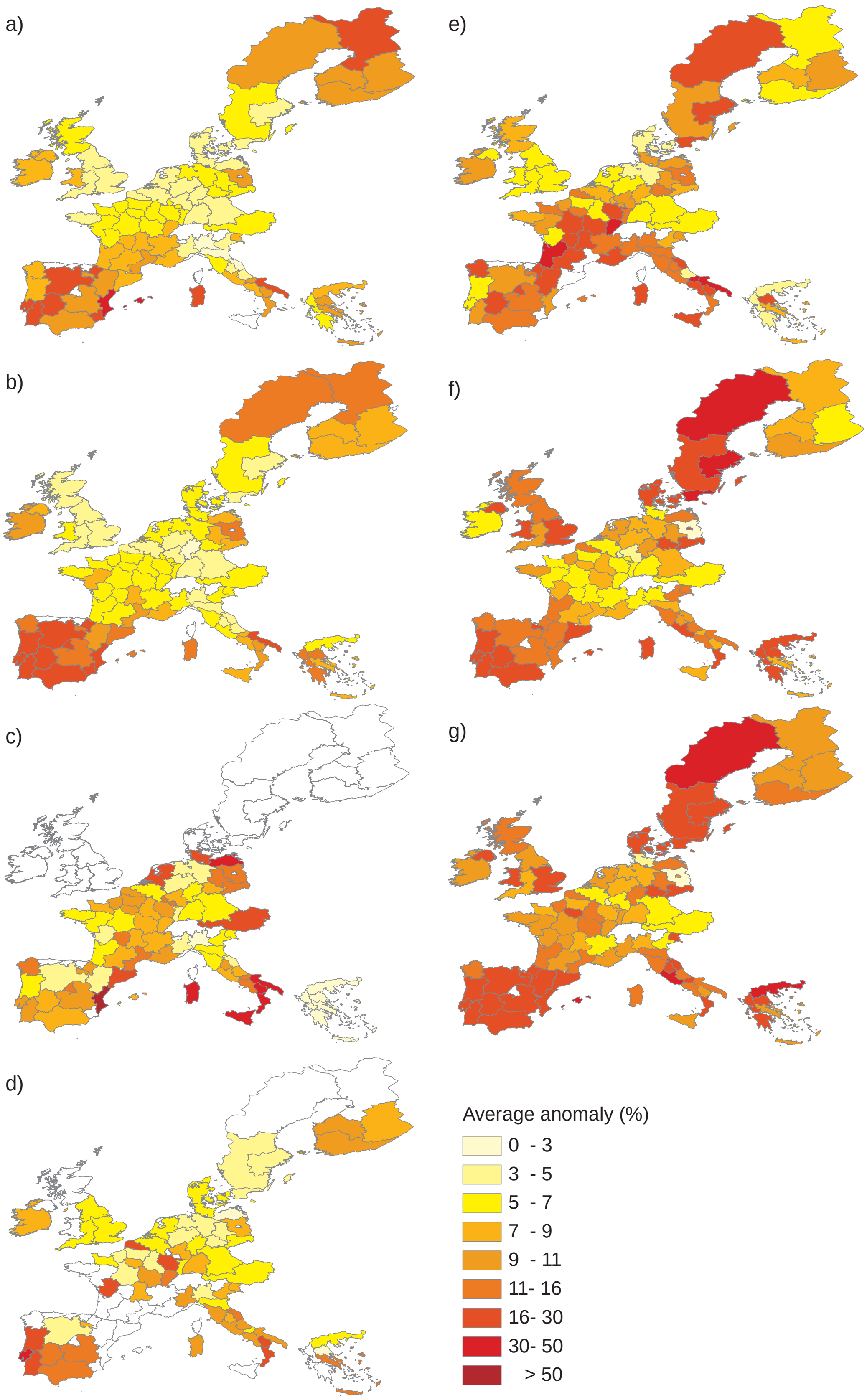

Figure 3.4 (in colour on p.178). Average relative anomaly (%) from 1990–2003 in 100 HARM regions for (a) wheat yield, (b) barley yield, (c) maize yield, (d) sugar beet yield, (e) potato yield, and the income variables (f) fnv/ha and (g) fnv/awu.

Table 3.5. Combined effects of variability in and averages of explaining variables on average relative anomalies at regional level from 1990–2003. Presented are the elasticity at the mean of the parameter estimates ε(b) per variable (bold: $p<0.05$; italic: $p<0.10$) and the R^2 of each model.

	Wheat		Barley		Maize		Sugar beet		Potato		Fnv/ha		Fnv/awu	
	Variability	Average	Variability	Average	Variability	Average	Variability	Average	Variability	Average	Variability	Average	Variability	Average
Ec_size	0.065	0.020	0.023	**0.106**	-0.013	0.066	-0.208	-0.041	**-0.314**	*-0.122*	0.004	0.038	-0.020	0.004
Fert/ha	-0.073	-0.114	**-0.135**	-0.035	0.139	*-0.304*	0.785	-0.022	-0.345	0.216	*0.922*	**-0.609**	0.773	-0.362
Prot/ha	**0.517**	-0.194	**0.560**	*-0.336*	-0.175	**0.249**	0.432	-0.015	**0.682**	-0.308	**0.422**	0.161	0.206	0.112
Irr_perc	**-0.088**	-0.003	**-0.148**	0.086	-0.007	**-0.118**	-0.109	-0.138	-0.041	**-0.336**	-0.052	**0.112**	-0.051	**0.182**
Gr/uaa	-0.016	-0.057	0.008	-0.072	0.076	0.091	0.107	-0.214	**0.199**	**-0.518**	0.028	-0.025	0.085	-0.014
Perm/uaa	-0.010	**-0.234**	-0.017	**-0.180**	-0.004	*0.075*	*0.097*	-0.179	-0.005	*0.188*	0.010	0.014	0.005	-0.044
Crop_pr	-0.037	-0.114	**0.264**	**0.169**	**0.521**	-0.015	*0.278*	**0.296**	**0.491**	0.039				
Tmean (25)	**-0.226**	*1.060*	-0.155	**1.541**	-0.011	*-0.490*	-0.114	0.797	-0.067	*-0.694*	**0.353**	**-0.729**	0.109	*-0.321*
Pmean (25)	**0.606**	-0.584	**0.539**	0.538	**-0.292**	**-1.187**	**-0.689**	-0.091	**-0.469**	**-1.480**	-0.122	-0.538	0.000	-0.721
Tmean (75)		**2.931**		**4.028**		*0.336*		**3.299**		-0.468		**-0.114**		0.018
Pmean (75)		-0.295		-0.204		**0.773**		0.808		**0.066**		-0.557		-0.501
Subs/ha	**-0.080**	0.004	**-0.115**	0.067	**-0.179**	0.099	0.110	-0.008	0.024	**-0.642**	-0.547	**-0.466**	-0.055	-0.017
R^2	0.579	0.647	0.654	0.760	0.369	0.549	0.637	0.540	0.662	0.536	0.372	0.400	0.259	0.391

Note: As for average *tmean* and *pmean* quadratic terms are included, the elasticity at the 25th percentile and 75th percentile are more indicative than the elasticity at the mean. The p-levels refer to the linear and the quadratic variable. For variability in *tmean* and *pmean* no quadratic term is included and the elasticity at the mean is presented. Variability in *tmean* is represented by average absolute anomalies instead of relative anomalies, as there is no absolute zero.

management variables on yield variability differs by crop. Several significant effects are observed. For example, a higher *irr_perc* decreases variability in maize and potato yields.

Variability in *fnv/ha* and *fnv/awu* is mainly influenced by variability in *fert/ha* and *prot/ha*, related to the intensity of farming. Variability in *tmean* increases variability in *fnv/ha*, in contrast to variability in crop yields. The GLM including average conditions shows that variabilities in *fnv/ha* and *fnv/awu* have a negative elasticity at the 25th percentile for *tmean*, but almost zero at the 75th percentile, implying lowest variability around the 75th percentile (11.9°C). Hence, although Figure 3.4f suggests a concave temperature effect, the model indicates that the high variability in some Mediterranean regions is mainly due to other factors. Applying more fertilizers (*fert/ha*) and receiving many subsidies (*subs/ha*) decrease income variability; a higher *irr_perc* increases income variability significantly. The effect of irrigation may be related to regions with a higher *irr_perc* being dryer, making agriculture riskier. The effect of average *pmean* is negative, but not significant.

Farm type level

Multilevel models correcting for regional effects show that for most crops yield variability significantly decreases with increasing farm size (Table 3.6). A low intensity has a significant positive impact on yield variability of all crops, except for wheat. Also, yield variability is significantly different among land use types. All land use types are included in the analysis as also on non-arable land use types field crops are cultivated. Yield variability of cereals is significantly lower on *arable/cereal* farms compared to other land use types, while yield variability of sugar beet and potato is lower on *arable/specialized crops* farms.

Variability in both *fnv/ha* and *fnv/awu* is larger on small and medium farms than on large farms. Variability is also significantly higher on low intensive farm types (10%) and medium intensive farm types (around 2%) compared to high intensive farms. The effect of intensity was also observed at the regional level (represented by *fert/ha*).

For income variability we compare arable farm types with other land use types. Variability in *fnv/ha* and *fnv/awu* is higher on arable farms than on *dairy cattle* farms, but lower than on farms with *pigs, horticulture* and *permanent crops.* For arable farm types the variability in *fnv/ha* is lowest on *arable/cereal* farms. As observed in the regional analysis more grassland area thus decreases income variability, and more permanent cropping area increases income variability.

The influence of average *tmean* is similar to the regional results for crop yield variability, but not for income variability. Thus, impacts on income at aggregated levels can be confounded by farm characteristics. Variability in *pmean* also affects yield variability, and in contrast to the regional level no negative effects are observed. More subsidies and variability herein lead to a higher variability in crop yields and income, which is also in contrast to the results from the regional analysis. Subsidies are coupled to regional yield levels, so the regional level impact may be confounded as higher yields lead to lower variability. A multilevel model corrects for this effect.

Table 3.6. Fixed effects in mixed models correcting for regional differences, of farm type dimensions (size, intensity and land use) and subsidies and climate on crop yield and income variability (relative anomalies) between 1990–2003 in the EU15.

	Wheat	Barley	Maize	Sugar beet	Potato	Fnv/ha	Fnv/awu
Intercept	**25.71**	**19.52**	**37.55**	15.05	10.65	9.31	*13.94*
Small scale	**2.84**	**1.81**	2.01	1.21	0.17	**7.91**	**10.18**
Medium scale	**1.62**	0.84	1.49	0.42	-0.65	0.72	1.10
Large scale							
Low intensity	0.32	*1.92*	**5.22**	**8.59**	*4.87*	**10.28**	**10.15**
Medium intensity	-1.00	*-1.29*	0.11	0.86	1.56	**2.26**	**3.25**
High intensity							
Arable/Cereal							
Arable/Fallow	-0.09	0.08	-2.03	-0.15	-1.60	1.60	-0.86
Arable/Specialised crops	0.16	0.94	1.52	**-2.33**	**-6.86**	0.94	1.74
Arable/Others	**4.18**	**2.87**	**5.18**	1.96	1.26	*2.41*	1.16
Dairy cattle/Permanent grass	**4.65**	1.92	**5.43**	3.79	1.55	**-3.79**	**-5.21**
Dairy cattle/Temporary grass	*3.07*	-1.80	**5.73**	2.47	5.56	**-6.03**	**-8.86**
Dairy cattle/Land independent	**11.05**	**10.20**	-2.19	8.31	-4.34	5.01	-3.97
Dairy cattle/Others	1.44	-0.85	1.93	*2.48*	2.02	**-3.33**	**-5.90**
Beef and mixed cattle/Permanent grass	1.34	0.59	3.36	**11.35**	*6.34*	-2.10	-2.93
Beef and mixed cattle/Temporary grass	1.35	-2.26	5.93	-3.22	-9.66	-0.99	-1.43
Beef and mixed cattle/Land independent	-3.66	-2.27	2.48			4.13	-1.32
Beef and mixed cattle/Others	3.70	-3.13	-1.63	1.83	-0.07	-2.23	-5.28
Sheep and goats/Land independent	5.34	4.17	6.52	-6.69	15.84	-1.71	*-8.78*
Sheep and goats/Others	**4.87**	0.65	**6.21**	2.63	0.13	**-3.58**	**-5.47**
Pigs/Land independent	2.22	3.07	3.55	2.79	0.18	**27.05**	**16.11**
Pigs/Others	-1.07	-1.88	-0.81	0.37	5.06	**40.09**	**36.51**
Poultry and mixed pigs/poultry	-1.61	1.12	3.79	-7.47	-3.05	10.42	1.45
Mixed farms	-0.04	-0.78	*2.44*	1.67	1.19	0.06	-1.76
Mixed livestock	-0.57	-0.66	0.47	1.17	-0.46	1.02	-2.46
Horticulture	**4.46**	**14.93**	*4.60*	**6.90**	**5.60**	**7.64**	-0.86
Permanent crops	**6.39**	**6.58**	**6.93**	**5.67**	**5.42**	**4.53**	*3.12*
Tmean (average; 25)	**0.39**	**0.60**	**-0.39**	**0.27**	0.34	0.03	0.15
Pmean (average; 25)	-0.18	-0.12	0.17	0.12	0.09	0.07	0.02
Tmean (average; 75)	**2.38**	**2.25**	**1.41**	**2.24**	0.77	0.27	**0.61**
Pmean (average; 75)	0.29	0.22	0.38	-0.19	-0.06	-0.21	*-0.29*
Subs/ha (average)	0.02	0.00	-0.01	**0.12**	0.04	**0.02**	0.00
Tmean (variability)	-0.11	**-0.13**	0.02	-0.11	**-0.19**	-0.08	*-0.08*
Pmean (variability)	**0.25**	0.08	**0.21**	0.08	0.00	-0.01	0.00
Subs/ha (variability)	*0.07*	0.03	0.00	0.08	**0.12**	**0.16**	**0.18**

Note: For farm type dimensions, parameter estimates of fixed effects are presented and significance levels ($p<0.05$: bold; $p<0.10$: italic) refer to the difference with the reference per dimension (large scale, high intensity, arable/cereal). The estimates remain (almost) constant when including either averages or variability in climate variables and *subs/ha*. For *tmean*, *pmean* and *subs/ha* elasticities are presented (as in Table 3.4 and 3.5).

3.4 Discussion

3.4.1 Scope and methods of analysis

This is one of the first empirical studies linking farm characteristics to impacts of climate change and variability on agriculture. Our analysis regresses observed data on climatic and policy conditions and farm characteristics against crop yields and income at regional and farm type level. Considering trends, variability and averages in the analysis allows for addressing the role of climate change, climate variability and prevailing climatic conditions for farm performance at different levels of organization. Inter-annual variability is not explicitly analysed as the regional differences in the direction of impacts of inter-annual climate variability do not allow a generic approach to obtain generic insights in the influence of management. Interactions between climate and management are explored for specific regions in Chapter 5.

Our aim in this study is not to estimate climate impacts for each region or farm type, but to obtain insight in the relative importance of climate and socio-economic factors and farm characteristics for explaining crop yield and income at different levels of organization. Analysing trends among regions instead of within regions reduces confounding of effects. We acknowledge that when trends are non-linear, relationships can still be confounded. Therefore, the trends are regressed against both trends and averages of explaining variables and at two levels of organization. This gives insight in confounding relationships. We have not explicitly considered technological development in our analysis, which has a larger impact on yield trends in Europe than climate (Ewert et al., 2005). However, technology development is a combination of several factors (of which some are considered in our analysis) and we do not attempt to explain the mechanisms by which it affects trends. Instead, our analysis provides information about the relative importance of factors for the variability in trends. This should serve further efforts in understanding and modelling temporal yield changes.

Temperature and precipitation data are averaged for the first six months of the year, which represent the main growing period. The start and length of the growing season differ depending on the region and crop, but using the same period allows better comparisons. Including or excluding other months does not have a large impact on the results. Again, our main aim is to obtain insights in the combined impacts of management and climate and not in specific estimates of climate impacts.

At the regional level intensity is represented by *fert/ha* and *prot/ha* in €/ha. The two-way relationship between these regional-level variables and dependent variables can violate the basic assumption of independence. Testing on endogeneity by using instrumental variables (Chapter 2) showed that these variables are exogenous. They are not corrected for price effects, since (1) price changes are relatively small in relation to differences among regions, (2) temporal changes in prices are similar among regions and (3) data on price indices are only available after 1995.

The used farm typology is a common typology for the whole EU15 (Andersen et al., 2006). Thresholds defining the farm type dimensions are the same for all regions. As only few classes are distinguished per farm type dimension (Table 3.3), the number of different farm types is small in some regions. Increasing the number of classes or changing the thresholds, especially for intensity, could provide additional detail on the impacts and adaptive capacity. Nevertheless, this study shows that with the limited number of farm types, differences in their responses to climate variability and trends are obvious.

3.4.2 Factors explaining trends and variability in farm performance at multiple levels

Climate change as well as prevailing climatic conditions have an impact on trends in crop yields in the EU15. The impacts are influenced by policy and management conditions however and differ depending on the level of organization (see summary in Figure 3.5). Our results suggest that the change in temperature has a larger impact on crop yield trends than the average temperature. Crop yield trends have been generally larger in temperate regions compared to Mediterranean regions (Calderini and Slafer, 1998; Ewert et al., 2005), but this is less apparent for the period from 1990−2003. Ewert (2005) suggested that relative yield changes are converging for EU15 countries. But, although the prevailing climatic conditions have a different impact on different spatial aggregation levels and different time periods, their high relative impacts indicate that regions with similar climatic conditions adapt in a similar way. The relative impact of temperature in explaining differences in crop yield trends among regions is large compared to those of policy or management variables. Nevertheless, consideration of these non-climatic effects is required to sufficiently explain differences in climatic effects across regions. Trends in economic size and fertilizer use clearly influence the differences in trends.

Lobell and Asner (2003) made a cross-section analysis and found that a 1ºC increase in temperature leads to a 17 % decrease in corn and soybean yields in the United States. However, they do not correct for other effects and their results suffer from omitted variable bias (Chapter 2; Kaufmann and Snell, 1997). Also, a generic estimate does not apply for specific regions. Only when assessing climate impacts for a specific region / farm type, reliable estimates of the impacts can be given. Tao et al. (2006), for example, determined the negative impacts of local increases in temperature on crop yields in China. But in order to show how socio-economic and management variables can reduce or increase climate impacts, regions and/or farm types need to be compared. The current study shows that climate and management interactions differ depending on the crop and between farm type and region, but some general response patterns are obtained.

A high variability in *pmean* has a large impact on crop yield variability and is of more concern than variability in *tmean*. At regional level a high variability in *pmean* can also lead to reduced yield variability of some crops, but the farm type level analysis shows that when we account for within regional differences, this is not the case. An adaptation strategy that reduces impacts of variability in *pmean* is a higher level of irrigation.

Our results confirm earlier observations (e.g. Thorhallsdottir, 1990) suggesting that the impact of climate on yield and income variability is especially important at higher aggregation levels. At the farm type level, farm characteristics are more important. Understanding of the mechanisms underlying climatic effects on crop yields at different levels of organization remains difficult. The present analysis is explorative in this respect, but our results suggest that the approach to model responses to climate change will differ depending on the aggregation level as (1) the importance of factors changes depending on the level and (2) resulting impacts at one aggregation level do not necessarily apply for other levels.

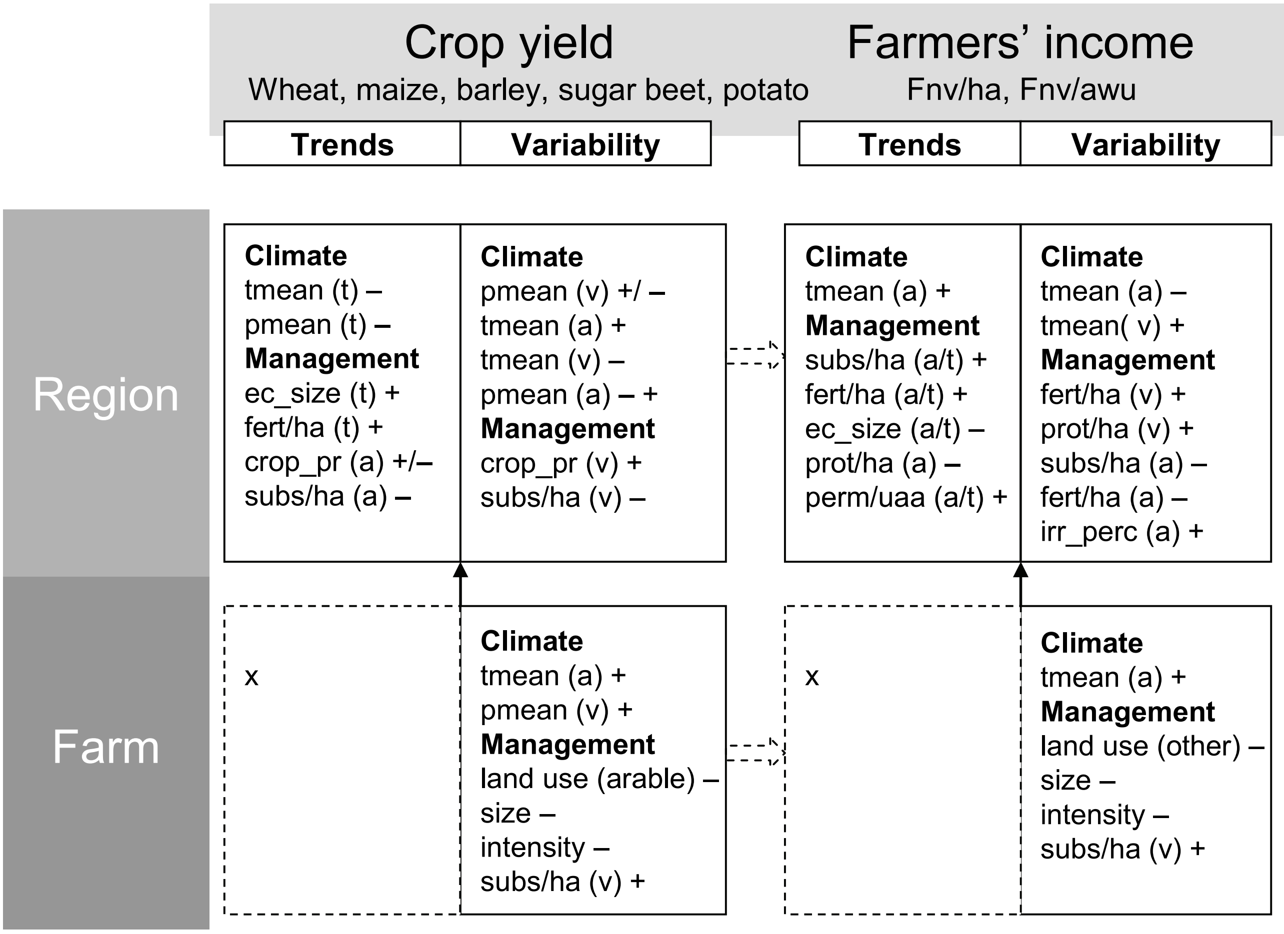

Figure 3.5. Summary presentation of impacts of climate and management on farm performance at two levels of organization. Impacts are: + = positive, + – = concave, –+ = convex, – = negative, +/– = differs per variable, x = no significant impacts. The variables are explained in Table 3.2 and 3.3 with (a) = average, (t) = trend and (v) = variability.

3.4.3 Vulnerability in crop productivity and income

Spatial variability in crop yields throughout the EU15 is not related to spatial variability in *fnv/ha* (Chapter 2). The present analysis shows that climate effects on crop yields and *fnv/ha* are also different when analysed over time. Variability in crop yields is larger (Table 3.4, 3.5 and 3.6) at higher temperatures, but this is not the case for variability in income. Also, despite the relatively low crop yields, *fnv/ha* is higher and increasing faster in Mediterranean regions, which is also observed for some crop yields (Table 3.4). This suggests that farmers in regions with low crop yields adapt by decreasing input costs, changing to other crops or increase subsidized activities (as *fnv* ≈ outputs – inputs + subsidies − taxes), but also change practices to increase yields. Higher product quality or increased market value due to scarcity may also have led to higher output prices (which are observed in the FADN data). High trends are sometimes accompanied by high variability, which may be due to adaptations which can increase farmers' income at the long-term but cause more risk at the short term. Other studies mentioned hazard exposure as being an important indicator for successful adaptation (e.g. Downing et al., 2001; Smit and Skinner, 2002). This seems valid for regions regularly exposed to high temperatures.

3.4.4 Adaptive capacity at multiple levels

Until now, many studies have quantified regional potential impacts of climate change with site-specific models. It was assumed that, by understanding these impacts, adaptive measures could be quantified and projections of actual impacts could be made (IPCC, 2001; Metzger, 2005). Although crop yield variability is larger in Mediterranean compared to temperate regions, impact of inter-annual climate variability is not necessarily larger (Chapter 4 and 5) and crop yield trends can still be high. The conclusion that Mediterranean regions are most vulnerable to climate change (e.g. Olesen and Bindi, 2002; Metzger et al., 2006) needs refinement. Importantly, the complex relationships between climate, management and farm performance cause potential impacts to vary not only among regions, but also among farm types within regions. Adaptation options are typically classified in autonomous and planned or proactive and reactive (Smit et al., 2001). However, explicit quantification of these adaptation types has proved difficult.

A high variability in precipitation has a negative impact on wheat and barley yields, but not on maize, sugar beet and potato yields. The latter crops are often irrigated. The area of irrigated crops has increased in most regions, as EU policies have stimulated irrigated agriculture. This partly explains why farmers' income increases more in Mediterranean regions compared to temperate regions and is less influenced by climate variability in these regions. However, water stress is already apparent, also in temperate regions (Alcamo and Henrichs, 2002) and if water is not managed wisely, drought risks will increase (Isendahl and Schmidt, 2006; Lehner et al., 2006). The short-term adaptation (or 'coping capacity') may eventually result in maladaptation on the long-term (Reilly and Schimmelpfennig, 2000).

Higher level planned adaptation is of crucial importance for farm performance and adaptation to climate change and variability (Smit and Wandel, 2006). Regional level adaptive capacity is related to awareness, technological and financial ability and indicators have been proposed to quantify these abilities (Smit et al., 2001; Schröter et al., 2003; Metzger et al., 2006). For the agricultural sector these indicators need to be further specified. The present study suggests that the influence of management factors may differ per farm performance measure, but that hazard exposure can stimulate adaptive responses.

3.5 Conclusions

Our analysis shows that climate has an impact on trends and variability in crop yields and farmers' income at regional and farm type level, but that the actual impact depends on socio-economic and management conditions. Farm types and regions adapt differently to climate change and variability. Climate effects on spatial variability in crop yields and income variables (representing long-term responses) cannot be directly translated into effects on temporal variability (representing short-term responses). Results suggest that in regions with a less favourable and more variable climate (e.g. the Mediterranean) actual adaptation is higher. Nevertheless, precipitation is of particular importance for explaining yield variability and assessing the impacts of changes in water supply and associated irrigation policies are of immediate concern.

As climate impacts do not only vary among regions but also among farm types, concepts to explicitly quantify potential impacts and adaptive capacity appear less practical. Studies that aim to assess the impacts of climate change on agriculture need to integrate the combined effects of climate variability and change, socio-economic conditions and farm characteristics, and have to consider both crop yields and farmers' income as this influences the type of adaptation. Only then it will be possible to projecting the actual impacts of climate change on farms and regions.

Chapter 4

Farm diversity decreases vulnerability to climate change

Abstract

Food production must adapt in the face of climate change. In Europe, projected vulnerability is particularly high in Mediterranean regions. Increasing agricultural diversity has been suggested as an adaptation strategy, but empirical evidence is lacking. We analysed the relationship between farm diversity (i.e. diversity among farm types) and the effects of climate variability on regional wheat productivity. An extensive dataset with information from more than 50,000 farms from 1990 to 2003 was analysed, along with observed weather data. Our results suggest that the diversity in farm size and intensity, particularly high in Mediterranean regions, reduces vulnerability of regional wheat yields to climate variability. Accordingly, increasing farm diversity is a strategy through which regions in Europe can adapt to unfavourable conditions, such as higher temperatures and associated droughts.

Keywords: Climate change, vulnerability, farm diversity, regional crop productivity

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4.1 Introduction

Food production is an important ecosystem service that is central to human welfare (Costanza et al., 1997). Climate change will increase risks for food production in large parts of the world (Gitay et al., 2001; Parry et al., 2004). In Europe, food production in Mediterranean regions is projected to be particularly vulnerable to climate change and associated increases in climate variability (Olesen and Bindi, 2002; Schröter et al., 2005). This is explained mainly by the negative effects of increasing temperatures and decreasing precipitation on crop productivity.

The extent to which systems are vulnerable to climate change depends on the actual exposure to climate change, their sensitivity and their adaptive capacity. In contrast to species in natural ecosystems, farmers, assisted by governments, can plan to adapt to climate change (e.g. Smit et al., 2001). Although there is increasing attention to adaptation, quantitative understanding of relationships which determine adaptation remains limited. Better understanding of adaptation is needed in order to improve projections of agricultural vulnerability and to prevent or alleviate climate change impacts.

A higher diversity is believed to increase the ability of systems to withstand shocks and thereby decrease vulnerability (Gunderson and Holling, 2002). It has been demonstrated that temporal stability of a natural ecosystem increases with increasing species diversity (Díaz and Cabido, 2001; Tilman et al., 2006). Also for agricultural systems it has been suggested that a higher diversity can decrease vulnerability (e.g. Fraser et al., 2005), but empirical evidence is lacking.

Agricultural diversity can be measured at different levels of organization (farm, region, country, etc.). At farm level, diversity relates to the diversity in farming activities (e.g. differences in the crops grown). As different crops respond differently to climate variability, higher crop diversity on farms can decrease the vulnerability of farmers' livelihood to climate variability (e.g. Ellis, 2000). At regional level, diversity relates to the diversity among farm types (e.g. differences in farm intensity). Farm diversity reflects diversity in management which largely influences crop productivity (Chapter 2 and 3).

Although adaptation strategies are mainly adopted at farm level, in this study we concentrate on the aggregated effects emerging at the regional level, as this is the level at which most impact studies are performed (IMAGE team, 2001, IPCC 2007b, Schröter et al. 2005). We are primarily interested in the vulnerability of regional crop productivity. Associated impacts on the vulnerability of farmers' livelihood are discussed. Accordingly, the objective of this Chapter is to analyse the relationship between farm diversity (i.e. diversity among farm types) and the regional effects of climate variability on crop productivity. The analysis is performed using data from an extensive farm survey across Europe. Some of the obtained results are additionally supported by a supplementary analysis of model simulations from a crop growth model (WOFOST).

4.2 Methodology

4.2.1 Data description

Our analysis is based on an extensive data set on farm characteristics and crop yields of individual farms throughout the EU15, provided by the Farm Accountancy Data Network (FADN)[1]. The FADN is the only source of micro-economic data from agricultural holdings in the EU15 that is harmonized, i.e. the book-keeping principles are the same in all countries. Regions are clustered into HARM regions, a harmonized division developed by the Dutch Agricultural Economics Research Institute (LEI). Data are collected from 1990–2003 in 100 HARM regions with more than 50,000 sample farms. These farms are aggregated into farm types based on land use, size and intensity (Table 3.3); important farm characteristics that influence farm performance (Chapter 2; Andersen et al., 2007). The farm typology is developed in the EU-funded SEAMLESS project (Andersen et al., 2006). Size classes are based on economic size units (related to standard gross margins), intensity classes on output per hectare, and land use classes on specialization and land use (e.g. arable/cereal or dairy cattle/temporal grassland). A farm typology offers a tool to synthesize farm management indicators, such as crop yields or fertilizer use. Farms grouped into the same type have a similar farm management (Andersen et al., 2007).

Daily temperature and precipitation data for the study period are obtained from a pan-European weather database[2]. Data are available on a 50 × 50 km grid resolution and are averaged per HARM region. Mean temperature (*temp)* and precipitation (*prec)* are calculated per region and per year for the main growing period between March and August. Also mean temperature and precipitation for individual months are calculated (i.e. $temp_{month}$ and $prec_{month}$). The study period (1990–2003) covers some of the warmest and driest years in the instrumental record of climate. As it is projected that European summers will experience a pronounced increase in the incidence of extreme warm and dry years (Schar et al., 2004), results from this study will be of interest for projections on climate change impacts.

4.2.2 Vulnerability analysis

The vulnerability of regional food production to climate change is measured by the regional effects of climate variability on crop productivity. We assume that regions with large effects of climate variability on crop productivity have a high vulnerability of food production to climate change and associated climate variability. The analysis considers wheat, being the most important crop in Europe and grown in almost all regions. We excluded all regions with less than 10 years of data and with less than 1% wheat (by area) in the arable area from the analysis.

Analysis of inter-annual wheat yield variability requires correction for the trend,

[1] Source: FADN-CCE-DG Agri and LEI.
[2] JRC-Agrifish MARS STAT (Monitoring Agriculture with Remote Sensing; www.marsop.info).

mainly caused by technology development (Ewert et al., 2005), which can distort the impact of climate variability. A linear trend is assumed and tested on stationarity (Chapter 3). Although not always significant, trends are calculated for all regions. The absolute anomaly from the trend is used in the analysis.

Regional effects of inter-annual climate variability on wheat yields are measured by the Pearson correlation coefficient (*r*) between wheat yield anomalies from a linear trend and *temp* [*r(yield,temp)*] and *prec* [*r(yield,prec)*]. The start and length of the growing season differ depending on the region and result in regional differences for the months that are most important for wheat growth. Therefore, we also calculated Pearson correlations between wheat yield anomalies and average temperatures and precipitations for the six individual months from March to August (i.e. 12 correlations per region).

Furthermore, we calculated Pearson correlations between *temp* and *prec* and simulated water limited (*Ywat)* and potential (*Ypot*) yields as simulated in the Crop Growth Monitoring System (based on WOFOST; Chapter 6, Lazar and Genovese, 2004). These correlations indicate the potential impact of *temp* and *prec* on wheat growth, without considering management and adaptation. Comparing these simulations with the results from the farm survey analysis should further clarify the importance of management and adaptation for explaining regional differences in yield responses to climate variability.

As *r(yield,prec)* is not significant in any of the regions and calculations based on individual months are similar to *r(yield,temp)* (section 4.3), further analysis focuses mainly on *r(yield, temp)*, for which results are especially interesting.

4.2.3 Measures of farm diversity

Farm diversity per region is measured in two ways. The first measure, the diversity in farm type yield variability (SD), demonstrates the diversity in the responses of farm types. Independently of the farm characteristics, this measure indicates the extent by which inter-annual yield variability varies for the different farm types present in the region. SD is measured as the standard deviation in the relative yield anomaly per year of all farm types in a region, averaged over the study period (1990–2003) as

$$SD = \sum_{t=1}^{N} sd(Y_{A,1}, Y_{A,2}, \ldots Y_{A,f})_t / N \text{ with } Y_{A,i} = \frac{100 \cdot (y_{it} - \sum_{t=1}^{N} y_{it} / N)}{\sum_{t=1}^{N} y_{it} / N} \quad (1)$$

where *sd* is the standard deviation of relative yield anomalies ($Y_{A,i}$) of farm types *i* (*i*=1,2,…f*)* per year *t* (*t*=1,2,…N). Yield anomalies per farm type and year are calculated from the actual yield (y_{it}) related to the average of the study period. No trend is considered at farm type level as few trends are significant and trends can be distorted by missing years (Chapter 3). Relative yield anomalies are considered, as absolute yields differ per farm type within a region and therefore relative anomalies can be better compared than absolute anomalies. Figure 4.6 in the results section includes a visual presentation of the calculation of the SD.

The second measure, which we refer to as farm diversity, demonstrates the diversity in the abundance of farm types. This measure indicates how diverse the farm types are in the farm characteristics (land use, size, intensity) that determine the farm typology. Farm diversity is expressed by land use diversity, size diversity and intensity diversity; based on the Shannon-Weaver index (Shannon and Weaver, 1949), indicating the number of farm types and evenness of farm types as

$$H' = -\sum_{i=1}^{f} \frac{w_i}{W} \ln \frac{w_i}{W} \tag{2}$$

where f is the number of farm types, w_i is the wheat area of farm type i and W is the total wheat area in a region. H' is calculated with the size (f is number of size types), intensity (f is number of intensity types) and land use (f is number of land use types) types as input. As the number of land use types (21) is large compared to size (3) and intensity (3) types, the three dimensions are separated.

Farm diversity can based on these three farm characteristics as these three factors were identified as having most influence on crop productivity and they synthesize farm management best (Chapter 2; Andersen et al., 2007). Although farms can differ in many factors, the farm types clearly differ in management indicators that influence adaptation, such as fertilizer and crop protection use.

4.2.4 Quantifying effects of farm diversity on vulnerability

Both types of measures of farm diversity have been related against *r(yield, temp)*. Our main objective is to analyse the relationship between farm diversity and regional effects of climate variability on crop productivity [i.e. *r(yield, temp)*]. Nevertheless, when analysing this relationship, we should take into account that differences in *r(yield, temp)* can be determined by many factors. By examining the diversity in farm type yield variability (SD), we test whether regional differences (e.g. in cultivars) can account for differences in *r(yield, temp)*. When there is a large diversity in yield responses of farm types, yield responses are mainly determined by differences among farm types, and not by regional differences. Subsequently, measuring the SD against *r(yield, temp)* indicates whether this diversity is related to *r(yield, temp)*.

Secondly, using a linear regression model, we tested how farm diversity influences *r(yield, temp)*. Farm diversity is expressed by diversity in land use, size and intensity; based on the Shannon-Weaver index (section 4.2.3). To account for other effects also the composition (i.e. presence of farm types) and prevailing climate conditions are included in the model. For temporal stability of natural ecosystems it was demonstrated that both composition and diversity are important (Tilman et al., 2007).

Also for agricultural adaptation the types of farms occurring in a region are likely to have an effect, independently of the diversity herein. Differences in the presence of farm types largely account for management factors, such as crop protection use (i.e. a high intensive farm uses more fertilizers than a low intensive farm). Composition is represented by the presence of different farm types for size (small, medium and large scale) and intensity (low, medium and high intensive) within a region, measured as the fraction of the total. For composition of land use we used the fraction of arable land in total agricultural area and the fraction of wheat area in the total arable land. Furthermore, prevailing climatic conditions are included in the regression model and represented by average *temp* and *prec* of the whole period. The backward procedure is used to ensure only significant relationships ($p<0.10$) are included.

4.3 Results

4.3.1 Effects of climate variability on wheat yields

Spatial variability in average wheat yield (from 1990–2003) is significantly negatively correlated to average *temp* (Figure 4.1). Wheat yields are thus lower in regions with higher temperatures. Therefore, it is expected that higher temperatures will generally have a negative effect on temporal variability in wheat yields. However, inter-annual yield variability is also affected by *temp* but *r(yield,temp)* varies among regions. Interestingly, *r(yield,temp)* is significantly negative ($r<-0.53$) in many temperate regions and low in most Mediterranean regions (Figure 4.2). The *r(yield,prec)* is not significant in any of the regions (Figure 4.3).

Results for *r(yield,temp)* are opposite from what would expected from simulations with crop models. Effects of higher temperatures are projected to be more negative for potential and water limited yields (*Ywat*) in Mediterranean regions compared to temperate regions (Figure 4.4). Therefore, we are interested in factors that explain the pattern for *r(yield,temp)*.

Even in many Mediterranean regions, where water limitation is expected to cause more problems for crop growth, yields are little related to the growing season precipitation (Figure 4.3). The results for *r(yield,temp)* are also rarely influenced by the aggregation of temperature variables. Spatial patterns of the effects of temperature of individual months, including the distinct negative effects on yield in temperate regions, are similar to the calculations based on six-months averages (Figure 4.5). Apparent is that in many neighbouring temperate regions, the same months account for the most negative (significant) temperature effect, while in many neighbouring Mediterranean regions different months account for the most negative (but small) temperature effect. Large and similar effects among neighbouring regions suggest that relationships are not just coincidental statistical relationships, but causal effects can be assumed, whereas the opposite is true for small and varying relationships.

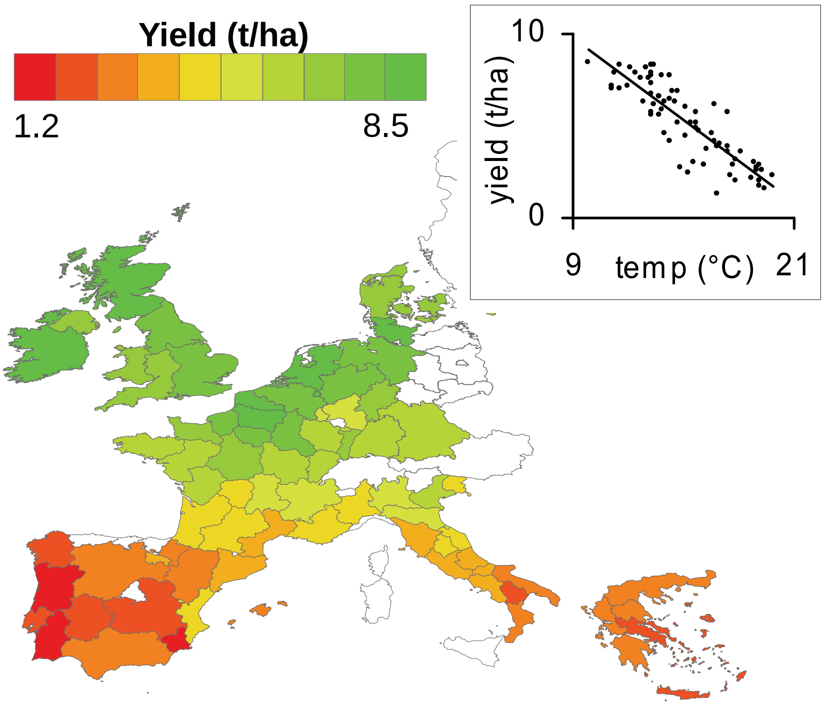

Figure 4.1 (in colour on p.179). Spatial distribution of average wheat yields (t/ha), and relationships to average temperature (temp, °C) from 1990–2003.

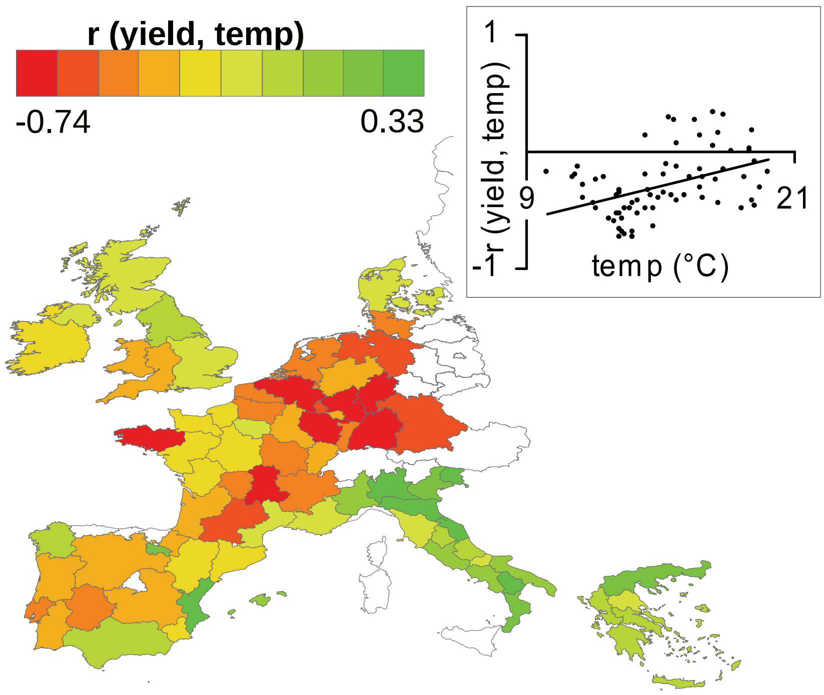

Figure 4.2 (in colour on p.179). Spatial distribution of the correlation between inter-annual variability in temp and wheat yield anomalies [r(yield,temp)], and relationships to average temperature (temp, °C) from 1990–2003.

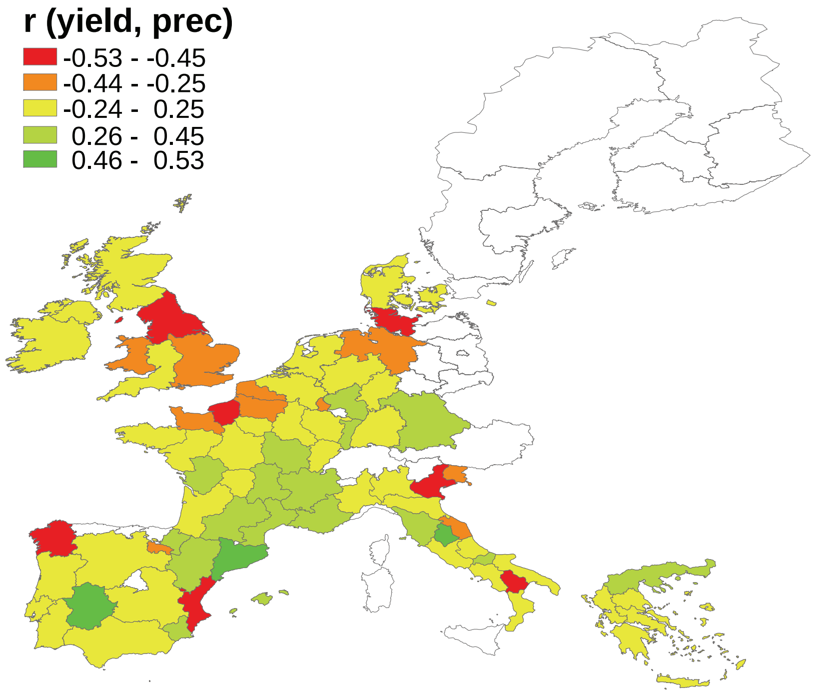

Figure 4.3 (in colour on p.180). Spatial distribution of the correlation between inter-annual variability in prec and wheat yield anomalies [r(yield,prec)]. The legend is different from Figure 4.2 to demonstrate the (non-) significant relationships (|r|>0.53).

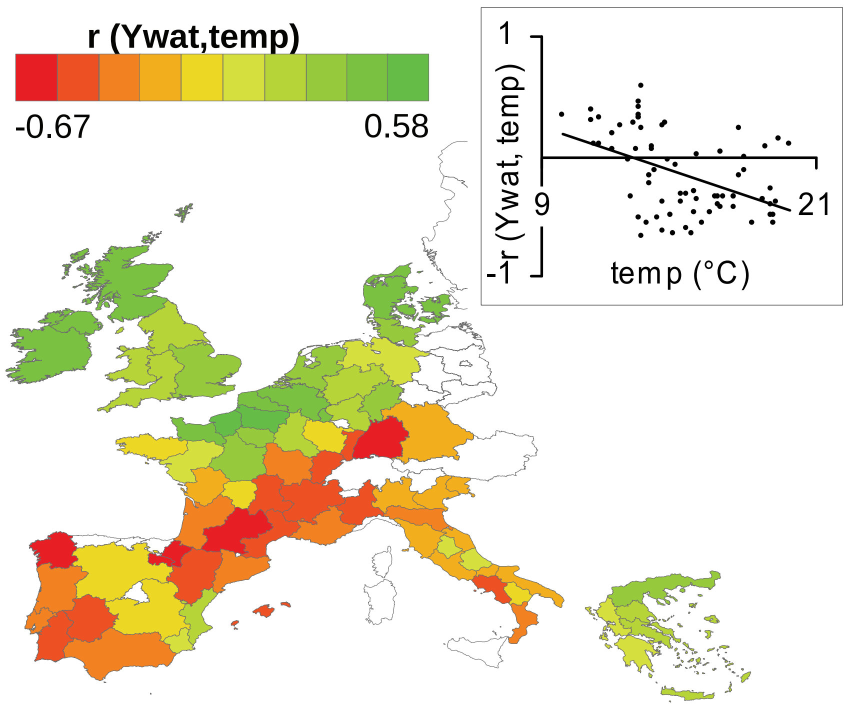

Figure 4.4 (in colour on p.180). Spatial distribution of the correlation between inter-annual variability in temp and water limited yields [r(Ywat,temp)], and relationships to average temperature (temp, °C) from 1990–2003.

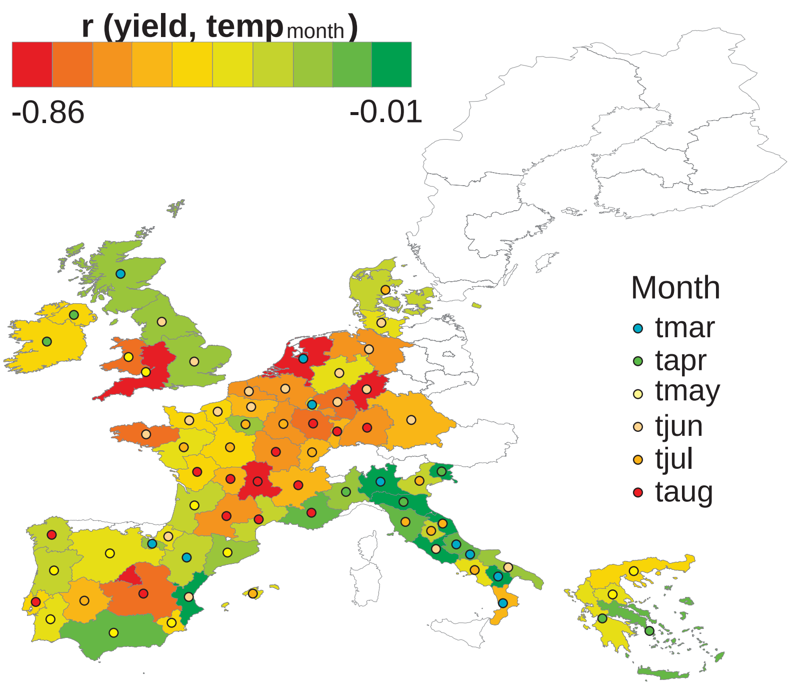

Figure 4.5 (in colour on p.181). Spatial distribution of the correlation between inter-annual variability in wheat yield anomalies and $temp_{month}$ (the monthly temperature variable with the largest negative effect) [r(yield,$temp_{month}$)], and relationships to average temperature (temp, °C) from 1990–2003.

4.3.2 Effects of farm diversity on regional vulnerability

The analysis on the inter-annual variability in farm type yields, revealed that in regions where temperature effects on yield are less negative, the diversity in farm type yield variability (SD) is larger (Figure 4.6, p = 0.04). Hence, where inter-annual variability in wheat yields differs more among farm types, the relationship with inter-annual temperature variability is less apparent.

Results from the regression model (Table 4.1) indicate that diversity in size and intensity reduce the on average negative effects from higher temperatures on regional wheat yields [*r(yield,temp)*]. Results are less pronounced but negative for land use diversity. This is likely related to similar land use types regarding wheat management (i.e. dairy cattle/temporary grass and beef and mixed cattle/temporary grass) being grouped in different land use types. Clearly, yield responses to temperature differ depending on the farm type and temperature effects on regional yields are less pronounced when farm diversity in a region is high. Farm diversity, in size and intensity, represents diversity in management strategies (e.g. cultivar choice, and fertilizer and pesticide use). The diversity in management strategies leads to low regional impacts of climate variability (Figure 4.6).

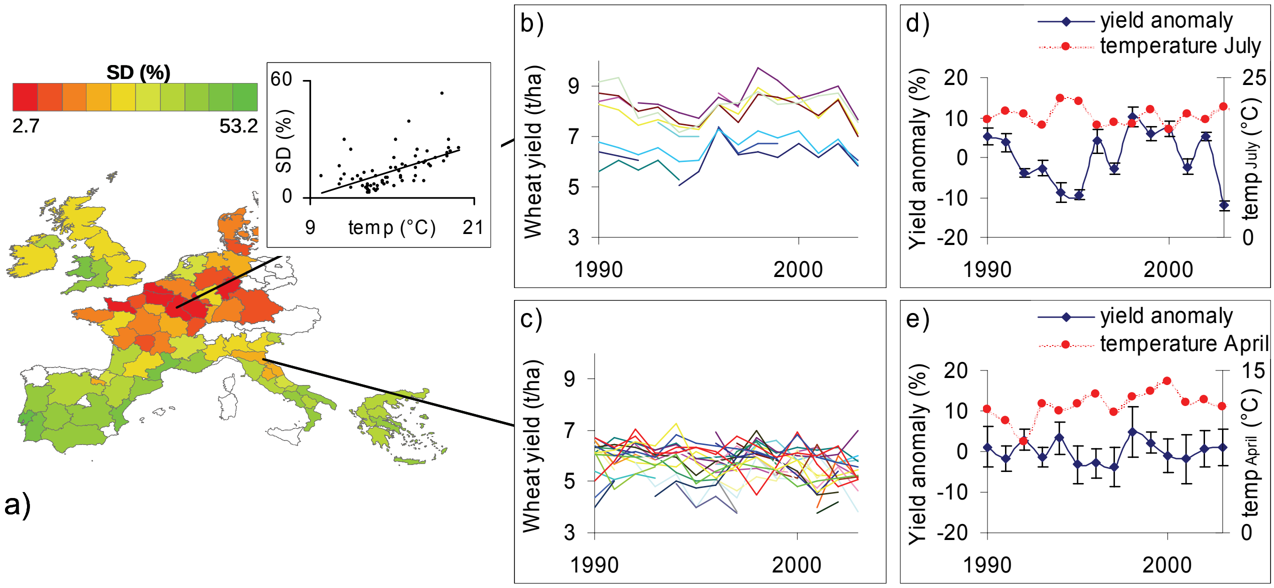

Figure 4.6 (in colour on p.182). (a) Spatial distribution of the diversity in farm type yield variability (SD, %), and relationships to average temperature (temp, °C) from 1990–2003. Wheat yield variability is similar for different farm types in (b) Champagne-Ardenne, while in (c) Emilia-Romagna the diversity in wheat yield variability is larger. In (d) Champagne-Ardenne standard deviations in the relative wheat yield anomaly for individual years are small (SD=3.7) and regional yield anomalies (from the trend) are significantly different from zero and correlated to temperature, (r=–0.66 with $temp_{July}$*, r=–0.44 with temp). However, in (e) Emilia-Romagna the standard deviations are large (SD=8.3) and regional yield anomalies are not significantly different from zero and are not significantly correlated to temperature (r=–0.13 with* $temp_{April}$*, r=0.33 with temp). Note, temperatures shown in (d) and (e) refer to the months with the largest negative correlation.*

Table 4.1. Results from the regression model with r(yield, temp) as dependent variable and farm diversity and composition and prevailing climate conditions as independent variables (see text for further explanation).

Variables	Estimates
Intercept	-0.70
Size diversity (SW)	0.91
Intensity diversity (SW)	0.85
Land use diversity (SW)	-0.49
Medium intensive farm (fraction)	0.46
Small scale farm (fraction)	0.44
Medium scale farm (fraction)	-0.73
R^2	0.53

In this study we are mainly interested in the effects of farm diversity, but farm type composition also has an impact. The *r(yield,temp)* is less negative in regions where the fraction of small scale farms is larger, whereas it is more negative where medium scale farms cover a larger part of the area. This is possibly related to small scale farmers having more flexibility to adapt management practices compared to larger farms. Regions with more small scale farming have also higher farm diversity as more farms cover the same area.

Wheat yields on medium intensive farms are less negatively impacted by *temp* compared to low and high intensive farms. The larger impacts for low intensive farms can be explained by the low technical ability to adapt practices. For high intensive farms the larger impact is possibly due to management optimized towards prevailing conditions. Management is aimed at achieving wheat yields close to potential yields. If potential yields are approached and management is not adapted year by year, yield variability will be mainly due to climate variability.

4.4 Discussion

4.4.1 Farm diversity and agricultural vulnerability

The conclusion that Mediterranean regions are most vulnerable to climate change (Olesen and Bindi, 2002; Metzger et al., 2006) needs refinement. Such statements are often derived from simulations with mechanistic crop models which strongly emphasize biophysical factors that determine potential and water limited yields. However, actual yields are largely influenced by regional socio-economic conditions and farm management. These factors are often not considered in crop models but can largely modify the climate change impacts (Ewert et al., 2007).

The small relationships between climate variability and wheat yield variability in many Mediterranean regions suggest that farm management here is largely adapted to climate variability. In regions where prevailing climatic conditions are less favourable for wheat growth, farm management is not aimed at achieving optimal yields. It seems more focussed at coping with climate variability: as risks are larger, more attention is paid to reduce the impacts of risks. In regions where prevailing climatic conditions are more favourable, farm management is more focused on achieving high yields. When risks are low, aiming for maximizing crop yields (and profit) is a rational objective, but when risks increase this strategy makes farmers more vulnerable. The resilience of a system decreases rapidly when maximum profit is approached (Fletcher and Hilbert, 2007). In this study we observe that especially in regions with high wheat yields, the impact of climate variability on wheat yields is high. Hence, the increasing climate variability associated with climate change will mainly decrease the stability of wheat yields in these regions and adaptation is needed to decrease vulnerability.

Other studies mentioned hazard exposure as being an important indicator for successful adaptation (e.g. Downing et al., 2001; Smit and Skinner, 2002). This seems valid for regions regularly exposed to high temperatures. When risks of higher temperatures and associated droughts are higher, farms need to adapt their management in order to cope with this. Apparently, farms tend to find different ways to manage climatic variability, leading to farm diversification. Farm diversity decreases vulnerability at the regional level, as the variety of responses at farm level lead to a negligible response at regional level. Farm diversity, in size and intensity, represent diversity in management strategies (e.g. cultivar choice, and fertilizer and pesticide use). The opposite but small effect of land use diversity suggests that increasing land use diversity is not a good adaptation strategy for reducing the negative impacts of higher temperatures on regional wheat yields.

Diversity in management strategies is primarily determined by biophysical conditions, farming objectives and perceptions; explaining these relationships is not an aim of this analysis, but may be important for planning adaptation. It is not argued that the adaptation in terms of farm diversification as currently observed is based on conscious planned adaptation. A characteristic feature of complex adaptive systems is self-organization without intent (Levin, 1998; Walker et al., 2004). Although the dynamics of socio-ecological systems (here: agricultural systems) are dominated by human actors (here: farmers) who do exhibit intent, the system as a whole does not. Adaptation can be planned by institutions, but a region is not an actor who can adapt. High farm diversity can be an emergent property in regions where farmers adapt their management in different ways.

Nevertheless, the observation that farm diversity can decrease the vulnerability of regional food production to climate variability points to a promising regional adaptation strategy for agriculture to climate change that has been largely overlooked so far. Implications for agriculture are considerable as present developments in many countries reduce farm diversity, which requires attention. Planned adaptation at higher aggregation levels is needed in order to cope with climate change and associated climate variability. Subsidy, support and incentive programs can shift the current trend which directs to more large, intensive and specialized systems, towards maintaining or enhancing the diversity in farming systems.

4.4.2 The empirical analysis

Climate effects on wheat yields are analysed based on the Pearson correlation coefficient between climate variables and wheat yields. The Pearson correlation coefficient does not measure the extent of the impact but whether or not there is a relationship between yields and climate. It is a simple, straightforward and appropriate measure for analyzing relationships between two variables. The stronger the relationship, the more yield variability can be attributed to climate variability. Yield variability not explained by climate variability, can be attributed to management (e.g. van Ittersum et al., 2003). The use of this simple measure can be debated, but it gives quick insights in a complex matter.

Nevertheless, when analysing complex systems, valid and reliable input data is required. We used climate variables that were aggregated from daily weather data. The validity of using these aggregated climate variables has been tested by comparing results with outputs from a crop simulation model. Crop simulation models use daily weather data to simulate yearly wheat yields. The results demonstrate that water limited yields (wheat in Europe is generally not irrigated) are clearly negatively related to the aggregated temperature variable in Mediterranean regions, and more often positively in temperate regions; contrary to relationships for actual yields. Using these aggregated climate variables to measure climate effects and to determine the impact of management and adaptation is thus justified.

We acknowledge that there can be various reasons for finding differences in climate effects on wheat yields in Europe. Regional differences in e.g. socio-economic conditions or cultivars, often exhibit a strong north-south gradient. However, the farm type yield variability (SD) as presented in Figure 4.6 clearly demonstrates that there is a larger heterogeneity in yield responses on different farm types in southern regions. If the main cause of the small climate effects would be related to growing different cultivars, this effect would be similar for all farm types and the SD would be smaller. The large SD demonstrates that diversity in management strategies is clearly important.

The focus in this study is on the effect of the diversity among farm types on regional vulnerability of food production. We did not study adaptation of individual farms, for which the role of diversification should be further explored. Diversification on-farm relates more to diversity in farming activities, not to diversity in wheat management. Chapter 3 demonstrated that income variability did not decrease on mixed farms compared to specialized farms. More advanced analyses are needed however to assess the impact of on-farm diversity for decreasing vulnerability to climate change and climate variability.

4.5 Conclusion

Temperature negatively affects regional wheat yields across Europe. However, effects of higher temperatures on wheat yields are smaller in Mediterranean regions compared to temperate regions. The diversity in farm size and intensity, particularly high in Mediterranean regions, reduces regional vulnerability of wheat yields to climate variability. Accordingly, farm diversification is a strategy through which regions in Europe can adapt to unfavourable conditions as to higher temperatures and associated droughts, which will increase with climate change.

Chapter 5

Economic impacts of climatic variability and subsidies on European agriculture and observed adaptation strategies

Abstract

In order to assess agricultural adaptation to climate impacts, new methodologies are needed. The translog distance function allows assessing interactions between different factors, and hence the influence of management on climate impacts. The Farm Accountancy Data Network (FADN) provides extensive data on farm characteristics of farms throughout the EU15. These data on inputs and outputs from 1990−2003 are coupled with climate data. As climate change is not the only change affecting European agriculture, we also include effects of subsidies and other changes on inputs and outputs of farms throughout Europe. We distinguish several regions and empirically assess (1) climate impacts on farm inputs and outputs in different regions and (2) interactions between inputs and other factors that contribute to the adaptation to these impacts.

Changes in production can partly be related to climatic variability and change, but also subsidies and other developments (e.g. technology, markets) are important. Results show that impacts differ per region, and that 'actual impacts' cannot be explicitly separated into 'potential impacts' and 'adaptive capacity' as often proposed. Farmers adapt their practices to prevailing conditions and 'potential impacts' are not quantifiable leaving it as a mainly theoretical concept. Factors that contribute to the adaptation also differ per region. In some regions more fertilizers or more irrigation can mitigate impacts, while in other regions this amplifies impacts. Prevailing conditions and farm type strategies should be explicitly considered to be able to project impacts of future changes.

Keywords: Adaptation, agriculture, climate change, economic vulnerability, frontier analysis

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5.1 Introduction

European agriculture is facing multiple challenges of global change. Global warming is already apparent and will impact future agriculture (Gitay et al., 2001). In the shorter term, liberalization will impact trade and production (van Meijl et al., 2006). Agricultural policies have long been focused on increasing food production and the viability of rural economies. In recent years, globalization of agricultural markets and environmental issues became major factors influencing the Common Agricultural Policy (CAP) in Europe. Farmers will need to adapt to climate change in the context of globalization and changing policies.

O'Brien and Leichenko (2000) introduced the concept of 'double exposure', proposing to consider the joint impact of both globalization and climate change. Several integrated projects have expanded this concept and consider 'multiple exposures' (e.g. Schröter et al., 2005; Westhoek et al., 2006). The narratives of the IPCC-Special Report on Emission Scenarios (SRES) (Nakícenovíc et al., 2000), which aimed at projecting CO_2 emissions, have not only been used to project climate change and its impacts, but also to develop scenarios that explicitly consider globalization and other drivers influencing global and European food production and land use (Ewert et al., 2005; Rounsevell et al., 2005; Rounsevell et al., 2006). Yet, there is little empirical evidence on how these drivers influence European agriculture.

The vulnerability of European agriculture can be determined by exposure, sensitivity and adaptive capacity (IPCC, 2001; Metzger, 2005). Exposure and sensitivity determine the potential impact; including the adaptive capacity will result in the residual or actual impact. The potential impact of climate change on agricultural yields is projected to be mainly positive for Northern Europe and mainly negative for Southern Europe (Gitay et al., 2001; Olesen and Bindi, 2002; Ewert et al., 2005). However, farmers can and do adapt in order to reduce negative impacts.

The cross-sectional analysis in Chapter 2 showed that next to climate, the farm characteristics input intensity, economic size and the type of land use are important factors influencing spatial variability in crop yields and farmers' income. The temporal analyses in Chapter 3 and 4 indicated that these farm characteristics also have an impact on trends and temporal variability in crop yields and farmers' income. Climate impacts do not only vary among regions, but also among farm types. Studies that quantified adaptive capacity based on generic socio-economic indicators (Schröter et al., 2003; Metzger et al., 2006) suggested that the Mediterranean regions had a lower adaptive capacity than temperate and Nordic regions. Chapter 3 and 4 however showed that the actual impacts of increasing temperatures are not more severe in Mediterranean compared to temperate regions, suggesting adaptation of farmers to prevailing conditions. Still, it is not clear how socio-economic conditions and farm management interact with climate to adapt to climate impacts.

An influential study in economic analysis of climate change was the study of Mendelsohn et al. (1994). The Ricardian approach however addresses spatial differences in climatic conditions, not temporal change. Also, adaptation is implicitly included in the impacts, but not explicitly addressed. An approach often used in econometric studies, but not yet applied in studies related to climate impacts, is frontier analysis (Farrell, 1957; Morrison Paul et al., 2000). Frontier estimation models provide a useful methodology to analyse determinants of technical efficiency and explore the contributions of inputs and other factors (e.g. climate, subsidies and management) on deviations from efficient production. Including multiple inputs and outputs in a translog distance function allows assessing interactions between e.g. climate and management (i.e. adaptation strategies).

In this Chapter we assess the impact of climate variability and subsidies on inputs and outputs of farms in several European regions in the context of other changes. We use a translog distance function representing multiple outputs, inputs, and external factors to analyse (1) the actual impact of climate variability and subsidies on multiple outputs (actual impact), (2) which inputs can decrease impacts of climate variability and subsidies (factors influencing adaptation), and (3) the impact of climate variability and subsidies on inputs (adaptation strategies). The focus is on arable farming, but other farm types are also included in the model.

5.2 Methodology

5.2.1 The translog distance function

The translog distance function is a special form of a frontier estimation model. Frontier econometric techniques allow noise from measurement error to be separated from the technical efficiency arising from farms not reaching the boundary or the 'best practice' technology, through a two-part error term in the estimation process. In a frontier estimation model the technical efficiency of an individual farm is measured via its deviation from the frontier (Figure 5.1).

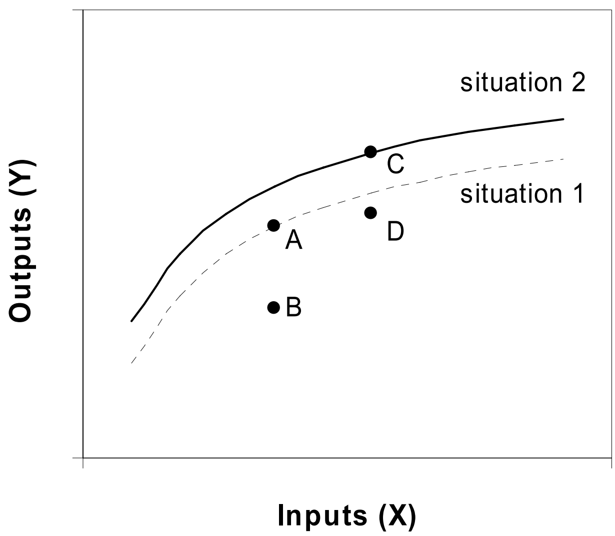

Figure 5.1. The production frontier. The production frontier determines the maximum output Y that can be achieved from a set of inputs X given the levels of external factors R. If in situation 1 a farm is operating at a point A, the farm is on the best practice frontier with an efficiency ratio of 1. If a farm is at point B then the farm is technically inefficient. In another region or at a later stage the frontier may shift to situation 2, for which C denotes an efficient farm and D denotes an inefficient farm.

Typically, the model includes one output and multiple inputs. In order to represent interactions between multiple outputs and inputs, the distance function is developed (Färe, 1988; Färe et al., 1994; Morrison Paul et al., 2000; Morrison Paul and Nehring, 2005), which is represented by

$$D_o(X,Y,R) = \min\{\Theta : Y/\Theta) \in P(X,R)\} \tag{1}$$

P(X,R) is the set of output vectors *Y* that can be produced using the input vector *X*, given the levels of external factors *R*. The distance function $D_o(X,Y,R)$ defines the maximum output *Y* possible to produce given input *X*, defined according to *P(X,R)*. The distance function then represents the distance from the frontier; if *Y* is on the production set boundary, the distance function is equal to 1. A value below 1 indicates a deviation of the farm from 'best-practice' production, technical efficiency.

A flexible form of the distance function is the translog functional form (Coelli and Perelman, 2000; Morrison Paul et al., 2000), because it incorporates all second-order (interaction) terms across outputs and inputs. It allows representation of substitution possibilities without restrictive assumptions about the shape of the technological relationship. The translog distance function takes the form

$$\begin{aligned}\ln D_{oi} = \alpha_0 &+ \sum_m \alpha_m \ln y_{mi} + \sum_k \alpha_k \ln x_{ki} + \sum_f \alpha_f \ln r_{fi} \\ &+ 0.5\sum_m\sum_n \beta_{mn} \ln y_{mi} \ln y_{ni} + 0.5\sum_k\sum_l \beta_{kl} \ln x_{ki} \ln x_{li} + 0.5\sum_f\sum_g \gamma_{fg} \ln r_{fi} \ln r_{gi} \\ &+ \sum_m\sum_k \beta_{mk} \ln y_{mi} \ln x_{ki} + \sum_m\sum_f \gamma_{mf} \ln y_{mi} \ln r_{fi} + \sum_k\sum_f \gamma_{kf} \ln x_{ki} \ln r_{fi}\end{aligned} \tag{2}$$

In this function, *o* indicates an output-orientated distance function and *i* denotes the farm. The summation sign over *m,n* implies summation over *M* outputs, *k,l* over *K* outputs and *f,g* over *F* external factors, with *α*, *β*, and *γ* parameters to be estimated. Restrictions required for homogeneity and symmetry (Coelli and Perelman, 2000; Morrison Paul et al., 2000) can be imposed by normalizing over one of the outputs y_1. In the normalized function $\ln D_{oi}/y_{1i}$, the distance or technical inefficiency measure ln D_{oi} can be rewritten as u_i. Adding the random error term v_i then leads to the translog function redefined in terms of $\ln y_{1i}$ as

$$\begin{aligned}\ln y_{1i} = \alpha_0 &+ \sum_m \alpha_m \ln y^*_{mi} + \sum_k \alpha_k \ln x_{ki} + \sum_f \alpha_f \ln r_{fi} \\ &+ 0.5\sum_m\sum_n \beta_{mn} \ln y^*_{mi} \ln y^*_{ni} + 0.5\sum_k\sum_l \beta_{kl} \ln x_{ki} \ln x_{li} + 0.5\sum_f\sum_g \gamma_{fg} \ln r_{fi} \ln r_{gi} \\ &+ \sum_m\sum_k \beta_{mk} \ln y^*_{mi} \ln x_{ki} + \sum_m\sum_f \gamma_{mf} \ln y^*_{mi} \ln r_{fi} + \sum_k\sum_f \gamma_{kf} \ln x_{ki} \ln r_{fi} + v_i - u_i\end{aligned} \tag{3}$$

where y^*_m is y_m/y_1. The summation sign over *m* now implies summation over *M−1* outputs as y^*_1=1. The random error term v_i is assumed to be $N(0,\sigma_V^2)$, and independent of the u_i, which accounts for technical inefficiency in production and is assumed to be independently distributed as truncations at zero of the $N(\eta,\sigma_U^2)$ distribution, where η is a parameter to be estimated. The function is slightly adapted by transforming the left side of the equation to be ln y_1 rather than −ln y_1. This reverses the signs of the parameter estimates resulting from a usual distance function, which facilitates comparing estimates with standard production function models (Coelli and Perelman, 1996; Morrison Paul et al., 2000). The technical efficiency (TE) is computed as $\exp(-u_i)$.

5.2.2 Data description and model specification

Farm data are obtained from the Farm Accountancy Data Network (source: FADN-CCE-DG Agri and LEI) from 1990−2003. The FADN provides extensive data on farm characteristics of individual farms throughout the EU15. Data have been collected annually since 1989; for East Germany, Finland and Sweden since 1995. They have been used to evaluate the income of farmers and the consequences of the Common Agricultural Policy. In total, 100 HARM regions are distinguished with more than 50,000 sample farms. To enable temporal analyses, a farm typology is developed based on the farm characteristics land use, size and intensity (Table 3.3). We distinguish 21 land use types, 3 size types and 3 intensity types. Instead of individual farms, the farm types are used as *i* in the model specification.

Monthly temperature and precipitation data are obtained from the MARS project (www.marsop.info). MARS data are available per grid cell of 50 × 50 km and are averaged per HARM region. Averaging the temperatures of the first six months (r_{tmean}) of each year, results in the mean temperature for the main growing period from 1990−2003. Also precipitation data is averaged to obtain the mean monthly precipitation (r_{pmean}) for the main growing period.

Outputs have been grouped into four groups (Table 5.1): production of cereals (y_{cer}; excluding grain maize), production of grain maize (y_{mai}; separated for its spatial relation as it is an important crop in southern Europe and responses differently to climatic conditions than other cereals), production of other arable crops (y_{othar}) and production of other agricultural activities (y_{othact}; e.g. livestock, permanent cropping). We are mainly interested in arable farming, as arable farming is assumed to be mostly affected by climate change and variability. We include other agricultural activities, as (1) inputs are also used for these activities and (2) the model results can give more information on differences in impacts.

Inputs included in the model are based on general input-output relations. Fertilizer and soil improvers (x_{fert}) and crop protection products (x_{prot}) are materials used to increase outputs. Economic size (x_{size}) is determined on the basis of the overall standard gross margin of the holding. It represents physical capital and labour, as labour is highly correlated to x_{size} (Chapter 2). We include irrigated area (x_{irr}) as it influences production and can influence climate impacts (e.g. Darwin, 1999; Schlenker et al., 2005). As we are interested in the interaction between climate and land use, we separate land uses into cereal area (x_{cer}), grain maize area (x_{mai}), other arable crop area (x_{othar}) and area with other agricultural activities (x_{othact}).

Table 5.1. Data description of variables included in the translog distance function.

Variable	Description
$y_{cer} = y_1$	Output of cereals, excluding grain maize (€)[1]
y_{mai}	Output of grain maize (€)[1]
y_{othar}	Output of other arable crops (€)[1]
y_{othact}	Output of other agricultural activities (€)[1]
x_{fert}	Input of fertilizers and soil improvers (€)[1]
x_{prot}	Input of crop protection products (€)[1]
x_{size}	Economic size (ESU; one ESU corresponds to a standard gross margin of €1200) [1]
x_{irr}	Irrigated area (ha) [1]
x_{cer}	Cereal area[1]
x_{mai}	Grain maize area[1]
x_{othar}	Area with other arable crops[1]
x_{othact}	Area with other agricultural activities[1]
r_{rmean}	Mean monthly temperature (°C) of first half year[2]
r_{pmean}	Mean monthly precipitation (mm) of first half year[2]
r_{subs}	Total subsidies (€)[1]
r_{year}	Time trend (1990=1, 1991=2,…,2003=14)[1]

[1] Source: FADN
[2] Source: MARS

Climatic conditions are external factors (or 'regional conditions' as defined in Chapter 1) that influence production. The mean temperature (r_{tmean}) and precipitation (r_{pmean}) of the main growing season per year per HARM region are related to the farm types. Subsidies are the main instrument of the CAP; we include total subsidies (r_{subs}) as an external factor in the model specification. Next to climate and subsidy changes, also other changes take place. Technological development, markets and other changes are captured in a time trend (r_{year}).

As impacts of temporal variability differ per region (Chapter 3 and 4), we apply the model separately for different regions. Within a selected region climatic and socio-economic conditions should be similar, but the number of farm types needs to be larger than the number of variables (including interaction variables) to ensure some degrees of freedom. Eight regions have been distinguished with different average $r_{tmean,}$ decreasing in the order of Greece, Spain, Italy, France, Germany, Benelux (Belgium, The Netherlands and Luxembourg), United Kingdom (UK) and Scandinavia (Scandin.: Finland, Sweden and Denmark). Most of these regions comprise one country, but several HARM regions. As climatic and socio-economic conditions can differ within regions, results also represent some spatial variability in farm performance.

Farm data that are represented in euros (y_m, x_{fert}, x_{prot}) are corrected for price effects using price indices. Eurostat (http://epp.eurostat.ec.europa.eu) provides price indices from 1995−2003, and absolute prices from 1990−2003. For years or countries where data are missing, price indices can be calculated based on the relationship between absolute prices and price indices from other years or other countries. Only for x_{prot} no comparable price data for 1990−1994 are available and 1995 data are used. We are confident that this doesn't influence results, as analyses without corrections for price effects showed that input prices have a very small impact. Zeros in the data are represented by a 0.0001 value, to enable calculation of ln values. As negative values can't be log-transformed, all r_{tmean} data are first transformed by adding 5ºC.

We use the LIMDEP econometric software version 7.0, April 2002, written by William H. Greene to estimate our model. Eq. 3 is estimated for eight regions with data from 1990−2003 per farm type. All parameters are logged, except for r_{year}. As we are interested in inter-annual variability, we do not use the random effects model, as this model will give a constant u_i per farm type over time. The estimated cross-section model will capture both temporal and spatial variability in production.

5.2.3 Analysing impacts and adaptation

Impact of external factors on overall output

We can use the distance function to construct farm performance measures (Morrison Paul et al., 2000; Morrison Paul and Nehring, 2005) that can give us more information on impacts of climate variability and subsidies on agricultural production. These measures can also indicate which factors contribute to adaptation (reducing impacts) and which factors are adapted to reduce impacts ('adaptation strategies').

The impact of external factors r_f on production (or contribution to) y_1 is measured by the elasticity

$$\varepsilon_{y1,f} = \partial \ln y_1 / \partial \ln r_f = \alpha_f + \sum_g \gamma_{fg} \ln r_{gi} + \sum_k \gamma_{fk} \ln x_{ki} + \sum_m \gamma_{fm} \ln y^*_{mi} \quad (4)$$

The elasticity represents the percentage change in output by 1% change in r_f. The change in y_1 represents change in overall production, since all other factors of the function (and hence the y_m/y_1 ratios) are fixed. The elasticity varies by observation, but is generally estimated at the mean.

The separate components of this elasticity measure represent the interaction effects. For example, the interaction between inputs and external factors $C_{fk} = \gamma_{fk} \ln x_k$. The interaction effects can increase or reduce the total impact of r_f on production. The C_{fk} components therefore represent indicators of adaptation to variability or change in temperature, precipitation and subsidies. When $\varepsilon_{y1,rpmean}$ is positive and $C_{rpmean,xirr}$ is negative, this implies that negative effects of decreasing precipitation can be reduced by increasing the irrigated area.

Impact of external factors and inputs on output composition

The impact of external factors r_f is not the same on all outputs y_m. The contribution of output y_m to total output can be measured by $\varepsilon_{y1,m}$, for which the measure is similar to $\varepsilon_{y1,f}$ (Eq. 4):

$$\varepsilon_{y1,m} = \partial \ln y_1 / \partial \ln y_m = \alpha_m + \sum_n \beta_{mn} \ln y^*_{ni} + \sum_k \beta_{km} \ln x_{ki} + \sum_f \gamma_{fm} \ln r_{fi} \quad (5)$$

Elasticity $\varepsilon_{y1,m} = \varepsilon_{Do,m}$ for all outputs except y_1. Due to homogeneity restrictions, the y_1 elasticity is computed as $\varepsilon_{Do,1} = -(1+\Sigma_m\varepsilon_{Do,m})$. For outputs, larger negative terms with respect to y_m imply a greater contribution of output y_m in total output relative to y_1 (y_{cer}). The sign of $\varepsilon_{y1,m}$ should be negative, consistent with the slope of the production possibility frontier, as −ln y_1 is adapted to ln y_1. The interaction terms with respect to the y_m variables can be interpreted as the effect of these variables on the contribution of y_m to total output relative to y_1. Hence, the impact of external factors on y_m is measured by $C_{mf} = \gamma_{fm}$ ln r_f (note that for r_{year} in this term it is not ln r_{year}, but r_{year}). A negative C_{mf} makes $\varepsilon_{y1,m}$ more negative and thus increases the value or contribution of output y_m relative to y_1 (the bias is 'output y_m− using').

From Eq. 4 we calculated C_{fk}, factors that are interpreted as indicators of adaptation. The x_k factors can change the impact of external factors r_f on overall output. Clearly, these input factors x_k also have their own effect on outputs. The components $C_{mk}= \beta_{km}$ ln x_k from Eq. 5 provide relative measures of the productive impact of x_k on output composition. Different measures can be compared. For example, if x_k can change the impact of r_{tmean} variability on total output (in Eq. 4), in Eq. 5 we can observe which outputs y_m are mostly impacted by x_k.

Influence of inputs on outputs and adaptation strategies

The components C_{mk} from Eq. 5 provide information on the impact of input factors x_k on specific outputs. The impact of x_k on total output is measured by

$$\varepsilon_{y1,k} = \partial \ln y_1 / \partial \ln x_k = \alpha_k + \sum_l \beta_{kl} \ln x_{li} + \sum_m \beta_{km} \ln y^*_{mi} + \sum_f \gamma_{fk} \ln r_{fi} \qquad (6)$$

We can assess the relative impact of intensity measures x_{fert}, x_{prot}, x_{irr}, economic size x_{size} and land uses x_{cer}, x_{mai}, x_{othar} and x_{othact} on production. As the absolute derivate $\partial y_1 / \partial x_k = \partial \ln y_1 / \partial \ln x_k \cdot (y_1 / x_k)$ corresponds to the marginal product for inputs MP_k, $\varepsilon_{y1,k}$ represent the 'output share' of x_k ($\varepsilon_{y1,k} = MP_k x_k y_1$). The sum of the output shares represents a scale economy measure, where $\Sigma\varepsilon_{y1,k} > 1$ implies increasing returns to scale; more inputs generate a more than proportionate increase in output (Morrison Paul and Nehring, 2005).

Also in Eq. 6 the interaction terms are of special interest. $C_{kf} = \gamma_{fk}$ ln r_f represents the effect of climate, subsidies or time (r_f) on input composition. For example, a positive $C_{xsize,rtmean}$ would imply an increase in $\varepsilon_{y1,xsize}$ and thus increasing output share from x_{size} at higher r_{tmean}. At higher r_{tmean} the x_{size} is thus larger, which can also be interpreted as farms with large x_{size} being better adapted to higher temperatures. If farms are allocatively efficient and aim to maximize outputs, they increase x_{size} at higher r_{tmean}.

Our farm typology is based on intensity, size and land use. Significant γ_{fk} estimates can indicate external factors (or 'regional conditions') that determine the presence of different farm types. If x_k share changes due to r_{tmean}, this can be considered as an adaptation strategy (it may however just as well be maladaptation). By this means we can also assess the impact of climate, subsidies and time on land use. A change of crop choice is considered to be an adaptation strategy (e.g. Smit and Skinner, 2002), and is often implicitly included in climate impact models (e.g. IMAGE team, 2001). Although only four land uses are distinguished, the C_{kf} measures can give some empirical evidence on crop choice changes in relation to climate change.

5.3 Results

5.3.1 Farm performance

In all regions the explained variance in outputs is very high, R^2s are close to 1. Many parameter estimates, including interaction terms, are significant. Effects of inputs and external factors are different in different regions however. The technical efficiency (TE) is high in all regions and ranges from Italy (TE = 0.85, sd = 0.07), Spain (TE = 0.86, sd = 0.07), United Kingdom (TE = 0.87, sd = 0.09), Scandinavia (TE = 0.88; sd = 0.09), Greece (TE = 0.88; sd = 0.07), France (TE = 0.90, sd = 0.04), Germany (TE = 0.90, sd = 0.06) to the Benelux (TE = 0.94, sd = 0.03). This suggests that farms are managed most efficiently in North-West Europe. In regions with lower average technical efficiency there are more farms further away from the frontier, the 'best practice' in the region. But it also indicates there is room for improvement. Significant differences between different farm types and years are observed, but as variables related to farm types and time are included as explaining variables (the frontier for technical efficiency is related to these variables), these will be reflected in the constructed measures.

5.3.2 Impacts and adaptation to changes in climate and subsidies

Climate impacts on production

The elasticity measures of the external factors $\varepsilon_{y1,f}$ (Table 5.2) indicate that the effect of r_{tmean} and r_{pmean} is fairly strong in relation to r_{subs} and r_{year} (Table 5.3) The effect is different per region however. In Greece a 1% increase in r_{tmean} would at the mean result in a 0.48% increase in total production. A large x_{irr} increases this positive effect significantly ($C_{rtmean,xirr}$). More irrigation can thus be considered as an adaptation to higher temperatures in Greece. In most other regions the effect of x_{irr} is small, while in Italy a larger x_{irr} enlarges the negative effect of r_{tmean}. This may be related to irrigated agriculture growing more water demanding crops (while higher r_{tmean} increases evapotranspiration and thus reduces water availability).

Also in Scandinavia the effect of r_{tmean} is positive; in other regions and especially France the effect is negative (Figure 5.2). Factors that reduce or increase impacts of r_{tmean} differ per region. For example, in Scandinavia and Greece x_{fert} reduces positive impacts; in France, Italy and the UK x_{fert} significantly reduces negative impacts, while in Spain x_{fert} amplifies negative impacts. These results may be due to activities related to fertilizer use and suggest that in Scandinavia, Greece and Spain and agricultural activities relying on a high fertilizer use are less profitable when temperatures increase, while the opposite is the case in other regions.

Table 5.2. The impact of climatic factors (external factors r_f) on total production ($\varepsilon_{y1,f}$) and factors that influence these impacts (C). Parameters in bold are significant with p<0.05, in italic with p<0.10.

		Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
α_{rtmean}		9.141	2.889	*-3.507*	-0.661	*2.658*	-0.643	6.586	0.230
$C_{rtmean,m}$	y_{mai}	-0.192	0.263	-0.091	**-1.943**	0.073	1.624		
	y_{othar}	0.094	0.108	**-2.005**	-0.003	0.068	0.039	-0.030	0.023
	y_{othact}	0.102	0.093	**0.218**	*-0.362*	-0.190	-0.172	0.248	**0.277**
$C_{rtmean,k}$	x_{fert}	-6.997	-1.471	**1.883**	**6.749**	1.086	0.173	*8.412*	**-2.641**
	x_{prot}	1.459	0.144	**2.177**	**4.259**	**-4.841**	0.073	-0.769	**1.092**
	x_{size}	0.605	**1.604**	0.034	**-6.675**	1.263	-0.390	-4.765	-0.505
	x_{irr}	**2.484**	0.058	**-0.127**	-0.001	-0.004	0.000	-0.011	-0.002
	x_{cer}	2.348	-0.003	**-2.988**	**4.419**	-0.018	-1.756	1.096	0.938
	x_{mai}	-1.310	-0.063	-0.032	**-3.700**	0.023	-0.276		
	x_{othar}	0.344	0.177	0.218	-0.557	-0.141	0.952	-0.155	-0.105
	x_{othact}	-0.239	-0.069	0.034	0.631	0.199	0.397	-0.614	-0.096
$C_{rtmean,f}$	r_{tmean}	-6.964	-3.613	1.432	-4.797	**-3.013**	-0.480	-4.740	0.010
	r_{pmean}	-0.889	-0.043	**2.324**	1.227	0.310	0.274	*-4.017*	0.312
	r_{subs}	0.404	-0.043	0.167	1.002	**2.448**	0.023	-1.961	0.550
	r_{year}	0.095	-0.208	0.097	-0.168	0.054	0.082	*0.586*	0.009
$\varepsilon_{y1,rtmean}$		0.484	-0.177	-0.166	-0.581	-0.025	-0.079	-0.134	0.092
α_{rpmean}		1.848	0.074	0.397	**1.984**	0.622	-1.231	0.125	0.042
$C_{rpmean,m}$	y_{mai}	0.026	**-0.065**	0.006	**0.203**	**-0.317**	*0.613*		
	y_{othar}	0.136	0.002	**-0.216**	-0.001	-0.023	0.042	**0.016**	-0.003
	y_{othact}	-0.011	**-0.044**	**0.059**	**0.142**	0.045	-0.037	0.044	0.070
$C_{rpmean,k}$	x_{fert}	**-1.838**	-0.047	**-1.306**	**-1.718**	-0.268	0.310	-2.900	*1.279*
	x_{prot}	0.935	0.021	**0.698**	0.461	*0.870*	0.005	0.962	-0.802
	x_{size}	-0.276	-0.091	*0.390*	0.177	-0.106	-0.214	*2.308*	-0.452
	x_{irr}	**-0.521**	-0.007	0.011	0.000	*0.020*	-0.001	0.029	0.012
	x_{cer}	0.097	0.025	**-0.267**	0.242	0.268	-0.537	-0.063	0.508
	x_{mai}	0.209	**0.015**	-0.005	**0.410**	*-0.076*	*-0.108*		
	x_{othar}	0.098	-0.006	-0.021	**-0.237**	0.068	0.218	-0.096	-0.219
	x_{othact}	**0.493**	0.009	0.052	-0.117	0.003	0.124	-0.034	-0.144
$C_{rpmean,f}$	r_{tmean}	-0.699	-0.034	**1.708**	0.819	0.200	0.185	*-2.531*	0.184
	r_{pmean}	-0.573	0.032	**-1.390**	**-1.453**	**-1.192**	0.854	*1.911*	0.143
	r_{subs}	0.164	**0.098**	0.030	**-0.933**	-0.265	0.025	0.443	-0.388
	r_{year}	-0.058	0.039	*-0.043*	0.048	**0.179**	**-0.339**	**-0.229**	**-0.291**
$\varepsilon_{y1,rpmean}$		0.030	0.020	0.102	0.026	0.028	-0.093	-0.015	-0.060

Note: Variables are described in Table 5.1 and measures are described in section 5.2.3. The elasticity $\varepsilon_{y1,f}$ is the sum of the intercept α_f and interaction terms C. Interaction terms represent the influence of outputs y_m, inputs x_j and external factors r_f on $\varepsilon_{y1,f}$.

Other factors that significantly change impacts of r_{tmean} on production, are among others x_{size} in France (smaller farms adapt better); x_{cer} in Italy (negative), Spain and France (positive); and y_{mai} and x_{mai} (negative) in France. Maize thus seems more vulnerable to higher temperatures than other cereals in France, but this is not necessarily the case in other regions. In Italy (and France and Benelux) a higher r_{pmean}

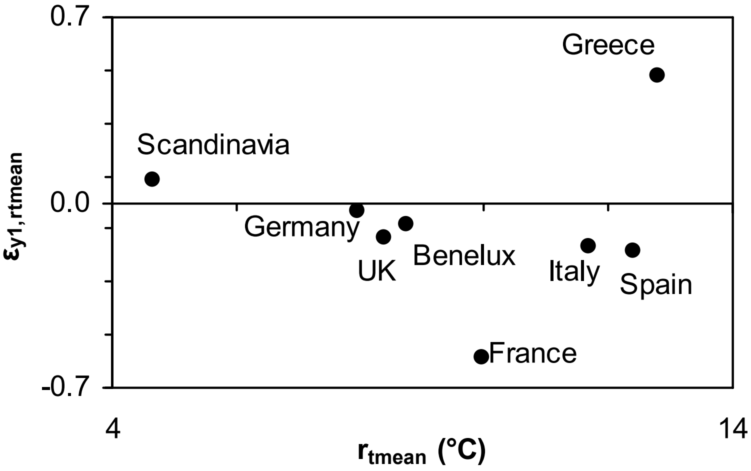

Figure 5.2. The impact of r_{tmean} on production y_1 ($\varepsilon_{y1,rtmean}$) per region in relation to the average r_{tmean} Note: averages are based on the farm type data included in the analysis. This average may differ from the averages based on regional temperatures. For example, in Germany more farms are located in relatively colder regions and therefore the average is lower than the average based on regional temperatures.

compensates for a high r_{tmean}, but the opposite is the case for the UK. Lastly, the only region where $C_{rtmean,ryear}$ is (almost) significant, is the UK. This positive interaction term suggests that adaptation to higher temperatures improves over the years in the UK, but not in other regions.

Next to changes in temperatures, also changes in precipitation have some impact. The effect of r_{pmean} is positive in most regions, but slightly negative in the Benelux, UK and Scandinavia (Figure 5.3). The negative effect is also increasing in time (negative $C_{rpmean,ryear}$) in these last regions (including Italy). Only in Greece x_{irr} substantially changes the $\varepsilon_{y1,rpmean}$. An influence of x_{irr} would be obvious, as irrigated

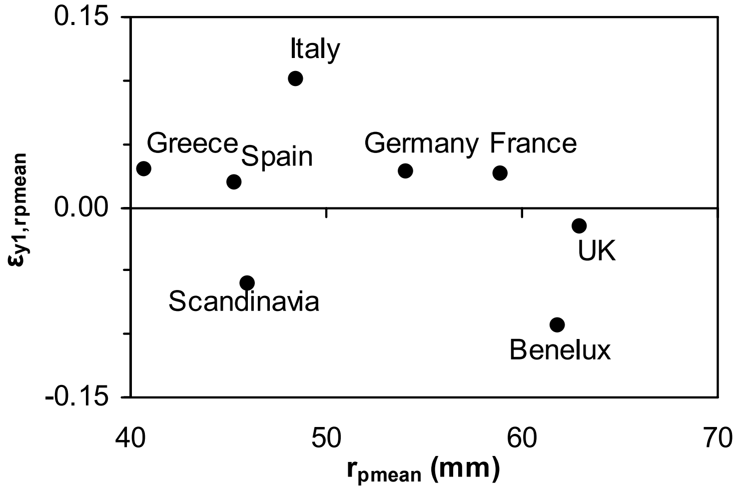

Figure 5.3. The impact of r_{pmean} on production y_1 ($\varepsilon_{y1,rpmean}$) per region in relation to the average r_{pmean}.

areas should be less vulnerable to variability in precipitation. High x_{fert} reduces the positive effect of r_{pmean} in many regions. This also means that a reduction in r_{pmean} has less impact when x_{fert} is high. In France, farms with larger x_{mai} and y_{mai} benefit more from more precipitation. The effect of output and area of other arable crops and other agricultural activities varies per region.

Policy impacts and time trends in production

Subsidies can increase positive impacts of r_{tmean} in Germany (Table 5.3; $C_{rtmean, rsubs}$ = 2.44), but the impact on the overall production is small ($\varepsilon_{y1,subs}$ = 0.003). So, subsidies can increase the adaptive capacity to climate change in some regions, while overall there is little impact. The negative intercept (α_{subs}=−0.566) is pushed to a slightly positive value by adding the complementary effects x_{fert}, x_{size} and r_{tmean}.

In general, the overall impact of subsidies is relatively small, but is significantly influenced by inputs, outputs and external factors. The impact of these factors differs per region. Subsidies are more important (contribute more to production) on large farms ($C_{rsubs,xsize}$) in Mediterranean regions and Germany, while less on large farms in Scandinavia. The impact of land uses differs, but the influence of subsidies generally decreases when x_{othar} or x_{othact} increases. As subsidies are mainly supplied for cereal areas, this is according to expectations. Also obvious is that the influence of subsidies decreases in time. As the focus in the CAP switched from increasing food production to more environmental issues, it is not surprising that subsidies contribute less to production.

Production has changed little over time for the years considered, but decreased slightly in France, Germany and Scandinavia. An increasing r_{pmean} negatively influences the time trend in production in the Benelux, Scandinavia, UK and Italy, and is positive for Germany. An increasing r_{tmean} increases the time trend in the UK. The impact of subsidies on the time trend is negative, as was already observed. Furthermore, land uses and outputs influence the time trend significantly in Mediterranean regions. More x_{mai} and y_{mai} decrease the time trend. A larger x_{othact} increases the time trend, while more y_{othact} (ceteris paribus, so with a constant area) has a negative effect. This implies that increasing areas for other agricultural activities have a positive impact, but where y_{othact} is very high (other agricultural activities with a high output/ha, e.g horticulture) this is not the case.

5.3.3 Impacts of climate, subsidies and inputs on output composition

Climate and policy impacts on output composition

Climate and subsidy changes have a different impact on different outputs and can hence influence output composition. Recall that for outputs, negative terms with respect to y_m denote a greater contribution of output y_m in total output relative to y_1 (y_{cer}). Positive cross-terms thus reduce the contribution of output y_m to total output when the associated variable increases.

We observe in Table 5.4 that output elasticities $\varepsilon_{y1,m}$ are indeed negative for all

Table 5.3. The impact of subsidies and time (external factors r_f) on total production ($\varepsilon_{y1,f}$) and factors that influence these impacts (C). Parameters in bold are significant with p<0.05, in italic with p<0.10.

		Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
α_{rsubs}		0.231	-0.052	-0.049	-0.201	**-0.566**	0.015	0.321	**-0.851**
$C_{rsubs,m}$	y_{mai}	**0.033**	0.000	**0.008**	-0.022	0.067	-0.015		
	y_{othar}	**0.306**	**0.015**	**-0.014**	0.001	-0.007	0.004	-0.002	0.015
	y_{othact}	**-0.071**	*-0.003*	-0.001	0.031	-0.028	-0.010	**0.054**	**0.126**
$C_{rsubs,k}$	x_{fert}	0.942	-0.015	0.049	0.159	**0.609**	-0.019	0.417	0.819
	x_{prot}	**-1.626**	-0.007	*-0.033*	0.206	*-0.352*	-0.034	*-0.261*	**0.911**
	x_{size}	*0.467*	**0.053**	*0.035*	-0.222	**0.291**	0.045	-0.204	**-1.434**
	x_{irr}	-0.183	**-0.009**	0.002	-0.001	-0.005	-0.001	-0.004	**0.012**
	x_{cer}	0.155	**0.013**	**-0.040**	0.183	-0.250	0.005	*0.163*	-0.249
	x_{mai}	**0.284**	0.000	**0.004**	-0.035	0.017	0.003		
	x_{othar}	**-0.377**	-0.002	-0.003	-0.016	**-0.190**	-0.008	0.013	*-0.251*
	x_{othact}	-0.013	-0.003	0.000	0.020	-0.050	0.003	**-0.305**	**-0.240**
$C_{rsubs,f}$	r_{tmean}	0.074	-0.009	0.035	0.165	**0.386**	0.005	-0.307	0.073
	r_{pmean}	0.038	**0.026**	0.009	**-0.231**	-0.065	0.007	0.110	-0.088
	r_{subs}	-0.220	-0.004	-0.003	-0.085	**0.183**	0.005	0.036	**1.234**
	r_{year}	-0.021	**-0.020**	**-0.007**	0.015	**-0.038**	-0.006	*-0.016*	*-0.092*
$\varepsilon_{y1,rsubs}$		0.017	-0.015	-0.009	-0.032	0.003	0.000	0.017	-0.016
α_{ryear}		-0.020	*0.108*	-0.005	0.053	**-0.114**	0.119	0.017	0.081
$C_{ryear,m}$	y_{mai}	*-0.005*	**-0.013**	*-0.004*	0.000	-0.021	*0.047*		
	y_{othar}	**-0.056**	0.006	**0.023**	0.000	-0.001	*0.021*	0.001	*0.004*
	y_{othact}	-0.004	**-0.007**	**-0.007**	0.005	0.002	0.002	0.006	0.009
$C_{ryear,k}$	x_{fert}	-0.112	0.019	-0.023	**-0.127**	0.057	**0.237**	-0.123	0.106
	x_{prot}	*0.105*	**-0.028**	-0.023	0.053	0.024	-0.128	0.002	0.080
	x_{size}	**0.152**	0.000	0.005	0.041	0.044	-0.074	-0.024	0.030
	x_{irr}	0.024	-0.001	0.002	0.000	**0.000**	**0.000**	0.002	**0.000**
	x_{cer}	**-0.105**	**0.013**	**0.032**	0.011	0.029	0.034	0.034	-0.009
	x_{mai}	*-0.037*	0.002	**-0.004**	-0.004	-0.005	**-0.009**		
	x_{othar}	**0.058**	-0.004	0.003	-0.002	**-0.032**	-0.054	-0.003	0.021
	x_{othact}	**0.034**	**0.010**	**0.010**	*-0.026*	*-0.019*	-0.015	*0.049*	-0.022
$C_{ryear,f}$	r_{tmean}	0.038	-0.073	0.037	-0.062	0.018	0.030	*0.199*	0.002
	r_{pmean}	-0.029	0.017	*-0.023*	0.027	**0.091**	**-0.182**	**-0.124**	**-0.128**
	r_{subs}	-0.047	**-0.033**	**-0.014**	0.034	**-0.079**	-0.010	*-0.034*	*-0.179*
$\varepsilon_{y1,ryear}$		0.011	0.003	0.002	-0.027	-0.003	0.017	0.021	-0.023

Note: Variables are described in Table 5.1 and measures are described in section 5.2.3. The elasticity $\varepsilon_{y1,f}$ is the sum of the intercept α_f and interaction terms C. Interaction terms represent the influence of outputs y_m, inputs x_j and external factors r_f on $\varepsilon_{y1,f}$.

outputs in all regions (except y_{othar} in Scandinavia, for which output is very small), thus more y_m will yield more total output. In most regions the impact of output from cereals ($\varepsilon_{Do,y1}$) is large relative to other outputs. So an increase in cereal yields (cereal output with constant area), has more impact on total output than increases in yields of other products. Maize output has a larger impact in Spain and Greece, while in the UK other agricultural activities have quite a large influence.

Table 5.4. The impact of other outputs, inputs and external factors (C) on total output composition ($\varepsilon_{y1,m}$). Parameters in bold are significant with p<0.05, in italic with p<0.10.

		Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
α_{ymai}		**-1.202**	**-0.329**	-0.056	**-1.502**	-0.284	**1.003**		
$C_{ymai,m}$	y_{mai}	**-0.124**	**-0.395**	**-0.009**	**0.038**	0.006	-0.497		
	y_{othar}	**-0.265**	**-0.145**	**0.038**	**-0.002**	**-0.022**	0.005		
	y_{othact}	**-0.092**	**-0.258**	**-0.017**	**-0.036**	-0.005	**-0.287**		
$C_{ymai,k}$	x_{fert}	0.563	0.187	0.010	**0.950**	0.130	0.022		
	x_{prot}	**-0.707**	0.118	-0.018	**0.250**	0.317	-0.904		
	x_{size}	**2.085**	**0.269**	**-0.092**	**-0.599**	0.080	**0.685**		
	x_{irr}	0.121	-0.008	**0.004**	**0.003**	*-0.006*	-0.002		
	x_{cer}	*0.241*	**0.042**	**0.046**	**-0.138**	-0.135	0.091		
	x_{mai}	**-0.963**	**0.080**	**-0.002**	*0.010*	0.002	**0.062**		
	x_{othar}	-0.075	**-0.065**	**0.009**	**-0.184**	-0.085	0.204		
	x_{othact}	-0.030	**-0.029**	**0.036**	**-0.114**	-0.038	-0.024		
$C_{ymai,f}$	r_{tmean}	0.589	-0.132	0.054	**1.337**	-0.021	-0.399		
	r_{pmean}	-0.103	**0.041**	-0.004	**-0.209**	**0.141**	*-0.223*		
	r_{subs}	**-0.547**	0.000	**-0.022**	0.093	-0.122	0.018		
	r_{year}	*0.035*	**0.019**	*0.006*	0.000	0.018	*-0.032*		
$\varepsilon_{y1,ymai}$		-0.473	-0.604	-0.018	-0.103	-0.024	-0.275		
α_{yothar}		-0.702	*-0.217*	*0.297*	**-0.202**	-0.120	-0.329	-0.083	0.185
$C_{yothar,m}$	y_{mai}	**0.058**	**0.135**	**-0.036**	**0.014**	**0.174**	-0.015		
	y_{othar}	0.151	**-0.036**	**0.050**	**-0.004**	**-0.007**	*-0.112*	**0.003**	**-0.003**
	y_{othact}	**0.117**	**0.178**	**0.124**	**0.092**	**0.352**	**0.218**	**0.037**	0.038
$C_{yothar,k}$	x_{fert}	0.838	-0.008	**0.871**	0.066	0.458	0.002	0.045	0.150
	x_{prot}	0.043	0.013	-0.050	**-0.130**	**-0.931**	-0.097	-0.055	0.040
	x_{size}	**-2.183**	**-0.257**	**-0.449**	**-0.384**	**-1.010**	0.059	-0.094	-0.588
	x_{irr}	0.031	-0.001	**-0.016**	**0.001**	0.004	-0.003	**0.006**	*0.001*
	x_{cer}	0.078	-0.006	**0.424**	**0.465**	**0.882**	0.070	**0.076**	**0.437**
	x_{mai}	**0.447**	**-0.034**	**-0.014**	**0.026**	**0.045**	0.013		
	x_{othar}	0.005	0.004	**0.045**	-0.008	-0.035	-0.017	-0.001	**0.117**
	x_{othact}	**-0.360**	**-0.008**	**-0.198**	**-0.064**	**0.094**	-0.065	0.001	0.023
$C_{yothar,f}$	r_{tmean}	0.064	0.050	**-1.134**	-0.012	0.152	0.030	0.066	-0.061
	r_{pmean}	0.117	0.001	**-0.166**	-0.007	-0.080	0.047	**-0.056**	0.012
	r_{subs}	**1.129**	**0.034**	**-0.037**	0.025	-0.096	0.015	0.024	-0.299
	r_{year}	**-0.095**	0.008	**0.033**	0.002	-0.009	*0.044*	-0.006	*-0.043*
$\varepsilon_{y1,yothar}$		-0.263	-0.145	-0.257	-0.122	-0.127	-0.139	-0.036	0.011
$\alpha_{yothact}$		-0.284	-0.056	**-0.265**	0.181	-0.065	-0.083	-0.506	0.058
$C_{yothact,m}$	y_{mai}	**0.028**	**0.234**	**0.021**	**0.050**	0.012	**0.610**		
	y_{othar}	**0.163**	**0.173**	**0.161**	**0.019**	**0.117**	**0.151**	**-0.011**	-0.015
	y_{othact}	0.000	0.001	0.001	**-0.176**	-0.014	-0.169	**-0.225**	*-0.109*
$C_{yothact,k}$	x_{fert}	-0.108	**-0.190**	**-0.299**	-0.312	**-0.721**	-0.141	0.352	-0.170
	x_{prot}	0.179	0.014	0.035	-0.114	0.229	0.370	0.117	**0.369**
	x_{size}	**-0.455**	**-0.170**	**-0.135**	0.079	**-0.705**	-0.387	-0.379	**-1.538**
	x_{irr}	**0.290**	0.005	**0.006**	**0.004**	**-0.017**	-0.002	**-0.090**	0.006
	x_{cer}	0.108	**-0.076**	**0.242**	**-0.370**	**1.114**	-0.480	**-0.473**	-0.087
	x_{mai}	**0.210**	**-0.054**	**0.008**	**0.138**	0.013	**-0.107**		
	x_{othar}	0.031	-0.003	0.005	**0.259**	0.008	0.130	0.035	-0.127
	x_{othact}	0.094	**0.006**	0.002	0.007	-0.032	0.065	*0.179*	0.032
$C_{yothact,f}$	r_{tmean}	0.095	0.042	**0.160**	*-0.344*	-0.140	-0.089	0.166	**0.294**
	r_{pmean}	-0.013	**-0.025**	**0.058**	**0.202**	0.051	-0.028	0.046	0.126
	r_{subs}	**-0.362**	*-0.006*	-0.003	0.181	-0.130	-0.027	**0.229**	**1.003**
	r_{year}	-0.010	**-0.009**	**-0.013**	0.013	0.004	0.002	0.011	0.037
$\varepsilon_{y1,yothact}$		-0.036	-0.115	-0.014	-0.182	-0.277	-0.187	-0.548	-0.122
$\varepsilon_{Do,y1}$		-0.228	-0.137	-0.712	-0.593	-0.572	-0.399	-0.417	-0.889

In France, maize output is significantly reduced relative to other cereals when r_{tmean} is higher (this can also be observed in Table 5.2, $C_{rtmean,ymai}$). The contribution of output of other agricultural activities rises with increasing r_{tmean}. In Italy the contribution of y_{othar} significantly increases with r_{tmean}, while y_{othact} decreases. Also in Scandinavia y_{othact} decreases relative to other cereals. Precipitation (r_{pmean}) has a significant influence on output composition in all regions, except for Greece and Benelux. More r_{pmean} decreases maize output relative to other cereals in Spain and Germany, and increases it in France. Maize is thus less influenced by lower precipitation in Spain and Greece, probably because maize is more often irrigated. Although not significant, the opposite effect of x_{irr} confirms this. Irrigated maize in France may be more dependent on fluctuations in water available for irrigation. Output of other arable crops (y_{othar}) is increased with a high r_{pmean} in Italy, UK and Scandinavia and output of other agricultural activities y_{othact} increases in Scandinavia and decreases in Italy and France.

Subsidies (r_{subs}) favour maize production and other agricultural activities relative to other cereals in Mediterranean regions. Output of other arable crops is decreased in Greece and Spain, but the opposite is the case in Italy. In Scandinavia more subsidies lead to a lower contribution of y_{othact}. Over time, the contribution of maize output has reduced in Mediterranean regions. The influence of r_{year} on the share of y_{othar} and y_{othact} differ per region.

Contribution of inputs and outputs to output composition

Also the influence of inputs differs per output. On farms with higher x_{fert}, an increase in y_{mai} has a smaller impact on total production (Table 5.4; $C_{ymai,xfert}$). This is also the case for y_{othar}, but the opposite is true for y_{othact}. For y_{mai} and y_{othar} this is according to agronomic relationships, with a decreasing marginal product when more fertilizers are used (e.g. Mengel, 1983). Other agricultural activities are a mix of livestock, permanent cropping, horticulture and other practices; the positive impact suggests more output from fertilizer intensive activities.

An increase in y_{othar} and y_{othact} has more effect on total output on farms with a larger economic size. This is variable for y_{mai}. In Greece, y_{mai} contribution can especially increase on small farms (positive $C_{ymai,xsize}$). Irrigation has a small effect on changes in output composition, but significant effects are observed. Increases in x_{irr} reduce the $\varepsilon_{y1,ymai}$ in Italy and France (an increase in y_{mai} has less effect on total output), while increasing it in Germany. Also for x_{othact} the effect is negative in these regions.

More area for a specific output doesn't necessarily lead to more relative output. In Greece and Italy more x_{mai} will raise the contribution of y_{mai}, but in Spain, France and Benelux it will reduce the contribution. Also for other arable crops and other agricultural activities more area often reduces the marginal product.

Outputs can also complement or substitute each other. Generally, the share of maize output increases more when also y_{othar} and y_{othact} increase. The elasticity of y_{othar} and y_{othact} however decrease relative to other cereals with higher y_{mai}, while y_{othar} and y_{othact} also negatively influence each other.

5.3.4 Influence of inputs on production and adaptation strategies

Intensity, size and adaptation

The contribution of fertilizer use, crop protection use, economic size, irrigation and land uses to production can be observed from $\varepsilon_{y1,k}$ (Table 5.5 and 5.6). The interaction terms C_{kf} indicate whether x_k is changed as a result of adaptation to climate, subsidies or in time in general.

A higher use of fertilizers (x_{fert}) has a positive contribution to outputs in most regions, but negative in the UK and Scandinavia. A negative contribution suggests that

Table 5.5a. Contribution of inputs to production ($\varepsilon_{y1,k}$) and adaptation strategies (C_{kf}). Parameters in bold are significant with $p<0.05$, in italic with $p<0.10$.

		Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
α_{xfert}		*1.809*	0.260	0.193	0.290	0.367	-0.391	-1.278	0.043
$C_{xfert,m}$	y_{mai}	-0.036	-0.075	-0.003	**-0.233**	-0.075	-0.016		
	y_{othar}	0.242	-0.004	**0.309**	0.002	0.034	0.001	-0.003	-0.008
	y_{othact}	-0.022	**-0.085**	**-0.082**	-0.055	**-0.161**	-0.047	0.086	-0.023
$C_{xfert,k}$	x_{fert}	-1.049	0.039	**-0.652**	-0.785	**-1.677**	0.927	0.054	-0.340
	x_{prot}	-0.527	0.016	-0.003	-0.042	-0.361	-0.080	0.075	-0.273
	x_{size}	0.208	**0.204**	-0.162	-0.135	**1.334**	-0.349	-0.562	-0.570
	x_{irr}	-0.205	0.003	**0.029**	-0.001	*-0.018*	**-0.019**	0.014	0.004
	x_{cer}	**0.855**	0.002	**0.360**	**0.486**	-0.067	-0.128	0.056	-0.054
	x_{mai}	-0.326	**0.023**	-0.006	**-0.513**	-0.014	0.003		
	x_{othar}	0.018	-0.002	0.002	**-0.188**	-0.158	-0.108	**0.095**	0.184
	x_{othact}	-0.085	-0.016	0.032	**0.441**	0.025	0.032	0.436	0.080
$C_{xfert,f}$	r_{tmean}	-1.363	-0.297	**0.378**	**1.138**	0.179	0.030	*1.363*	**-0.378**
	r_{pmean}	**-0.456**	-0.012	**-0.357**	**-0.434**	-0.068	0.079	-0.746	*0.311*
	r_{subs}	1.003	-0.014	0.047	0.162	**0.637**	-0.017	0.432	0.877
	r_{year}	-0.054	0.011	-0.012	**-0.058**	0.028	**0.112**	-0.058	0.059
$\varepsilon_{y1,xfert}$		0.012	0.052	0.073	0.075	0.004	0.029	-0.038	-0.087
α_{xprot}		0.035	0.002	**-0.682**	**-0.874**	-0.179	0.011	0.174	-0.171
$C_{xprot,m}$	y_{mai}	**0.046**	-0.053	0.007	**-0.063**	-0.186	0.650		
	y_{othar}	0.013	0.006	-0.019	**-0.005**	**-0.071**	-0.023	0.005	-0.002
	y_{othact}	0.039	0.007	0.010	-0.021	0.052	0.126	0.032	**0.055**
$C_{xprot,k}$	x_{fert}	-0.544	0.017	-0.004	-0.043	-0.369	-0.082	0.085	-0.300
	x_{prot}	-0.077	0.021	**0.089**	**0.885**	**3.278**	0.444	**-1.094**	**0.067**
	x_{size}	**1.282**	-0.044	0.101	-0.204	**-0.940**	-0.554	**1.021**	-0.306
	x_{irr}	*0.335*	-0.001	0.005	**0.004**	*-0.015*	0.013	-0.001	0.000
	x_{cer}	-0.280	0.059	-0.018	**-0.549**	-0.391	-0.404	0.105	0.055
	x_{mai}	**0.406**	0.010	0.002	**-0.107**	-0.043	*-0.127*		
	x_{othar}	**-0.442**	*-0.017*	**-0.037**	**0.187**	0.050	0.170	0.030	*-0.146*
	x_{othact}	**0.510**	**0.022**	**0.042**	-0.092	0.006	0.018	-0.078	*-0.211*
$C_{xprot,f}$	r_{tmean}	0.293	0.032	**0.461**	**0.735**	**-0.816**	0.013	-0.140	**0.172**
	r_{pmean}	0.239	0.006	**0.201**	0.119	*0.227*	0.001	0.278	-0.215
	r_{subs}	**-1.787**	-0.007	*-0.033*	0.215	*-0.376*	-0.030	*-0.303*	**1.074**
	r_{year}	*0.052*	**-0.018**	-0.013	0.025	0.012	-0.062	0.001	0.048
$\varepsilon_{y1,xprot}$		0.121	0.041	0.112	0.214	0.240	0.164	0.113	0.119

Table 5.5b. Continued.

		Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
α_{xsize}		-0.667	-0.281	*0.461*	**1.845**	0.065	**0.873**	1.050	**1.174**
$C_{xsize,m}$	y_{mai}	**-0.187**	**-0.152**	**0.044**	**0.207**	-0.064	**-0.639**		
	y_{othar}	**-0.889**	**-0.156**	**-0.225**	**-0.020**	**-0.104**	0.018	0.010	**0.043**
	y_{othact}	**-0.134**	**-0.106**	**-0.052**	0.020	**-0.219**	-0.170	-0.130	**-0.288**
$C_{xsize,k}$	x_{fert}	0.294	**0.286**	-0.229	-0.190	**1.849**	-0.466	-0.796	-0.792
	x_{prot}	**1.754**	-0.055	0.135	-0.281	**-1.274**	-0.718	**1.286**	-0.387
	x_{size}	0.435	0.201	0.252	0.846	**0.826**	1.109	0.147	**3.369**
	x_{irr}	0.216	-0.014	**-0.032**	**-0.004**	**0.062**	-0.005	**0.091**	-0.008
	x_{cer}	**-0.660**	-0.083	**-0.540**	**-0.656**	**-1.659**	0.423	*-0.367*	**-1.220**
	x_{mai}	**-1.482**	**0.036**	**0.023**	**0.421**	-0.027	**0.113**		
	x_{othar}	**0.673**	0.012	-0.029	-0.051	**0.331**	-0.163	**-0.100**	0.309
	x_{othact}	-0.050	**-0.035**	**0.111**	*-0.154*	-0.113	-0.007	0.013	0.296
$C_{xsize,f}$	r_{tmean}	0.166	**0.453**	0.010	**-1.586**	0.289	-0.090	-1.093	-0.100
	r_{pmean}	-0.097	-0.033	*0.151*	0.063	-0.037	-0.073	*0.840*	-0.153
	r_{subs}	*0.702*	**0.072**	*0.047*	-0.320	**0.421**	0.052	-0.299	**-2.136**
	r_{year}	**0.104**	0.000	0.004	0.026	0.030	-0.047	-0.016	0.023
$\varepsilon_{y1,xsize}$		0.180	0.142	0.129	0.167	0.376	0.209	0.637	0.130
α_{xirr}		*-0.826*	0.008	0.090	0.019	-0.023	-0.027	-0.075	**-0.078**
$C_{xirr,m}$	y_{mai}	-0.013	0.007	**-0.007**	**0.016**	*-0.010*	-0.009		
	y_{othar}	0.015	-0.001	**-0.028**	**-0.001**	-0.001	0.005	**0.002**	*-0.001*
	y_{othact}	**0.101**	0.005	**0.008**	**-0.018**	**0.012**	0.004	**0.083**	0.007
$C_{xirr,k}$	x_{fert}	-0.342	0.008	**0.146**	0.032	*0.053*	**0.159**	-0.055	0.043
	x_{prot}	*0.543*	-0.003	0.025	**-0.101**	*0.045*	-0.105	0.002	0.003
	x_{size}	0.256	-0.024	**-0.114**	**0.071**	**-0.136**	0.032	**-0.246**	-0.053
	x_{irr}	-0.046	**0.010**	*0.004*	0.000	**-0.004**	-0.002	**0.011**	0.000
	x_{cer}	**0.525**	-0.003	-0.017	**-0.081**	0.023	0.010	**0.221**	-0.018
	x_{mai}	-0.107	-0.002	*-0.003*	**0.034**	-0.002	0.001		
	x_{othar}	**-0.260**	-0.001	-0.003	0.001	**0.016**	-0.021	0.006	*0.021*
	x_{othact}	-0.121	0.004	0.000	0.007	**0.022**	**-0.047**	0.060	**-0.057**
$C_{xirr,f}$	r_{tmean}	**0.809**	0.027	**-0.127**	0.004	0.002	-0.001	0.007	-0.003
	r_{pmean}	**-0.216**	-0.004	0.015	-0.003	*-0.016*	0.002	-0.029	0.029
	r_{subs}	-0.326	**-0.021**	0.010	0.015	0.015	0.006	0.015	**0.120**
	r_{year}	0.019	**-0.001**	0.004	-0.002	0.000	0.001	-0.004	**-0.001**
$\varepsilon_{y1,xirr}$		0.010	0.011	0.003	-0.005	-0.004	0.009	-0.002	0.012

fertilizers are used in abundance. In both regions the impact of climate variables is significant, but contrasting. At higher r_{tmean} the contribution of x_{fert} increases in the UK, and also in Italy and France. In Scandinavia the impact of x_{fert} decreases at higher r_{tmean}. In most regions a low r_{pmean} also increases the contribution of x_{fert}, suggesting that fertilizer use has less effect with more rainfall. The x_{cer} has a large contribution to $\varepsilon_{y1,xfert}$ in Greece, Italy and France, implying that the area of cereal areas has a positive impact on the impact of fertilizers on total output. This is also apparent from the $C_{xfert,m}$ terms, which are mostly negative and thus other outputs are less important in relation to y_{cer}. Subsidies generally increase the importance of x_{fert}. There is relatively little change in time, but the impact of r_{year} is significantly negative in France and positive in Benelux.

Crop protection use mainly contributes to production in Mediterranean regions where permanent cropping (part of x_{othact}) is high. In other regions none of the land uses really seems to benefit from more x_{prot}. The effect of climatic conditions is quite substantial however. Both at higher r_{tmean} and higher r_{pmean} an increasing x_{prot} has more effect. This suggests that a higher use of crop production products is applied as an adaptation strategy to more pests and diseases occurring at higher temperatures and more precipitation. In Germany the importance of x_{prot} however reduces with higher r_{tmean}. The contribution of x_{prot} also reduces in most regions when subsidies increase.

In all regions farm size has a positive impact on total production ($\varepsilon_{y1,xsize}$). The contribution of x_{size} rises at an increasing rate ($C_{xsize,xsize}$). In Greece and Spain, the intercept is negative, but is pushed to a positive value by other effects. In Greece x_{prot} and r_{subs} are complementary with x_{size}; in Spain x_{fert} and r_{subs} raise the effect of x_{size}, while also r_{tmean} is nearly significant and has a high value. A higher x_{cer}, decreases the effect of increasing farm size; for other land uses the effect varies per region. In France, at high r_{tmean} an increase in x_{size} has less effect. Only in the UK and Italy r_{pmean} has an impact and it indicates more returns to increasing x_{size} when rainfall is high. Higher subsidies contribute to the positive effect of x_{size} in Mediterranean regions and Germany; in Scandinavia subsidies decrease the elasticity of x_{size}.

An increase in irrigated area can only slightly change total output, but the $\varepsilon_{y1,xirr}$ is significantly influenced by many factors. In Greece, at higher r_{tmean} and lower r_{pmean} the contribution increases more. Irrigation is thus an important adaptation option here. The low elasticity of x_{irr} in e.g. Spain and Italy is surprising, but interesting. It implies that a change in irrigated area has a small impact on total production. The intercept and own cross-effect are positive, but are adapted by other factors. In Italy, at higher r_{tmean} increasing x_{irr} reduces impact on total output. Hence, irrigation seems not a good adaptation strategy to higher temperatures in Italy. In Spain, climatic conditions have a small effect, but subsidies decrease the impact of x_{irr}. Also in other regions the effects of climate are small; other effects differ per region but can be large.

Land use and adaptation

The type of land use on a farm can, not surprisingly, have a large influence on agricultural production (Table 5.6). It should be noted that the homogeneity of groups of land uses x_k is different. Maize area (x_{mai}) is distinguished separately, other cereals (x_{cer}) are a relatively homogenous group, but within the groups of other arable crops (x_{othar}) and other agricultural activities (x_{othact}) heterogeneity can be large. So, if within the group x_{othact} a change in permanent cropping area contributes highly and a change in area for specific livestock activities contributes little to total output, the average $\varepsilon_{y1,xothact}$ can be close to zero. For our purpose, to look at these activities in relation to arable cropping this grouping suffices however.

The elasticities of land uses are similar to elasticities of associated y_m. Only in Mediterranean regions and in France, there is a relationship with climatic conditions. Effects differ however; e.g. an increase in x_{cer} has more effect at high r_{tmean} and high r_{pmean} in Spain and France and less in Italy. Nevertheless, land use changes are

Table 5.6a. Contribution of land uses ($\varepsilon_{y1,k}$) to production and related adaptation strategies (C_{kf}). Parameters in bold are significant with p<0.05, in italic with p<0.10.

		Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
α_{xcer}		**-1.576**	**0.465**	**1.338**	*-0.662*	0.716	**2.219**	*0.724*	**1.302**
$C_{xcer,m}$	y_{mai}	*-0.032*	**-0.055**	**-0.037**	**0.060**	0.137	-0.141		
	y_{othar}	0.047	-0.009	**0.358**	**0.031**	**0.115**	0.035	**-0.011**	**-0.036**
	y_{othact}	0.047	**-0.110**	**0.158**	**-0.116**	**0.440**	-0.352	**-0.224**	-0.018
$C_{xcer,k}$	x_{fert}	**1.782**	0.007	**0.857**	**0.860**	-0.118	-0.284	0.109	-0.086
	x_{prot}	-0.566	0.172	-0.040	**-0.947**	-0.675	-0.873	0.182	0.079
	x_{size}	**-0.975**	-0.193	**-0.910**	**-0.823**	**-2.112**	0.704	*-0.505*	**-1.385**
	x_{irr}	**0.654**	-0.004	-0.008	**0.006**	-0.013	-0.003	**-0.113**	-0.003
	x_{cer}	**0.239**	**0.239**	**0.239**	**0.239**	**0.239**	0.239	**0.239**	0.239
	x_{mai}	*-0.256*	**-0.005**	-0.012	0.076	0.044	0.008		
	x_{othar}	-0.036	**-0.088**	**0.086**	**0.093**	-0.121	0.459	0.014	0.226
	x_{othact}	**-0.403**	**-0.047**	**-0.230**	**-0.244**	0.019	-0.032	**0.167**	0.200
$C_{xcer,f}$	r_{tmean}	0.954	-0.002	**-1.427**	**1.317**	-0.005	-0.670	0.346	0.212
	r_{pmean}	0.050	0.020	**-0.173**	0.108	0.121	-0.304	-0.032	0.195
	r_{subs}	0.344	**0.041**	**-0.092**	0.330	-0.460	0.010	*0.329*	-0.421
	r_{year}	**-0.107**	**0.024**	**0.039**	0.009	0.026	0.036	0.032	-0.008
$\varepsilon_{y1,xcer}$		0.166	0.456	0.144	0.337	-1.648	1.052	1.257	0.497
α_{xmai}		**1.573**	**0.448**	0.123	**2.057**	0.360	**-1.448**		
$C_{xmai,m}$	y_{mai}	**0.173**	**0.490**	**0.006**	*-0.008*	-0.014	**0.512**		
	y_{othar}	**0.364**	**0.221**	**-0.039**	**0.003**	**0.034**	-0.035		
	y_{othact}	**0.123**	**0.362**	**0.017**	**0.072**	0.029	**0.416**		
$C_{xmai,k}$	x_{fert}	-0.920	**-0.348**	-0.043	**-1.506**	-0.148	-0.040		
	x_{prot}	**1.111**	-0.130	0.016	**-0.306**	-0.429	*1.454*		
	x_{size}	**-2.964**	**-0.386**	**0.125**	**0.877**	-0.200	**-0.991**		
	x_{irr}	-0.180	0.011	*-0.005*	**-0.004**	0.008	0.001		
	x_{cer}	*-0.347*	**0.022**	-0.039	0.126	0.252	-0.042		
	x_{mai}	**1.187**	**-0.066**	-0.001	**0.042**	**-0.007**	**-0.047**		
	x_{othar}	0.133	**0.090**	**-0.012**	**0.254**	0.100	-0.306		
	x_{othact}	0.026	**0.035**	**-0.071**	**0.141**	0.055	0.029		
$C_{xmai,f}$	r_{tmean}	-0.721	0.193	-0.051	**-1.830**	0.038	0.557		
	r_{pmean}	0.146	**-0.056**	-0.011	**0.304**	*-0.198*	*0.322*		
	r_{subs}	**0.854**	0.000	**0.027**	-0.105	0.178	-0.030		
	r_{year}	*-0.051*	-0.018	**-0.014**	-0.005	-0.024	**0.050**		
$\varepsilon_{y1,xmai}$		0.508	0.868	0.029	0.112	0.036	0.404		

generally more impacted by other drivers than climatic conditions. Especially in Mediterranean regions there is a significant change in time in the contribution of land uses. Over time, the marginal product of x_{othact} increases and of x_{mai} decreases, but the value of $C_{xmai,ryear}$ is small compared to the other terms adding up to $\varepsilon_{y1,xmai}$. In Greece, the positive impact of x_{subs} on $\varepsilon_{y1,xmai}$ is much larger. Also for other land uses in other regions x_{subs} has an impact. The output share from x_{othar} and x_{othact} generally decreases with more subsidies.

The different land uses are not always complementary among each other, but in several cases the interaction terms with other land uses are positive. In France for

Table 5.6b. Continued.

		Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
α_{xothar}		0.398	-0.048	-0.053	0.031	0.145	-0.411	-0.097	0.024
$c_{xothar,m}$	y_{mai}	0.009	**0.057**	**-0.006**	**0.080**	0.082	-0.236		
	y_{othar}	0.002	0.003	**0.031**	-0.001	-0.004	-0.006	0.000	**-0.011**
	y_{othact}	0.012	-0.003	0.002	**0.082**	0.003	0.071	0.021	-0.030
$c_{xothar,k}$	x_{fert}	0.032	-0.005	0.004	**-0.335**	-0.266	-0.179	**0.233**	0.326
	x_{prot}	**-0.785**	*-0.033*	**-0.066**	**0.324**	0.082	0.273	0.065	*-0.235*
	x_{size}	**0.874**	0.018	-0.039	-0.064	**0.400**	-0.202	**-0.174**	0.393
	x_{irr}	**-0.285**	-0.001	-0.001	0.000	**-0.009**	0.004	-0.004	*0.004*
	x_{cer}	-0.031	**-0.059**	**0.068**	**0.094**	-0.115	0.341	0.018	0.254
	x_{mai}	0.086	**-0.013**	**-0.003**	**0.154**	0.017	0.043		
	x_{othar}	0.064	**0.019**	**0.027**	**-0.028**	**-0.008**	*0.026*	**0.002**	**-0.144**
	x_{othact}	**0.213**	**0.011**	0.005	-0.018	0.001	-0.017	0.041	0.018
$c_{xothar,f}$	r_{tmean}	0.123	0.078	0.083	-0.167	-0.039	0.271	-0.062	-0.027
	r_{pmean}	0.044	-0.003	-0.011	**-0.107**	0.029	0.092	-0.061	-0.094
	r_{subs}	**-0.736**	-0.004	-0.006	-0.030	**-0.333**	-0.011	0.034	*-0.477*
	r_{year}	**0.051**	-0.006	0.003	-0.001	**-0.026**	-0.043	-0.003	0.020
$\varepsilon_{y1,xothar}$		0.072	0.011	0.038	0.014	-0.042	0.016	0.013	0.021
$\alpha_{xothact}$		-0.445	0.046	0.007	**-0.395**	-0.016	**-0.267**	-0.174	0.183
$c_{xothact,m}$	y_{mai}	0.003	**0.021**	**-0.021**	**0.044**	0.036	0.031		
	y_{othar}	**-0.184**	**-0.006**	**-0.120**	**-0.004**	**0.012**	-0.028	0.000	-0.002
	y_{othact}	0.035	**0.004**	0.001	0.002	-0.012	0.040	*0.063*	0.007
$c_{xothact,k}$	x_{fert}	-0.151	-0.029	0.054	**0.693**	0.041	0.059	0.632	0.137
	x_{prot}	**0.877**	**0.034**	**0.068**	-0.141	0.010	0.033	-0.100	*-0.328*
	x_{size}	-0.063	**-0.044**	**0.135**	*-0.172*	-0.136	-0.009	0.014	0.363
	x_{irr}	-0.128	0.003	0.000	0.000	**-0.012**	**0.011**	-0.023	**-0.010**
	x_{cer}	**-0.343**	**-0.026**	**-0.165**	**-0.217**	0.018	-0.026	**0.124**	0.216
	x_{mai}	0.016	**-0.004**	**-0.016**	**0.076**	0.009	-0.005		
	x_{othar}	**0.206**	**0.009**	0.005	-0.016	0.001	-0.019	0.024	0.018
	x_{othact}	0.024	-0.003	**0.013**	**-0.091**	0.017	**-0.059**	-0.080	*-0.054*
$c_{xothact,f}$	r_{tmean}	-0.083	-0.025	0.012	0.167	0.055	0.127	-0.144	-0.023
	r_{pmean}	**0.217**	0.004	0.024	-0.047	0.001	0.058	-0.013	-0.060
	r_{subs}	-0.025	-0.005	-0.001	0.032	-0.088	0.005	**-0.457**	**-0.439**
	r_{year}	**0.029**	**0.011**	**0.009**	*-0.019*	*-0.015*	-0.013	*0.034*	-0.021
$\varepsilon_{y1,xothact}$		-0.015	-0.007	0.005	-0.086	-0.080	-0.064	-0.101	-0.013

example, x_{cer}, x_{mai} and x_{othar} are positively related, implying that an increase in one land use would increase the contribution of the other land use to total output. Some diversification would thus positively influence total production. In Greece, an increase in x_{cer} reduces $\varepsilon_{y1,xmai}$ and $\varepsilon_{y1,xothact}$; only x_{othar} and x_{othact} are complementary here.

With few exceptions, x_{size} negatively influences the elasticity of land uses, especially $\varepsilon_{y1,xcer}$. On larger farms it is thus less beneficial to increase x_{cer}. Higher x_{fert} generally increases the marginal product of cereals. A higher x_{irr} also contributes positively to $\varepsilon_{y1,xcer}$ in Greece and France, but negatively to elasticity of other land uses. Also in other regions there is a small impact of x_{irr}, but varying per land use.

5.3.5 Returns to scale

In section 5.2.3 we mentioned that a $\Sigma\varepsilon_{y1,k}>1$ implies increasing returns to scale; more inputs generate a more than proportionate increase in output. Summing up all input elasticities from table 5.5 and 5.6 gives values slightly larger than 1 for most of the regions. The scale economy measure is highest for Spain (1.27), then Benelux (1.16), Italy (1.05), Greece (1.05), France (1.04), Germany (1.03), Scandinavia (1.01) and lowest in the UK (0.98).

In Spain and Greece $\varepsilon_{y1,xmai}$ contributes mostly to the scale effect, in other regions ε_{y1xcer}. Also $\varepsilon_{y1,xsize}$ has a high contribution, especially in the UK. This also implies that substitutability (Eq. 7) between these and other inputs is difficult. When $\varepsilon_{y1,k}>\varepsilon_{y1,l}$ a switch means decreasing returns to inputs and thus difficulty in x_k to x_l substitution. The effect of external factors can be measured by summing up the C_{kf}. The effect of r_{tmean} on $\Sigma\varepsilon_{y1,k}$ is highly positive for Spain (0.52), slightly positive for UK, Benelux and Greece and negative for Scandinavia, France and Germany and very negative for Italy (−0.66). The effect of r_{pmean} is generally small, but >0.20 for Benelux, UK and Scandinavia. Subsidies have substantial impact in France (0.30), the UK (−0.25) and Scandinavia (−1.94). Technological development, markets or other changes did not have a substantial impact on scale economies (<0.10).

5.4 Discussion

5.4.1 Methodological discussion

For the assessment of climate impacts on agriculture new methodologies are needed. Existing methodologies have proved their value, but interactions between climate impacts, other drivers and management are still not well understood. Crop model simulations have projected in which regions potential impacts on crop yields are highest (Gitay et al., 2001). These models however serve well at the field level, but validation for regional applications of these models remains unsatisfactory as important other factors and relationships are not considered (Tubiello and Ewert, 2002). Economists have mainly applied the Ricardian approach (Mendelsohn et al., 1994), and showed that economic impacts are smaller than crop models would suggest (Mendelsohn and Dinar, 1999). An important question, 'how does adaptation influence climate impacts?' cannot be answered however. It is obvious that farmers adapted to changes in the past and will do so in the future. As farmers continuously adapt to prevailing conditions (successful or not), only theoretically we can speak of 'potential impacts', adaptive capacity' and 'residual impacts' (IPCC, 2001; Metzger, 2005). In practice, 'potential impacts' are not quantifiable. In every region, on every farm, socio-economic conditions and management influence production, and changes are taking place. Neglecting this will yield results that have no meaning for practical situations.

In this study we use the translog distance function, to empirically assess climate impacts in different regions and the factors that contribute to adaptation to these impacts. This is one of the first studies where interactions between climate and management are explicitly considered. As we are mainly interested in temporal differences, we do not correct for random effects. A random effects model with panel data would change the focus to spatial differences. We select several regions and compare the responses. Applying several models instead of one, causes that generalization of the results is difficult. It however gives insight in the diversity of responses between regions and farm types. The large differences in different regions suggest that models should focus more on smaller and homogenous regions instead of averaging data and results for large and heterogeneous regions.

We use data from farm types instead of individual farms in the model specification. One farm type comprises at least 15 farms. Although individual data would provide more detail, using this data is not possible for privacy reasons. Using grouped data instead of individual farm data in frontier analysis is not uncommon (e.g. Heshmati and Kumbhakar, 1997). The FADN data of the EU are the only source of micro-economic data that is harmonized, i.e. the bookkeeping principles are the same in all countries (http://ec.europa.eu/agriculture/rica/index_en.cfm). Although the source is considered reliable, it is possible that unreliable data points have some influence on the results.

5.4.2 Actual impacts and adaptive capacity

Crop model studies generally project more severe climate change impacts on crop yields in southern Europe compared to northern Europe (Olesen and Bindi, 2002). In Chapter 2 we suggested that farms with higher yields would have a higher capacity to adapt to changing conditions, as they were able to adapt to prevailing conditions. In general, farms with higher intensity, farm size and more arable land obtain higher crop yields. But, in regions were crop yields are higher, income per hectare is not necessarily higher. Also, a temporal analysis showed that although crop yields are generally lower in warmer regions, increases in temperatures do not have more severe effects on crop yields in these regions (Chapter 3 and 4). These results indicate that determining the adaptive capacity of European agriculture is not straightforward.

There is no single measure for the adaptive capacity of European agriculture, as it depends on the temporal reference, sphere (internal/external/cross-scale), knowledge domain (socio-economic/biophysical/integrated), vulnerable system, attribute of concern and the hazard considered (Füssel, 2006). Adaptation to long-term climatic conditions (Chapter 2) can therefore differ from adaptation to short-term temporal climate change and variability (Chapter 3 and 4). In the current study we compare eight regions, for which the mentioned six dimensions are the same. We assess cross-scale integrated vulnerability and adaptation of agricultural production of (arable) farmers to climate variability and subsidies from 1990−2003 in these eight EU regions. Hence, their vulnerability and adaptive capacity can be compared. Adaptation to inter-annual climate variability is indicative of adaptation strategies adopted on the short-term. Their effect on the long-term should therefore be discussed. Our focus is on arable farming in Europe, but analysed in context of other agricultural activities. Outputs of four agricultural activities (attributes of concern) are analysed, as adaptation strategies differ for different activities. These outputs can be related to crop yields, as (1) we correct for prices and (2) changes are ceteris paribus effects, thus with constant areas.

As mentioned in section 5.4.1, the theoretical separation of 'potential impacts' and 'adaptive capacity' cannot be quantified in practical situations. We take Greece as an example. Although temperatures are already high, Greece is the only region next to Scandinavia where temperature (r_{tmean}) has a positive impact on production. Modelling the impact of higher temperatures on potential crop yields in Greece, would result in negative effects for most crops (Olesen and Bindi, 2002). But, actual yields are only slightly related to potential yields. Crops that are less suitable for a Mediterranean climate, such as wheat, are managed suboptimally (considering yield maximization as the objective), resulting in a large yield gap (Chapter 2). Inputs are reduced and used for other agricultural activities.

Table 5.7 shows that around 30% of the Greek agricultural area is used for cereal production (x_{cer}) but the output compared to other outputs (y_{cer}/x_{cer}) is indeed small. From Table 5.5 we observed that with a higher cereal area (x_{cer}), increasing fertilizer use (x_{fert}) and irrigation (x_{irr}) can be beneficial but overall the effect on the outputs of increasing these inputs ($\varepsilon_{y1,xfert}$ and $\varepsilon_{y1,xirr}$) is negligible. This confirms that these 'inputs' are suboptimally used for cereal production, but not for overall production. Still, increasing these inputs increases the marginal product of cereal area and thus total output. However, adaptation to climate variability can focus on output stabilization (risk minimization) instead of output maximization (Smit and Skinner, 2002). After all, a higher fertilizer use (x_{fert}) reduces the effect of higher temperatures ($\varepsilon_{y1,rtmean}$). A second form of adaptation to higher temperatures is to switch to a more heat resistant crop-mix. The largest part of the area in Greece is occupied by other arable crops (Table 5.7). These also give relatively the highest output (y_{othar}/x_{othar}).

Hence, as Greek agriculture has to some extent adapted its system to prevailing conditions, we cannot speak of 'potential impacts' and 'adaptive capacity'. We can observe 'actual impacts' and some factors that contribute to adaptation. In the last 14 years, on average increasing temperatures had a positive impact on production. One factor that contributed largely to this positive impact was irrigation. For now, irrigation can mitigate impacts of higher temperatures and lower precipitation. An important consideration for the future is thus to analyse the availability of irrigation water, as water availability is expected to decreases, especially in Mediterranean regions (Isendahl and Schmidt, 2006; Lehner et al., 2006).

Interestingly, irrigation contributes negatively to the effect of r_{tmean} in Italy, while there is no effect in Spain, which is also the case for r_{pmean} for both regions (Table 5.2). This implies that increasing irrigated area is not a good adaptation strategy considering projected climate change in these regions. Van der Dries (2002) earlier showed in an extensive analysis in Portugal that traditional farmers not relying on irrigation can better cope with variability in water availability than modern farmers, which are

Table 5.7. Averages of climate variables[a] *(r_{tmean} in °C, r_{pmean} in mm) and percentages of y_m and x_k in Σy_m and Σx_k. The ratios indicate the output y_m per area x_k relative to other outputs.*

	Greece	Spain	Italy	France	Germany	Benelux	UK	Scandin.
r_{tmean}	12.8	12.4	11.7	9.9	7.9	8.7	8.4	4.6
r_{pmean}	40.7	45.3	48.4	58.9	54.1	61.8	62.9	46.0
y_{cer}	4.9	12.0	5.2	11.9	12.0	1.7	17.0	13.5
y_{mai}	4.6	2.0	4.6	3.7	0.6	0.1		
y_{othar}	67.8	49.9	55.9	32.8	16.9	42.3	19.5	13.5
y_{othact}	22.6	36.1	34.3	51.6	70.6	55.9	63.5	73.0
x_{cer}	30.5	42.1	21.8	30.4	39.4	7.1	22.8	50.6
x_{mai}	6.7	1.8	8.5	7.1	1.5	0.5		
x_{othar}	22.9	11.8	26.3	22.3	25.0	62.5	9.5	20.3
x_{othact}	39.8	44.3	43.3	40.2	34.1	30.0	67.7	29.1
y_{cer}/x_{cer}	0.2	0.3	0.2	0.4	0.3	0.2	0.7	0.3
y_{mai}/x_{mai}	0.7	1.1	0.5	0.5	0.4	0.3		
y_{othar}/x_{othar}	3.0	4.2	2.1	1.5	0.7	0.7	2.1	0.7
y_{othact}/x_{othact}	0.6	0.8	0.8	1.3	2.1	1.9	0.9	2.5

[a] Averages are based on farm type data included in the analysis. Average may differ from regional averages (e.g. in Germany relatively more farms are located in colder regions of Germany).

dependent on irrigation water. The small-scale traditional farmers adjust practices and cropping patterns to the local environment and varying weather conditions. Modern farmers, stimulated and subsidized by the European Union, achieve high outputs, but are highly dependent.

Output maximization and risk minimization are often conflicting objectives (e.g. Just, 2003; Sinebo, 2005). A low technical efficiency is often explained as being related to risk aversion, as risk aversion likely causes greater departure from profit maximization (Just, 2003). As technical efficiency is lower in regions with a more variable climate, risk aversion seems to play a larger role in these regions. Increasing farm size causes decreasing risk aversion (Just, 2003). Results indicate that this decreasing risk aversion also results in a higher vulnerability to climate variability. In all regions, increasing x_{size} increases the marginal product. Also, returns to scale are found for almost all regions. But, when we look at regions where average x_{size} is large (e.g. France, UK, Benelux), x_{size} amplifies the negative impact of r_{tmean}. Especially in France, $\varepsilon_{y1,rtmean}$ is very negative.

It is clear that indicators of regional-level adaptive capacity (Schröter et al., 2003; Brooks et al., 2005; Haddad, 2005) do not suffice to estimate which factors reduce vulnerability of European farmers. Adaptation and vulnerability of European farmers depend on (1) the output they produce, (2) farm characteristics, such as the type of land use, type of crop, intensity, farm size and interactions between these factors and (3) regional conditions, such as long-term climatic conditions and socio-economic conditions. However, these factors strongly interact resulting in different responses among regions.

5.4.3 Adaptation strategies

There are many different types of adaptation strategies to reduce impacts of climate change (Smit and Skinner, 2002), for which profitability and hence adoption rate is different in different situations. Several of these strategies have been assessed in this study. Adaptation strategies that can decrease the yield gap (i.e. the difference between potential and actual yield) are e.g. adjustment of fertilizer use, pest and weed control and irrigation management. At higher r_{tmean} the contribution of x_{fert} increases in Italy, France and the United Kingdom, implying that intensive farmers adapt better, while it decreases in Scandinavia. The projections for northern Europe are that with higher potential yields at higher temperatures, more fertilizers will be used (Olesen and Bindi, 2002). This might have negative impacts on the environment. Results suggest that the marginal product of fertilizers actually decreases, suggesting that until now this was not an efficient adaptation strategy to adapt to higher temperatures. A higher crop protection has both positive and negative impacts, while increasing irrigated area only has a positive impact in Greece.

Economic adaptation to climate change also involves the choice of crop species and other agricultural activities. Models considering climate - land use interactions, generally relate land use changes to changes in potential production (e.g. IMAGE team, 2001). The frontier analysis in this study indicates that land use changes are influenced by climatic conditions (again, differently in different regions), but that subsidies and the general trend (e.g. technology and markets) have a larger impact. Including these factors influencing climate – land use interactions will improve reliability of future projections of land use changes.

The increasing returns to scale suggest that increasing inputs would be beneficial in all regions. One key aspect of economic performance and viability not considered in this study however, is off-farm income. Especially for small farms this is important, and allowing for this component of farm 'output' suggests less scale economies and a higher technical efficiency (Morrison Paul and Nehring, 2005). As the FADN database does not provide data on off-farm income, we could not analyse the impact of this. The larger the farm, the less labour is available for off-farm activities. Therefore, smaller farms may be better able to cope with output variability. Reilly (2002) suggested that medium scale farms were most vulnerable, as there is little labour available for off-farm activities, and also little capital to adapt to changing conditions. This study indicates that adaptation strategies differ per farm type, but as regional conditions differ largely, the efficiency of adaptation strategies also varies and is not always consistent with theoretical assumptions.

5.5 Conclusion

In this study we use the translog distance function, to empirically assess (1) impacts of climate and subsidies on agricultural production in different regions and (2) interactions with inputs and other factors which contribute to adaptation to these impacts. In the last 14 years various changes took place in both inputs and outputs. These changes can partly be related to climatic variability and change, but also subsidies and other developments (e.g. markets, technological development) are important. Our results show that impacts differ per region, and that ‘actual impacts’ cannot be explicitly separated into ‘potential impacts’ and ‘adaptive capacity’ as often proposed. Farmers adapt their practices to prevailing conditions and ‘potential impacts’ are not quantifiable leaving it as a mainly theoretical concept. Factors that contribute to adaptation also differ per region. In some regions more fertilizers or more irrigation can mitigate impacts, while in other regions this amplifies impacts. Prevailing conditions and farm type strategies should be explicitly considered to be able to project impacts of future changes.

Chapter 6

Regional crop modelling in Europe - The impact of climatic conditions and farm characteristics on maize yields

Abstract

Impacts of climate change on regional crop yields are commonly assessed using mechanistic crop simulation models. These models, however, simulate potential, water- and nitrogen-limited yields, which do not always relate to actual yields. Differences in farm characteristics have been reported to affect regional yield variability through impacts on management but are not considered in crop models. In this Chapter we investigate the performance of the Crop Growth Monitoring System (CGMS), based on the WOFOST model, to simulate actual regional maize yields for the 15 old member states of the European Union (EU15). Differences between simulated and actual maize yields are analysed using backward linear regression models in which climatic conditions and farm characteristics are included.

The analysis of spatial yield variability shows that higher temperatures tend to increase actual yields, which is not evident from simulated potential yields. The temporal analysis of yield variability also indicates that in Mediterranean regions higher temperatures have a more positive impact on actual yields than on the simulated potential yields. The opposite is the case for temperate regions. This suggests that farmers in Mediterranean regions have adapted to higher temperatures, for example by growing more heat resistant cultivars, an adaptation strategy not considered in the crop model.

Farm characteristics explain some of the differences between simulated and actual yields. Unsatisfactory simulations in spatial yield variability are partly explained by the maize area as proportion of the total arable area, farmers' income and irrigation. Improving estimations of temporal variability in actual maize yields requires regional specific models that relate to the farm characteristics important in the region. In regions that are more regularly exposed to higher temperatures and lower precipitation the diversity among farm types in yields and yield responses is higher than in other regions, resulting in poor model performance. Diversity can be considered as a regional adaptation mechanism to climate variability in Europe.

As management differs per region, farm type and year, modelling regional impacts of climate change and variability based on mechanistic crop models is only sufficient if the variety of management activities in a region is considered adequately. However, representative input parameters are difficult to obtain and to project for the future, which highlights the need for simplified approaches to represent management activities in a region. Farm characteristics provide some link to management and including them in a regional crop model can improve the simulation of climate variability impacts and hence yield projections.

Keywords: Crop model, climate change, climate variability, management, adaptation

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6.1 Introduction

Climatic conditions are the main factors determining crop yields (e.g. van Ittersum et al., 2003). Projected climate change will therefore impact future agricultural productivity (IPCC, 2001). Climate impacts on crop yields are generally assessed with mechanistic crop models (Gitay et al., 2001). However, crop models simulate potential, water and nitrogen limited yields, which are not always related to actual yields (Landau et al., 1998). Crop models are developed to address direct effects of weather, they do not address secondary effects (e.g. pest and diseases; Jamieson et al., 1999). Also, the validity of model outputs depends on the quality of data used. Input data are not always readily available and crop models calibrated on specific sites cannot directly be applied to other regions (e.g. Ewert et al., 2002).

To overcome these limitations, statistical regression models have been applied to analyse the impact of climatic conditions and change on actual yields at regional and higher levels (Chapter 2; Kaufmann and Snell, 1997; Landau et al., 2000; Chen et al., 2004; Bakker et al., 2005). Regression models can be applied in different regions and can readily include management variables and other factors determining actual crop yields. Nevertheless, statistical models are even more site or region specific and results depend on the variables included. They do not have the elegance of crop models, which start from first principles and process based mechanistic responses.

When modelling the impact of climate change on future crop yields, an important aspect is the ability to simulate adaptation strategies (e.g. Easterling et al., 2003). Mechanistic crop models can simulate changes in cultivars and sowing dates, but the extent to which these are adopted is unknown. Statistical models provide some insights in farm characteristics influencing management and adaptation to climatic and socio-economic conditions (Chapter 2, 3, 4 and 5). Farm characteristics can represent management practices which influence potential yields (changes in cultivars and sowing dates) and/or the gap between potential and actual yield (e.g. changes in fertilizer or crop protection use).

Chapter 2 and 3 have shown that farm characteristics explain a large part of the spatial and temporal variability of crop yields in Europe and that these should be considered in addition to climatic conditions for regional yield projections. Climatic conditions are assumed to be well represented in a crop model. Accordingly, the remaining deviation of simulated data from observations should be attributable to crop management and associated farm characteristics, factors not considered in a crop model.

In this Chapter we investigate the performance of the Crop Growth Monitoring System (CGMS), based on the WOFOST model, to simulate actual regional maize yields in the EU15 (the 15 member countries of the European Union before the extension in 2004). Maize is considered as it is (1) one of the most important crops in the EU15, and (2) a summer crop, where yield statistics do not confound with winter crops.

Table 6.1. Explanations and/or problems causing deviations between simulated and actual yields.

Errors in simulated yields: Model structure of biophysical processes

- Certain climatic conditions are not included in the crop model, such as frosts, winds and hail (Landau et al., 2000; Lazar and Genovese, 2004).
- Different approaches exist to model the influence of radiation on crop growth (e.g. van Ittersum et al., 2003), but the interaction between rainfall and radiation is not clear (Landau et al., 2000).
- Depletion of soil water content can be overestimated (Eitzinger et al., 2004).
- Crop models perform better in regions where yield is determined by water limitation (Landau et al., 1998).
- Crop response in sensitive periods is not taken into account.

Errors in simulated yields: Quality of input data and parameterization

- Uncertainties in soil and weather data (de Wit et al., 2005).
- Management strategies such as cultivar choice and sowing date are included in the crop model, but data on these parameters is difficult to obtain. As adaptation to climate change and variability, management strategies can be changed (e.g. Parry et al., 1999).
- Parameter estimation and calibration problems can occur in simulation models. Calibration algorithms are more suited for application at the field level than at the regional level because calibration on just a few state variables of some experiments does not necessarily result in a model that is robust at regional level (de Koning et al. 1993).
- Bias of spatial average (Hansen and Jones, 2000); even if location estimates are truly representative, yields simulated at representative locations will not represent the spatial average due to aggregation error.

Errors in simulated yields: Secondary effects not included

- The occurrence of pests and diseases are more probable with wetter conditions (Landau et al., 1998; Landau et al., 2000), but in crop models more precipitation is generally positive.
- Workability (tillage, harvesting, application of fertilizer and crop protection) can be negatively influenced by wet conditions (Rounsevell et al., 2003).
- Interaction with intercropped species or weeds decrease yields (van Ittersum et al., 2003).
- Regional socio-economic conditions, farm characteristics and related management strategies (fertilizer application, crop protection, irrigation, etc.) influence yield levels and inter-annual variability (Chapter 2 and 3; Landau et al., 2000).

Error in measured actual yields

- Errors in yield measurements can occur. In e.g. the Netherlands, national yield statistics in are estimated by experts in 60 regions, no real measurements of actual yields are involved. The average values of official national yields are probably quite accurate but for prediction purposes it is necessary that year to year fluctuations are correct. In some regions the 'signal-to-noise ratio' might be low: measurement error is larger than model error (de Koning et al., 1993).
- Statistics of several crops are aggregates of different types of these crops. Data on spring wheat and winter wheat is aggregated; potato figures apply to the total of early and late varieties, etc.
- Heterogeneity in environment. Local climatic conditions and physical site characteristics can lead to higher and lower potential and actual yields compared to regional averages.
- Changes in crop area can influence the regional average yields in different ways than locally observed in the field.
- Harvest and post-harvest losses can influence yield measurements.

Different reasons can explain deviations between simulated and actual yields. These are related to (1) the representation of climatic conditions and management in the crop model which are determined by the model structure, the quality of the input data and the parameterization [Table 6.1, partly based on van Oijen and Ewert (1999)], and (2) errors in measured actual yields. We focus mainly on the representation of management in the model, but will discuss our results based on the causes of errors as listed in Table 6.1.

Differences between simulated and actual maize yields are analysed using backward linear regression models in which climatic conditions and farm characteristics are included. The analysis indicates (1) the validity of simulated climate impacts on regional maize yields in Europe, (2) factors that can improve regional crop modelling and (3) factors that influence adaptation.

6.2 Methodology

6.2.1 Data description

Simulated yield data

Within the MARS project (Monitoring Agriculture with Remote Sensing; www.marsop.info) potential and water limited yields of various crops are estimated across Europe. The Crop Growth Monitoring System (CGMS; Lazar and Genovese, 2004; de Wit et al., 2005) estimates yearly regional crop yields since 1975 using the widely applied and validated crop model WOFOST (Supit et al., 1994; Wolf and van Diepen, 1995; Rabbinge and van Diepen, 2000). Potential ($Y_{pot,sim}$) and water limited ($Y_{wat,sim}$) maize yields are simulated for each suitable land unit, represented by a unique combination of soil, grid (50 × 50 km) and administrative unit. The simulated yields are aggregated over NUTSX[1] (X = 0, 1 and 2) regions. Simulated NUTS yields are the weighted averages of the simulated yields on the land units within a NUTS region, using the estimated suitable crop area within that region as the weighting factor. The dry matter yields are converted to fresh matter yields by assuming a moisture content of 13%.

The MARS Crop Yield Forecasting System (MCYFS) combines the simulated crop yields from the CGMS with yield statistics to forecast crop yields. The MARS project provides technical support and expertise to the European Commission's Directorate General for Agriculture (DG-Agri). Per NUTS2 region, along with the trend one indicator is used to project the influence of inter-annual climate variability. Despite the development of other techniques such as remote sensing, the influence of inter-annual climate variability on crop yields is still best projected by the CGMS (Boons-Prins et al., 1993; Lazar and Genovese, 2004). Currently, in most regions water limited maize yield (of storage organs or biomass) is the best indicator (in comparison to other techniques such as remote sensing) of the influence of climate variability. In a few

[1] Nomenclature des Units Territoriales Statistiques: Countries (NUTS0), regions or provinces (NUTS2) and aggregates of regions and provinces (NUTS1) within a country as distinguished by Eurostat.

southern European regions potential maize yield simulated by the CGMS is the best indicator. But even though the CGMS provides the best basis for projecting the impact of climate variability on actual regional maize yields, in many regions no relationships are found between simulated and actual yields (Boons-Prins et al., 1993; Lazar and Genovese, 2004). Improving simulation results can thus improve yield forecasts and future projections of climate impacts.

Actual yield data

Two sources of actual maize yield data are used in the analysis. This allows comparing data to test for errors in yield measurements and hence, reliability of the data. Eurostat (http://epp.eurostat.ec.europa.eu) provides long-term time series on average maize yields ($Y_{av.a,act}$) at regional level (NUTS1/NUTS2). The Farm Accountancy Data Network (source: FADN-CCE-DG Agri and LEI) provides data from 1990−2003 at regional and farm type level. In order to compare the different regional divisions of the EU15 used by Eurostat (NUTS) and FADN, a harmonized division (HARM) is created by the Dutch Agricultural Economics Research Institute (LEI). In total, 100 HARM regions are distinguished with more than 50,000 sample farms. Farm types are distinguished based on land use, size and intensity (Chapter 3; Andersen et al., 2006).

From the FADN database we use the regional average maize yields ($Y_{av.b,act}$) and the maximum ($Y_{max.b,act}$) and minimum ($Y_{min.b,act}$) maize yield obtained by any farm type per region. Projecting the regional average yield is the main aim of the MCYFS and other crop models used in climate change impact studies. It is assumed that the maximum yield obtained by any farm type is indicative of the biological potential yield in a region and thus interesting for comparison with $Y_{pot,sim}$ (see also section 6.2.2). Observations with maize yields higher than 32 tons/ha, the theoretical maximum maize yield (Tollenaar, 1985) are excluded from the analysis. The minimum yield is indicative of maize yields on farms far from the 'best-practice'. The difference between $Y_{max.b,act}$, $Y_{av.b,act}$ and $Y_{min.b,act}$ can thus give some indication of diversity in management practices.

Climatic conditions and farm characteristics

For each farm type and region in the FADN database, data are available on farm characteristics from 1990−2003 (Table 6.2). These farm characteristics can explain part of the yield variability between farm types and regions (Chapter 2) and may also explain differences between simulated and actual yields. We select data on intensity (fertilizer use per hectare, *fert/ha*; crop protection use per hectare, *prot/ha*; irrigated area percentage, *irr_perc*), on size (economic size, *ec_size*), land use (percentage of maize in arable area, *maize_pr*), farmers' income (farm net value added per annual work unit, *fnv/awu*) and policies (total subsidies per hectare, *subs/ha*).

As *fert/ha* and *prot/ha* are measured in euros and not in tons, the measures are corrected for prices using country level price indices from Eurostat. Eurostat provides price indices from 1995−2003, and absolute prices from 1990−2003. For years or countries where data are missing, price indices can be calculated based on the

Table 6.2. Description of variables. All variables are year and regional specific.

Variable	Description
Maize yields	
$Y_{pot,sim}$	Simulated potential yield with standard sowing date (tons/ha); CGMS
$Y_{wat,sim}$	Simulated water limited yield with standard sowing date (tons/ha); CGMS
$Y_{av.a,act}$	Actual average yield (tons/ha); Eurostat
$Y_{av.b,act}$	Actual average yield (tons/ha); FADN average per region
$Y_{min.b,act}$	Actual minimum yield (tons/ha); FADN minimum of a farm type per region
$Y_{max.b,act}$	Actual maximum yield (tons/ha); FADN maximum of a farm type per region
Climatic conditions	
Tgrow	Mean temperature (ºC) from April through September
Pgrow	Mean precipitation (mm) from April through September
Farm characteristics	
Fert/ha	Costs of fertilizers and soil improvers per hectare (€)
Prot/ha	Costs of crop protection products per hectare (€)
Irr_perc	Irrigated percentage of utilized agricultural area (%)
Ec_size	Economic size (ESU)[a]
Maize_pr	Maize area / total arable area (%)
Fnv/awu	Farm net value added / annual work unit (€)[b]
Subs/ha	Total subsidies / utilized agricultural area (€)

[a] The economic size is determined on the basis of the overall standard gross margin of the holding. It is given in European Size Units (ESU); one ESU corresponds to a standard gross margin of €1200.

[b] Corresponds to the payment for fixed factors of production (land, labour, capital), whether they are external or family factors. As a result, holdings can be compared irrespective of the family/non-family nature of the factors of production employed. Fnv = total output – total intermediate consumption + balance current subsidies and taxes – depreciation.

relationship between absolute prices and price indices from other years or other countries. For *prot/ha* no comparable data for 1990−1994 are available and data from 1995 are used to correct prices for these years. We are confident however that this doesn't influence results (models with *fert/ha* and *prot/ha* not corrected for prices give similar results).

Monthly temperature and precipitation data for each year of the study period (1990−2003) are provided by the MARS project. Data are available per grid cell of 50 × 50 km and are averaged per HARM region. Averaging the temperatures from April to September (*tgrow*), results in the yearly mean temperature for the main growing period for grain maize. Also precipitation data are averaged to obtain the mean precipitation (*pgrow*) for the growing period each year.

6.2.2 Comparison of simulated and actual yields

Spatial variability

In order to model future regional maize yields correctly, the main focus should be on improving the modelling of temporal variability. However, there are also spatial differences in yield which may not be affected in the same way by climate and management as inter-annual differences. We therefore explicitly compare spatial variability in simulated and actual yields and analyse the effects of climate and farm characteristics on model deviations.

Average maize yields from 1990−2003 are calculated per HARM region from yearly averages for Eurostat yields ($Y_{av.a,act}$) and averages ($Y_{av.b,act}$), minimum ($Y_{min.b,act}$) and maximum ($Y_{max.b,act}$) of FADN yields, simulated potential ($Y_{pot,sim}$) and water limited ($Y_{wat,sim}$) yields. Pearson correlation coefficients (r) between these variables can show relationships, and maps can provide a visual presentation of the spatial variability in actual and simulated maize yields. The relationship between $Y_{av.a,act}$ and $Y_{av.b,act}$ gives an indication of the reliability of observed actual yield data

In order to assess which climatic conditions and farm characteristics explain the difference between actual and simulated year specific yields, we apply backward linear regression models as

$$y_{mit} = \beta_{0mt} + \beta_{mnt} \cdot x_{nit} + e_{mit} \quad (1)$$

The dependent variables y_{mit} are the differences between actual and simulated yields $Y_{max.b,act} - Y_{pot,sim}$, $Y_{av.b,act} - Y_{pot,sim}$ and $Y_{av.b,act} - Y_{wat,sim}$, where m represents one of these three variables. We focus on these three differences for the reasons explained in Table 6.3. The climatic conditions (including quadratic terms) and farm characteristics from Table 6.2 are included as explaining variables x_n. Furthermore, β_{0mt} is the intercept, β_{mnt} are the parameter estimates and the residual $e_{mit} \sim N(0,\sigma^2)$. The model is performed for each of the 14 years t (1990−2003) and all regions i that grow grain maize (depends per year; around 70 out of 100) are included. As relationships determining spatial variability in actual and simulated yields can be different among years, for each year a regression model is applied. The backward procedure is used to select variables x_n. The backward procedure starts with all variables included and removes one variable each iteration until all parameter estimates β_{mnt} have a significance of $p<0.10$. The number of years in which a variable has a significant influence, indicates the importance of a variable explaining the differences between actual and simulated yields. This value and the sign of β_{mnt} are of main interest to us and are considered in the results. The intercepts β_{0mt}, parameter estimates β_{mnt} and residuals e_{mit} are not presented, as the main aim is to identify important factors, not to use estimates for other models.

Temporal variability

The assessment of temporal variability in maize yields from 1990−2003 is performed per region. Firstly, actual yields of different sources $Y_{av.a,act}$ (Eurostat) and $Y_{av.b,act}$ (FADN) are compared to test the reliability of the statistical data. It can be assumed that when a high Pearson correlation (r) is observed between data from different sources and difference in means (DM) is small, the data are reliable. Reliability can vary among regions. Secondly, relationships between actual yields $Y_{max.b,act}$ and $Y_{av.b,act}$ and simulated yields $Y_{pot,sim}$ and $Y_{wat,sim}$ are measured. Both the correlation and DM are calculated. The correlation indicates the statistical relationship for the inter-annual

Table 6.3. Dependent variables and aim of analysis.

Variable	Type of scale	Aim of analysis
$Y_{max.b,act} - Y_{pot,sim}$	Spatial	$Y_{max.b,act}$ is indicative of the biological potential yield in a region. The spatial variability in the deviation from $Y_{pot,sim}$ indicates whether long-term climate effects on potential yields are well represented by the CGMS.
$Y_{av.b,act} - Y_{pot,sim}$	Spatial	Crop yield forecasts aim to predict average regional yields. The deviation between $Y_{av.b,act}$ and $Y_{pot,sim}$ not attributable to unsatisfactory representation of climate effects can be attributable to crop management, which can be represented by farm characteristics.
$Y_{av.b,act} - Y_{wat,sim}$	Spatial	As above. The comparison with $Y_{wat,sim}$ indicates where water limitation plays a role.
$Y_{max.b,act} - Y_{pot,sim}$	Temporal	Temporal changes in the deviation between $Y_{max.b,act}$ and $Y_{pot,sim}$ in a region indicate whether the effects of inter-annual climate variability are well represented by the CGMS.
$Y_{av.b,act} - Y_{pot,sim}$	Temporal	Temporal changes in the deviation between $Y_{av.b,act}$ and $Y_{pot,sim}$ that are not attributable to unsatisfactory representation of climate effects, but to farm characteristics can indicate adaptation in management to inter-annual climate variability.
$Y_{av.b,act} - Y_{wat,sim}$	Temporal	As above, but specifically informative for regions where water limitation has an impact on maize yields.

variability; the DM indicates the correspondence in the level of maize yield. Taking these measures instead of the Root Mean Square Error (RMSE), allows distinguishing between different causes of actual yields not corresponding to simulated yields (i.e. inter-annual variability and level of maize yields).

The reasons for actual yields not coinciding with simulated yields can be explained by climatic conditions and farm characteristics. Factors contributing to explaining the difference between simulated and actual yields may vary among regions. Therefore, we apply a backward linear regression model per region as

$$y_{mit} = \beta_{0mi} + \beta_{mni} \cdot x_{nit} + e_{mit} \qquad (2)$$

Here, y_{mit} are the dependent variables $Y_{max.b,act} - Y_{pot,sim}$, $Y_{av.b,act} - Y_{pot,sim}$ and $Y_{av.b,act} - Y_{wat,sim}$, where m represents one of these three variables (Table 6.3). The climatic conditions (including quadratic terms) and farm characteristics from Table 6.2 are included as x_n. Also, *year* (*year* = 1, 2...14) is included as a variable. Only few significant trends are found, but including *year* can account for changes not represented by other variables and partly prevents that trends are related to variables accidentally correlated to *year*. The backward procedure is used to select variables x_n and ensures that only significant variables ($p<0.10$) are included. The model is performed for each of the 64 regions i having at least 10 or more years of data and if available, 14 years t (1990−2003) are included. The number of regions for which a variable has a significant influence, indicates the importance of a variable explaining the differences between actual and simulated yields. As for the spatial analysis, estimates of intercepts β_{mi}, parameter estimates β_{mni} and residuals e_{mit} are not presented.

In order to indicate the explanatory power of climatic conditions compared to farm characteristics, we also apply models with (1) only average climatic conditions (*tgrow* and *pgrow* and their quadratic terms) and (2) only farm characteristics and *year*. The R^2s of these models indicate the explanatory power of different factors.

6.2.3 Farm diversity and regional yields

Relationships between actual and simulated yields are also measured at farm type level. Temporal variability in maize yields can vary widely among different farm types within regions. Yields on certain farm types are more related to potential yields, others to water limited yields. However, relationships differ among regions.

Obtaining general relationships for the impact of climatic variability on specific farm types is difficult, but diversity in farm type responses seems to influence average regional yields. Therefore, this is further explored. Two measures are calculated. Firstly, we calculate the difference in mean between $Y_{max.b,act}$ and $Y_{min.b,act}$ from 1990−2003 per region. This indicates the range in the level of maize yields, representing diversity in average practices. Secondly, we measure response diversity. For $Y_{max.b,act}$, $Y_{av.b,act}$ and $Y_{min.b,act}$ in each year and each region $y_t - y_{t-1}$ is calculated. The standard deviation of this measure per year and region indicates the diversity in responses of farms with high yields, average yields and low yields.

These measures of maize yield diversity and response diversity are related to how average actual yields $Y_{av.b,act}$ correlate to simulated yields. As maize yield in different regions is related to different simulated yields, the maximum correlation (r) with either potential or water limited yield is used as a measure for 'model performance'.

6.3 Results

6.3.1 Spatial variability

The spatial pattern of actual average regional yields from 1990−2003 is similar for Eurostat ($Y_{av.a,act}$) and FADN ($Y_{av.b,act}$) statistics (Figure 6.1a, b); the Pearson correlation between these two sources of actual yields is r=0.76 (Table 6.4). This indicates that the FADN data are reliable and can be used in the remainder of this section. Lowest average maize yields are observed in Portugal, southern Italy and several German, French and Spanish regions. In these regions also low minimum maize yields ($Y_{min.b,act}$) are found (Figure 6.1e), but low $Y_{min.b,act}$ are also found in other regions. The highest maximum yields ($Y_{max.b,act}$) are observed in Mediterranean regions (Figure 6.1c). The spatial variability in actual maize yields throughout the EU15 is not well reproduced by the simulations for potential ($Y_{pot,sim}$) and water limited yields

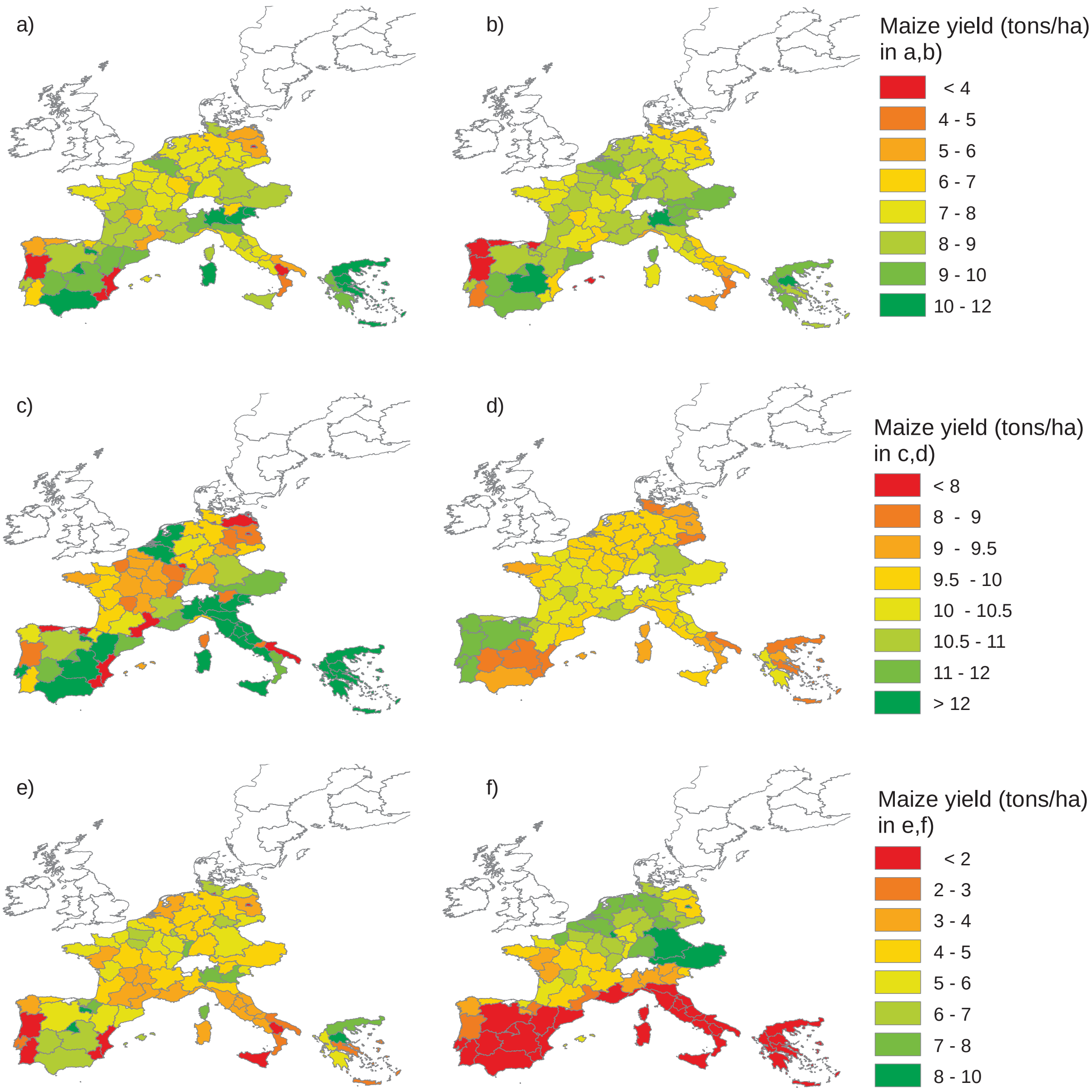

Figure 6.1 (in colour on p.183). Spatial variability in average actual and simulated maize yields (tons/ha) from 1990–2003 with (a) average based on FADN, $Y_{av.b,act}$, (b) average based on Eurostat, $Y_{av.a,act}$ (c) maximum based on FADN, $Y_{max.b,act}$ (d) simulated potential yield, $Y_{pot,sim}$, (e) minimum based on FADN, $Y_{min.b,act}$ and (f) simulated water limited yield, $Y_{wat,sim}$.

Table 6.4. Pearson correlation coefficients (r) between averages of simulated and actual yields from 1990-2003 across regions (as in Figure 6.1).

	$Y_{av.a,act}$	$Y_{av.b,act}$	$Y_{max.b,act}$	$Y_{min.b,act}$	$Y_{pot,sim}$
$Y_{av.b,act}$	0.76				
$Y_{max.b,act}$	0.34	0.53			
$Y_{min.b,act}$	0.45	0.55	-0.10		
$Y_{pot,sim}$	-0.21	-0.17	-0.14		
$Y_{wat,sim}$	0.00	-0.17	-0.46	-0.23	0.18

($Y_{wat,sim}$) (Figure 6.1 d,f). The actual yields have very low correlations, and often negative, with simulated yields (Table 6.4).

The differences between actual and simulated yields (see also Figure 6.2 in next section) are analysed with backward linear regression models. Table 6.5 shows the number of years in which specific variables have a significant effect. As for *tgrow* and *pgrow* quadratic terms are also included, concave (+−; a positive linear term and a negative quadratic term) and convex (−+; a negative linear term and a positive quadratic term) effects are indicated. Concave effects are mainly positive in the range of *tgrow* and *pgrow* observed, while convex effects are mainly negative.

On average, 23% of the difference between observed maximum and simulated potential yields ($Y_{max.b,act} - Y_{pot,sim}$) can be explained (Table 6.5; mean R^2). A positive relationship is observed between *tgrow* and $Y_{max.b,act} - Y_{pot,sim}$. At low *tgrow* $Y_{max.b,act} - Y_{pot,sim}$ is mainly negative, while at high *tgrow* the deviation is mainly positive (Figure 6.1c, d and 6.2d). This suggests that the model performs best for intermediate to warm temperatures, while potential yields are underestimated at high temperatures. Most other variables have a significant effect on $Y_{max.b,act} - Y_{pot,sim}$ in only few of the 14 years. The positive effect of *maize_pr, fnv/awu* and *fert/ha*, suggest that maximum yields can also be increased by good management.

For observed average yields, the importance of farm characteristics is more pronounced than for maximum yields. The difference between $Y_{av.b,act} - Y_{pot,sim}$ is generally higher if *tgrow, fnv/awu, maize_pr* and *irr_perc* are high. A high *fnv/awu, maize_pr* and *irr_perc* represent management practices decreasing the yield gap (i.e potential − actual yield). Farms with higher income use more possibilities to increase yields; in regions where the maize area is larger, the crop is more important and more

Table 6.5. Variables explaining the spatial variability in the difference between actual ($Y_{av.b,act}$ or $Y_{max.b,act}$) and simulated ($Y_{pot,sim}$ or $Y_{wat,sim}$) yields in the EU15 from 1990-2003. For each year a backward regression analysis is performed. The values indicate the number of years that a variable has a significant effect ('+' = positive, '−' = negative, '+−' = concave, '−+' = convex). The minimum, maximum and mean R^2 over all years are presented.

	$Y_{max.b,act}-Y_{pot,sim}$					$Y_{av.b,act}-Y_{pot,sim}$					$Y_{av.b,act}-Y_{wat,sim}$				
	+	−	+−	−+	Total	+	−	+−	−+	Total	+	−	+−	−+	Total
Tgrow	7	1	0	2	10	6	1	1	3	11	7	0	6	0	6
Pgrow	1	2	1	1	5	3	1	0	2	6	0	5	0	6	11
Fert/ha	2	0			2	1	1			2	1	3			4
Prot/ha	0	1			1	3	1			4	5	0			5
Ec_size	0	0			0	3	1			4	0	6			6
Irr_perc	0	1			1	5	0			5	4	0			4
Maize_pr	2	0			2	9	0			9	6	0			6
Fnv/awu	2	0			2	9	0			9	3	0			3
Subs/ha	2	2			4	0	0			0	0	3			3
R^2 min					0.04					0.11					0.49
R^2 max					0.47					0.63					0.75
R^2 mean					0.23					0.24					0.64

effort is put into it; and irrigation reduces water limitation. The positive impact of *tgrow* on the simulation accuracy may be a result of the underestimation of potential yields or a smaller yield gap in warmer regions (actual yields reach potential yields). Results on the difference between $Y_{max.b,act} - Y_{pot,sim}$ (see above) suggest that underestimation of potential yields can partly explain the positive impact of *tgrow*. Management practices that reduce the yield gap but are not represented by farm characteristics can be confounded with *tgrow*, if they are mainly applied in warmer regions.

For $Y_{av.b,act} - Y_{wat,sim}$ also the effect of *tgrow* is clearly positive, while the effect of *pgrow* is negative. As $Y_{wat,sim}$ is lower in warm and dry regions, where $Y_{av.b,act}$ is high, $Y_{av.b,act} - Y_{wat,sim}$ is especially high in these regions. Maize is generally a more important crop in these regions and the high significance levels for *maize_pr* show that this has an effect on yields. Currently, water limitation doesn't seem to be a large problem in Mediterranean regions, as maize is almost always irrigated. The effect of *irr_perc* is always positive, but as there is also a spatial pattern in irrigation practices, this effect is partly reflected in climatic variables. The negative effect of *ec_size* can indicate higher actual yields on smaller farms, but might also be related to the low $Y_{wat,sim}$ in regions with smaller farms.

6.3.2 Temporal variability

Relationships between actual and simulated yields

The high correlation between FADN and Eurostat data on actual average yields $Y_{av.b,act}$ and $Y_{av.a,act}$, suggests that maize yield data are very reliable in France, Germany and northern Italy (Figure 6.2a; $r>0.45$ corresponds to $p<0.10$; $r>0.53$ corresponds to $p<0.05$). In several other regions the temporal variability in $Y_{av.b,act}$ is fairly different from $Y_{av.a,act}$. The spatial pattern in Difference in Mean (DM) is more variable, but smallest in French regions (Figure 6.2b). In many southern regions $Y_{av.b,act}$ is higher than $Y_{av.a,act}$, while in northern regions the opposite is the case. When analysing the relationships between actual and simulated yields, we need to take into account that for several regions statistical data on actual yields is not coherent. Nevertheless, the spatial pattern for $Y_{av,act} - Y_{pot,sim}$ or $Y_{av,act} - Y_{wat,sim}$ is similar for both datasets. This can be observed comparing the (much smaller) DM between $Y_{av.b,act}$ and $Y_{av.a,act}$ in Fig 6.2b with the DM between $Y_{av.b,act}$ and $Y_{pot,sim}$ or $Y_{wat,sim}$ in Figure 6.2h and 6.2j . In the remainder of this section we use $Y_{av.b,act}$ for actual average yields.

In most regions, $Y_{max.b,act}$ is not related to $Y_{pot,sim}$ (Figure 6.2c). Also, $Y_{max.b,act}$ is usually higher than $Y_{pot,sim}$ (Figure 2d). DM is smallest in Germany and France, but the temporal variability in $Y_{max.b,act}$ is different from $Y_{pot,sim}$. We do not consider the difference between $Y_{max.b,act}$ and $Y_{wat,sim}$ in the remainder of the analysis, as Figure 6.2f shows that $Y_{max.b,act}$ is not water limited ($Y_{max.b,act}$ is higher than $Y_{wat,sim}$ in all regions). Still, in some regions the inter-annual variability in $Y_{max.b,act}$ is significantly related to $Y_{wat,sim}$ (Figure 6.2e).

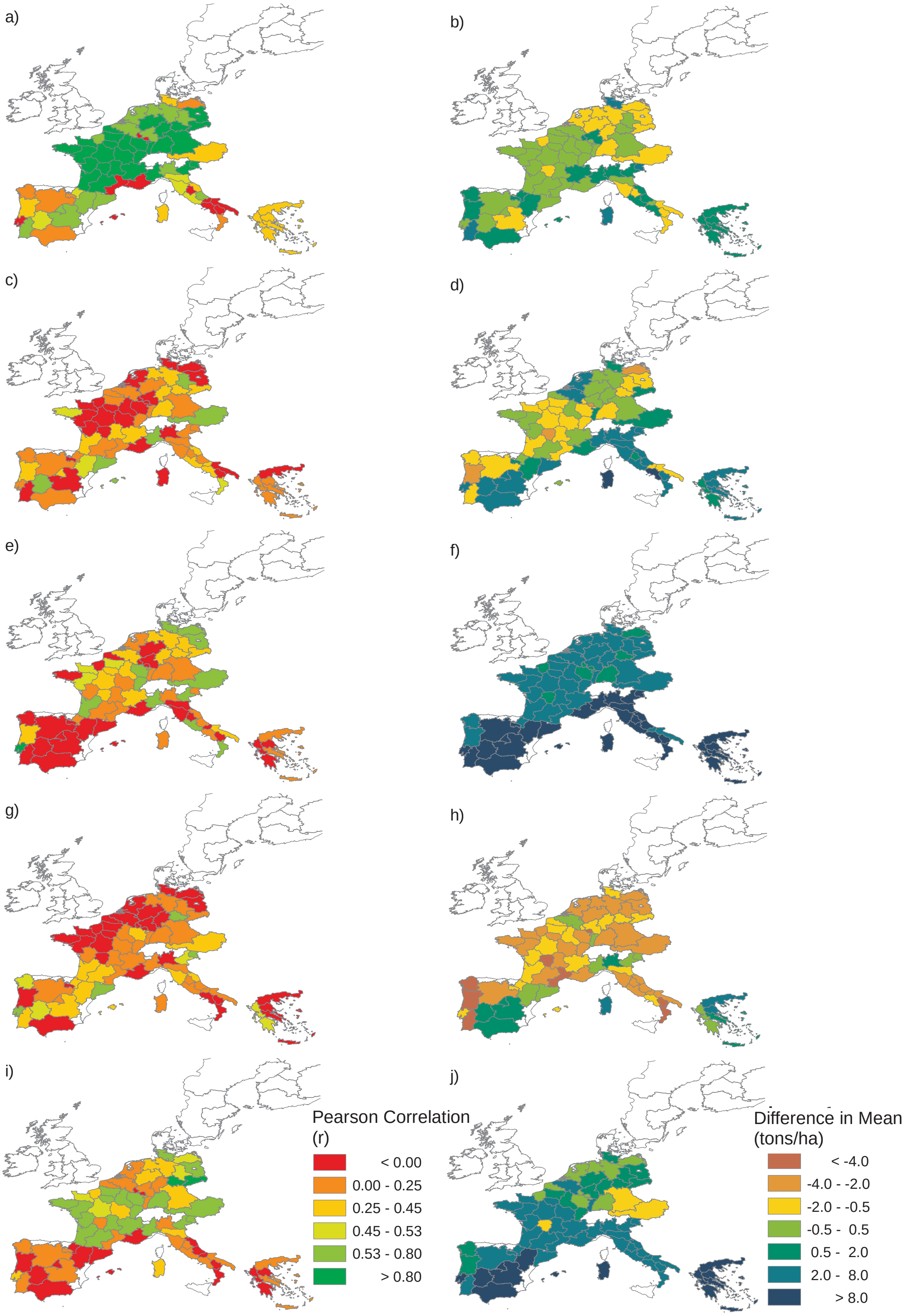

Figure 6.2 (in colour on p.184). Pearson correlations (r) and the Difference in Mean (DM; tons/ha) between temporal variability in actual and simulated yields per HARM region with (a),(b) $Y_{av.b,act} - Y_{av.a,act}$, (c),(d) $Y_{max.b,act} - Y_{pot,sim}$, (e),(f) $Y_{max.b,act} - Y_{wat,sim}$, (g),(h) $Y_{av.b,act} - Y_{pot,sim}$ and (i),(j) $Y_{av.b,act} - Y_{wat,sim}$. An $r>0.45$ corresponds to $p<0.10$; $r>0.53$ corresponds to $p<0.05$.

Only in few regions the $Y_{av.b,act}$ is significantly ($r>0.53$, $p<0.05$) related to $Y_{pot,sim}$ (Figure 6.2g). These regions are mainly located in southern Europe. In some of these regions also the DM is small, suggesting that average yields are indeed close to potential yields and respond to climate variability in a similar way. $Y_{av.b,act}$ is higher than $Y_{pot,sim}$ in several regions in Greece, Spain, northern Italy and Belgium (Figure 6.2h). This was also observed in section 6.3.1, and suggests that simulated potential yields are underestimated in these regions. $Y_{av.b,act}$ is related to $Y_{wat,sim}$ in many regions in France, Germany, Austria and northern Italy (Figure 6.2i). In northern France, Germany and Austria also the small DM indicates a good representation, but in southern France and northern Italy the DM is far above zero (Figure 6.2j). In the latter regions $Y_{wat,sim}$ can thus indicate the influence of climate variability, but the level of $Y_{av.b,act}$ is higher.

Factors explaining difference between actual and simulated yields

The regression models can explain between 0 and 100% of the differences between $Y_{max.b,act} - Y_{pot,sim}$, $Y_{av.b,act} - Y_{pot,sim}$ and $Y_{av.b,act} - Y_{wat,sim}$, depending on the variable and region (Table 6.6). The mean R^2 is around 0.80; models including only climatic conditions explain around 35% and only farm characteristics around 50%, which suggest that these factors are additive. There is no clear spatial pattern in the explained variance, but there is in the explaining variables.

For $Y_{max.b,act} - Y_{pot,sim}$ the effect of *tgrow* is mainly positive in southern regions and negative in northern regions. As southern regions generally have a higher *tgrow,* this means that the positive effect of *tgrow* is not only less pronounced spatially (section 6.3.1), but also temporally in southern regions. The negative effect of *tgrow* in northern regions indicates that maximum yields are not optimal in warm, probably drier years. This is likely related to water limitation, as the effect of *pgrow* is mainly positive (or concave). High maximum yields are easier obtained with high precipitation, but the concave relationships indicates an optimum for precipitation above which it decreases the marginal effect (effect becomes smaller or even negative).

Although variable per region, $Y_{max.b,act} - Y_{pot,sim}$ is also affected by farm characteristics. The positive effect of *year* in many regions indicates that optimal yields that can be obtained are still increasing. *Year* is positively correlated to several farm characteristics (in many regions to *subs/ha, ec_size* and *fnv/awu*), so causal effects can be confounded. The most obvious effect is from *irr_perc*, as this variable is little related to other variables. Effects of *ec_size* are mainly positive, but often negative when *year* is included and therefore difficult to interpret. The effect of *subs/ha* is mainly negative, especially in northern regions, suggesting that high subsidies do not stimulate productivity.

Climatic conditions and farm characteristics influencing $Y_{max.b,act} - Y_{pot,sim}$ are similar for $Y_{av.b,act} - Y_{pot,sim}$. Furthermore, using high *prot/ha* generally decreases $Y_{av.b,act} - Y_{pot,sim}$, but in several, mainly southern regions, the effect is positive. A negative effect may imply that more *prot/ha* is used in years with higher potential yields, but that these higher inputs generally do not result in higher yields. In several southern regions also the effect of *ec_size* is negative, suggesting that smaller farms come closer to potential yields.

Effects are also similar for $Y_{av.b,act} - Y_{wat,sim}$. Climatic conditions have more effect (higher R^2) in regions where the correlation between $Y_{av.b,act}$ and $Y_{wat,sim}$ is already high (e.g. France, Germany). This is related to peaks and dips due to high temperatures and low precipitation being less severe for $Y_{av.b,act}$ than for $Y_{wat,sim}$ The influence of farm characteristics is especially high in Mediterranean regions (high R^2). Both f*ert/ha* and *prot/ha* are generally positive in southern Europe, and more often negative in northern regions, so in drier conditions (low $Y_{wat,sim}$) using more fertilizers and crop protection products has relatively more effect. In general, although the direction of influence of farm characteristics differs among regions, they explain a large part of the variance.

Table 6.6. Variables explaining the temporal variability in the difference between actual yields $Y_{av.b,act}$ and $Y_{max.b,act}$ and simulated yields $Y_{pot,sim}$ and $Y_{wat,sim}$ in the EU15 from 1990−2003. For 64 regions an analysis is performed; the values indicate the number of regions for which a variable has a significant effect ('+' = positive, '−' = negative, '+−' = concave, '−+' = convex). The R^2s refer to the max(imum) and mean of models with all variables included (all), only climatic conditions (cc) and only farm characteristics (fc).

	$Y_{max.b,act}$-$Y_{pot,sim}$					$Y_{av.b,act}$-$Y_{pot,sim}$					$Y_{av.b,act}$-$Y_{wat,sim}$				
	+	−	+−	−+	Total	+	−	+−	−+	Total	+	−	+−	−+	Total
Tgrow	12	11	7	4	34	16	6	7	6	35	18	1	8	5	32
Pgrow	14	6	14	5	39	7	5	20	6	38	2	19	5	14	40
Year	23	8			31	28	8			36	21	13			34
Fert/ha	12	15			27	13	16			29	18	12			30
Prot/ha	13	11			24	12	19			31	19	10			29
Ec_size	15	9			24	12	16			28	13	20			33
Irr_perc	14	6			20	22	4			26	11	9			20
Maize_pr	14	12			26	13	15			28	12	13			25
Fnv/awu	14	18			32	16	19			35	11	14			25
Subs/ha	10	18			28	11	19			30	13	16			29
R^2 max all					1.00					1.00					1.00
R^2 max cc										0.97					0.93
R^2 max fc										0.93					0.99
R^2 mean all					0.72					0.80					0.78
R^2 mean cc										0.36					0.35
R^2 mean fc										0.52					0.50

6.3.3 Temporal yield variability on different farm types

In some regions there is large diversity in extent and variability of $Y_{max.b,act}$, $Y_{av.b,act}$ and $Y_{min.b,act}$ (Fig 6.3a); in other regions the diversity is small (Figure 6.3c). In Figure 6.3 we observe that in the region Franche-Compte the actual yields ($Y_{max.b,act}$, $Y_{av.b,act}$ and $Y_{min.b,act}$) vary in a similar way, and also that $Y_{av.b,act}$ is related to simulated water limited yields (compare Figure 6.3 c and d; r = 0.79). In Bayern there is more difference between extent and variability of $Y_{max.b,act}$, $Y_{av.b,act}$ and $Y_{min.b,act}$. Relationships with simulated yields are also smaller, the correlation between $Y_{av.b,act}$ and $Y_{wat,sim}$ is 0.42.

Relating the diversity in maize yield level (mean $Y_{max.b,act} - Y_{min.b,act}$) and response diversity (standard deviation in $y_t - y_{t-1}$) from all regions to the model performance (highest r between $Y_{av.b,act}$ and simulated yields) indicates that the relationship with response diversity is highly significant (r = −0.32 (p = 0.009), while also the relationship with diversity in maize yield (r = −0.21, p = 0.093) is nearly significant. Hence, in regions with more diverse yield responses, which are mainly warmer and drier regions, average regional yields $Y_{av.b,act}$ are less influenced by climatic variability as simulated by the model. Diversity in management practices within a region may underlay the yield response diversity among farm types and provide an adaptation mechanism at the regional level to climatic variability, reducing actual impacts.

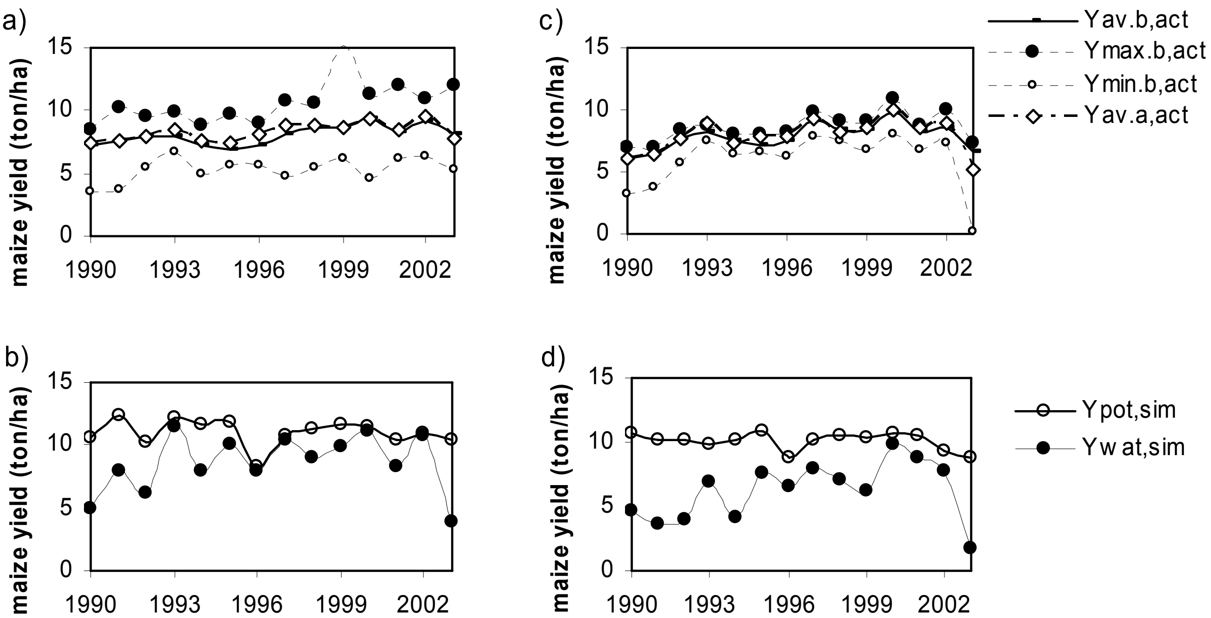

Figure 6.3. Actual (a, c) and simulated (b, d) yields in Bayern (a, b) and Franche-Comte (c, d).

6.4 Discussion

6.4.1 Data sources and methodology

The WOFOST model used in the CGMS is a widely validated and applied crop model (Supit et al., 1994; Wolf and van Diepen, 1995; Rabbinge and van Diepen, 2000). Projections from the CGMS of the impact of climate variability on crop yields are published regularly (http://mars.jrc.it/bulletins.htm). Estimates of climate change impacts on regional crop yields in Europe (e.g. Wolf and van Diepen, 1995) are used to indicate the impact of climate change on European agriculture (Olesen and Bindi, 2002). Investing the performance to estimate regional yields by the CGMS is thus of wide interest.

Using statistical data to validate model outputs can be problematic however. Although bookkeeping principles of data collection are the same in all countries, the method of collecting regional yield data can still differ per region or country and might not always be accurate. By using two datasets (FADN and Eurostat) we give an indication of the data reliability. The FADN provides a very extensive dataset, including both yields and farm characteristics of more than 50,000 European farms. Extent and detail of this database is unique and a good basis for the analysis.

Time series are short and relationships that we describe are not necessarily causal. We apply regression models for many regions to identify climatic conditions and farm characteristics that can explain the difference between simulated and actual yields. Factors that are found significant in many regions can be assumed to be important. As we expect that a combination of climatic conditions and farm characteristics influence the difference between simulated and actual yields, we choose backward models to select the significant variables. Backwards models start with all variables included and can thus detect variables that have a combined impact.

6.4.2 Factors influencing differences between simulated and actual yields

The CGMS is better able to simulate maize yields in temperate regions than in Mediterranean regions. In Mediterranean regions maize is usually irrigated, while the crop model performs better in regions where yield is determined by water limitation [as also observed by Landau et al. (1998)]. In Mediterranean regions, higher temperatures often increase actual maize yields instead of decreasing them as simulated by the CGMS and other crop models (e.g. Kapetanaki, 1997). It is likely that farmers in Mediterranean regions use more heat resistant cultivars to adapt to higher temperatures. This was also suggested as the main reason for the less severe impacts of the 2003 heat wave in Mediterranean regions compared to temperate regions (Ciais et al., 2005). The CGMS should thus be re-calibrated using observations from more recently released cultivars.

In order to represent the impact of climate change and variability on actual yields, specific attention should be devoted to the yield gap (Ewert et al., 2005). Secondary effects influencing the yield gap are not well understood, but are represented by management factors not considered in crop models. Several farm characteristics which play a role determining management activities and the regional yield gap have been identified: a larger maize area in arable land (*maize_pr*), higher farmers' income (*fnv/*awu) and more irrigation (*irr_perc)*. The positive effect of maize area and irrigation on maize yields was also found in Chapter 2. Within regions, farms with a higher fertilizer use also have higher maize yields (Chapter 2), but among regions this is not the case. In many regions fertilizers are used in abundance and increases will decrease the marginal effect on maize yields (Chapter 5). There is no clear effect of farm size (*ec_size)*, but the positive effect of farmers' income indicates that it is not the size of the farm that matters, but how resources are used. A higher regional average farmers' income can be related to technological and financial ability to adopt new practices.

Farm characteristics decreasing the yield gap do not necessarily decrease the impact of temporal climate variability; the influence of specific farm characteristics differs per region. As starting conditions are different in different regions, interactions between climate and management are also different (Chapter 5). It is however clear that regional diversity in management practices (and to some extent, in biophysical conditions) decreases the impact of climatic variability (as projected by simulated yields) on average actual yields. Projections on regional impacts of climate change and variability are thus difficult to make in diverse regions as (1) simulations do not represent regional averages and (2) regional averages do not represent individual farmers.

Also in regions where simulated yields represent actual yields well, inter-annual variability is overestimated, as often observed (Hansen and Jones, 2000). Some attribute this to aggregation error, some to model error. Looking at regions in our study where aggregation error seems small (Figure 6.3 c,d), inter-annual variability is also overestimated by simulated water limited yields. The overestimation of depletion of soil water content can be responsible for this (Eitzinger et al., 2004). De Wit et al. (2005) however showed that although the CGMS underestimates effects of rainfall, at regional level the uncertainty in precipitation and radiation has little influence on yield estimates in the CGMS. Also, a number of studies have demonstrated that the uncertainty in soil data has relatively little influence on the aggregated regional simulation results (Easterling et al., 1998; Mearns et al., 2001; Mathe-Gaspar et al., 2005). The reduction in transpiration, which indicates the extent to which the crop suffers from drought, is determined by soil water content and the critical soil water content. The latter depends on the evaporative demand of the atmosphere and the crop type; estimates may need adjustment.

Management practices can also reduce the impact of limited water availability. Temporal variability in farm characteristics (e.g. *fert/ha*, *prot/ha*, *irr_perc*) can partly represent this. But as effects are largely dependent on management practices that change little over time, re-calibration of parameters influencing the reduction in transpiration will contribute most to better representation of temporal variability in actual yields.

6.5 Concluding remarks

Crop models are a good basis to simulate the impact of climate change and variability on regional yields. But although the Crop Growth Monitoring System (CGMS) performs well in many regions, especially in Mediterranean regions projections of the impact of climate variability do not reflect the impact on observed actual maize yields. For reliable projections of the impacts of climate change and variability on crop yields consideration of management and adaptation effects is required.

Results from the spatial and temporal analysis of the model performance suggest that farmers in Mediterranean regions have adapted to higher temperatures, for example by growing more heat resistant cultivars. Again, such adaptation mechanisms are not considered in the model but are particularly important for long-term projections of climate change impacts.

As management differs per region and farm type, the elegance of a crop model is not sufficient to project regional impacts of climate change and variability. Processes influencing potential, water and nitrogen limited yield are well understood, but secondary effects cannot be addressed. Farm characteristics can partly represent these secondary effects. Hence, including these in a regional crop model can improve the simulation of climate variability impacts crop yields. Therefore, more effort should be made to understand the relationships between farm characteristics and crop management activities and their impacts on yield.

Chapter 7

Impacts of land-use change on biodiversity. An assessment of agricultural biodiversity in the European Union

Abstract

The objective of this Chapter is to assess land-use intensity and the related biodiversity in agricultural landscapes of the EU25 for the current situation (i.e. 2000), and explore future trends, based on the four EURURALIS scenarios up to 2030.

Data from the Farm Accountancy Data Network (FADN) were used to classify farm types in 100 regions of the EU15, according to agricultural intensity. For the ten New Member States (EU10), which are not yet considered by the FADN, country level data were used to obtain similar farm types. Three processes were considered for the assessment of future trends in agricultural land-use intensity: (1) land-use change, (2) conversion into organic farming, and (3) changes in productivity of crop and grassland production.

An ecosystem quality value was attributed to each farm type according to dose-effect relationships between pressure factors and biodiversity compared to the value for an undisturbed situation. The biodiversity in agricultural landscapes was then calculated as the average ecosystem quality multiplied by the relative area size of each farm type within a region. A similar method of attributing ecosystem quality values to other land-use types allowed comparison between different land-use types.

Referring to the current situation, results indicate the lowest ecosystem quality values to be found in intensively used agricultural areas in lowlands (e.g. the Netherlands and northern France) and irrigation systems (e.g. Greece), whereas relatively high values are found in Spain and the New EU Member States. Scenario results show that for the A1 scenario (Global economy), the highest loss in ecosystem quality will take place in all regions in croplands and grasslands. The B2 scenario (Regional communities) provides the best opportunities to improve ecosystem quality of agricultural landscapes. In most scenarios, agricultural land is decreasing, while the remaining agricultural areas tend to be used more intensively. The negative impact of intensification on biodiversity is partly set off by (active or spontaneous) nature development on abandoned agricultural areas, but the overall trend seems to be generally negative.

The strength of this methodology is that it provides a quick overview of land-use intensity change and biodiversity trends. Through the use of this farm-type level of analysis we have provided a good picture of the differences in land-use intensity and the related biodiversity between the EU regions and the scenarios.

Keywords: Biodiversity, agricultural landscapes, land-use intensity, European Union

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7.1 Introduction

Land-use change is an important form of global pressure affecting biodiversity (e.g. Sala et al., 2000; UNEP, 2002; UNEP-RIVM, 2003; Zebisch et al., 2004). The most important type of land use in Europe is agriculture, with 34% of the European terrestrial area used for crop production and 14% for grassland (Verburg et al., 2006). Higher-scale studies on the effects of land-use change on biodiversity have focused mainly on 'major land-use types' with little attention paid to the intensity of land use (e.g. Sala et al., 2000). Agricultural landscapes are considered to be homogenous matrices. In practice, there is a large heterogeneity in farming systems and management practices. Low-intensity farming systems are critical to nature conservation and protection of the rural environment (Bignal and McCracken, 1996), while large-scale input-intensive systems can cause major environmental problems in agricultural and surrounding non-agricultural ecosystems (Donald et al., 2001; Benton et al., 2002).

The biodiversity in agricultural landscapes depends largely on the intensity of land use, so an assessment of changes in agricultural biodiversity at the European scale needs spatially explicit information on land-use intensity. We can distinguish between input intensity, which is measured by input variables, e.g., chemical fertilizer, pesticides, and output intensity, measured as production per unit land area and time (Turner and Doolittle, 1978). Farming systems differ regionally in intensity and have, in the past, shown large changes. Post-war agricultural policies in the EU focused mainly on increasing agricultural productivity by promoting technical innovations and by ensuring the rational development of agricultural production (as laid down in article 33 of the EC Treaty). These policies can be considered successful in as far as they have resulted in increased yields and enhanced capacity for self-sufficiency. However, increased agricultural intensity has also resulted in an increasing pressure on biodiversity, and this is likely to continue (Tilman et al., 2001). Petit et al. (2001) indicated that agricultural intensification would be the most important form of pressure on biodiversity in the coming decades.

In response to biodiversity loss, environmental objectives and landscape preservation in recent years have become prominent issues in the EU Common Agricultural Policy (CAP) and related environmental policies. The EU has committed itself to halt biodiversity loss by 2010 (EU, 2002).

This study reported on here is incorporated into the EURURALIS project (Klijn et al., 2005), a scenario study aiming to stimulate discussion on the future of Europe's rural areas (Westhoek et al., 2006). In this study we aim to: (1) assess the land-use intensity and relating biodiversity in agricultural landscapes in the EU25, for the current situation (2000) and to (2) analyse the impact of (agricultural) land-use change on biodiversity for the four EURURALIS scenarios for 2010, 2020 and 2030.

The database of the EU Farm Accountancy Data Network (FADN) and other farming statistics were used to classify farm types according to land-use intensity. Attribution of ecosystem quality values to farm types was based on a literature review carried out for the GLOBIO3 modelling development[1]. Ecosystem quality values for other land use types, using the same methodology, were attributed, so that biodiversity tradeoffs between agricultural intensification and expansion of extensively managed agricultural land can be analysed. The EURURALIS scenario storylines and outcomes of the GTAP (Global Trade Analysis Project) model (Hertel, 1997; van Meijl et al., 2006), IMAGE (Integrated Model to Assess the Global Environment) (IMAGE team, 2001; Eickhout et al., 2007) and CLUE (Conversion of Land Use and its Effects) (Veldkamp and Fresco, 1996; Verburg et al., 2006) models used in EURURALIS were used to model future changes in land-use intensity and biodiversity.

Section 7.2 elaborates on the methodological building blocks, in other words, the data sources and the modelling framework, while section 7.3 describes how these were used to produce the results on ecosystem quality presented in section 7.4. Section 7.5 discusses results and supporting methods, with section 7.6 presenting our concluding remarks.

7.2 Data sources and modelling framework

7.2.1 FADN database and other sources of farm statistics

The Farm Accountancy Data Network (FADN-CCE-DG Agri and LEI) contains data on the level of the individual farm enabling farms to be grouped on the basis of a range of variables. A broad set of data is available to link the sample farms with a land-use intensity gradient to differentiate between farm types. Data have been collected since 1989. The database for the year 2000 includes data on more than 50,000 sample farms across the EU15. The Dutch Agricultural Economics Research Institute (LEI) has created a division in 100 (sub)national regions, the so-called HARM regions, in order to allow comparisons of different regional divisions of the EU15 used by Eurostat (NUTS2) and FADN. The distribution of certain farm types within a HARM region can be assessed by multiplying all sample farms within a region by their Utilized Agricultural Area (UAA) and the number of farms they represent.

FADN considers the following land-bound production types: specialist field crops, specialist permanent crops, specialist grazing livestock, mixed cropping and mixed crops/livestock. The activity that is the largest in terms of economic size, determines the production type. For example, a farm that obtains more than 66% of its total standard gross margin from the sale of field crop products belongs to the 'specialist field crops' production type, irrespective of the surface area dedicated to it.

FADN provides data on a number of variables that are related to the land-use intensity in terms of input intensity: irrigated area, type of grassland, number of livestock units per hectare, conventional or organic farming, expenditures on inputs (fertilizer and soil improvers, crop protection products, feeding stuffs for grazing livestock) and expenditures on major land improvements. FADN also provides data on

[1] http://www.globio.info

output intensity, e.g. crop yields (in tons/ha) and crop and livestock output (in euros).

Because of the lack of farm accounting data at the sub-national level in the New Member States of the EU (EU10), statistics at country level were taken to distinguish farm types in the New Member States. The farming systems of the Food and Agriculture Organization of the United Nations (FAO) as described by Dixon et al. (2001) provide a useful framework to link the socio-economic conditions of farms with the agro-ecological condition of the environment (Tekelenburg et al., 2003). Complementary, statistics on agricultural land use at country level from FAO (FAO, 2002), EEA (European Environment Agency) (Petersen and Hoogeveen, 2004), Eurostat and IFOAM (International Federation of Organic Agriculture Movements) (Yussefi and Willer, 2003) were used. Data on Cyprus were not available.

7.2.2 Attributing ecosystem quality values to farm types

Introduction

In order to measure biodiversity loss we adopted the indicator ‘trends in abundance and distribution of selected species’ appearing on the list endorsed by the Malahide EU-Stakeholder Conference[2]. Biodiversity is expressed as the mean abundance of species originally present in natural ecosystems relative to their abundance in undisturbed situations, which we call the ecosystem quality. The maximum value is 100% and indicates an undisturbed natural situation, while 0% represents a completely transformed/destroyed ecosystem without any wild species left. This indicator is close to the natural capital index (NCI) concept (Ten Brink, 2000).

Alkemade et al. (2006) assessed the impact of different land uses on the relative species abundance, the ecosystem quality, for the GLOBIO3 modelling development. Agro-ecosystem quality is the result of combined effects of several pressures on the landscape scale of analysis. We focus on the impact of land-use intensity, which includes the combined effects of ploughing frequency, fertilizer and pesticide applications, and specialization of production, monoculture, and crop or grass productivity. Tilman et al. (2001), Zechmeister and Moser (2001), Gaston (2000) and Wilson et al. (2003) showed a strong correlation between land-use intensity and biodiversity loss.

A literature review was carried out on the following to determine the dose-effect relationship of the intensity of agricultural land use on biodiversity:

- land-use biodiversity loss gradients (comparison between land-use systems and the pristine, or low human impact, situation);
- pair-wise comparison of biodiversity impact between different farm types (separate for cropping and grassland systems);
- pair-wise comparison of impact on biodiversity for conversion from conventional farming into organic farming.

[2] http://www.eu2004.ie/templates/document_file.asp?id=17810

Here we adapt these results for the European situation. As in Europe the primary vegetation is largely unknown we assumed that most of land use change processes now occurring in the tropics, are not fundamentally different from what occurred in Europe (Lambin et al., 2001). A table was drawn up on the basis of the literature review, and complemented by the authors on the basis of their knowledge and experience, to indicate the ecosystem quality for farm types on the basis of land use and production intensity in the European context (Table 7.1).

Table 7.1. Summary of ecosystem quality per farm type.

Ecosystem quality[a]	Farm types	Production systems
100%	No production	Primary vegetation
40%	Extensive grassland management	Medium to high cattle density on natural grassland
35%	Extensive organic farming	Low-External-Input and Sustainable Agriculture (LEISA), Permaculture
25%	Extensive farming	Traditional farming Extensive farming Low-External-Input Agriculture (LEIA)
20%	Intensive organic farming	Rainfed organic farming
20%	Intensive grassland management	Grassland production based on ploughing, reseeding and fertilization
15%	Highly intensive organic farming	Organic farming in developed countries (where conventional agriculture is based on long term soil and water investments)
10%	Intensive production systems	Intensive agriculture Integrated agriculture High-External-Input Agriculture (HEIA) Conventional agriculture
5%	Highly intensive production systems	Irrigation based agriculture Integrated agriculture Drainage based agriculture Additional soil levelling practices Regional specialization Specialization of production at the farm and landscape level.

[a] Expressed as percentage of the original pristine situation (see text for further explanation).

Conventional farming on cropland

Comparison of several land-use−biodiversity loss gradients showed that ecosystem quality decreases as agricultural practices intensify. Alkemade et al. (2006) classified the many production systems described into three broad classes: agroforestry systems (Wood et al., 1982; Fujisaka et al., 1998; Jones et al., 2003) with an average ecosystem quality of 50%, extensive agriculture (Beck et al., 2002; Vallan, 2002; Davies et al., 2003; Wilson et al., 2003) with an ecosystem quality of 25% and intensive agriculture (Wood et al., 1982; Fabricius et al., 2003; Jones et al., 2003) with an ecosystem quality of 10%. The differences between ecosystem quality values could be confirmed by other authors, who had not compared remaining species richness or abundance compared to the pristine situation. Perfecto et al. (1997) and Erwin and Scott (1980) showed that high levels of fertilizers and pesticide applications depress ecosystem quality to a large extent. Siebert (2002) found that in intensive non-shaded cacao production less than 5% of the original plant species are observed. We could conclude a remaining ecosystem quality in intensive agriculture of 10%. Extrapolation of this relationship for highly intensive production systems on the basis of additional long-term water and soil investments such as irrigation, drainage and soil levelling practices would result in half the ecosystem quality (5%). The specialization of agricultural production at landscape level (a historical process going back to the 1950s in Europe by which arable farms are concentrated in one region and livestock production in another) also depresses ecosystem quality to the same extent. Robinson and Sutherland (2002) calculated an average decrease of 26% for birds, Bradburry et al. (2000) recorded a Yellow Hammer decline of 10% per year and Aebisher (1991) recorded a 4.1% decline annually, halving the abundance in 20 years.

Conventional farming on grassland

Intensification of extensively used grasslands and abandonment without replacement of natural grazers may both lead to decreased species richness and/or a decreased average abundance of species (Tasser and Tappeiner, 2002). No consistent optimal grassland productivity for maximum biodiversity could be found in grassland ecosystems, but maximum species richness was always found at light grazing regimes. In the Mediterranean, maximum biodiversity on grassland is reached at 25% productivity. For pristine natural grassland ecosystems, where grazing by wild herbivores is part of the natural situation, as well as long-term highly valued semi-natural grasslands, where domesticated animal grazing takes place, the expected ecosystem quality ranges from 80–100% under light grazing for 0.2−0.4 livestock units per hectare (LU/ha) and 40−50% under heavy grazing for more than 0.7 LU/ha (Stuarthill, 1992; Gibson et al., 1993; Roques et al., 2001; Cagnolo et al., 2002; Alados et al., 2003). Abandoned grassland suffers a loss in ecosystem quality of some 25% with reference to optimal grazing density, i.e. 75% ecosystem quality would remain (Smith and Rushton, 1994; Tucker and Heath, 1994; Poschlod et al., 1997; Sternberg et al., 2000; Cagnolo et al., 2002).

Management intensity (fertilization and reseeding) has been found to be a good predictor (R^2=0.73) of grassland vegetation type in mainland Scotland (Wilson et al., 2003). Each grassland vegetation type consists of a typical composition of plant and animal species as well as a typical grazing and/or grassland management regime. Management intensity is negatively correlated with vegetation types of high species richness. In the case of fertilization of permanent grassland, the ecosystem quality decreases to 20% on average; in other words, it drops to half the expected ecosystem quality of extensively managed grassland with heavy grazing regimes (Bullock et al., 2001; Di Giulio et al., 2001; Ujazdowski, 2002; Wilson et al., 2003). The ecosystem quality of intensively managed grassland corresponds then to the situation between extensive (25%) and intensive (10%) cropland management.

Organic farming

Pair-wise comparison between conventional and organic farming showed on average a 2.7 times increase in the species abundance of five species groups: 2.1 times for birds (e.g. Brae et al., 1988; Tew et al., 1992; Bradbury et al., 2000); 2.9 times for plants (e.g. Hald and Reddersen, 1990; Tew et al., 1992; Frieben and Köpke, 1995); 3.2 times for insects (e.g. Dritschilo and Wanner, 1980; Hokkanen and Holopainen, 1986; Hald and Reddersen, 1990; Kromp, 1990; Feber et al., 1997); 2.4 times for mammals (e.g. Tew et al., 1992); and 1.8 times for earthworms (e.g. Blakemore, 2000). Bengtsson et al. (2005) estimated an increase in mean species abundance by 50%, based on an in depth meta-analysis. Very intensive conventional farming was taken as the benchmark in all studies. The conversion of more extensive land-use types into organic farming will result logically in a decreasing gain (Frieben, 1997; Soil Association, 2000; Stolton, 2002). We translated this into an average absolute gain of 10% for conversion of any type of conventional cropland or grassland farming into organic farming. This implies a tripling for very intensive systems (i.e. from 5% to 15%), a doubling for intensive agriculture (from 10% to 20%) and a 1.4 times gain for extensive agriculture into Low-External-Input and Sustainable Agriculture (from 25% to 35%).

7.2.3 EURURALIS scenario storylines and core models

Scenario storylines

Scenarios are alternative images of how the future might unfold; these function as appropriate tools for analysing how driving forces can influence biodiversity and other ecosystem services (Alcamo, 2001). The EURURALIS scenarios (Westhoek et al., 2006) used in this study, as inspired by the IPCC-SRES scenario families (Nakícenovíc et al., 2000) and subsequent studies, is structured along two dimensions: lean government (A) versus ambitious government regulation (B); and globalization (1) versus regionalization (2). This results in four scenarios: Global economy (A1), Continental markets (A2), Global co-operation (B1) and Regional communities (B2).

Environmental legislation and socio-economic pressures to intensify or extensify agricultural production differs among the scenarios (Westhoek et al., 2006). Technological developments (e.g. to enhance yields) are assumed to increase in the order B2≈A2<B1<A1, whereas environmental legislation tends to become more restrictive, in the order A1≈A2<B1<B2. Organic farming is particularly promoted in the B scenarios. Demographic pressure, which for the EU increases in the order B2<A2<B1<A1, also plays a role in land-use change processes, as it co-determines the demand for residential and industrial/business areas as well as for agricultural products.

The storylines presented by Westhoek et al. (2006) do not specifically describe changes in land-use intensity and related farm types. One could argue that, for example, in the B1 scenario, agricultural land-use intensity may present convergence into more similar farm types. Technology development, decrease in land prices and restrictive environmental legislation might induce some extensification of the highly intensive classes; whereas the decrease in government support envisaged for this scenario might cause movement towards bigger and more uniform parcels to benefit from the economies of scale, which would particularly affect the more extensive land-use classes.

EURURALIS core models

Core models used in EURURALIS are GTAP, IMAGE and CLUE. A modified version of the global general equilibrium Global Trade Analysis Project (GTAP) model (Hertel, 1997; van Meijl et al., 2006) was used in iteration with the integrated assessment model IMAGE (IMAGE team, 2001; Eickhout et al., 2007) to quantify changes in agricultural area at national level. GTAP models the economic consequences of the scenarios, whereas IMAGE takes account of technological and environmental developments. The land-use changes are allocated spatially by CLUE at a resolution of 1x1 km^2 (Veldkamp and Fresco, 1996; Verburg et al., 2006).

7.3 Methodology

Figure 7.1 presents a schematic outline of the methodology used in this study to determine ecosystem quality for the current (i.e. 2000) and the future situation.

7.3.1 Assessment of agricultural intensity in 2000

EU15 farm typology

The distribution of different farm types throughout the EU15 was analysed with data from the Farm Accountancy Data Network (FADN-CCE-DG Agri and LEI) for the year 2000. Additionally, data from 1990 and 1995 were used to look at recent changes and to check the consistency of the data. As mentioned in section 7.2.1, FADN production types are distinguished on the basis of the economic size of production. Therefore, all individual farms were reclassified in four land-use types based on the extent of land use: cropping systems, permanent cropping systems, grassland and arable grazing livestock. In the final biodiversity assessment, cropping systems and permanent cropping systems were aggregated to cropland and grassland systems and arable grazing livestock systems to grassland. The results of this reclassification and the ecosystem quality attributed to each class are given in Table 7.2 (cropland) and Table 7.3 (grassland).

All (FADN's) specialist field crops were allocated to cropping systems because 92% of all farms have more than 66% of their land in cropland. The remaining area is mainly temporary grassland, which can differ per year. Specialist permanent crops were all allocated to permanent cropping systems. Although many specialist permanent crops also grow field crops and/or have grassland, growing permanent crops is the main activity.

Specialist livestock types often have a large area of cropland; for this reason this production type was divided into two land-use types: grassland systems (>66% grassland) and arable grazing livestock systems (<66% grassland). The mixed

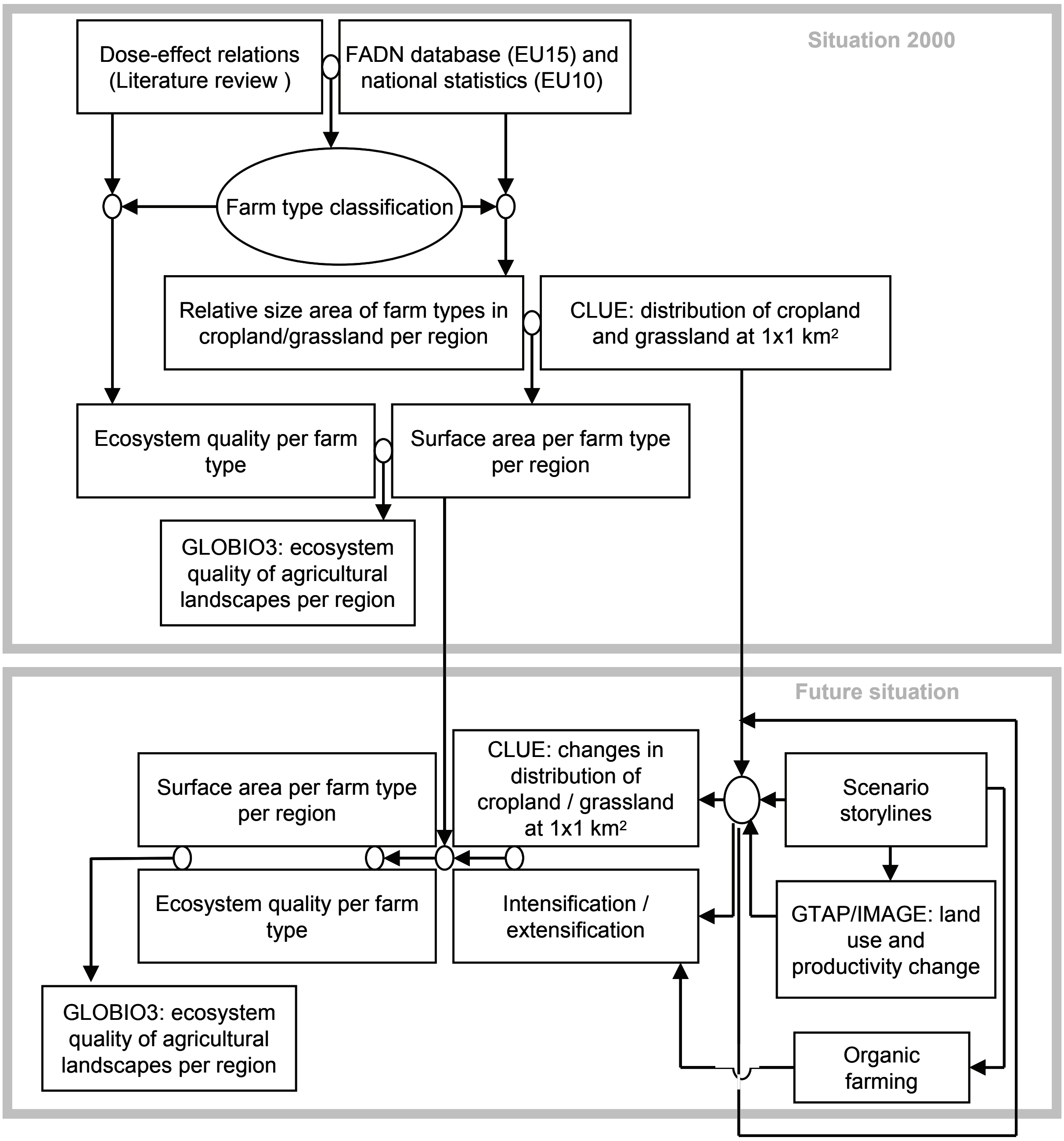

Figure 7.1. Schematic outline of methodology used in this study to determine ecosystem quality. The scenario storylines were developed by Westhoek et al. (2006). GTAP, a global economy model, and IMAGE, an integrated assessment model, were used iteratively to quantify area changes in agricultural land use and land productivity at the country level (van Meijl et al., 2006; Eickhout et al., 2007). The CLUE model (Verburg et al., 2006) allocated (changes in) land use to a 1×1 km^2 grid level.

production types were divided into the classes with similar criteria as for the other production types. Farms with more than 66% grassland area allocated to grassland systems, 33−66% to arable grazing livestock, and less than 33% to cropping systems or permanent cropping systems, depending on the dominant land use.

Table 7.2. Classification of (annual and permanent) cropping systems.

	Criterium Organic	Criterium Irrigation	Criterium Intensity[a]	Class[b]	Ecosystem quality
Irrigated	Non-organic	Irrigation		17 (37)	5%
Highly intensive	,,	No irrigation	>250 euro/ha	16 (36)	5%
Intensive	,,	,,	80−250 euro/ha	15 (35)	10%
Extensive	,,	,,	< 80 euro/ha	11 (31)	25%
Highly intensive organic	Organic	Irrigation OR	> 250 euro/ha	14 (34)	15%
Intensive organic	,,	No irrigation	80−250 euro/ha	13 (33)	20%
Extensive organic	,,	,,	< 80 euro/ha	12 (32)	35%

[a] Intensity = costs of: fertilizer and soil improvers, crop protection products and feedingstuffs for grazing livestock.
[b] Classes without brackets are for cropping systems, with brackets for permanent cropping systems; in Figures 7.2 and 7.3 farm types are indicated with these class numbers.

Table 7.3. Classification of livestock systems (grassland and arable grazing livestock).

	Criterium grassland	Criterium intensity	Class[d]	Ecosystem quality
Natural grassland	Rough grassland in UAA[a] > 66%	LU/ha[b] < 0.3	41	100%
Extensive pasture	Permanent + rough grassland in UAA > 66%	LU/ha < 1.0 Input costs[c] < 80 euro/ha	42	40%
Intensive pasture	Grassland in UAA > 66%	LU/ha < 2.0 Input costs < 250 euro/ha	44	20%
Highly intensive pasture	,,	LU/ha > 2.0 OR Input costs > 250 euro/ha	45	20%
Extensive arable grazing livestock	Grassland in UAA< 66%	LU/ha < 1.0 Input costs < 80 euro/ha	43	32.5% = (40+25)/2
Intensive arable grazing livestock	,,	Input costs 80−250 euro/ha	46	15% = (20+10)/2
Highly intensive arable grazing livestock	,,	Input costs > 250 euro/ha	47	15% = (20+10)/2

[a] UAA = Utilised Agricultural Area.
[b] LU/ha = Livestock Units/hectare.
[c] Input costs = costs of: fertilizer and soil improvers, crop protection products and feedingstuffs for grazing livestock.
[d] In Figures 7.2 and 7.3 farm types are indicated with these class numbers.

Within each land-use type, farm types were distinguished on the basis of land-use intensity. For croplands, input costs on fertilizers and soil improvers and crop protection products have been used as the main indicators to distinguish between extensive and intensive systems. Furthermore, indicators are formed based on whether irrigation takes place on the farm and whether farming is organic to give information on the land-use intensity. The type of grassland in combination with livestock density (expressed as livestock units per ha) is the best generally applicable indicator for grassland.

If any irrigation takes place on the farm, we assume that soil and water improvements have been made to improve the productivity of the land. Based on the notion that in cases where land improvement investments are high, annual input costs are also high, both irrigated and high input farms were allocated to the highest land-use intensity class.

Thresholds for input costs were based on statistical analysis and previous work in the ELPEN project[3] and IRENA project[4] (Andersen et al., 2004b). Various thresholds have been used in previous classifications. For extensive systems, 40, 80 and 150 euro/ha have been applied as a maximum level for input costs. Choices for thresholds depend on the land-use type, the application and whether regional differences have been taken into account. Although in different regions differences in farming systems and in the environment could require different indicators and thresholds, a common typology is more appropriate for our needs because it allows for direct cross-sectional comparisons.

We decided to apply a maximum of 80 euro/ha spent on inputs for extensive systems and a minimum of 250 euro/ha for highly intensive systems, with intensive systems in between. Analysis of variance and post hoc multiple comparisons showed these groups to be significantly different in other indicators of production intensity, such as crop output per hectare and the yield of maize and wheat. Variation within groups is lowest when these thresholds are applied.

Organic farming systems were divided in three intensity classes. Based on the literature findings (see section 7.2.2) conventional production systems converted into organic farms were assumed to increase ecosystem quality in their fields by an average of 10%. The relative gain for intensive systems is higher, but the resulting ecosystem quality is lower in absolute terms than for extensive organic farming. In the FADN database, data on organic farming were missing for some regions (Italy, France). Eurostat data on organic farming per land-use type were used to make up for missing data and for regions where percentages were very low, and probably less reliable (Greece, Belgium). For livestock systems, organic farming was not explicitly included in the farm type classification. Where available, FADN data were used to represent organic farming in livestock systems (in % per region). Eurostat data were used if no other data were available. For regions where FADN lacks data whereas Eurostat shows

[3] www.macaulay.ac.uk/elpen
[4] webpubs.eea.eu.int/content/irena/index.htm

that organic farming is present, complementing the database with Eurostat data was assumed to give the best estimates.

Thresholds for livestock systems are based on the literature review and previous projects mentioned earlier. The literature consulted offered no clues to distinguish intensive and highly intensive grassland systems in terms of ecosystem quality. Nevertheless, to improve insights in differences between regions and years, we do identify these types as different classes. The ecosystem quality on arable grazing livestock systems was taken as the average of the related intensity class of cropland and grassland.

EU10 (New Member States) farm typology

The available statistics for the New Member States do not differentiate between production systems so much as by the FADN database, but a general overview can be obtained by assigning area of land to the farm type classes of cropland and grassland production systems.

For cropland, the area of 'irrigated' agriculture was taken from FAO data (FAO, 2002). IFOAM country statistics (Yussefi and Willer, 2003) were used to indicate the fraction of organic farming per country. The percentages of the extensive farm types and the intensive farm types were estimated on the basis of the farm structure share of family farms (FAO, 2002) and the description of farming systems by Dixon et al. (2001). The FAO data were not available for the Baltic States and Cyprus and Malta. For these countries, we assumed that after subtraction of irrigated and organic areas, 50% of the agricultural area is occupied by extensive and 50% by intensive production systems.

EEA statistics (Petersen and Hoogeveen, 2004) provide information on the area of different types of grassland. Mountain grassland was considered as 'natural grassland' with 100% ecosystem quality. Extensive grazing in semi-natural area is 'extensive pasture' with a low livestock density. Permanent grassland (without further differentiation) is similar to 'intensive pasture' with reseeding and fertilization.

Calculation of ecosystem quality

The ecosystem quality EQ_{il} of agricultural landscapes, as conditioned by land use, is calculated for each HARM region (EU15) or country (EU10) i, for cropland (l=c) and grassland (l=g) separately as

$$EQ_{il} = (\Sigma_{k=1,n} RS_{ki} \cdot EQ_{ki}) \tag{1}$$

where RS_{ki} is the relative area size of the farm types k with ecosystem quality EQ_{ki} in HARM region or country i.

The ecosystem quality on organic farms is assumed to be 10% higher than on conventional farms. Hence, the added value of organic farming O_{il} is calculated for each HARM region or country i as

$$O_{il} = 0.1 \cdot RS_{organic,il} \tag{2}$$

where $RS_{organic,il}$ is the relative area size of organic farming of cropland or grassland in a HARM region or country i. O_{il} is added to EQ_{il}.

7.3.2 Modelling future changes in agricultural intensity

Scenarios

Based on the scenario storylines, assumptions could be made on how the distribution of farm types will change. To be consistent with the land-use change models used in EURURALIS, changes in farm types are not modelled explicitly, but are based on the scenario assumptions and results of the other models. Hence the change in farm types is linked to land-use changes calculated by CLUE (Verburg et al., 2006) and the productivity changes assessed by GTAP-IMAGE (van Meijl et al., 2006; Eickhout et al., 2007) as schematically indicated in Figure 7.1.

Three processes were considered for the assessment of future trends in agricultural ecosystem quality: (1) land-use change (e.g. from cropland to grassland or nature) (2) conversion into organic farming, and (3) changes in productivity of crop and grassland production.

Land-use change analysis

Firstly, an overlay was made of the CLUE_2010 map of each scenario (Verburg et al., 2006) with the CLUE_2000 map, and the difference map with all changes was calculated. Secondly, the database of the land-use types in the year 2000 was compared with the difference map. Thirdly, for each grid-cell represented in the land-use types database and the corresponding area of the CLUE_2010−2000 map, assumptions were made on where transitions take place and, as a consequence, what the impact on ecosystem quality would be (Table 7.4).

Table 7.4. Estimated impact of land use changes on ecosystem quality.

Land use	Scenario	Ecosystem quality of other land use type converted into agriculture	Ecosystem quality of area converted from agriculture into any other land use type
Cropland	A1	5%	Average + 5%
,,	A2	5%	Average + 5%
,,	B1	10%	Average
,,	B2	20%	Average
Grassland	A1	20%	Average + 10%
,,	A2	20%	Average + 10%
,,	B1	30%	Average
,,	B2	40%	Average

It is assumed that in the A scenarios, agricultural areas taken out of production are mainly the extensive production systems. The 'most extensive farm types present in the region' is translated into the 'average ecosystem quality + 5%/10%' for cropland/grassland. The economic orientation in these scenarios implies that farmers aim at high economic efficiency with less concern for the environment. Results from GTAP/IMAGE show that crop yields are increasing fast especially in the A1 scenario. Intensive farm types are generally more efficient in terms of crop yields and income than extensively managed systems. The ecosystem quality is therefore assumed to be 5% on new cropland and 20% on new grassland. In the B scenarios, there will be more environmental restrictions. New land taken into production is subject to this, so the assumption is that this land is more extensive than the average.

The result of these steps is the database for 2010, containing the fractions of surface area occupied by each land-use type and the corresponding land-use conditioned ecosystem qualities. The ecosystem quality EQ_{il} of agricultural landscapes as conditioned by land use is calculated as in Eq. 1. These steps are repeated for 2020 and 2030.

Conversion into organic farming

According to the storylines, organic farming is expected to expand, particularly in the B scenarios. In A1, there are few, if any, government incentives for organic farming. Besides, organic products become relatively more expensive due to the liberalization of agricultural markets. On the other hand, incomes are relatively high and some consumers are prepared to pay in order to satisfy their preference for organic products which many associate with 'healthy' rather than 'environment friendly' consumption. Some of these products are imported from third countries. In B1, there are moderate government incentives for organic farming. Little change is expected in the relative price of organic products as compared to conventional food because, apart from subsidies, the effects of liberalization are roughly compensated by developments of specific technologies and plant varieties in addition to the higher standards required for conventional products. Incomes are slightly lower than in A1, but even so, more consumers are prepared to pay the extra costs. Consumer preferences for organic products are even stronger in B2. Besides, due to market protection and strong government support, the price gap between organic and conventional is the smallest of all the scenarios. For A2, consumer preference for organic food is similar to A1, but consumption of organic products from EU farmers is assumed to be higher due to import barriers and the smaller price gap with respect to conventional products, even though incomes are somewhat lower than in A1. These deliberations resulted in assumptions on the increase of agricultural area used for organic farming ($RS_{organic,il}$) in relation to 2000; these are presented in Table 7.5. The effects on biodiversity of the changes in the area of organic farming are taken into account by recalculating O_{il} according to Eq. 2.

Table 7.5. Conversion of conventional into organic farming in absolute percentages in relation to 2000.

	2010 (%)	2020 (%)	2030 (%)
A1	5	5	5
B1	5	10	15
A2	5	8	10
B2	5	10	20

Changes in productivity of crop and grassland production

General effects of intensification or extensification per scenario in a 30-year period are estimated by the productivity increase for crops and grassland. For the baseline, only the input intensity was taken into account. Farm types were deliberately based on input intensity, as input level defines effects on the ecosystem quality in the first place. However, changes in input intensity are not explicitly modelled, while GTAP and IMAGE do provide model results on changes in productivity on the country level. These estimates were applied to the underlying HARM regions. As there is a clear relation between input intensity and productivity within regions, productivity changes can be used as a proxy for changes in agricultural intensity. The relative increase in productivity is translated into a relative change in average ecosystem quality. For the A scenarios, the applied dose-effect relationship from productivity increase to biodiversity loss is: 1% productivity increase corresponding to a relative ecosystem quality loss of 1%. This corresponds to the trend of the past 150 years. The average increase in production intensity from the pre-industrial 1850 to the current 2000 production systems of 15% per 10 years has lowered ecosystem quality from 20−25% to 5−10% in absolute terms. In the A scenarios there are few incentives to decrease the environmental pressure in agriculture or to maintain and improve biodiversity.

In the B scenarios, the awareness that environmental pressure of agriculture should be decreased is high, and maintaining or improving wild biodiversity in the agricultural landscape (multifunctionality of the land) is an important issue. The impact on biodiversity is expected to be lower in the B scenarios because productivity increase is expected with (partly) environmental-friendly technology development. The dose-effect relationship from productivity increase to biodiversity loss is therefore 1% productivity increase, corresponding to 0.5% relative ecosystem quality loss.

Intensification will cause higher biodiversity loss in absolute terms in more extensive land uses. A 10% loss of ecosystem quality from extensive agriculture of 25% results in 2.5% loss in the A scenarios, while in intensive agriculture, with 5% ecosystem quality, the loss is only 0.5%.

7.3.3 Agricultural ecosystem quality in context

The impact on overall biodiversity in a region (in terms of NCI) is not only a function of the average ecosystem quality in the agricultural landscapes, but also of the relative size of nature area and the average ecosystem quality of natural ecosystems. Whether a decreasing agricultural area is positive or negative for overall biodiversity depends on whether abandoned agricultural land is replaced by nature areas or urban areas. The CLUE model (Verburg et al., 2006) provides information on changes in the relative area size of cropland, grassland and nature. Verboom et al. (2007) have performed a biodiversity assessment of nature areas. The impact of change in agricultural land use on overall biodiversity in the EU25 was analysed by comparing the Natural Capital Index (NCI) between different years and scenarios. The NCI is calculated as:

$$NCI_i = \sum_{l=c,g,n} EQ_{il} * RS_{il} \qquad (3)$$

where EQ_{il} is the ecosystem quality of a land-use type l (cropland, grassland and nature) in a region i; RS_{il} is the relative area size.

7.4 Results

7.4.1 Distribution of farm types in the European Union

The occurrence of farm types differs per HARM region. In Figure 7.2 we present the occurrence of farm types in the EU15 per country. Figure 7.3 presents the farm type distribution in the New Member States (EU10), where similar farm types have been identified, but put into fewer classes.

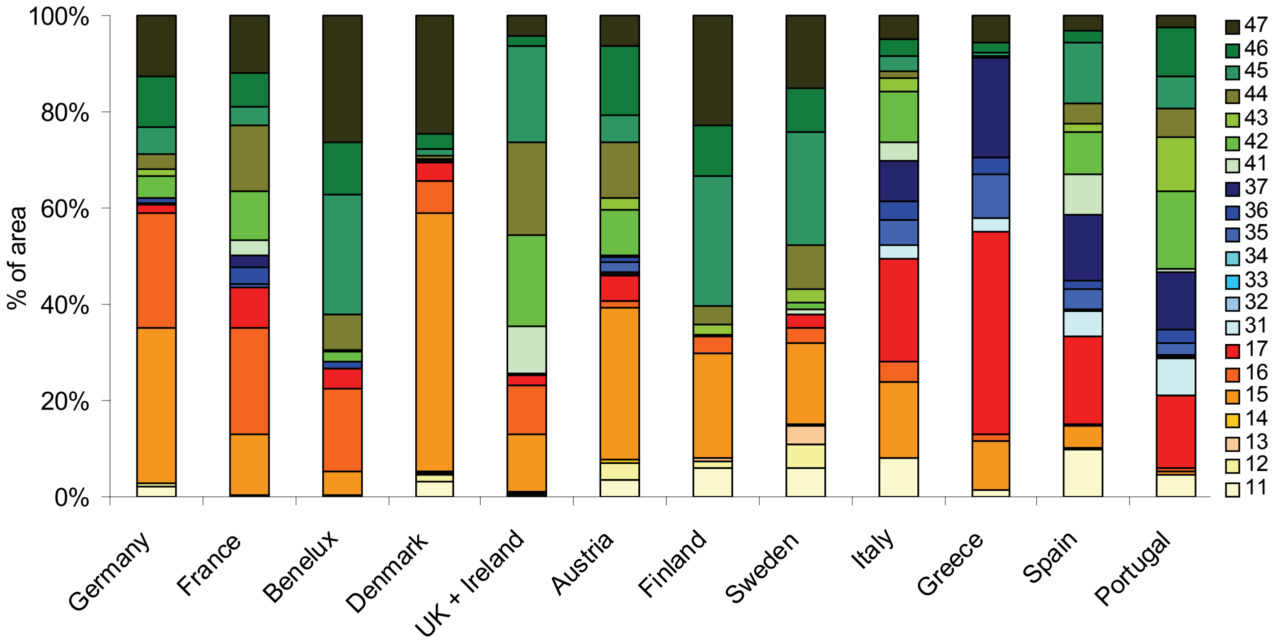

Figure 7.2 (in colour on p.185). The distribution of farm types in different countries in the EU15. Farm type classes are labelled in Table 7.2 and 7.3.

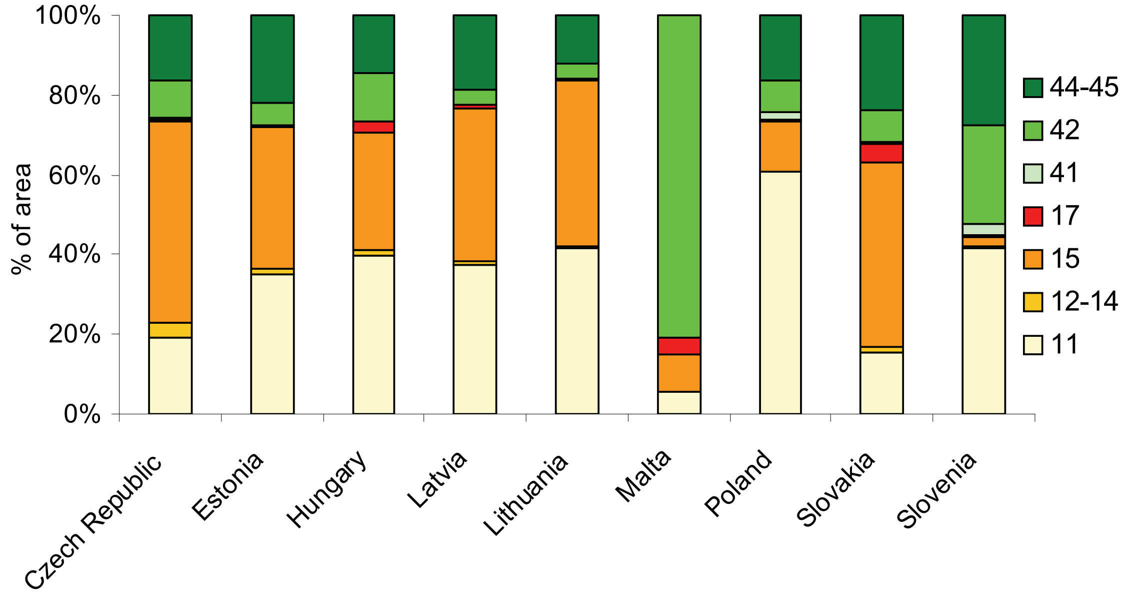

Figure 7.3 (in colour on p.185). The distribution of farm types in different countries in the New Member States. Farm types are not distinguished as much as in the EU15, but they are assumed to be similar to farm types labelled in Table 7.2 and 7.3.

It is clear that in the Mediterranean regions, the percentage of irrigated farming as well as extensive farming is higher than in other regions in the EU15. In Scandinavia, farming is also relatively extensive and there are high levels of organic farming. It should be noted that the livestock systems in Sweden and Finland seem to be relatively intensive, but organic farming is very common. Farming is, in general, the most intensive in north-west Europe. Farming in the New Member States is much more extensive than in most countries in the EU15.

The relative size area of different land-use types also varies. In general, there is less grassland in more southern regions. Permanent cropping systems do occupy a large part of the area here. We also see that the arable grazing livestock systems (classes 43, 46 and 47) occupy almost as much of the area in the EU15 as the grassland systems (classes 41, 42, 44, 45). In the New Member States, cropland occupies a much larger part of the area than grassland.

When farm type distributions of 1990, 1995 and 2000 are compared (results not shown) we see that the average input intensity has not changed much in this period. Intensive as well as extensive farms have decreased in area a little in favour of medium intensive farm types. Irrigated farming has increased a little. The average input intensity is relatively stable, but inputs are used more efficiently, as productivity increases in most regions. Apparently, the large intensification of agricultural production has mainly taken place before 1990 and currently there is some stabilization.

7.4.2 Ecosystem quality in 2000

Ecosystem quality is on average 10% of its original pristine value in cropping and permanent cropping systems in the EU25, with a range of 6−24% among regions. The ecosystem quality in grazing systems is much higher: 26% on average with a range from 15% to 82% (respectively regions with mainly intensively fertilized and/or re-seeded permanent grassland and extensive (semi) natural grazing). The lowest ecosystem qualities are found in intensively used agricultural areas in lowlands (e.g. the Netherlands and northern France) and in irrigation systems (e.g. Greece). Ecosystem qualities for cropland are relatively high in the New Member States (e.g. 22.3% and 24% for cropland in respectively Slovenia and Poland), the Iberian Peninsula, southern Italy and Scandinavia. These regions also have a high ecosystem quality for grassland. The highest values for grassland are found in Scotland, southern Spain and the Alps. This is mainly due to the high abundance of rough grassland in these areas. The influence of organic farming is low in most regions as its percentage is below 4% in these regions. In Italy, Austria, Finland and Sweden organic farming takes place on around 10% of the area. With an extra ecosystem quality of 10%, this increases the average ecosystem quality in these regions with 1%. Figure 7.4 presents the ecosystem quality in cropland in 2000 at the top. Figure 7.5 shows the ecosystem quality in grassland in 2000.

Ecosystem quality as well as the relative area size is indicated. In some regions (e.g. Greece), ecosystem quality in cropland is very low, but agriculture is only a minor land-use type in the region. The impact on overall biodiversity in such regions is therefore relatively low.

7.4.3 Scenario results

Scenario results on trends in ecosystem quality are also presented in Figures 7.4 and 7.5. In the scenario ‘Global economy’ (A1), the highest loss of ecosystem quality takes place in all regions in croplands as well as in grasslands, as a result of intensification. Productivity increases a lot in this scenario and this will have a large influence on the ecosystem quality, especially in croplands. In the scenario ‘Continental markets’ (A2), there is a small decrease in ecosystem quality in croplands, and a small increase in grasslands due to changes in land-use intensity. The ‘Global co-operation’ (B1) scenario shows a small increase in ecosystem quality of cropland in the centre of the EU15, while there is a small decrease in the New Member States, and many southern and northern regions. Productivity increases considerably in the B1 scenario, but is partly obtained with environment friendly measures. In most EU15 regions, these environment friendly production techniques can stop biodiversity loss. In the ten New Member States, productivity is currently very low and productivity increases will cause ecosystem quality loss. Finally, the ‘Regional communities’ (B2) scenario shows an increase in ecosystem quality in almost all regions.

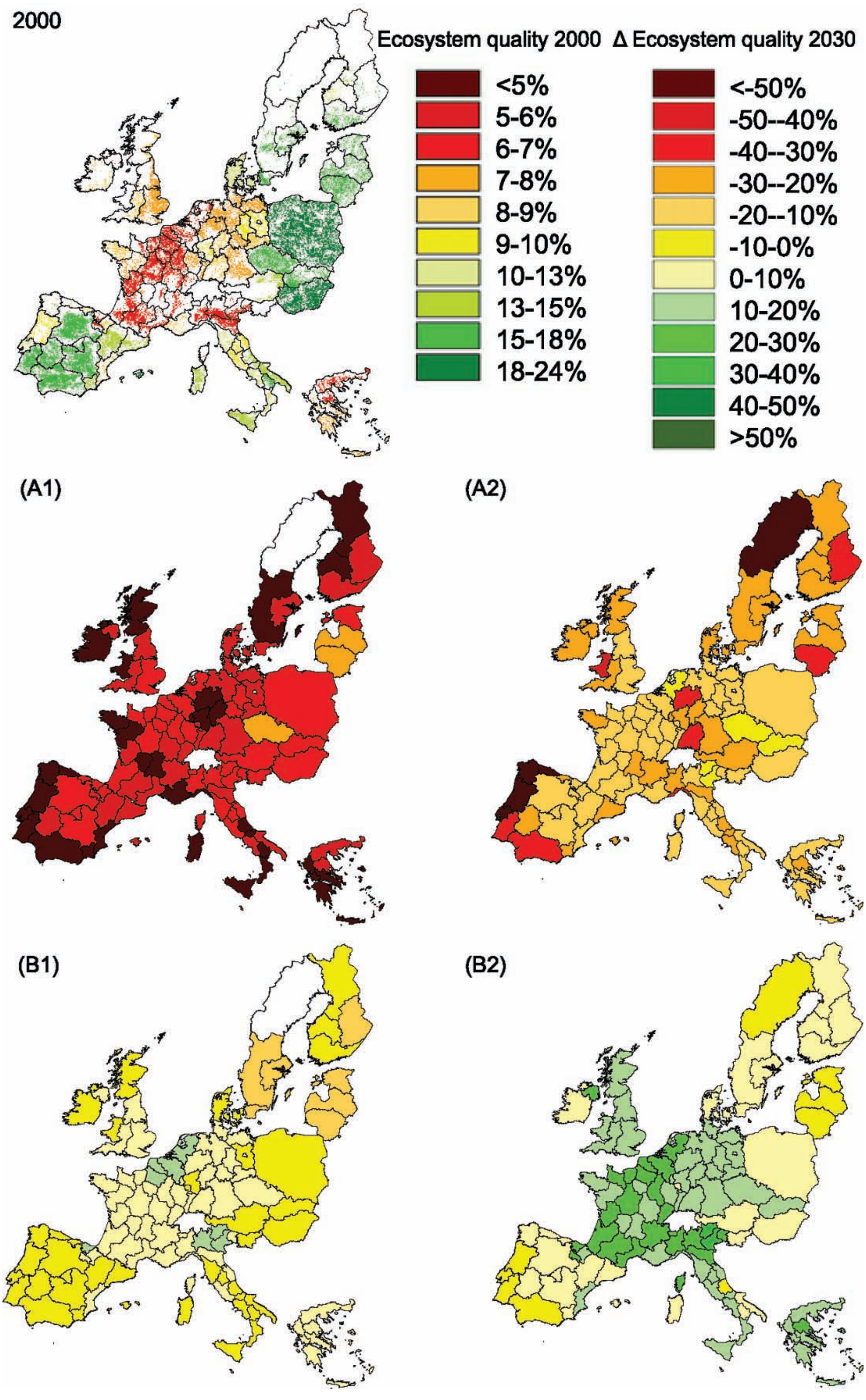

Figure 7.4 (in colour on p.186). Ecosystem quality (%) of cropland in 2000 and relative change ((EQ2030−EQ2000)/EQ2000) in four scenarios for 2030. For the year 2000 an overlay is made with the CLUE 2000 map to indicate the areas of cropland.

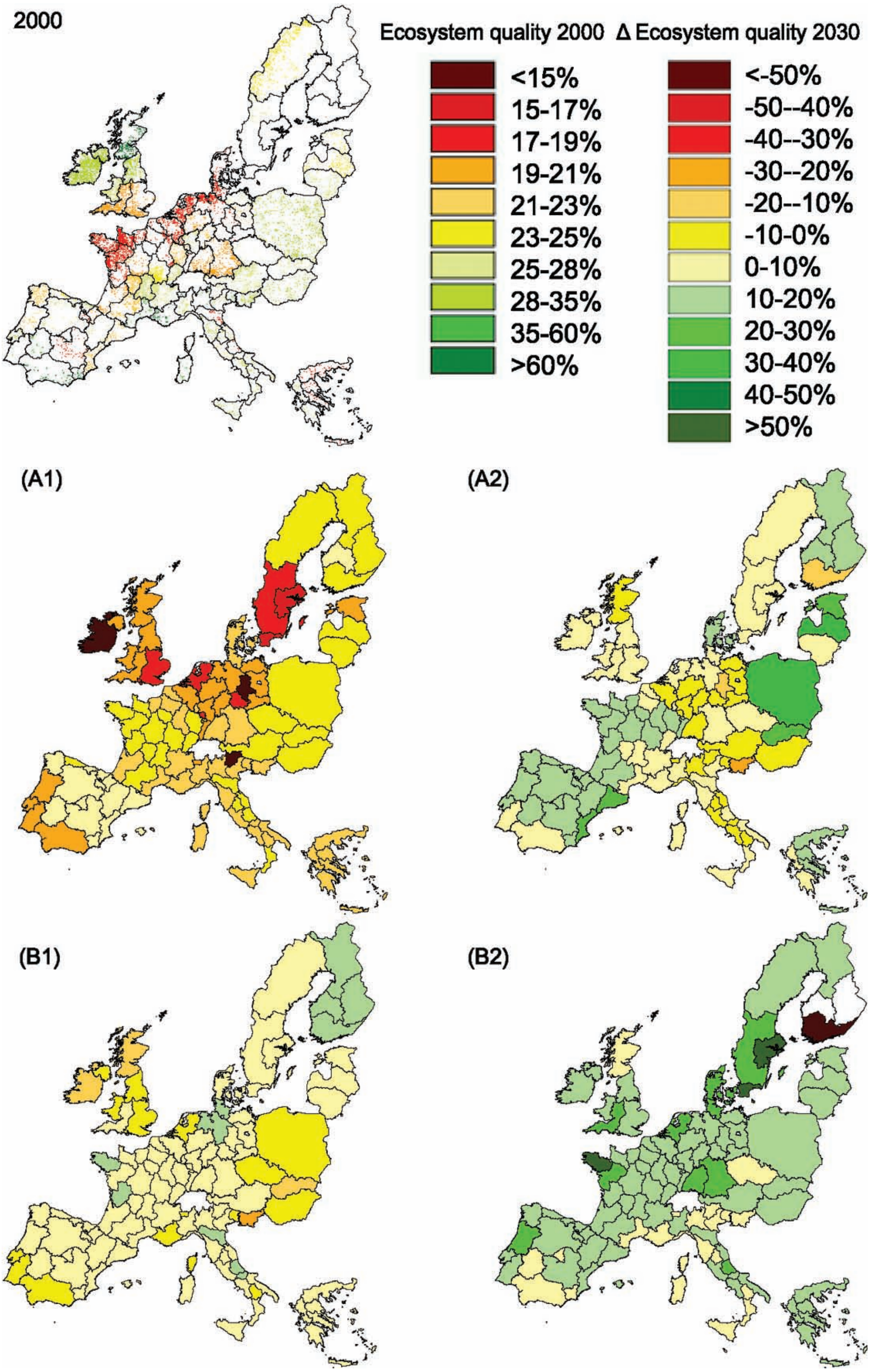

Figure 7.5 (in colour on p.187). Ecosystem quality (%) of grassland in 2000 and relative changes ((EQ2030−EQ2000)/EQ2000) in four scenarios for 2030. For the year 2000 an overlay is made with the CLUE 2000 map to indicate the areas of grassland. Note the colours have a different meaning than in Figure 7.4.

The divergence in changes in ecosystem quality is the result of macroeconomic and environmental storylines of the scenarios. Land-use change has a larger influence in the A1 scenario (average change due to land-use change in EQ for Europe in absolute terms is −1.2%) than, for example, in the B2 scenario (+0.07%). The impact of conversions into organic farming on ecosystem quality ranges from 0.5% (A1) to 2% (B2) in absolute terms. Technology indicators such as agricultural productivity change from the IMAGE model (output production intensity) showed average country increases between 2% (B2 in Czech Republic) and 53% (A1 in Portugal) for crop productivity and between −23% (productivity decrease for B2 in Hungary) and 50% (A1 in Ireland) for grassland productivity.

7.4.4 Agricultural ecosystem quality in context

In most scenarios, agricultural land area is decreasing, cropland area faster than grassland area (Verburg et al., 2006). As the ecosystem quality of grassland is much higher than cropland, this positively influences the average agricultural ecosystem quality in agricultural landscapes. In the B scenarios, nature development will take place on many agricultural lands that are abandoned. In the A scenarios, the extent of urban development on former agricultural land is also large. The impact of changes in ecosystem quality and relative area size of agricultural landscapes on the average NCI in Europe are presented in Table 7.6.

In the A1 scenario, the decrease in agricultural ecosystem quality is so large that decreases in agricultural area do not seem to be able to compensate for the increasing intensity. Although there will be a small increase in nature area, a large part of the former agricultural land becomes urban area. This results in a negative impact on the NCI. In the A2 scenario, ecosystem quality as well as agricultural area is relatively stable in relation to the other scenarios, and impacts are, in general, not that large. The relatively stable agricultural ecosystem quality in combination with an increasing area of nature in the B1 scenario seems to be positive for the NCI. In the B2 scenario the relatively high increase in agricultural ecosystem quality is accompanied by a decrease

Table 7.6. Change in average biodiversity in Europe, calculated by the NCI.

	Cropland		Grassland		Nature		Total	NCI[a]
	EQ[a]	RS[a]	EQ	RS	EQ[b]	RS	Area[c]	
2000	12.48	33.32	26.29	14.73	46.29	46.15	94.20	29.39
2030 A1	7.51	27.86	22.11	14.05	46.50	47.84	89.75	27.44
2030 A2	10.29	31.58	28.60	15.27	46.98	45.03	91.88	28.77
2030 B1	12.43	27.60	26.20	14.77	46.67	49.67	92.04	30.48
2030 B2	13.60	28.27	30.06	14.78	48.42	48.92	91.97	31.97

[a] EQ = ecosystem quality; RS = relative size area (source: Verburg et al. 2006); NCI = Natural Capital Index = Σ(EQ*RS).

[b] Results on ecosystem quality of nature are taken from Verboom et al. (2007).

[c] The total area captured in the biodiversity assessment is not 100%. Remaining area is mainly urban/residential area, for which we assume 0% ecosystem quality.

in agriculture area and increase in nature patches, which results in a positive influence on the NCI.

7.5 Discussion

7.5.1 Biodiversity

The farm type level of analysis provides a good indication of the differences in ecosystem quality between EU regions and scenarios. Results become especially interesting when those for different land-use types are integrated. The ecosystem quality in 2000 in cropland is lowest in the Benelux, France, northern Italy and northern Greece. These represent either the highly productive regions where farming is very intensive, and/or where irrigation takes place on most of the farms. For grassland, the distribution is slightly different. The ecosystem quality is very high in the Alps of southern France and northern Italy. In these regions, cropland management is relatively intensive, while grassland management is very extensive.

In regions where grassland occupies a major part of the agricultural area (e.g. The Netherlands) the average ecosystem quality in agricultural landscapes (cropland and grassland together) can be relatively high, even when crop production is very intensive. The ecosystem quality of intensively managed grasslands is still 20%, compared to 25% of extensively managed croplands. Regions with a high percentage of cropland in their agricultural area have the lowest average ecosystem quality. These are northern France, Germany, northern Italy and Greece. The northern United Kingdom has much more grassland in its agricultural area and thus shows a high average ecosystem quality in agricultural landscapes.

In cropland, the ecosystem quality decreases faster than in grassland, as production intensity increases faster. Increasing productivity also means that less land is needed for production. In some areas, this causes a large decrease in cropland, while grasslands do not decrease; they even expand in some regions. In Bretagne, Pays-de-la-Loire, Galicia, south-west France, southern Italy, northern Scandinavia and Scotland, we see that a very large part of the cropland area is abandoned or replaced by nature areas or grassland, especially in the A1 scenario (Verburg et al., 2006). As a result – in contrast to the general decline in ecosystem quality in the A1 scenario – these specific regions present an overall improvement.

In A2, changes in cropland and grassland balance each other out. Decreases in ecosystem quality of cropland and grassland together are highest in Spain, New Member States and Scandinavia. The impact on the average NCI in Europe is small. In the B1 scenario crop productivity increases most in Spain, Ireland and the New Member States. In Spain this is accompanied by a high decline in cropland area and so a lower influence on the NCI. In the New Member States cropland area does not decrease much and the impact on the NCI is negative. The B2 scenario is positive for all regions, but mostly for the Netherlands, Bretagne and Italy.

Regions that seem to be the most vulnerable to biodiversity loss due to agricultural practices are the New Member States, Scandinavia, Ireland and Spain. These are the regions with the highest losses or lowest gains in all scenarios.

7.5.2 Quality of data sources

The FADN database is very extensive and provides detailed information on individual farms. A particular strength of using the FADN data for a typology of farming systems is that it directly relates to the management practices of the farms. There is no other source that contains data on the level of individual farms that gives so much insight into farm management practices. There are also some limitations though.

In total FADN represents 52% of the farms and 86% of the Utilized Agricultural Area in the EU15, when compared to the data in the Farm Structural Surveys (Andersen et al., 2004b). Economically small and 'non-professional' farms are excluded from the database. Especially in mountainous areas and on other marginal land, these farms may occupy a large proportion of the area. It is possible that exclusion of these farms will underestimate the ecosystem quality in agricultural landscapes.

Another weakness of FADN is that its major unit of data collection is the Utilized Agricultural Area (UAA), not the area actually occupied by the agricultural business. The use of common land, the grazing of fallows and seasonal lets are excluded from consideration. As many variables have been used on a per hectare basis, this may influence results. The data indicates, for example, that grasslands are used very intensively in Greece, while grazing on common land may in practice decrease the pressure on the land.

Production costs are used as proxy indicators for agricultural input intensity, as FADN does not provide data on absolute amounts of inputs. The amount of money spent on inputs is not necessarily directly related to the absolute amounts used on the farm. Prices of fertilizers and crop protection products are very similar throughout the EU15 though, and can, therefore, serve as a good proxy. Andersen et al. (2004a) show input costs to be clearly related with nitrogen surplus.

FADN will collect data in the future for the New Member States as well. Currently, data are not yet available. We could not explicitly identify farm types in these regions, but with country level data on agricultural land use we were able to link different types of land-use intensity to the production intensity gradient related to farm types. Although the approaches are based on different data sources, we are confident that reliable comparisons can be made between regions and scenarios.

The farm type distribution is linked to the CLUE land-use maps. CLUE does not distinguish between cropping and permanent cropping land, so all these kinds of farm types were allocated to cropland. It is assumed that arable grazing livestock systems in the field are identified as grassland in land-use maps. A comparison of the Utilized Agricultural Area from FADN with the extent of cropland and grassland in the CLUE maps showed that in most regions the extent of these land-use types where very similar. FADN represents 80% of all land identified as agricultural land in the CLUE maps. The largest deviation occurs in regions with a large extent of rough grassland. In FADN this land is included as agricultural land whereas CLUE identified most of these areas as nature rather than pastures In Scotland for example, the average ecosystem quality of grassland is very high, but with the overlay of the CLUE map not all grassland area considered is presented.

A major source of uncertainty is the assignment of ecosystem quality values to the different farm types. As the natural situation or primary vegetation in Europe is largely unknown, the comparison between a land use type and its corresponding primary vegetation is not directly possible. Therefore we used figures from other parts of the world, especially the tropics and assumed that basically the same processes would have happened in Europe. Some European studies confirm the global figures (e.g. Wilson et al., 2003). Another difficulty is that in many situations the species richness of extensively used cropland and grassland is higher than in European forests. We must however not confuse these secondary and heavily used plantation forests with primary forests. More additional studies are needed to uncover some of these issues.

7.5.3 Uncertainty in future changes

To be consistent with the other models used in the EURURALIS project, we based the methodology for assessing future changes in biodiversity on the output of these models. Changes in farm types can be modelled explicitly, but the direction in which the distribution will develop can only be based on scenario assumptions. By using the output from other models, changes in farm types are modelled implicitly, but the scientific basis is more coherent.

Whether the land-use changes from agriculture to other land-use types and vice-versa will have the impact as estimated in the land-use change analysis cannot be said with certainty. For example, intensive agricultural land can also be taken out of production in the A1 scenario. Based on the storylines, we can assume though, that it will be mainly marginal production land that will be taken out of production. In a globalized economic world, agricultural production will become more efficient.

Projected productivity increases have a large influence on changes in ecosystem quality. GTAP and IMAGE project changes in productivity per country. For this assessment we applied the national values to the underlying HARM regions. In practice, there might be more divergence. In Italy, for example, productivity differs a lot between northern and southern regions. Ewert et al. (2005) showed that when historical changes are compared, there is a convergence in relative changes between currently more and less productive regions.

In the baseline, no ecosystem quality values below 5% were assigned to farm types. Based on current findings in the field, the average value for very intensive farms is 5%. We assume that, in the future, productivity changes on intensive farms can further reduce ecosystem quality. The uncertainty in the impacts of productivity changes is reflected in the different assumptions made in different scenarios.

7.5.4 Influence of agricultural landscapes on overall biodiversity

Here we have presented the methodology to assess the ecosystem quality in agricultural landscapes as determined by land-use intensity. The influence on overall biodiversity expressed as NCI in the EU25 has been calculated. The aggregated impact on the NCI should also take other pressures into account: climate change, air pollution and fragmentation influence ecosystem quality in nature as well as in agricultural areas. These pressures have been taken into account for nature areas (Verboom et al., 2007) but for agricultural landscapes we focussed on the influence of land-use intensity only.

The ecosystem quality of different land use types is estimated separately; effects of one land use on another are only partly taken into account. The effects of agriculture on biodiversity in nature areas are assessed by the extent of fragmentation and N-deposition (Verboom et al., 2007). We did not use the land-use allocation models to analyse the influence of nature areas on agriculture. Patches of nature in agricultural landscapes may increase assemblage of some species in the fields (Jeanneret et al., 2003). The influence of these nature areas is already implicitly included in the farm type classification. In the B2 scenario for example, the extensive farm types are more abundant, and in the land-use maps we see more nature patches in agricultural landscapes. The resolution of 1 km^2 is very high for analysing land-use change in Europe (Verburg et al., 2006), but is still too low to assess interactions between these land-use types. Although an influence can be assumed, experimental studies do not provide information on which we could base dose-effect relationships for the distance to nature areas and the abundance of nature areas in agricultural landscapes on this scale.

7.5.5 Farm type classification

The classification of farm types in this study has not specifically been developed for this biodiversity assessment. The farm type classification can also be used for other modelling purposes, for example, to increase insights in land-use change processes or to analyse adaptation behaviour of farmers. Farm types can be extended with other dimensions, which reflect the socio-economic situation of the farm. We may then be able to model changes in farm types explicitly. Increasing spatial explicitness through combining the data with other data sources (e.g. potential yields, N-deposition) may also contribute to land-use change modelling. FADN can provide data on the altitude class of a farm and whether the farm is located in a Less Favoured Area; these data can give more information on the specific location of a farm. Based on 'helicopter-view data' such as climate, soil type and distance to markets, land-use change models may identify certain regions as marginal, but farm management data could show that farms are still managing fairly well in terms of economic and agricultural productivity. The farm type approach thus not only provides a good basis for biodiversity assessments but also for other purposes.

7.6 Concluding remarks

The strength of our methodology is that it provides a quick overview of differences in land-use intensity and biodiversity in agricultural landscapes between regions and scenarios. Results of research at the field and farm level were combined to establish dose-effect relationships for different farm types. Although agricultural intensity is the sum of many agricultural practices, dose-effect relationships cannot be assessed separately. We can compare regions and scenarios and the results for agricultural landscapes with nature areas. Grassland with a high ecosystem quality value can be mainly found in the Mediterranean (except Greece), the Alps and northern UK. Croplands with a high ecosystem quality value are mainly found in Mediterranean and Scandinavian countries and Austria. Here are farm types that are worth protecting to preserve agricultural biodiversity. In the scenario results we see that the ecosystem quality in most of these regions stays higher than in the regions with currently a low ecosystem quality. It does drop quickly though in especially the A1 scenario. In the B2 scenario the opportunities for increasing biodiversity in agricultural landscapes are the best. Low productivity increases and more environment friendly production techniques are positive for the biodiversity in the farmers' fields. Although more intensive agriculture leaves more land for nature, the impact on overall biodiversity seems to be generally negative. It appears that the EU objective to stop biodiversity loss caused by agricultural intensification can only be reached if policies are aimed at more environment-friendly production as described in the B scenarios.

Chapter 8

General discussion and conclusions

8.1 Objectives and design of the study

The main objective of this thesis is to assess how adaptation influences the impact of climate change and climate variability on European agriculture. The aim is to improve insights into adaptation processes in order to include adaptation as a process in assessment models that aim to develop quantitative scenarios of climate change impacts at regional level. Special reference is made to IMAGE (Integrated Model to Assess the Global Environment; MNP, 2006), a widely used model with global coverage to develop plausible scenarios for future developments and their environmental impacts quantified for different regions. By including adaptation in impact assessments, actual impacts of climate change and the vulnerability of agricultural systems can be better quantified.

The main part of this thesis focused on empirical analyses with historical data, improving insights in adaptation. Realistic adaptation processes are not well understood and therefore hard to quantify (Smit et al., 2001; Easterling et al., 2007). Adaptation is not a process that can be captured by a single indicator; it occurs at different scales, for different purposes and involves different strategies.

A thorough understanding of current management is needed in order to understand adaptation in management. Identifying and quantifying specific management and adaptation strategies is possible for case studies at specific farms in specific regions (e.g. Bharwani et al., 2005). But as farms, regions and adaptation strategies vary widely, up-scaling and generalization is difficult (e.g. O'Brien et al., 2004; Mendelsohn, 2007). Nevertheless, for understanding adaptation processes at higher aggregation levels, adaptation processes at lower aggregation levels cannot be ignored. Therefore, in our approach we used farm-level data to obtain insights in farm-level management and adaptation processes, but we did not explicitly analyse the behaviour of individual farms. The aim is to understand adaptation at regional level and variability herein.

The main findings are summarized in Figure 8.1, specified per Chapter, each dealing with one research question, and are further synthesized in section 8.2. Section 8.3 discusses how adaptation should be considered in the vulnerability framework. In section 8.4 research question VII is elaborated on and recommendations are given for including adaptation in the integrated assessment model IMAGE in order to improve projections of climate change impacts on agriculture. Limitations and relevance of this work are discussed in sections 8.5 and 8.6, respectively, and final conclusions are given in section 8.7.

8.2 Adaptation to climate change in European agriculture

The first studies that considered adaptation quantitatively in impact assessments, developed regional indices determining adaptive capacity based on general socio-economic conditions (Yohe and Tol, 2002; Schröter et al., 2003; Brooks et al., 2005; Haddad, 2005). The regional scale adaptive capacity index that is developed for

	Research question	Main findings	Ch
I	Spatial variability	Good regional socio-economic conditions, a larger farm size, higher intensity and specialized land use improve farm performance and hence influence the impact of spatial climate variability	2
II	Trends and temporal variability	Factors important for spatial variability clearly influence trends and variability in farm performance, but regional adaptation to climatic conditions seems mainly dependent on prevailing conditions (i.e. hazard exposure)	3
III	Farm diversity	Farm diversity, particularly high in Mediterranean regions, can be considered as a strategy to adapt to unfavourable conditions such as higher temperatures and associated droughts	4
IV	Adaptation strategies	Farmers adapt differently in different regions as they are adapted to prevailing conditions and hence, actual impacts cannot be explicitly seperated into potential impacts and adaptive capacity	5
V	Crop model projections	Especially in Mediterranean regions projections of the impacts of climate variability on maize yields do not reflect actual impacts. Consideration of management and adaptation is required.	6
VI	Agricultural biodiversity	Low intensive agriculture requires more area, but will have less impact on overall biodiversity	7
VII	Adaptation in impact assessment models	Adaptation should not be seen anymore as a last step in a vulnerability assessment, but as integrated part of the models used to simulate crop yields and other ecosystem services provided by agriculture.	8

Figure 8.1. Summary results from the thesis Chapters based on the research questions as formulated in Chapter 1.

Europe, an aggregated index based on for example GDP per capita and R&D expenditure, suggests that Mediterranean regions have a lower generic adaptive capacity compared to northern European regions (Schröter et al., 2003; Metzger et al., 2006). As also sensitivity to climate change is projected to be more severe in

Mediterranean regions (Olesen and Bindi, 2002; Ewert et al., 2005), the vulnerability of the agricultural sector is projected to be highest in these regions (Schröter et al., 2005; Metzger et al., 2006).

Adaptation in agriculture is clearly dependent on regional socio-economic conditions, but for a thorough understanding of agricultural adaptive capacity, also sector and farm specific conditions should be taken into account. For several regions vulnerability or adaptive capacity indices specific for agriculture are developed (Nelson et al., 2005; Eakin et al., 2006). However, there is little empirical evidence about the importance of the different factors from which these indices are derived. Furthermore, adaptation processes that occur at different aggregation levels and relate to different ecosystem services (e.g. crop yields, farmers' income) cannot be captured with one regional adaptive capacity index (Füssel, 2007). Therefore, in this study we considered agricultural and climatic data to analyse the importance of different factors explaining adaptation at multiple levels and for different ecosystem services.

As a first step it was important to assess the impact of current management on farm performance under different climatic conditions. The analysis of spatial variability in farm performance (Chapter 2) demonstrates that yields of most crops and farmers' income (per working unit) are higher in regions with a temperate climate and better socio-economic conditions. It can be argued that farms and regions that perform well are well adapted, which would confirm that Mediterranean regions have a lower adaptive capacity compared to northern European regions. However, farmers' income per hectare is not related to crop yields and is especially high in many Mediterranean regions with typically lower crop yields. This suggests that farmers in these regions grow more profitable crops to increase farmers' income per hectare (whereas the smaller farm size explains the lower farmers' income per working unit). Also, crops that have relatively high potential yields (e.g. maize) are managed better – resulting in high actual yields – than crops with low potential yields (e.g. wheat; Chapter 2 and 6). Optimal management thus depends on what to optimize; if a crop (e.g. wheat) is not important, management will not concentrate on increasing its yields, but on other crops with potentially higher yields. Vulnerability and adaptive capacity will thus differ among ecosystem services (e.g. for yields of different crops, farmers' income per hectare or per working unit).

In order to explain the impact of management on farm performance, farm level data were considered in the analysis. Clearly, farm performance (as measured by yield and income) differs per farm and is largely dependent on three farm characteristics: farm size, intensity and land use (Chapter 2). Crop yields and farmers' income increase with increasing farm size (i.e. economic size) and farm intensity (i.e. fertilizer use, crop protection use, irrigation). Also, land use (i.e. arable land area, crop area) significantly influences farm performance.

The next step was the analysis of adaptation in management. Farm characteristics that represent differences in current management – farm size, intensity and land use – have been used to develop a farm typology to assess trends and temporal variability in farm performance (Chapter 3). As time series are short (1990–2003) main focus was on the adaptation to climate variability. It can be assumed that farms and regions that are able to adapt to climate variability, will also have some capacity to adapt to climate change (Kates, 2000; Challinor et al., 2007).

Interestingly, farms that perform well and seem better adapted to prevailing conditions do not adapt better to climate variability (and change). Regions and farm types that obtain higher crop yields and farmers' income have lower (relative) variability herein (Chapter 3), but relationships between crop yield or income variability and climate variability are generally stronger than for regions or farm types with low crop yields and farmers' income (Chapter 4, 5 and 6).

Bharwani at el. (2005) had similar findings related to farm types in Lesotho. Poor farmers adapted better to climate variability than richer farmers who respond mainly to market signals. For richer farmers this leads to better average farm performance, but larger decreases in bad years. As richer farmers have only few strategies, they are more cautious and only change if they trust the forecasts. Hence, they are more vulnerable to sudden shocks.

Also Van de Dries (2002) showed that small-scale traditional farms can better cope with climate variability than modern intensive farms. Nevertheless, a small extensive arable/cereal farm may have a high capacity to adapt in Spain, but a low capacity to adapt in Germany. Adaptation in management is not only determined by farm characteristics, but also largely by regional socio-economic, policy and climatic conditions and farmer's objectives and perceptions, influencing awareness. At regional level, a mechanism is observed that clearly influences adaptation and should be considered in impact assessments: a higher exposure to extreme climatic conditions stimulates adaptation (Chapter 3, 4, 5 and 6). As the farm types are generally adapted to prevailing conditions, farms in less favourable areas are not necessarily more vulnerable than farms in favourable areas. This was also concluded for Australian (Nelson et al., 2005) and African agriculture (Challinor et al., 2007).

Adaptation strategies comprise for instance change in crop choice, fertilizer and irrigation management (Chapter 5) and growing more heat resistant cultivars (Chapter 6). Efficient adaptation strategies differ largely per region however (Chapter 5), and are not only dependent on changes in climatic conditions, but also on other factors, such as markets and technology. Importantly, at the regional level an important adaptation is farm diversification, in farm size and intensity (Chapter 4 and 6). A larger number of farm types with different strategies to adapt, results in smaller impacts of climate variability at the regional level.

Hence, financial and technological ability (represented by farm size and intensity) largely influence current management, but adaptation in management to climate change seems mainly determined by awareness (and objectives). More favourable regions (i.e. temperate regions) and better endowed farm types (i.e. larger scale and higher intensity) are generally more affected by climate variability. Although they have more financial and technical capital to adapt, their awareness seems currently low and this limits their adaptive capacity.

Actual adaptation does not depend on a weighted average of several determinants of adaptive capacity, such as financial ability, technological ability and awareness, but it is highly dependent on the weakest determinant (Tol and Yohe, 2007). Therefore the role of policies and research to increase awareness is important. Accurate climate projections are needed to raise awareness and make adaptations beneficial (Bharwani et al., 2005). Ziervogel (2004) shows that farmers start to trust forecasts when these are correct for three years in a row. Transferring this to the European situation would suggest that the high temperatures in the last decade, together with climate change projections, will soon stimulate adaptation strategies to climate change in temperate regions.

Adaptation to climate change can be in line with adaptations to other changes, such as the shift in focus of the CAP (EU Common Agricultural Policy) from food production to more environmental objectives. Policies that stimulated modern intensive agriculture have led to both higher vulnerability to climate variability and environmental degradation (e.g. van der Dries, 2002; Anderies et al., 2006). If farms focus less on achieving high average crop yields and income, and more on reducing the impacts of risks, this will be beneficial for agricultural biodiversity (Chapter 7).

Farms adapt continuously to prevailing conditions. Hence, in order to project impacts of climate change and other changes on future crop yields and other ecosystem services, the dynamic nature of adaptation should be considered. The separation of potential impacts and adaptive capacity is theoretically a useful concept, but cannot be quantified for practical situations. Management and technology have a large impact on current crop yields, farmers' income and agricultural biodiversity, and only accurate simulation of current management allows assessing the impact of climate change and adaptation on future agriculture.

8.3 Adaptation in the vulnerability framework

Integrated assessment models that aim to develop quantitative scenarios of climate change impacts, such as IMAGE, are used to assess the vulnerability of different sectors and different regions. When assessing vulnerability and the role of adaptation to reduce vulnerability, an important question is: when is a system vulnerable? When is adaptation successful in reducing vulnerability and when should it be considered as maladaptation? Vulnerability assessments generally aim at comparing vulnerability among systems (e.g. Metzger, 2005; Schröter et al., 2005). But being more or less vulnerable than other systems does not imply that a system is actually vulnerable. The IPCC definition of vulnerability is 'the degree to which an ecosystem system is sensitive to global change plus the degree to which the sector that relies on this service is unable to adapt to the changes (IPCC, 2001). No objective threshold can however be provided that judges a certain degree as vulnerable. Schröter et al. (2005) compared the relative change in ecosystem services, but thresholds were not considered.

Resilience theory focuses more on thresholds (www.resalliance.org). Resilience is considered as the opposite of vulnerability and is defined as the ability to absorb disturbances, to be changed and then to re-organize and still have the same identity (retain the same basic structure and ways of functioning) (Gunderson and Holling, 2002). Adaptive capacity is the ability to learn from the disturbance.

Whether the identity of a system remains the same, depends on how the properties of the system are defined and valued. When a farmer shifts from growing wheat to rape seed, the system has changed in terms of crops grown, but it is still an arable farm. If farmers' income can be sustained, the farm is not vulnerable. But when more farmers switch crops, wheat production at a higher aggregation level may decline and can be considered vulnerable. In order to measure perceived vulnerability, stakeholders are needed to define the important properties and values of a system (Patt et al., 2005; Meinke et al., 2006).

Adaptation inherently implies that parts of the system will change. The theory of Panarchy suggests that socio-ecological systems are never static, and they tend to move through four, recurring phases, known as the adaptive cycle (Gunderson and Holling, 2002). Two phases of growth (forward loop) are followed by two phases of reorganization (back loop). Adaptive cycles occur on different temporal and spatial scales. Considering European agriculture in the last decades, crop yields and farmers' income mainly showed linear trends (Chapter 3, Calderini and Slafer, 1998; Ewert et al., 2005) at different temporal and spatial scales. It can be argued that European agriculture has been in a forward loop since World War II (Holling, 2004). In the 21th century crop yields and income in Europe may continue to increase (Ewert et al., 2005), but there might also be thresholds which cause the system to fall into a back-loop crisis. This study did not reveal any thresholds at regional level that are or are likely to be exceeded. Despite sudden changes in policies (e.g. CAP reform in 1992) and climate (e.g. heatwave in 2003), no sudden changes in agricultural performance were observed. It is likely that the adaptive cycle operates more on the short-term, with continuous learning loops. The results from our study suggest that adaptation is dynamic and farmers continuously adapt to prevailing conditions (section 8.2). Also Sterk et al. (2006) showed that farmers adapt their management gradually over the years.

The influence of adaptation on reducing vulnerability should be considered in this context. Adaptation is dynamic, but whether it is successful depends on the local situation. Fletcher and Hilbert (2007) show with a simple model that the resilience of a system decreases rapidly when maximum profit is approached. This suggests that when risks are low, aiming for maximizing profit can be a rational objective, but when risks increase, this strategy makes farmers vulnerable. This explains why farms in more favourable areas that obtain high crop yields and income, are relatively vulnerable to climate variability (section 8.2). When risks (i.e. hazard exposure) increase, farmers adapt their objectives and hence, management.

An approach that is useful to measure resilience in case studies is presented by Bennett et al. (2005). Instead of looking at the state in future projections compared to the current state, they propose to measure resilience by (1) the state of the system relative to the location of the threshold, (2) the sensitivity of the system to further movement, which is dominated by feedback strength, internal to the system (i.e.

adaptation) and (3) the rate at which the system is moving towards the threshold, which is dominated by shocks or controls imposed from outside the system (i.e. exposure). Considering these measures, adaptation is successful when it can change the state or change the threshold in order to widen the gap between the two and hence, the rate at which the system is moving towards the threshold. The location of the threshold is where the state of the system changes.

Agricultural systems have several properties at different scales which all have their own thresholds. Relationships exist among these properties that influence each others states, thresholds and the rates at which they move towards each other. An analysis of resilience (or vulnerability) based on the approach of Bennett et al. (2005) is illustrated for irrigated farming and farmers' livelihood (Table 8.1, Figure 8.2). We add a fourth measure of resilience, the effects of changes on other properties or services, as a change in one property can have large, and more important, effects on other properties.

For the resilience of irrigated farming water demand (i.e. state) and water availability for agriculture (i.e. threshold) are important variables to consider. The fact that water availability is lower and projected to decrease more in the Mediterranean compared to North-West Europe does not necessarily imply that irrigated farming in the region is more vulnerable. As demonstrated in Figure 8.2a water availability can decrease, but if water demand also decreases, the gap between state and threshold

Table 8.1. Examples of measures of resilience based on Bennett et al. (2005).

Measures	Irrigated farming	Farmers' livelihood
State of the system relative to the location of the threshold	Water demand relative to water availability for agriculture (Figure 8.2a)	Outputs (including subsidies) relative to threshold at which inputs (including taxes) are too high for a sustainable income (Figure 8.2e)
Sensitivity of the system to further movement; dominated by feedback strength, internal to the system (≈ adaptation)	Relative change (adaptation) in water demand to changes in water availability for agriculture (reflected in Figure 8.2b,c)	Relative change in outputs and to changes in yields or prices; depend on direct effects and agricultural adaptation (e.g. change of crop or use of inputs) (reflected in Figure 8.2 f,g)
The rate at which the system is moving towards thresholds; dominated by shocks or controls imposed from outside the system (≈ exposure)	Rate of change in water demand relative to water availability due to biophysical (climatic) and socio-economic changes (Figure 8.2d)	Rate of change in output and subsidies relative to inputs and taxes due to biophysical (climatic) and socio-economic changes (Figure 8.2h)
Effects of changes in state or threshold on other properties or services	Effects of changes in water demand and water availability on crop yields and farmers' income (Figure 8.2e)	Effects of changes in outputs and inputs on e.g. crop choice, regional land use

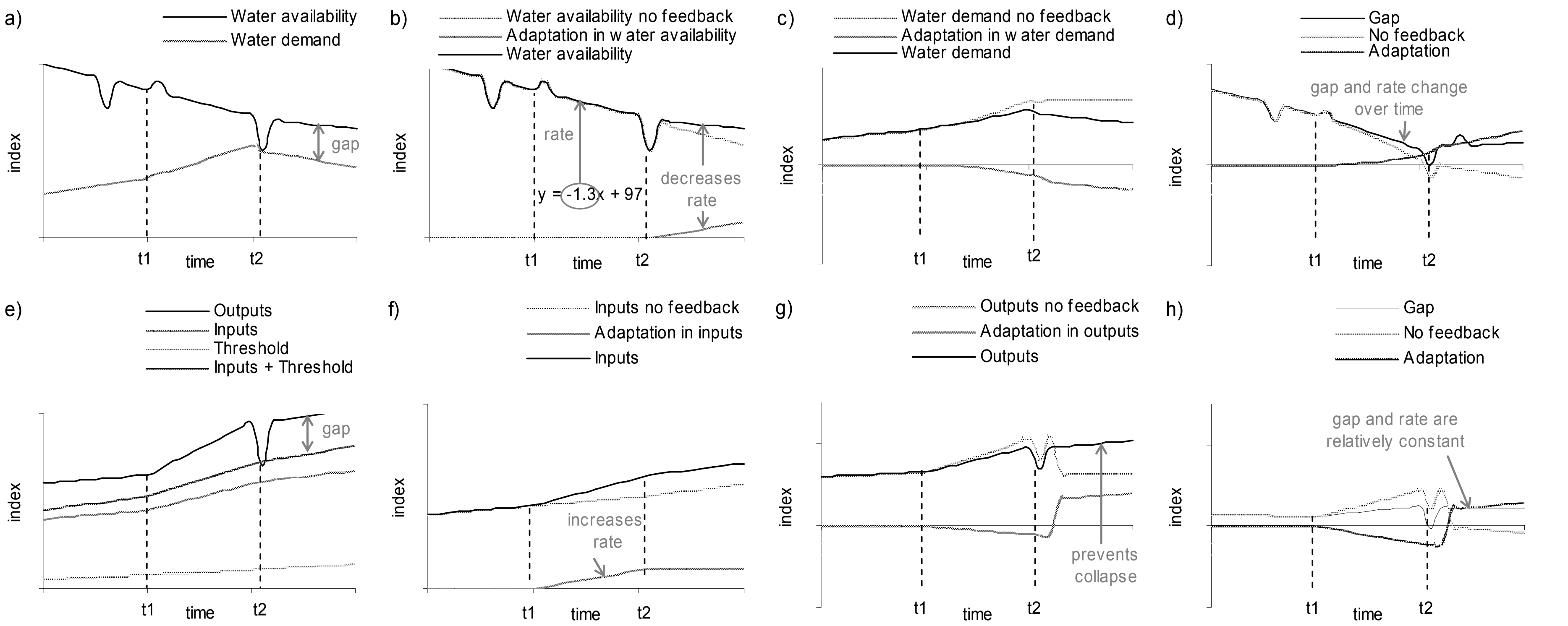

Figure 8.2. Example demonstrating measures of resilience (Table 8.1) for irrigated farming (a-d) and farmers' livelihood (e-h) for region X to indicate how adaptation influences resilience. (a) The gap between water availability (threshold) and water demand (state); (b) change in water availability due to exogenous changes (no feedback) and change due to adaptation and resulting water availability; (c) change in water demand due to exogenous changes and change due to adaptation and resulting water use and (d) the resulting rate at which the system is moving towards the threshold, including an indication of how adaptation decreases this rate. Figures (e-h) demonstrate the same measures for farmers' livelihood. Here, the threshold is larger than zero. Lines indicating adaptation show how adaptation strategies prevent the system from moving further to the threshold and possibly preventing a collapse.

increases. Adaptation is successful when water demand for irrigated farming is reduced, by for example increasing water use efficiency or change of crop choice (Figure 8.2c). Adaptation can also take place outside of the agricultural sector, by increasing water availability, for example by improving water storage (Figure 8.2b). Both types of adaptation will decrease the rate at which the system is moving towards the threshold (Figure 8.2d). The analyses in this thesis, based on crop yields and farmers' income, suggest that water limitation currently does not have larger impact on Mediterranean agriculture compared to North-West Europe. An analysis of vulnerability at the long-term requires simulating the four measures of resilience (Table 8.1). A decrease in resilience may not be apparent when thresholds are not approached, but near the threshold surprising changes in the system may be observed (Anderies et al., 2006; Groffman et al., 2006). Yields of irrigated crops will drop fast when water availability is not sufficient.

In the example for region X in Figure 8.2 little inter-annual variability is considered, only for clarity. The first decrease in water availability (halfway t_1) doesn't have any effect, as the gap between state and threshold is large. At t_1 the rate at which the system is moving towards the threshold is increasing and some conscious adaptation in water demand starts to take place. Water demand without feedbacks is a function of the land use, crop and livestock requirements and climatic conditions. Water demand with feedbacks includes adaptation, which is influenced by the four measures of resilience. A decreasing gap (between state and threshold) and an increasing rate (at which the system moves towards the threshold) stimulate adaptation. A year like t_2 in which the state reaches the threshold and large impacts on crop yields and farmers' income are observed, will especially stimulate the adoption of adaptation strategies. Water demand is further adapted (Figure 8.2c) and water management is also better planned in order to increase water availability for agriculture (Figure 8.2b). As a result, irrigated farming continues to be resilient. A practical example is presented by Ostrom (1990), who demonstrated how institutional arrangements in Valencia, Spain, manage the use of irrigation water efficiently by adapting water allocation based on water availability.

Decreasing water demand may imply successful adaptation for the resilience of irrigated farming, but can have a direct effect on crop yields and consequently on outputs (in euros). Outputs (including subsidies) should exceed inputs (including taxes) with a certain amount for a sustainable farmers' income. Currently, the gap between outputs per hectare and inputs per hectare suggests a higher resilience for Mediterranean farmers, compared to farmers in e.g. northern France (Chapter 2). In order to cope with changing climate and decreasing subsidies to stay resilient, more adaptation is needed in northern France compared to many Mediterranean regions.

Figures 8.2e–h demonstrate that short-term adaptation from t_1 to t_2, when water demand and inputs are increased, can be maladaptation in the long-term, when t_2 is approached. As the gap between state and threshold is large enough at t_1, increases are possible, with positive effects on farmers' income (i.e. the gap in Figure 8.2e). However, the increase in water demand causes a deficit in water availability at t_2, which affects farmers' income largely. This will cause some farmers to go out of business. After t_2, awareness of the risks of climate change and consequently, adaptation increases. Adaptation strategies such as change of crops decrease the water demand, but also outputs. Nevertheless, adapting the system to the conditions can prevent the system from a collapse (which requires reorganization of the system instead of small adaptations) and thus makes it more resilient.

In the two examples the thresholds for measuring resilience are relatively straightforward. Defining thresholds for crop yields, which determine when farmers stop growing a crop, is less straightforward. Projecting the vulnerability of specific crops is of importance for food production and, as growing crops forms the basis of arable farming, farmers' livelihood. In IMAGE 2.2 thresholds are only based on relative crop productivity (IMAGE team, 2001); regions with lowest crop yields stop growing the crop, which is compensated by other regions. Rounsevell et al. (2005) used, in a study on European land use change, the location of less favoured areas to determine where crops go out of production. At farm level, bio-economic farm models are often used to assess land use change (Janssen and van Ittersum, 2007). In these models maximizing profit is usually assumed as the main objective of farmers; hence, crop profitability, based on productivity and prices, relative to other crops determines crop change.

Clearly, thresholds for crop yield should be based on more than relative crop productivity. Thresholds are regional and farm specific. Crop productivity should be related to input and output prices and subsidies, in order to determine crop profitability relative to other crops (see Figure 1 in Mendelsohn and Dinar, 1999) and to other regions. But importantly, several factors constrain or stimulate crop or land use change: crop demand, traditions, water availability for irrigation, machinery, farm characteristics, possibilities for off-farm income and farmers' objectives and perceptions. In regions where land prices are high and output prices low, the threshold for crop yield is higher. Also farm characteristics are important as an arable/cereal farm is more dependent on high crop yields than a dairy farm. Unpublished results from our analyses indicated that differences in crop diversity between regions with 1°C difference are much larger than between years with 1°C difference. This implies that factors not related to crop profitability are clearly important; regional and farm specific conditions determine land use and crop choice.

The non-linear dynamics and multiple factors that operate at different scales make analysis of thresholds complicated (Groffman et al., 2006). Nevertheless, as assumed thresholds for crop yields, determining when farmers start or stop growing a crop, often have large effects on results from climate change impact assessments, improving assumptions to determine thresholds is of importance. For example, when the threshold is being a less favoured area or not, further analysis of climate impacts on crop yields will be of little importance.

As agriculture continuously adapts to changing conditions, it is generally expected that in most European regions agriculture will also be able to cope with future changes. Our analyses also suggest this. However, the historical examples of agricultural systems that suddenly collapsed (e.g. the Classic Maya empire), were mainly highly complex systems that performed well before shocks (often related to climate change) caused them to collapse (deMenocal, 2001; Diamond, 2005). Systems that perform well generally have the technical and financial capacity to adapt, but when awareness of changes that potentially have a large impact is lacking, they are especially vulnerable. In some cases, adaptations to maintain current farming systems may not be fruitful in the long-term and a shift to other farming systems is required to maintain resilience (e.g. Anderies et al., 2006). Uncertainties in the importance of different aspects determining adaptive capacity and on the location of thresholds clearly indicate the need for further exploration of the vulnerability of different farm types and regions to climate change.

8.4 Adaptation in integrated impact assessment modelling

Empirical analyses have provided insights in adaptation to climate change and climate variability, but regression estimates shouldn't be directly used in forecasts. In order to assess the influence of current management and adaptation in management on farm performance - and consequently the impacts of climate change - an integrated assessment model is needed that assesses both bio-physical and socio-economic processes accurately and includes feedbacks among different model components. IMAGE (MNP, 2006) provides such a framework, as it explicitly simulates linkages between agriculture and other sectors. However, in the current version of the model agricultural management processes are underrepresented. Adaptation can therefore not be accurately represented and impacts of changes (e.g. decreasing crop yields) are under- or overestimated.

Models simulating the impact of climate change on agriculture generally ignore most of the feedbacks between the different parts of the system. Crop yields are determined by biophysical processes that can be simulated by a stand-alone crop model, but also by management and technology development, for which information is needed from other sources or model components. In cases where crop models are actually coupled to other models, such as land use or economic models, outputs from crop models are used as inputs to other models; there is no loop back into the crop models (e.g. IMAGE team, 2001; Bharwani et al., 2005; Parry et al., 2005).

IMAGE uses a management factor based on statistics and extrapolations to account for the effect of management and technology on crop yields. For IMAGE 2.4 a first interaction with another model component was established. The linkage between GTAP, a global trade model, and IMAGE resulted in an adaptable management factor (van Meijl et al., 2006). In order to simulate realistic adaptation processes, more linkages and feedbacks should be established (Figure 8.3). Especially important is that the crop model should be focussed on simulating actual yields instead of potential and water limited yields.

Crop management relates explicitly to the timing and dose/amount of agro-management activities (planting; nutrient; water; weed, pests and diseases; soil) and

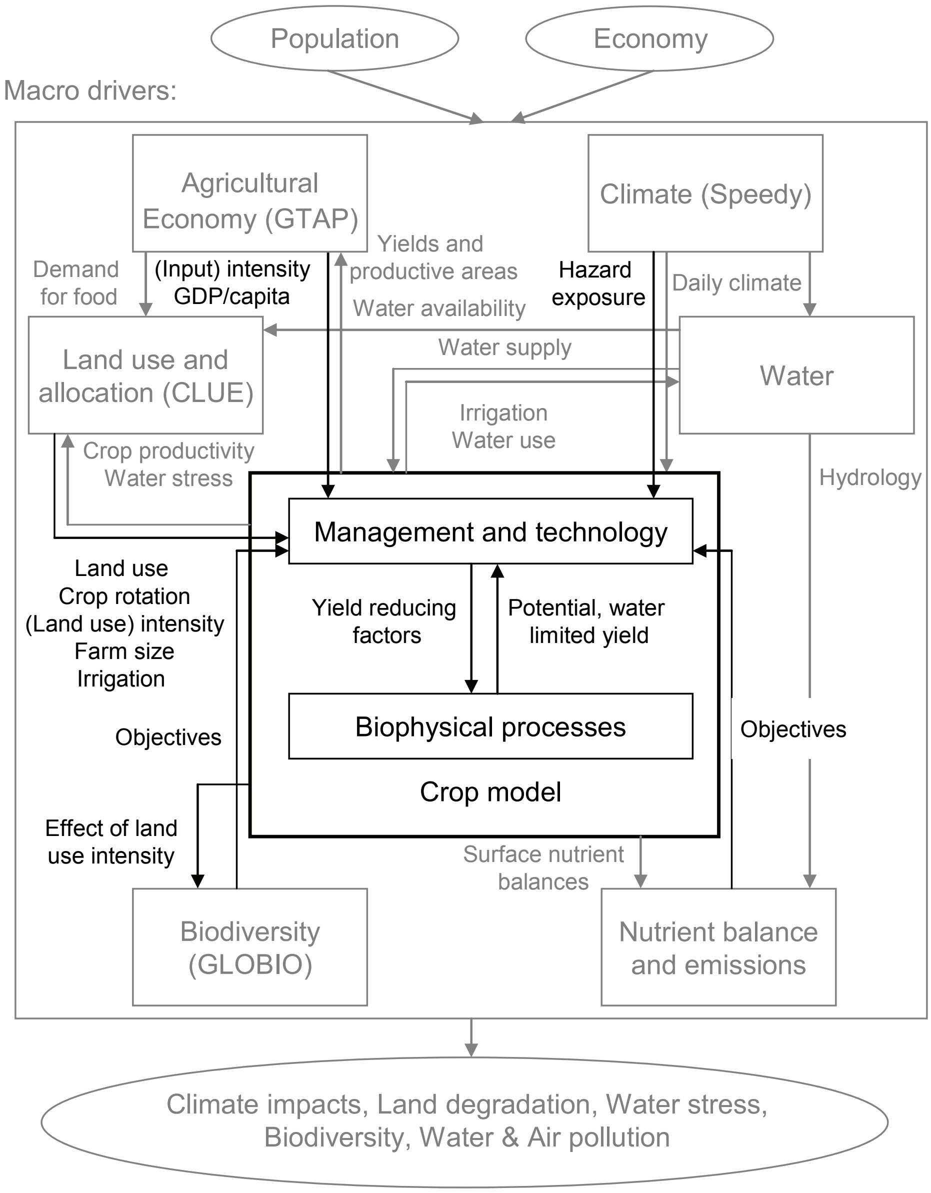

Figure 8.3. Scheme showing the planned improvements of the terrestrial environmental system model and climate model for IMAGE 3.0 (adapted from Ewert, 2004). The black arrows show the relationships particularly important to address agricultural management and adaptation.

choices regarding to species and cultivars. At field level agro-management activities can be explicitly modelled, but at regional level this is not preferred as (1) data is not available, (2) there is large heterogeneity in management activities at regional level, and (3) when up-scaling crop growth from field to regional level the sensitivity of the system to different processes changes. Accordingly, the most promising way to simulate adaptation processes is to link management and adaptation to management types, based on regional conditions, farm characteristics and crop characteristics (Figure 8.4). This allows the use of a simplified approach for the modelling of biophysical processes, but requires a more accurate approach for processes determining actual yields.

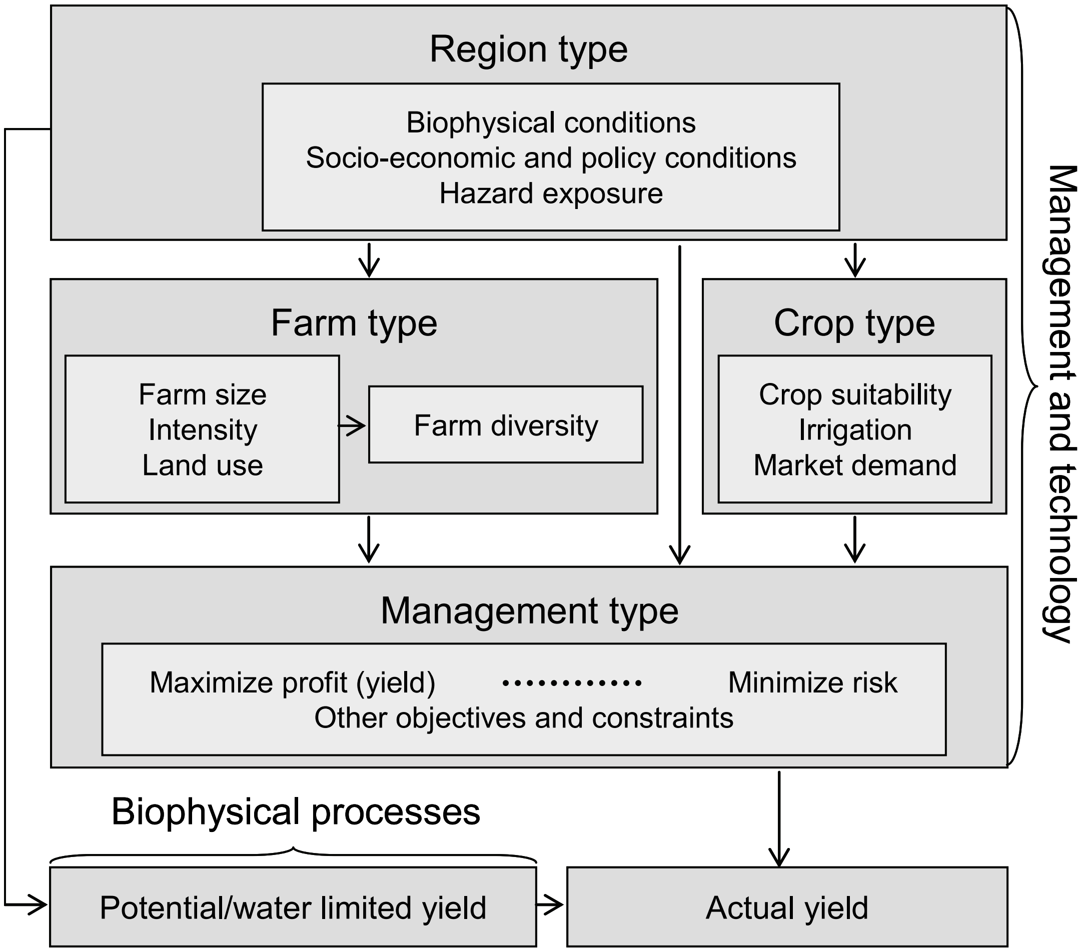

Figure 8.4. Factors to consider when simulating the influence of climatic conditions and management and adaptation on crop yields (and consequently farmers' livelihood).

In Chapter 7, a similar approach was used to analyse agricultural biodiversity in the current situation and to explore future trends. Based on a literature review and expert knowledge, an ecosystem quality was attributed to each farm type. Similarly, management and adaptation rules can be attributed to each farm type. As management and adaptation also depend on regional conditions and the crop type, these should be included in the management typology.

With regard to the regional conditions, the effects of prevailing conditions and hazard exposure on farmers' objectives and constraints are important. Hazard exposure is the perceived climate variability (modelled in IMAGE with the climate model Speedy) and the related impact on variability in potential/water limited crop yields. Farms in favourable regions (high potential crop yields, high financial and technological ability) with low hazard exposure generally focus mainly on profit and yield maximization and farms in less favourable regions (low potential crop yields, lower financial and technological ability) with higher hazard exposure (increasing awareness) will put more effort in reducing the impacts of risks. By evaluating regional conditions year by year in the model, adaptation will be stimulated if hazard exposure increases. Adaptation at regional level implies a change in the distribution of management types: on average each farm slightly adapts its management.

At farm level, management and adaptation is clearly dependent on the farm characteristics farm size, intensity and land use. Different farm types can be grouped into management types with larger, more intensive and specialized farms focussing more on profit and yield maximization, while smaller, less intensive and mixed farms focus more on risk minimization. Farm typologies developed for other continents also have strong links with farm size, intensity and land use and can thus be used for global assessments (e.g. McConnell and Dillon, 1997; Dixon et al., 2001). As increasing farm diversity decreases risks, a diversity factor may be used for simulations at regional level.

Lastly, also crop characteristics are important for crop management. For example, in Greece, maize has high potential yields and is irrigated. Therefore, management is aimed at achieving high crop yields and crop management is adapted to changing conditions (e.g. heat resistant cultivars). Wheat in these regions is a crop with low potential and water limited yields and is generally not irrigated. As there is still a market demand for wheat, farmers do grow wheat. However, crop management is not aimed at achieving high wheat yields, but mainly at achieving relatively stable yields.

By simulating agricultural management based on management types with specific objectives and constraints, adaptation will be inherently part of the simulations. As Chapter 5 demonstrated, different farms and regions adapt differently and relating specific adaptation strategies directly to farm or management types is not possible. The adoption of adaptation strategies depends on the local situation and the objectives of the management types.

There are several challenges and decisions to be made on the detail and complexity in the use of management types. Firstly, each region contains several management types, but it may be more feasible to base simulations on one regional management type. Secondly, management types change over time and this change needs to be simulated. Assumptions can be based on scenario narratives, literature (e.g. Zimmermann et al., 2007) and results from this study. Thirdly, the relationship between management types and actual yields can be based on detailed simulation of farm management or on a relatively simple management factor. Detailed simulation of farm management requires a bio-economic model with strong linkages to the biophysical processes in the crop model and to the other model components, such as land use and the agricultural economy (Figure 8.3). Such a model is most promising when adaptation processes are to be captured accurately. When developing such a model is not feasible, a management factor can be used, but this factor needs to be dynamic and influenced by processes that stimulate adaptation. Fourthly, in order to capture adaptation strategies, these strategies need to be included in the modelling framework. For example, if persistent high temperatures stimulate the use of more heat resistant cultivars, this should be an option in the crop model. If irrigation depends on water availability and water demand, the linkages between the water, land use and crop model need to be able to respond to changes herein.

Hence, the main challenge for improving the simulation of agricultural management and adaptation comprises (1) the development of a management typology, (2) establishing relationships between farm, region and crop types to management types, (3) establishing relationships between management types and actual yields and (4) creating linkages between other model components (e.g. land use, agricultural economy) and the management typology; outputs from other model components mainly determine the management types occurring in a region.

8.5 Limitations

Adaptation varies per region and per farm. Biophysical processes are well understood and principles are valid in different regions, but socio-economic processes and farmer behaviour are highly complex, not well understood and difficult to generalize. For understanding adaptation at higher aggregation levels, statistical regression models are the most appropriate tools. Collecting primary data at the farm level was not possible within the scope of this thesis, but the availability of extensive databases on European agriculture provided a unique opportunity to assess impacts of and adaptation to climate change in different regions and on different farms. Nevertheless, the data availability is limited. There is no data on farmers' objectives and perceptions. Furthermore, no data is available on specific management and adaptation strategies. By analysing the influence of farm characteristics on farm performance and linking this to other studies from the literature, assumptions can be made on objectives and strategies, but validation is not directly possible. In order to test these assumptions and understand what farmers do, local studies on adaptation strategies to climate change are needed. Only with detailed surveys the decision-making processes and adaptation strategies that are adopted can be assessed. These should be structured in such a way that comparison between different regions and farms is possible.

Another limitation of the farm data is that the exact location of the farms is unknown for privacy reasons. Hence, the impact of small-scale variability in climate and particularly soil conditions can not be assessed. It is assumed that farms are equally distributed throughout the regions. The analyses showed that explaining variables can be considered exogenous, thus these assumptions can be justified. Nevertheless, more detailed information on the location of the farms would have strengthened the analysis.

Also statistical regression models have their limitations. Climatic variables that have an impact on farm performance need to be aggregated, but relationships between climate and farm performance may be more complex than can be employed in regression models. Extreme dry or wet events, especially in periods relevant for specific growth stages may have an impact that is not captured in aggregated climate data. We tested different aggregated climate variables and used crop model simulations, based on daily weather data, in order to validate the use of aggregated climate data. These indicated that for capturing the effect of management and adaptation, the aggregated variables suffice. Nevertheless, locally specific climate events may have more impact.

Furthermore, there are several aspects of vulnerability and adaptation that cannot be easily assessed with statistical regression models and that remain to be studied. Although it is suggested that farms in regions with higher hazard exposure adapt faster, the rate of adaptation and its dependency on thresholds remains unknown. Also, technology development has a large impact on farm performance, but interaction with climate change adaptation is difficult to project. The impact of technology development can be extrapolated from historical trends (e.g. Ewert et al., 2005), which may also be done for the impact of technology on climate change adaptation.

Despite the limitations, the analyses clearly improved insights in the influence of adaptation on reducing impacts of climate change and variability. Although many processes remain to be studied, the analyses have revealed some important aspects that need to be considered when projecting the impacts of climate change on agriculture.

8.6 Relevance

This study is especially relevant as it gives better understanding on how adaptation reduces impacts of climate change and climate variability on farm performance. Most studies until now focussed on potential impacts which were mainly assessed based on biophysical models. As knowledge on current management and adaptation strategies is still small, these are generally not explicitly included in impact assessment models and hence, impacts are over- or underestimated. Therefore, in this study we explored where adaptation took place, what determines adaptation and where more adaptation is needed.

Results are important for developing scenarios on climate change impacts. The study shows that although crop models are good tools for assessing climate change impacts on potential crop yields; the models should be adapted when assessing climate change impacts on actual yields. Factors that are important to consider in integrated impact assessment models are identified in this study.

It is clear that adaptation can largely reduce potential impacts which implies that climate change is not an inevitable problem, but farmers, assisted by governments, can adapt. The most sensitive regions considering biophysical conditions are not the most vulnerable, as farmers in these regions have adapted to the prevailing conditions and will therefore also have some capacity to adapt to changing conditions. Farming systems in currently favourable regions might need to adapt management and focus more on reducing the impacts of risks, as risks will likely increase.

In several European countries national programmes for adaptation to climate change have been launched. This study demonstrates that planning adaptation is indeed important. Governments can assist farmers by increasing technological and financial ability of farmers and increasing awareness of climate change and possible adaptation strategies. Subsidy, support and incentive programs can increase the technological and financial ability of farmers and may shift the current trend towards more large, intensive and specialized systems to maintaining or enhancing the diversity in farming systems. Farm diversity has shown to decrease regional vulnerability. Furthermore, awareness of farmers can be increased by education and information programs.

8.7 Conclusions

Adaptation can largely reduce the impacts of climate change and climate variability on European agriculture. This study suggests that actual impacts of climate change and associated climate variability will be less severe for Mediterranean regions than projected by earlier studies. Impacts of climate variability on crop yields and farmers' income are generally more pronounced for temperate regions. Farmers adapt their management to prevailing climatic, socio-economic and policy conditions. This current management influences adaptation strategies that can be adopted in the future and hence the impacts of climate change.

At farm level, crop yields and farmers' income increase with increasing farm size and farm intensity. Also land use (e.g. arable land area, crop area) significantly influences farm performance. But interestingly, farms that seem better adapted to prevailing conditions do not adapt better to climate change and variability. Regions and farm types that obtain higher crop yields and farmers' income have lower (relative) variability herein, but relationships between crop yield or income variability and climate variability are generally stronger than for regions or farm types with low crop yields and farmers' income. This suggests that financial and technological ability have a positive influence on current management, but adaptation in management to climate change and climate variability is mainly determined by awareness and objectives.

Awareness increases with hazard exposure. At regional level, a higher exposure to high temperatures relates to a higher diversity among farm types, which decreases regional vulnerability. Responses to climate variability differ depending on the farm type, resulting in less pronounced climate effects in regions where farm diversity is high.

As actual impacts of climate change and climate variability on crop yields differ largely from potential impacts, based on simulations of potential and water limited crop yields, crop models need improvement to simulate actual crop yields. The differences relate to management and adaptation, which both depend on regional conditions, farm characteristics and crop characteristics. Information on these characteristics can be obtained from other models (e.g. economic and land use models) but requires adequate linking. Although mechanistic modelling of all the processes determining crop yield and agricultural performance is not feasible, for reliable projections of the impacts of climate change on agriculture models are needed that represent the actual situation and adaptation processes more accurately.

Finally, farmers continuously adapt to changes, which affects the current situation as well as future impacts. Therefore, adaptation should not be seen anymore as a last step in a vulnerability assessment, but as integrated part of the models used to simulate crop yields and other ecosystem services provided by agriculture.

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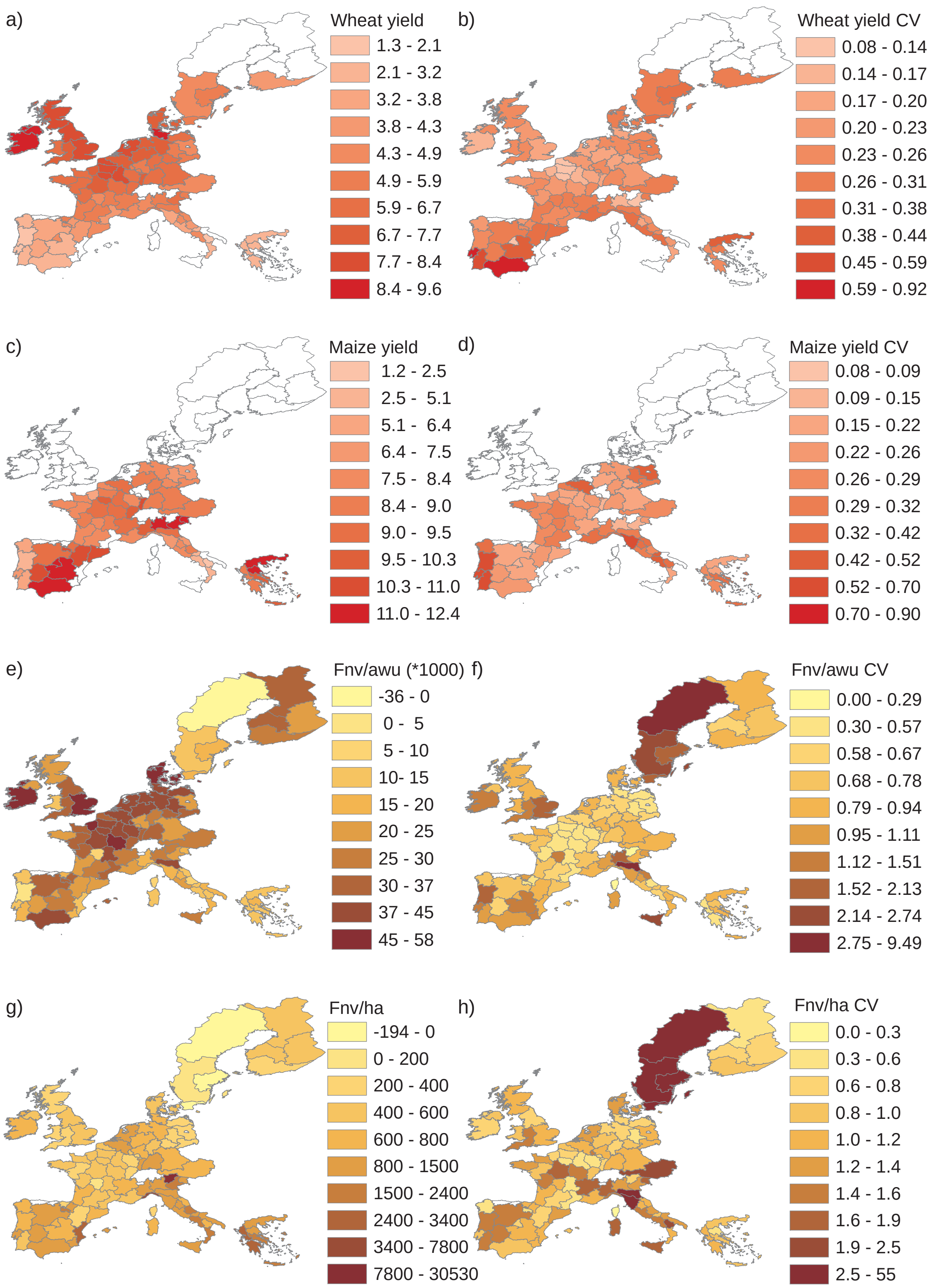
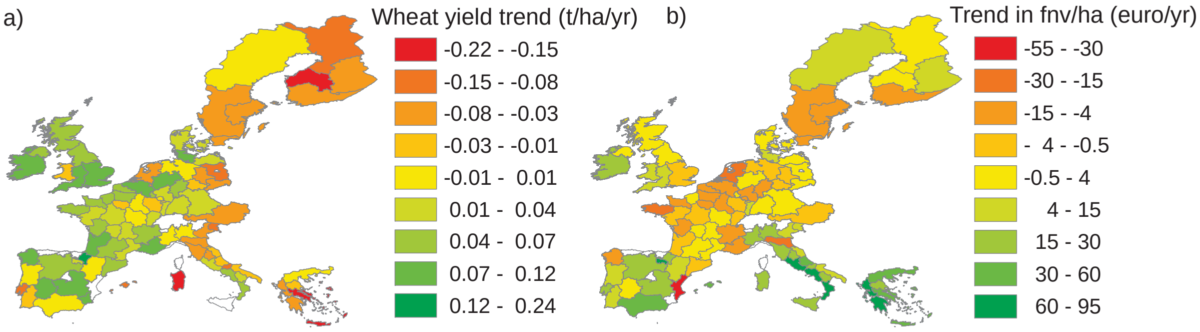
Colour Figures

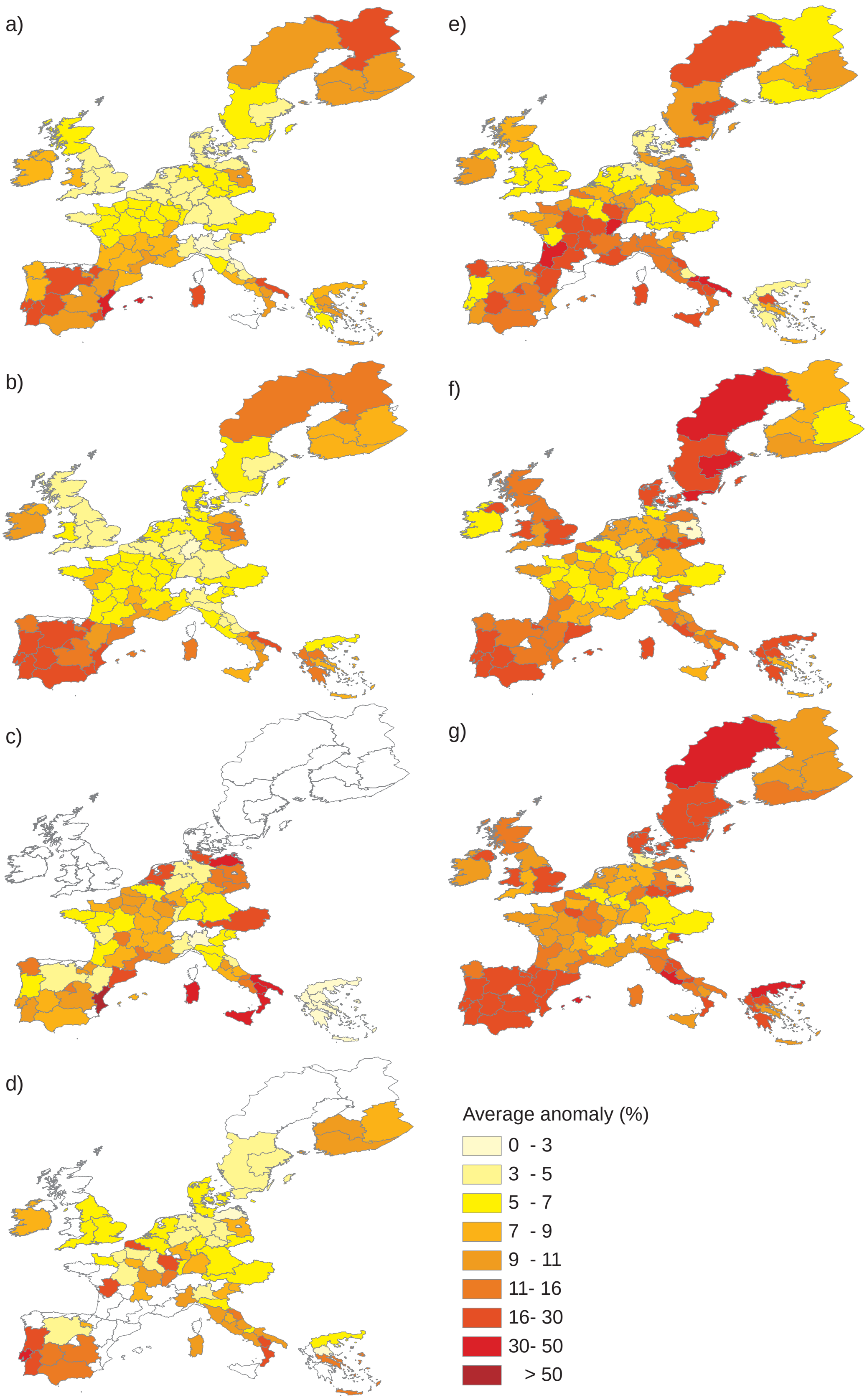
For many Figures in this thesis colours are essential. The Figures are included in the Chapters in black and white and are repeated here in colour. Colour Figures included in this section are:



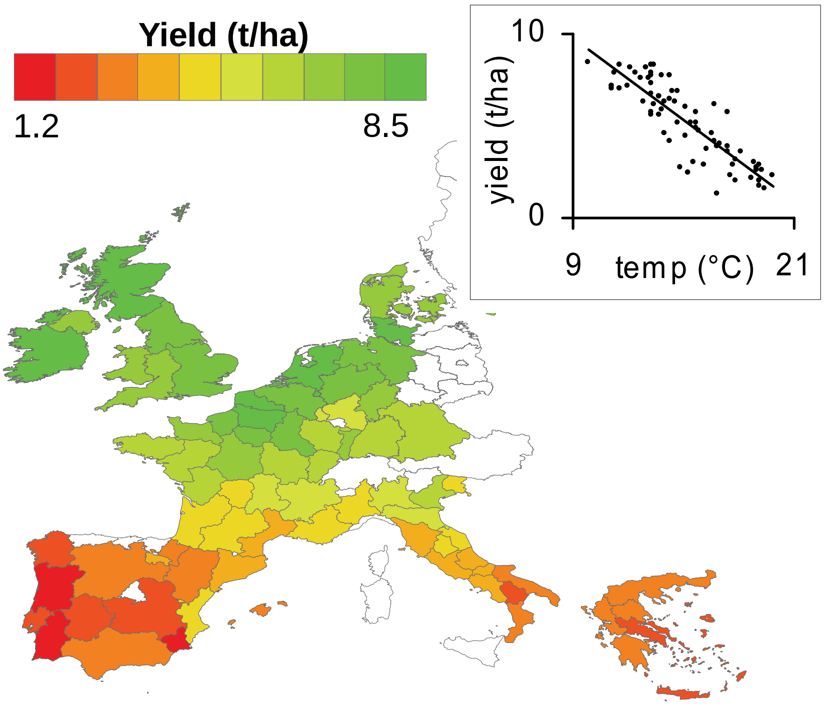
Colour Figure 2.3. Spatial variability of crop yields (tons/ha) and income variables (€) in 2000 between and within HARM regions for (a) average wheat yield, (b) CV of wheat yield, (c) average maize yield, (d) CV of maize yield, (e) average of farm net value added/annual work unit (fnv/awu), (f) CV of fnv/awu, (g) average of farm net value added/hectare (fnv/awu) and (h) CV of fnv/ha. Only values for regions where more than 15 farms grow the crop considered are presented.



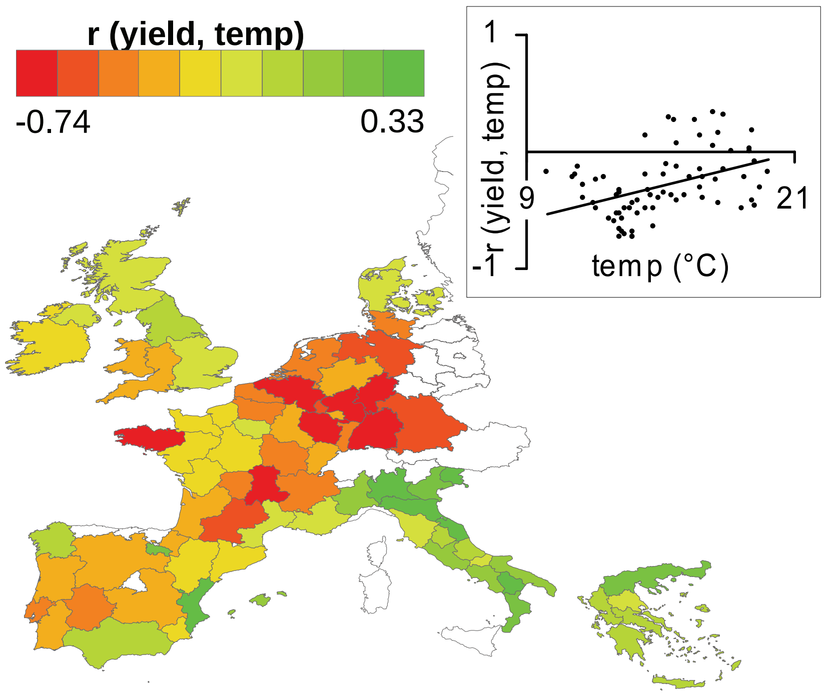
Colour Figure 3.3. Selected examples of trends from 1990−2003 in (a) wheat yield (t/ha/yr) and (b) fnv/ha (farm net value added per hectare in euro/yr)



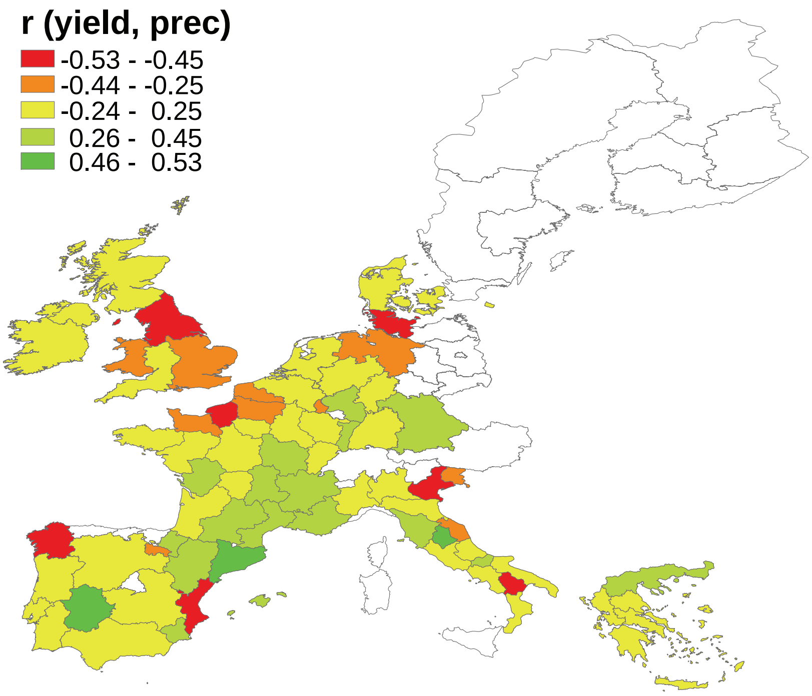
Colour Figure 3.4. Average relative anomaly (%) from 1990–2003 in 100 HARM regions for (a) wheat yield, (b) barley yield, (c) maize yield, (d) sugar beet yield, (e) potato yield, and the income variables (f) fnv/ha and (g) fnv/awu.



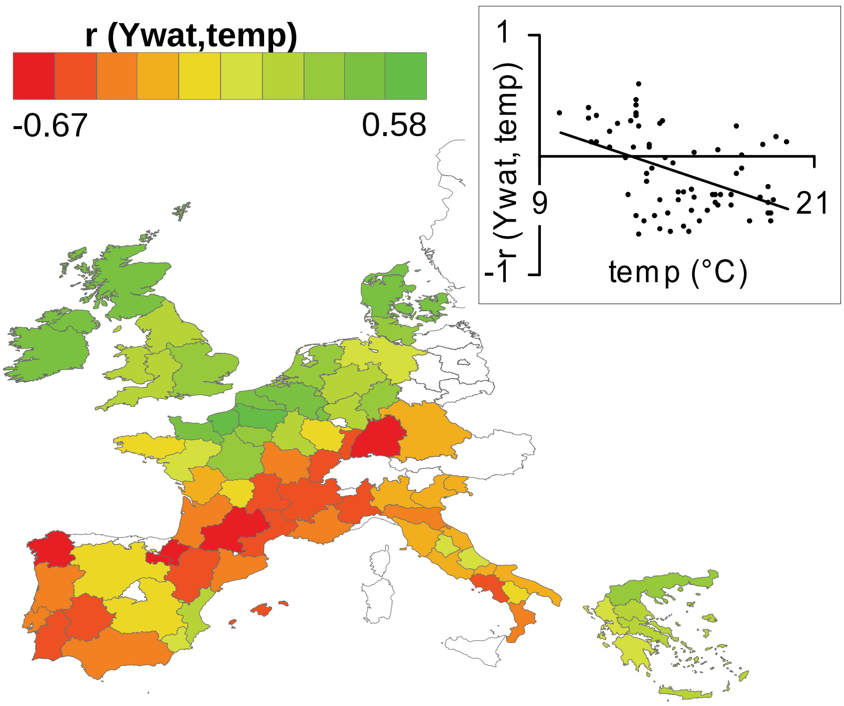
Colour Figure 4.1. Spatial distribution of average wheat yields (t/ha), and relationships to average temperature (temp, °C) from 1990–2003.



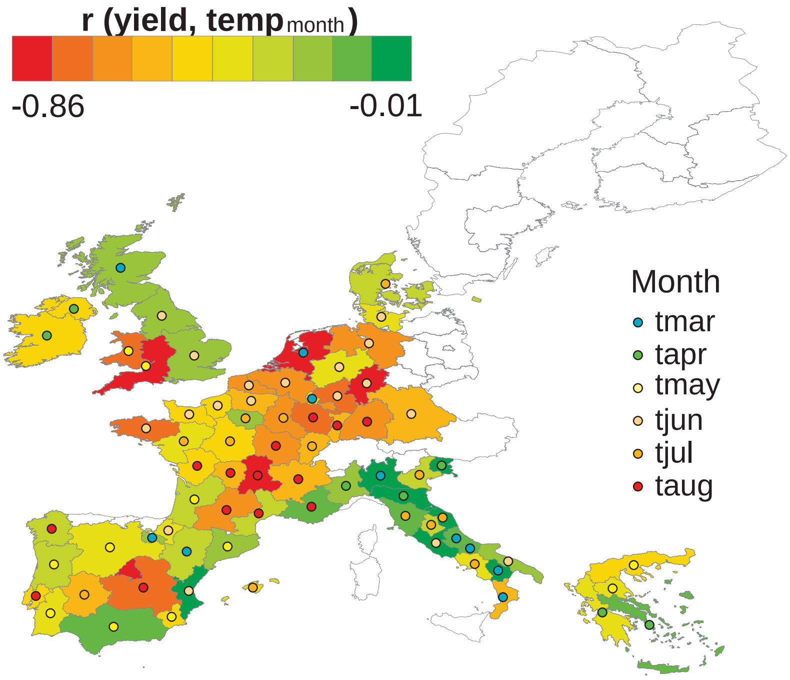
Colour Figure 4.2. Spatial distribution of the correlation between inter-annual variability in temp and wheat yield anomalies [r(yield,temp)], and relationships to average temperature (temp, °C) from 1990–2003.



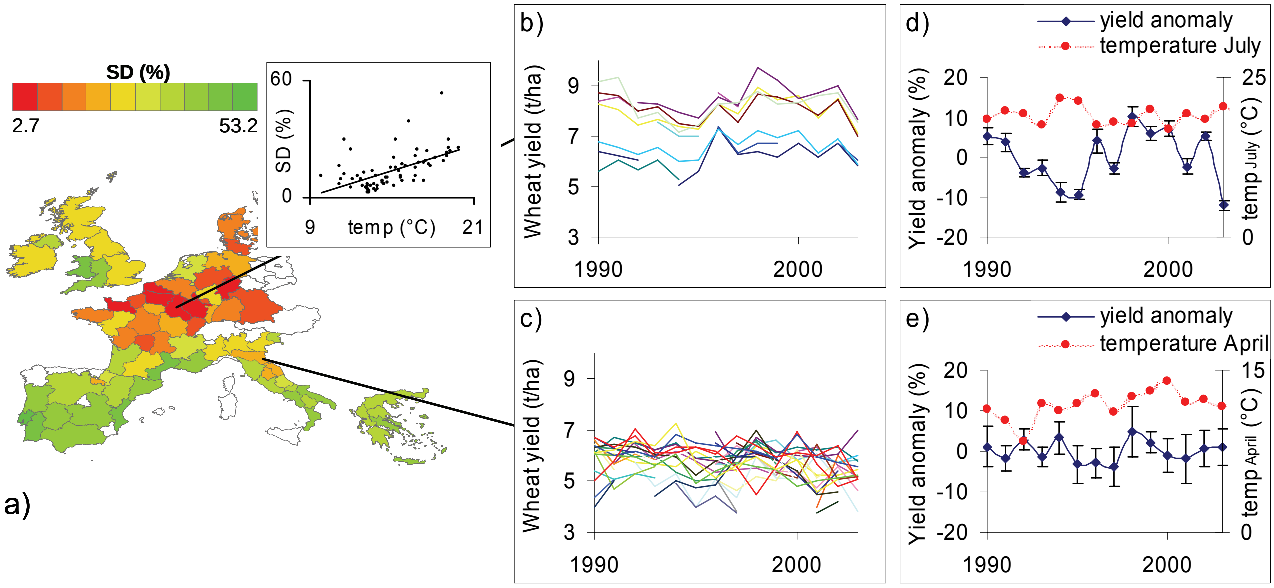
Colour Figure 4.3. Spatial distribution of the correlation between inter-annual variability in prec and wheat yield anomalies [r(yield,prec)]. The legend is different from Fig. 4.2 to demonstrate the (non-) significant relationships (|r|>0.53).



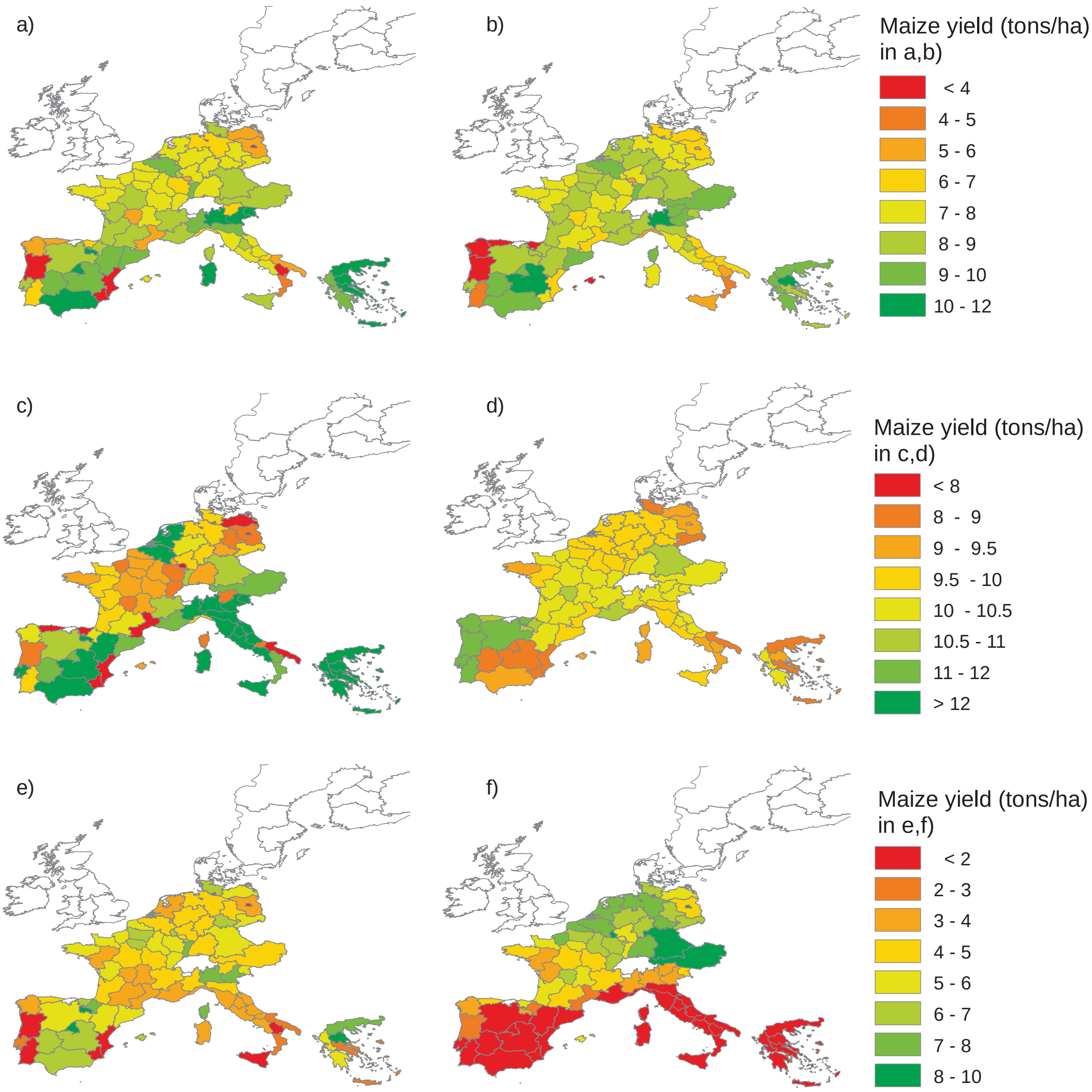
Colour Figure 4.4. Spatial distribution of the correlation between inter-annual variability in temp and water limited yields [r(Ywat,temp)], and relationships to average temperature (temp, °C) from 1990–2003.



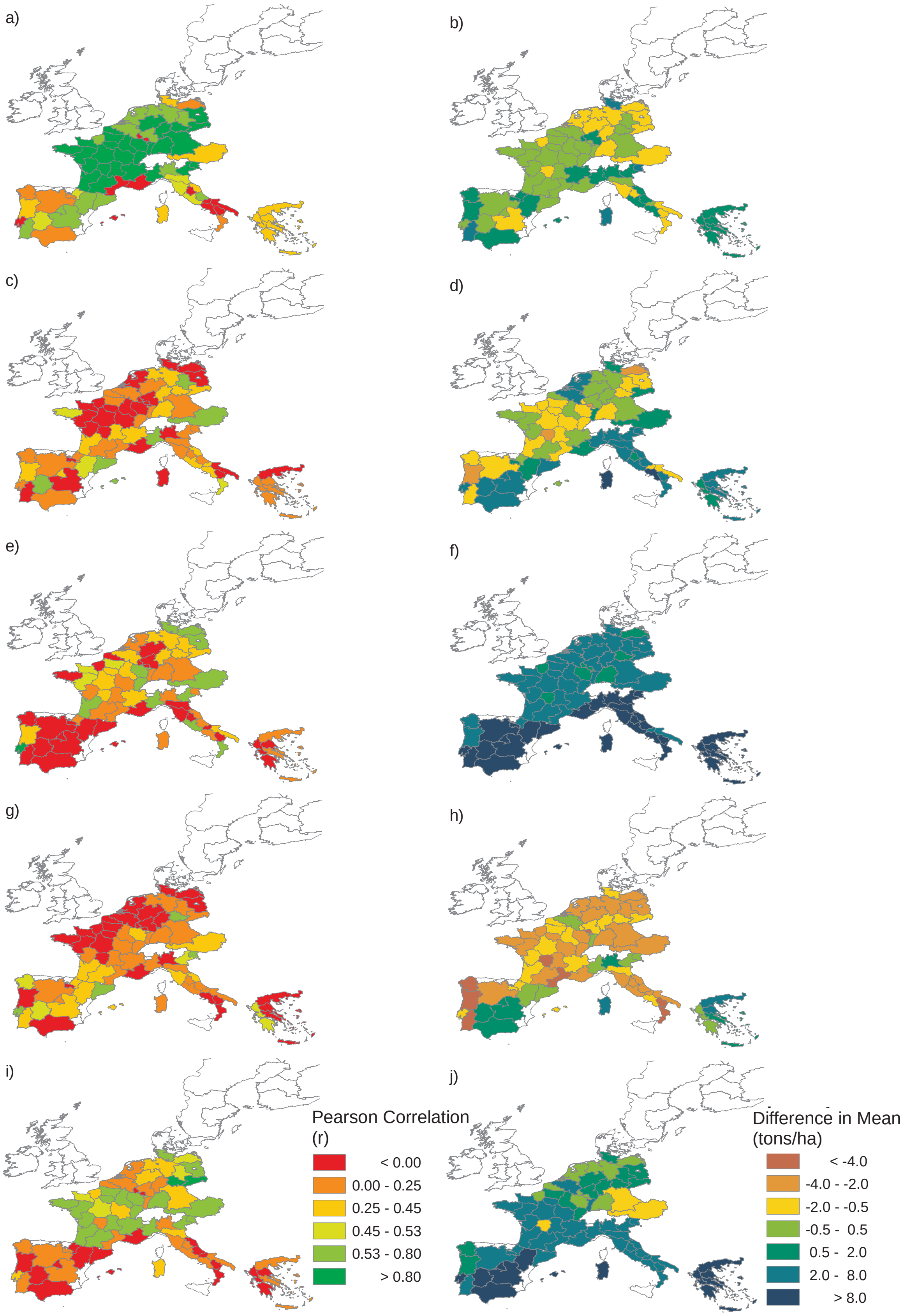
Colour Figure 4.5. Spatial distribution of the correlation between inter-annual variability in wheat yield anomalies and $temp_{month}$ (the monthly temperature variable with the largest negative effect) [r(yield,$temp_{month}$)], and relationships to average temperature (temp, °C) from 1990–2003.



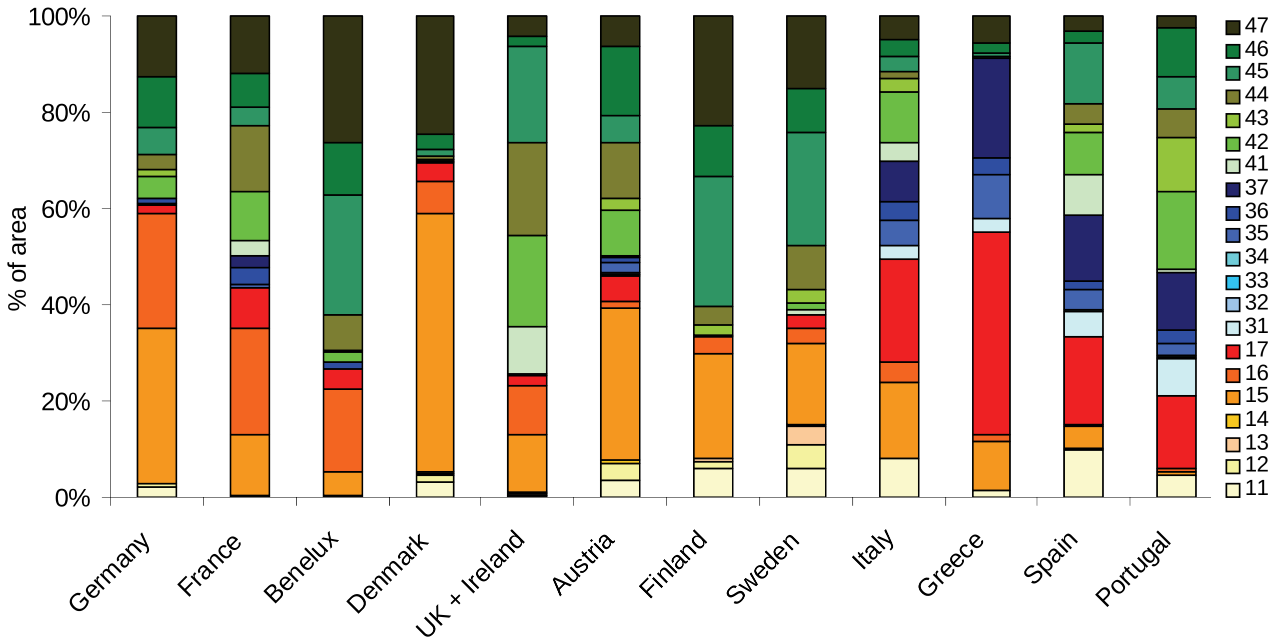
Colour Figure 4.6. (a) Spatial distribution of the diversity in farm type yield variability (SD, %), and relationships to average temperature (temp, °C) from 1990–2003. Wheat yield variability is similar for different farm types in (b) Champagne-Ardenne, while in (c) Emilia-Romagna the diversity in wheat yield variability is larger. In (d) Champagne-Ardenne standard deviations in the relative wheat yield anomaly for individual years are small (SD=3.7) and regional yield anomalies (from the trend) are significantly different from zero and correlated to temperature, (r=–0.66 with $temp_{July}$, r=–0.44 with temp). However, in (e) Emilia-Romagna the standard deviations are large (SD=8.3) and regional yield anomalies are not significantly different from zero and are not significantly correlated to temperature (r=–0.13 with $temp_{April}$, r=0.33 with temp). Note, temperatures shown in (d) and (e) refer to the months with the largest negative correlation.



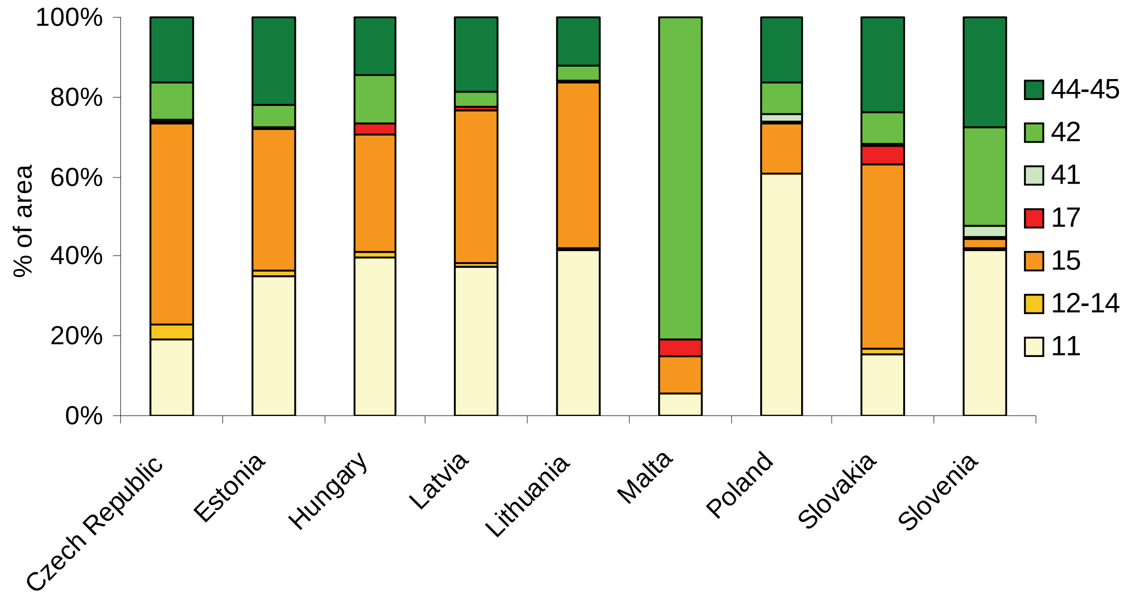
Colour Figure 6.1. Spatial variability in average actual and simulated maize yields (tons/ha) from 1990–2003 with (a) average based on FADN, $Y_{av.b,act}$, (b) average based on Eurostat, $Y_{av.a,act}$ (c) maximum based on FADN, $Y_{max.b,act}$ (d) simulated potential yield, $Y_{pot,sim}$, (e) minimum based on FADN, $Y_{min.b,act}$ and (f) simulated water limited yield, $Y_{wat,sim}$.



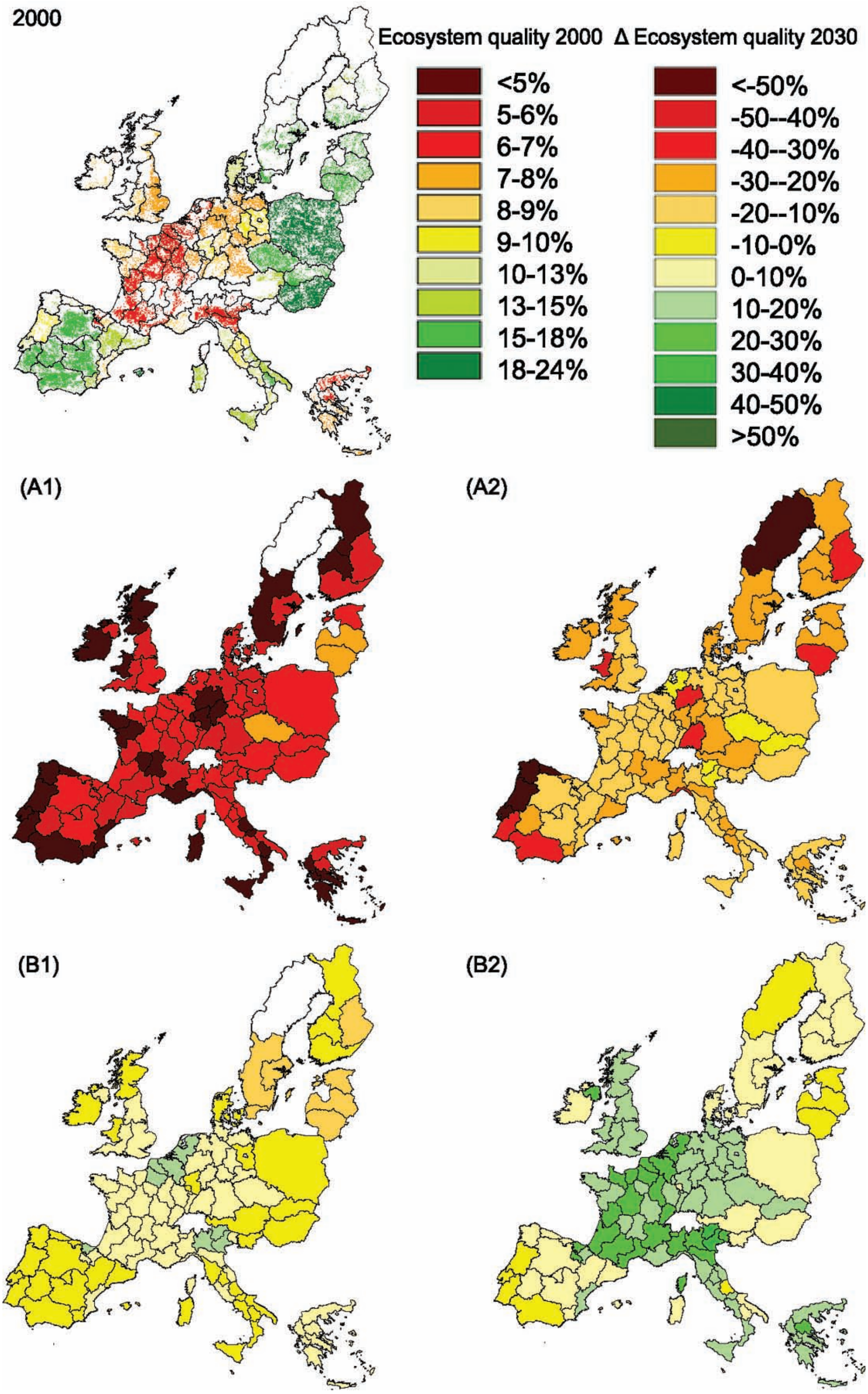
Colour Figure 6.2. Pearson correlations (r) and the Difference in Mean (DM; tons/ha) between temporal variability in actual and simulated yields per HARM region with (a),(b) $Y_{av.b,act} - Y_{av.a,act}$, *(c),(d)* $Y_{max.b,act} - Y_{pot,sim}$, *(e),(f)* $Y_{max.b,act} - Y_{wat,sim}$, *(g),(h)* $Y_{av.b,act} - Y_{pot,sim}$ *and (i),(j)* $Y_{av.b,act} - Y_{wat,sim}$. *An* $r>0.45$ *corresponds to* $p<0.10$; $r>0.53$ *corresponds to* $p<0.05$.



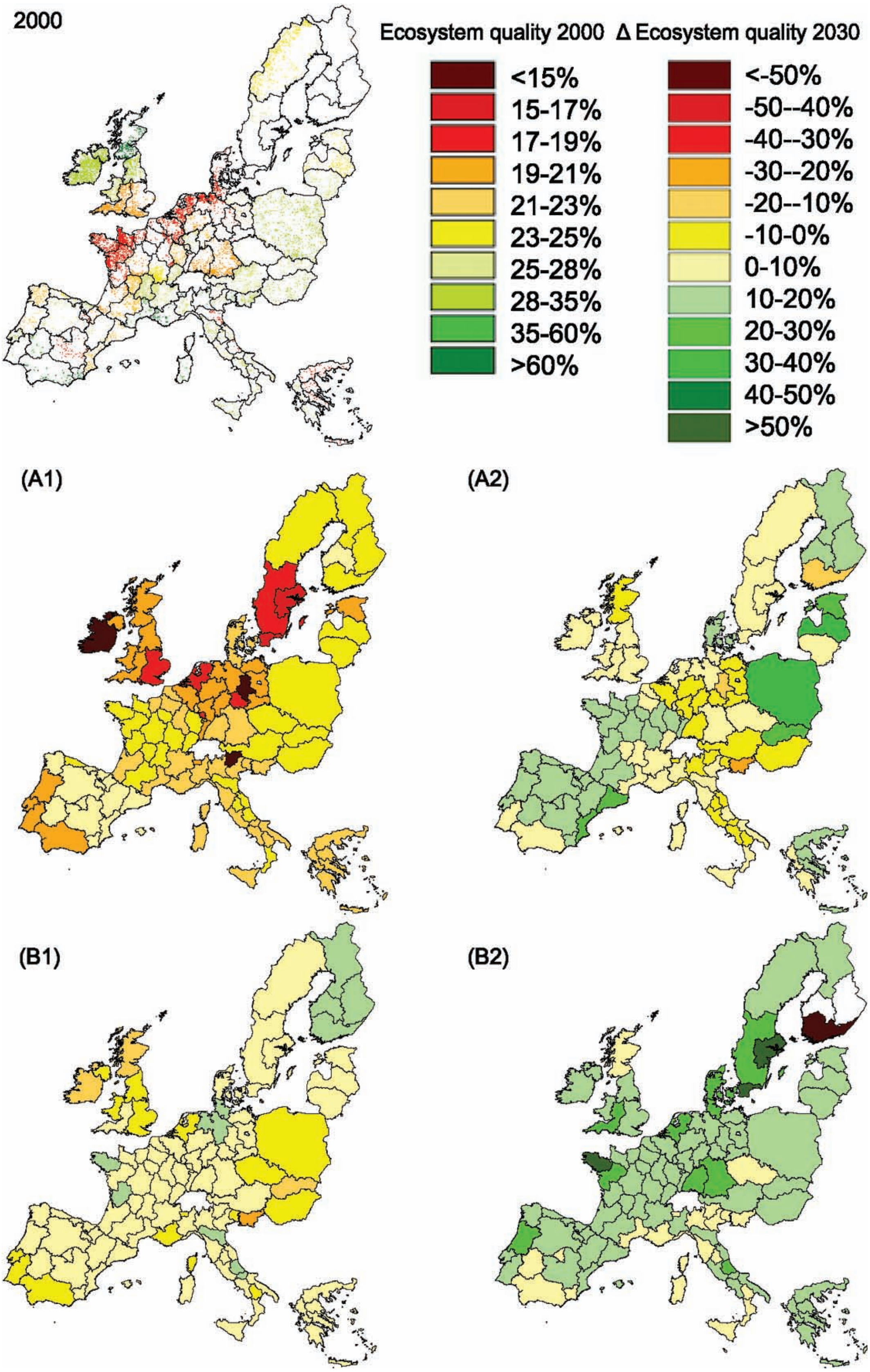
Colour Figure 7.2. The distribution of farm types in different countries in the EU15. Farm type classes are labelled in Table 7. 2 and 7.3.



Colour Figure 7.3. The distribution of farm types in different countries in the New Member States. Farm types are not distinguished as much as in the EU15, but they are assumed to be similar to farm types labelled in Table 7. 2 and 7.3.



Colour Figure 7.4. Ecosystem quality (%) of cropland in 2000 and relative change ((EQ2030−EQ2000)/EQ2000) in four scenarios for 2030. For the year 2000 an overlay is made with the CLUE 2000 map to indicate the areas of cropland.



Colour Figure 7.5. Ecosystem quality (%) of grassland in 2000 and relative changes ((EQ2030−EQ2000)/EQ2000) in four scenarios for 2030. For the year 2000 an overlay is made with the CLUE 2000 map to indicate the areas of grassland. Note the colours have a different meaning than in Figure 7.4.

Summary

Climate change is considered as one of the main environmental problems of the 21st century. Global average surface temperature has increased with 0.74 ± 0.18 °C in the last century and is projected to increase by another 1.1 – 6.0 °C in this century. Assessments of climate change impacts on European agriculture suggest that in northern Europe, crop yields increase and possibilities for new crops and varieties emerge. In southern Europe, adverse effects are expected. Here, projected increases in water shortage reduce crop yields and the area for cropping, which directly affects the livelihood of Mediterranean farmers.

The extent to which systems are vulnerable to climate change depends on the actual exposure to climate change, their sensitivity and their adaptive capacity. Exposure and sensitivity determine the potential impacts that occur given the projected climate change without considering adaptation. The actual impact is the impact that remains after accounting for adaptation. The adaptive capacity refers to the ability to cope with climate change including climate variability and extremes in order to (1) moderate potential damages, (2) take advantage of emerging opportunities, and/or (3) cope with its consequences. Most quantitative studies that address the vulnerability of agricultural systems have focused on exposure and sensitivity, while adaptive capacity is often highly simplified.

The main objective of this thesis is to **assess how adaptation influences the impact of climate change and climate variability** on European agriculture. The aim is to improve insights into adaptation processes in order to include adaptation as a process in assessment models that aim to develop quantitative scenarios of climate change impacts at regional level.

Changes in climatic conditions will affect crop yields at the field level through biophysical relationships and these impacts are commonly assessed with crop models. The dynamic nature of climate effects is well understood for potential and water-limited yields. Actual farm yields, however, are also affected by other factors, such as pests and diseases, which depend on farm management. Hence, **farm management and adaptation herein largely influence the actual impacts** of climate change and climate variability on crop yields. The impacts on **crop yields** represent the impacts on food production, an important ecosystem service. Ecosystem services are the direct or indirect benefits that people obtain from (agro-)ecosystems. Farm management also determines the relationship with other ecosystem services that we consider important for agricultural vulnerability: **farmers' income and agricultural biodiversity**. We assume that farm performance concerning these three ecosystem services is influenced by two groups of factors related to **(1) farm characteristics and (2) regional conditions**, such as biophysical, socio-economic and policy factors.

The availability of extensive datasets for Europe provided a unique opportunity to analyse farm performance in relation to climate and management, and hence, improve insights in agricultural adaptation. Climatic conditions do not only vary over time, they

also vary spatially. Therefore, in Chapter 2 we analysed the **impacts of current management on farm performance under different climatic conditions**. The analysis demonstrates that yields of most crops and farmers' income (per working unit) are higher in regions with a temperate climate and better general socio-economic conditions. It can be argued that farms and regions that perform well are well adapted, which would confirm earlier studies stating that Mediterranean regions have a lower adaptive capacity compared to northern European regions. However, spatially, farmers' income per hectare is not related to crop yields and especially high in many Mediterranean regions with typically lower crop yields. This suggests that farmers in these regions grow more profitable crops to increase farmers' income per hectare (whereas the smaller farm size explains the lower farmers' income per working unit). Also, crops that have relatively high potential yields (e.g. maize) are managed better – resulting in high actual yields – than crops with low potential yields (e.g. wheat). Optimal management thus depends on what to optimize; if a crop (e.g. wheat) is not important, management will not concentrate on increasing its yields, but on other crops with potentially higher yields. Adaptation in management and vulnerability will therefore **differ per ecosystem service** (e.g. yields of different crops, farmers' income per hectare or per working unit).

Farm characteristics that influence management, and hence farm performance, have been analysed at the farm level. Clearly, farm performance differs per farm and is largely dependent on three farm characteristics: **farm size, intensity and land use.** Crop yields and farmers' income are generally increasing with increasing farm size (i.e. economic size) and farm intensity (i.e. fertilizer use, crop protection use, irrigation). Also land use (i.e. arable land area, crop area) significantly influences farm performance.

Current management – related to regional conditions and farm characteristics – and its relation to farm performance reflect management in and adaptation to prevailing conditions and therefore influences adaptation to climate change. Accordingly, farm characteristics that determine current management – farm size, intensity and land use – have been used to develop a **farm typology** to assess trends and temporal variability in farm performance.

In Chapter 3 trends and temporal variability have been compared among regions and among farm types in order to analyse the effect of regional conditions (e.g. climate) and farm characteristics on farm performance. The temporal analyses demonstrate that regions (i.e. temperate) and farm types (i.e. large scale, high intensive, arable) that obtain higher crop yields and farmers' income per working unit have lower (relative) variability herein. However, this is only partly due to climate variability and in contrast, the variability in farmers' income per hectare decreases with increasing temperature. Furthermore, the trend in farmers' income is higher in warmer regions, while the trend in crop yields is mainly related to the trend in temperature (i.e. climate change) and not to prevailing climate conditions. Hence, results suggest that **effective adaptation to variable climatic conditions occurs in**

Mediterranean (i.e. warmer) regions.

One of the strategies that seems to stimulate adaptation to climate variability at regional level is a high farm diversity (i.e. diversity among farm types); therefore, this was further explored in Chapter 4. The analysis considers wheat, being the most important crop in Europe and grown in almost all regions. Results demonstrate that the **diversity in farm size and intensity, which is particularly high in Mediterranean regions, reduces vulnerability** of regional wheat yields to climate variability. Yield responses to temperature differ depending on the farm type and temperature effects on regional yields are less pronounced when farm diversity is high. Farm diversity is particularly high in regions that are regularly exposed to high temperatures and associated droughts, and thus appears to be **stimulated by hazard exposure**.

Adaptation strategies at farm level that have been or will be effective also vary per region. In Chapter 5 we assessed adaptation strategies in eight regions by using the translog distance function. The translog distance function allows assessing interactions between multiple inputs and outputs and hence, the influence of management on climate impacts. As climate change is not the only change affecting European agriculture, also effects of subsidies and other changes on inputs and outputs of farms throughout Europe are included. Results clearly demonstrate that **climate impacts and adaptation strategies differ per region**, and that 'actual impacts' cannot be explicitly separated into 'potential impacts' and 'adaptive capacity' as often proposed. Farmers adapt their practices to **prevailing conditions** and 'potential impacts' are not quantifiable leaving it as a mainly theoretical concept. For example, in Greece, increasing irrigated area can be considered as an adaptation strategy as it increases the positive effect of higher temperatures on total outputs. In most other regions the effect of irrigated area is small, but in Italy increasing irrigated area enlarges the negative effects of higher temperatures on total outputs. This difference in influence of adaptation strategies on climate impacts in regions with comparable climates, highlights the importance of prevailing (climate, socio-economic and policy) conditions on management. This is not considered in crop models.

For reliable projections of climate impacts on crop yields, current management and adaptation in management should thus be better represented in crop models. In Chapter 6 we investigated whether **the influence of management on crop yields simulated in a crop model can be represented by farm characteristics**. Differences between simulated and actual maize yields were analysed using backward linear regression models in which climatic conditions and farm characteristics are included.

The analysis of spatial yield variability shows that higher temperatures tend to increase actual maize yields, which is not evident from simulated potential maize yields. Also the temporal analysis of yield variability indicates that in Mediterranean regions higher temperatures have a more positive impact on actual maize yields than on the simulated potential maize yields. The opposite is the case for temperate regions. This again suggests that farmers in Mediterranean regions have adapted to higher temperatures, for example by growing more heat resistant cultivars, an adaptation strategy not considered in the crop model. Farm characteristics that explain some of the differences between actual and simulated yields are similar to farm characteristics that influence farm performance as found in Chapter 2: the maize area as proportion of the total arable area relates to land use; farmers' income relates to farm size and irrigation relates to intensity. These factors are mainly important for simulating average yields. Improving simulations of temporal variability in actual maize yields requires regional specific models that relate to farm characteristics important in the regions (as also found in Chapter 5). As observed in Chapter 4, in regions that are more regularly exposed to higher temperatures and lower precipitation the diversity in yields and yield responses among farm types is higher than in other regions. This results in small relationships between actual yields and simulated potential or water limited yields, of which the latter reflect the potential impacts of climate variability. Hence, actual climate impacts are largely different from potential climate impacts.

As changes in climatic conditions have a direct influence on crop yields, our main focus is on assessing impacts on crop yields. The relationship with farmers' income could directly be analysed with the available data. But European agriculture also faces other changes. An ecosystem service increasingly important is agricultural biodiversity as is illustrated by the Common Agricultural Policy of the European Union, which has shifted its focus from food production to more environmental objectives. Therefore European farmers need to consider agricultural biodiversity when adapting to changing conditions. Chapter 7 is included to (1) demonstrate that there are **trade offs between different ecosystem services** and to (2) present how a **farm typology can be used in impact assessments**.

An adapted farm typology was used to assess the biodiversity in agricultural landscapes of the EU25 for the current situation (i.e. 2000) and explore future trends, based on four scenarios up to 2030. An ecosystem quality value was attributed to each farm type according to dose-effect relationships between pressure factors (e.g. fertilizer use) and biodiversity compared to the value for an undisturbed situation. The biodiversity in agricultural landscapes was then calculated as the average ecosystem quality multiplied by the relative area size of each farm type within a region. Referring to the current situation, results indicate the lowest ecosystem quality values to be found in intensively used agricultural areas in lowlands (e.g. the Netherlands and northern France) and irrigation systems (e.g. Greece), whereas relatively high values are found in Spain and the New EU Member States. Scenario results show that for the A1 scenario (Global economy), the highest loss in ecosystem quality will take place in the croplands and grasslands of all regions. The B2 scenario (Regional communities) provides the best opportunities to improve ecosystem quality of agricultural landscapes. In most scenarios, agricultural land is decreasing, while the remaining agricultural areas tend to be used more intensively. The negative impact of intensification on biodiversity is partly set off by (active or spontaneous) nature development on abandoned agricultural areas, but the overall trend seems to be generally negative.

Hence, increasing farm intensity is not a good strategy when maintaining agricultural biodiversity is an important objective. And the analyses in the other Chapters demonstrated that although farms or regions with high intensity obtain higher yields and farmer's income and lower (relative) variability herein; relationships between crop yields and income variability and climate variability are generally stronger than for farms or regions with lower crop yields and farmer's income. **Adaptation to climate change and climate variability can thus be compatible with adaptations to stop biodiversity loss**. Focusing less on achieving high crop yields and income and more on reducing the impacts of risks, will decrease the vulnerability to climate change and variability and will be beneficial for agricultural biodiversity.

Concluding, **adaptation can largely reduce the impacts of climate change and climate variability** on European agriculture. This study suggests that actual impacts of climate change and associated climate variability will be **less severe for Mediterranean regions** than projected by earlier studies. Impacts of climate variability on crop yields and farmers' income are generally more pronounced for temperate regions. Farmers adapt their management to prevailing climatic, socio-economic and policy conditions. This current management influences adaptation strategies that can be adopted in the future and hence the climate impacts.

As actual impacts of climate change and climate variability on crop yields differ largely from potential impacts, based on simulations of potential and water limited crop yields, **crop models need improvement to simulate actual crop yields**. The differences relate to management and adaptation, which depend on regional conditions, farm and crop characteristics. Information on these characteristics can be obtained from other models (e.g. economic and land use models) but requires adequate linking.

Although mechanistic modelling of all the processes determining crop yield and agricultural performance is not feasible, for reliable projections of the impacts of climate change on agriculture, models are needed that represent the actual situation and adaptation processes more accurately. **Farmers continuously adapt to changes**, which affects the current situation as well as future impacts. Therefore, adaptation should not be seen anymore as a last step in a vulnerability assessment, but **as integrated part of the models** used to simulate crop yields and other ecosystem services provided by agriculture.

Samenvatting

Klimaatverandering wordt gezien als één van de belangrijkste milieuproblemen van de 21e eeuw. De gemiddelde temperatuur op aarde is gedurende de vorige eeuw toegenomen met 0,74 ± 0,18 °C en de verwachting is dat deze in deze eeuw verder zal toenemen met 1,1 – 6,0 °C. Studies op het gebied van klimaatverandering duiden er op dat gewasopbrengsten in Noord-Europa zullen stijgen en dat er mogelijkheden voor nieuwe gewassen en variëteiten zullen ontstaan. In Zuid-Europa worden tegenovergestelde effecten voorspeld. Door de verwachte toenames in watertekorten zullen gewasopbrengsten en het landbouwareaal dalen, wat direct invloed heeft op de broodwinning van mediterrane boeren.

De mate waarin systemen kwetsbaar zijn voor klimaatverandering hangt af van de blootstelling aan klimaatverandering, de gevoeligheid hiervoor en het aanpassingsvermogen. De blootstelling en de gevoeligheid bepalen de potentiële effecten van klimaatverandering zonder rekening te houden met adaptatie. De werkelijke effecten zijn de effecten die overblijven als adaptatie wel in ogenschouw wordt genomen. Het aanpassingsvermogen heeft betrekking op het vermogen om om te gaan met klimaatverandering, inclusief variabiliteit en extremen in het klimaat, door (1) de potentiële schadelijke effecten te beperken, (2) gebruik te maken van nieuwe mogelijkheden en/of (3) om te gaan met de gevolgen. De meeste kwantitatieve studies die de kwetsbaarheid van de landbouw hebben geanalyseerd, hebben zich gericht op de blootstelling en de gevoeligheid, terwijl de analyse van het aanpassingsvermogen sterk vereenvoudigd is.

De centrale doelstelling van dit proefschrift is om te **onderzoeken hoe adaptatie de effecten van klimaatverandering en klimaatvariabiliteit op de Europese landbouw beïnvloedt**. Het doel is om inzichten in adaptatieprocessen te verbeteren, zodat adaptatie als een proces kan worden ingepast in modellen die scenario's voor de effecten van klimaatverandering op regionaal niveau ontwikkelen.

Veranderingen in klimaatomstandigheden hebben direct effect op gewasopbrengsten op veldniveau. Deze effecten worden over het algemeen gemodelleerd met gewasmodellen op basis van biofysische relaties. Voor potentiële en water gelimiteerde gewasopbrengsten is de dynamiek van klimaateffecten bekend. De werkelijke gewasopbrengsten worden echter ook beïnvloed door andere factoren, zoals plagen en ziekten. Deze zijn voornamelijk afhankelijk van het management op het boerenbedrijf. Daarom **beïnvloeden management en adaptatie hierin voor een groot deel de werkelijke effecten** van klimaatverandering en klimaatvariabiliteit op gewasopbrengsten. De effecten op **gewasopbrengsten** vertegenwoordigen de effecten op de voedselproductie, een belangrijke ecosysteemdienst. Ecosysteem diensten zijn het directe of indirecte nut dat mensen uit (agro-)ecosystemen halen. Het management heeft ook invloed op de relatie met andere ecosysteemdiensten die we als belangrijk beschouwen voor de kwetsbaarheid van de landbouw: **het inkomen van boeren en de agrarische biodiversiteit**. De prestaties van landbouwbedrijven op basis van deze drie

ecosysteemdiensten, worden beïnvloed door twee groepen factoren die gerelateerd zijn aan **(1) karakteristieken van landbouwbedrijven en (2) regionale omstandigheden** zoals de biofysische en socio-economische omstandigheden en beleid.

De beschikbaarheid van uitgebreide datasets voor Europa creëerde een unieke mogelijkheid om de prestaties van landbouwbedrijven in relatie tot klimaat en management te onderzoeken, en op basis hiervan de inzichten in adaptatie te verbeteren. Klimaatomstandigheden veranderen niet alleen in de loop van de tijd, maar ze verschillen ook ruimtelijk. Daarom hebben we in hoofdstuk 2 **de invloed van het huidige management op de prestaties van landbouwbedrijven onder verschillende klimaatomstandigheden** geanalyseerd. De analyse laat zien dat de opbrengsten van de meeste gewassen en het inkomen per boer hoger zijn in regio's met een gematigd klimaat en betere socio-economische omstandigheden. Het kan worden beargumenteerd dat boeren en regio's die beter presteren ook goed aangepast zijn. Dit zou eerdere studies bevestigen die verklaren dat mediterrane regio's een lagere aanpassingscapaciteit hebben dan noordelijke Europese regio's. Echter, ruimtelijk gezien is het inkomen van boeren per hectare niet gerelateerd aan gewasopbrengsten per hectare, en is vooral hoog in veel mediterrane regio's met over het algemeen lage gewasopbrengsten. Dit suggereert dat de boeren in deze regio's gewassen verbouwen die meer geld opbrengen om het inkomen per hectare te verhogen (terwijl de kleine schaal van bedrijven ervoor zorgt dat het inkomen per boer relatief laag is). Ook worden gewassen die relatief hoge potentiële opbrengsten geven (zoals maïs) beter verzorgd – wat resulteert in relatief hoge werkelijke opbrengsten – ten opzichte van gewassen met lage potentiële opbrengsten (zoals tarwe). Optimaal management hangt dus af van wat er geoptimaliseerd moet worden: als een gewas (zoals tarwe) niet belangrijk is, zal het management zich ook niet concentreren op het verhogen van de opbrengsten van dit gewas, maar op andere gewassen met hogere potentiële opbrengsten. Adaptatie in management en kwetsbaarheid zullen dus **verschillen per ecosysteemdienst** (zoals opbrengsten van verschillende gewassen, het inkomen per boer of per hectare).

Karakteristieken van landbouwbedrijven die het management en daardoor de prestaties van landbouwbedrijven beïnvloeden zijn geanalyseerd op bedrijfsniveau. Het is duidelijk dat de prestaties van landbouwbedrijven verschillen per bedrijf en dat het grotendeels afhankelijk is van drie karakteristieken van het landbouwbedrijf: **de grootte, de intensiteit en het landgebruik**. Gewasopbrengsten en het inkomen van boeren nemen over het algemeen toe als de grootte van het bedrijf (d.w.z. bedrijfsomvang) en de intensiteit (d.w.z. het gebruik van kunstmest, gewasbescherming en irrigatie) toeneemt. Ook het landgebruik (d.w.z. het akkerbouwareaal, het gewasareaal) heeft een significant effect op de prestaties van landbouwbedrijven.

Het huidige management – gerelateerd aan regionale omstandigheden en bedrijfskarakteristieken – en de relatie tot de prestaties van landbouwbedrijven reflecteert management in en adaptatie aan de overheersende omstandigheden en beïnvloedt derhalve adaptatie aan klimaatverandering. Daarom zijn de bedrijfskarakteristieken die het huidige management bepalen – de grootte, intensiteit en landgebruik van een bedrijf – gebruikt om een **bedrijfstypologie** te ontwikkelen om trends en de temporele variabiliteit in de prestaties van landbouwbedrijven te evalueren.

In hoofdstuk 3 zijn trends en temporele variabiliteit vergeleken tussen regio's en bedrijfstypen om het effect van regionale omstandigheden (zoals klimaat) en bedrijfskarakteristieken op de prestaties van landbouwbedrijven te analyseren. De temporele analyse toont aan dat regio's (d.w.z. gematigd) en bedrijfstypen (d.w.z. groot, intensief, akkerbouw) die hoge gewasopbrengsten en inkomens per boer behalen, hier een lagere (relatieve) variabiliteit in hebben. Echter, dit is slechts gedeeltelijk afhankelijk van klimaatvariabiliteit en daar staat tegenover dat de variabiliteit in het inkomen per hectare lager is bij hogere temperaturen. Bovendien is de trend in het inkomen van boeren hoger in warmere regio's, terwijl de trend in gewasopbrengsten vooral gerelateerd is aan de trend in temperatuur (d.w.z. klimaatverandering) en niet aan de overheersende klimaatsomstandigheden. De resultaten suggereren dus dat er **effectieve adaptatie aan variabele klimaatomstandigheden heeft plaatsgevonden in mediterrane (d.w.z. warmere) regio's.**

Eén van de strategieën die adaptatie aan klimaatvariabiliteit op regionaal niveau lijkt te stimuleren is een grote diversiteit aan bedrijven; daarom is dit verder onderzocht in hoofdstuk 4. De analyse is uitgevoerd op basis van tarwe omdat dit het belangrijkste gewas is in Europa en het in bijna alle regio's verbouwd wordt. De resultaten tonen aan dat **de diversiteit in de grootte en intensiteit van bedrijven, die vooral hoog is in mediterrane regio's, de kwetsbaarheid van regionale tarwe opbrengsten voor klimaatvariabiliteit vermindert**. De veranderingen in opbrengsten ten opzichte van klimaatvariabiliteit verschillen per bedrijfstype en de effecten van de temperatuur op regionale opbrengsten is daardoor kleiner als de diversiteit in bedrijven groot is. De diversiteit in bedrijven is vooral groot in regio's die vaak worden blootgesteld aan hoge temperaturen en droogtes die hiermee gepaard gaan, en lijkt dus **gestimuleerd te worden door blootstelling aan risico's**.

Adaptatiestrategieën op bedrijfsniveau die effectief zijn geweest of zullen zijn, zullen ook per regio verschillen. In hoofdstuk 5 zijn adaptatiestrategieën in acht regio's geëvalueerd door gebruik te maken van de 'translog distance'-functie. De 'translog distance'-functie geeft de mogelijkheid om de interacties tussen meerdere inputs en outputs te onderzoeken, en maakt het dus mogelijk om de invloed van management op klimaateffecten te evalueren. Omdat klimaatverandering niet de enige verandering is die de Europese landbouw beïnvloedt, zijn ook de effecten van subsidies en andere veranderingen op inputs en outputs van Europese landbouwbedrijven meegenomen. De resultaten tonen duidelijk aan dat **klimaateffecten en adaptatiestrategieën verschillen per regio**, en dat werkelijke effecten niet – zoals vaak voorgesteld – expliciet kunnen worden onderscheiden in potentiële effecten en het aanpassingsvermogen. Boeren passen hun praktijken aan aan de **overheersende omstandigheden** en potentiële effecten zijn niet kwantificeerbaar, waardoor het vooral een theoretisch concept blijft. In Griekenland kan bijvoorbeeld het vergroten van het geïrrigeerde gebied worden beschouwd als een adaptatiestrategie omdat dit het positieve effect van hogere temperaturen op de totale outputs versterkt. In de meeste andere regio's is het effect van irrigatie klein, maar in Italië versterkt het uitbreiden van het geïrrigeerde gebied juist het negatieve effect van hogere temperaturen op de outputs. Dit verschil in de invloed van adaptatiestrategieën op klimaateffecten in gebieden met een vergelijkbaar klimaat, maakt duidelijk dat de overheersende omstandigheden – in zowel klimaat als op socio-economisch gebied en in beleid – een groot effect hebben op management en adaptatie. Dit wordt niet in ogenschouw genomen in gewasmodellen.

Voor meer betrouwbare voorspellingen van klimaateffecten op gewasopbrengsten, moeten het huidige management en adaptatie in management beter vertegenwoordigd worden in gewasmodellen. In hoofdstuk 6 hebben we onderzocht of **de invloed van management op gewasopbrengsten zoals gesimuleerd in gewasmodellen kan worden vertegenwoordigd door bedrijfskarakteristieken**. Verschillen tussen gesimuleerde en werkelijke maïs opbrengsten zijn geanalyseerd met behulp van lineaire regressiemodellen. Met behulp van de backward procedure zijn klimaat-factoren en bedrijfskarakteristieken geselecteerd die een significant effect hebben op dit verschil.

De analyse wat betreft de ruimtelijke variabiliteit geeft aan dat hogere temperaturen een positief effect hebben op werkelijke maïsopbrengsten, wat niet het geval is voor gesimuleerde potentiële maïs opbrengsten. In mediterrane regio's hebben hogere temperaturen ook een positiever effect op de temporele variabiliteit in werkelijke maïs opbrengsten dan op de potentiële maïsopbrengsten. Het tegenovergestelde is het geval voor gematigde regio's. Dit suggereert wederom dat boeren in mediterrane regio's zich hebben aangepast aan de hogere temperaturen, bijvoorbeeld door het verbouwen van meer hitteresistente rassen, een adaptatiestrategie die niet in ogenschouw wordt genomen in het gewasmodel. Bedrijfskarakteristieken die de verschillen tussen de werkelijke en de gesimuleerde gewasopbrengsten verklaren, zijn vergelijkbaar met de bedrijfskarakteristieken die de prestaties van landbouwbedrijven beïnvloeden volgens hoofdstuk 2: het maïsareaal als fractie van het akkerbouw areaal is gerelateerd aan landgebruik, het inkomen van boeren is gerelateerd aan de grootte van bedrijven en irrigatie is gerelateerd aan de intensiteit van een bedrijf. Deze factoren zijn vooral belangrijk bij het bepalen van de gemiddelde opbrengsten. Het verbeteren van simulaties voor de temporele variabiliteit in werkelijke opbrengsten vraagt om regiospecifieke modellen die de bedrijfskarakteristieken die belangrijk zijn in de regio's in ogenschouw nemen. Dit bleek ook uit hoofdstuk 5. Een interessant gegeven is echter dat, zoals ook in hoofdstuk 4 is aangetoond, in regio's die vaker blootgesteld worden aan hogere temperaturen en daarmee gepaard gaande droogtes, de diversiteit in opbrengsten en in de variabiliteit in opbrengsten tussen bedrijven hoger is dan in andere regio's. Dit heeft tot gevolg dat de relaties tussen werkelijke en gesimuleerde potentiële of watergelimiteerde opbrengsten – welke de potentiële effecten van klimaatvariabiliteit vertegenwoordigen – relatief klein zijn. Daardoor verschillen de werkelijke klimaateffecten sterk van de potentiële klimaateffecten.

Omdat klimaatverandering een directe invloed heeft op gewasopbrengsten, is het onderzoek voornamelijk gericht op het evalueren van gewasopbrengsten. De relatie met het inkomen van boeren kon direct geanalyseerd worden met de beschikbare data. Maar de landbouw in Europa wordt ook geconfronteerd met andere veranderingen. Een ecosysteemdienst die steeds belangrijker wordt is de agrarische biodiversiteit. Dit wordt geïllustreerd door het gemeenschappelijke landbouwbeleid van de Europese Unie, waarin de aandacht verlegd is van voedselproductie naar meer milieu-gerelateerde doelstellingen. Europese boeren zullen dus rekening moeten houden met de agrarische biodiversiteit als ze zich aanpassen aan veranderingen. Hoofdstuk 7 is onderdeel van dit proefschrift om (1) aan te tonen dat er **uitwisselingen zijn tussen verschillende ecosysteemdiensten** en (2) te presenteren **hoe een bedrijfstypologie gebruikt kan worden bij de beoordeling van effecten**.

Om de biodiversiteit in agrarische gebieden van de 25 landen in de Europese Unie in kaart te brengen voor de huidige situatie (d.w.z. 2000) en om toekomstige ontwikkelingen tot 2030 te verkennen, is een aangepaste bedrijfstypologie gebruikt. Aan ieder bedrijfstype is een ecosysteemkwaliteitswaarde toegekend op basis van dosiseffectrelaties tussen factoren die het systeem onder druk zetten (zoals het gebruik van kunstmest) en biodiversiteit. De referentiewaarde hierbij is de ongerepte situatie. De biodiversiteit in agrarische gebieden is vervolgens berekend door de gemiddelde ecosysteemkwaliteit te vermenigvuldigen met de relatieve grootte van het gebied per bedrijfstype in een regio.

Wat betreft de huidige situatie laten de resultaten zien dat de laagste ecosysteemkwaliteitswaarden te vinden zijn in intensieve landbouwgebieden in laaggelegen gebieden (zoals Nederland en Noord Frankrijk) en in geïrrigeerde gebieden (zoals Griekenland). Relatief hoge waarden zijn te vinden in Spanje en de nieuwe lidstaten. De resultaten voor scenario's tot 2030 duiden er op dat in het A1-scenario (Mondiale markt) in alle regio's het grootste verlies in ecosysteemkwaliteit zal plaatsvinden in zowel akkerbouwgebieden als graslanden. Het B2-scenario (Zorgzame regio) biedt de beste mogelijkheden om de ecosysteemkwaliteit in agrarische gebieden te verhogen. In de meeste scenario's neemt het landbouwareaal af, terwijl de overgebleven landbouwgebieden intensiever worden gebruikt. Het negatieve effect van het verder intensiveren op de biodiversiteit wordt gedeeltelijk gemitigeerd door (actieve of spontane) natuurontwikkeling op verlaten landbouwgebieden, maar de algemene trend lijkt over het algemeen negatief.

We kunnen dus concluderen dat het verder intensiveren van de landbouw geen goede strategie is als het behoud van agrarische biodiversiteit een belangrijke doelstelling is. Daarnaast is in de andere hoofdstukken aangetoond dat hoewel bedrijven of regio's met hogere intensiteit hogere gewasopbrengsten en inkomen en een lagere (relatieve) variabiliteit hierin behalen, de relatie met de klimaatvariabiliteit over het algemeen sterker zijn dan voor bedrijven of regio's waar gewasopbrengsten en het inkomen van boeren laag zijn. **Adaptatie aan klimaatverandering en klimaatvariabiliteit is dus verenigbaar met adaptaties om het verlies van biodiversiteit te stoppen**. Als landbouwbedrijven zich minder richten op het behalen van hoge gewasopbrengsten en inkomen, en meer op het verminderen van de effecten van risico's, zal de kwetsbaarheid voor klimaatverandering en klimaatvariabiliteit verminderen, en kan dit een gunstige invloed hebben op de biodiversiteit in agrarische gebieden.

Op basis van deze studie kunnen we concluderen dat **adaptatie grotendeels de effecten van klimaatverandering en klimaatvariabiliteit op de Europese landbouw kan verminderen**. De studie suggereert dat de werkelijke effecten van klimaatverandering en de hiermee gepaard gaande klimaatvariabiliteit **minder erg zijn voor mediterrane gebieden** dan voorspeld door eerdere studies. De effecten van klimaatvariabiliteit op gewasopbrengsten en het inkomen van boeren zijn over het algemeen sterker voor gematigde regio's. Boeren passen hun management aan aan de overheersende omstandigheden in het klimaat, de economie en het beleid. Dit huidige management heeft invloed op adaptatiestrategieën die gebruikt kunnen worden in de toekomst en dus op de klimaateffecten.

Omdat de werkelijke effecten van klimaatverandering en klimaatvariabiliteit op gewasopbrengsten in grote mate verschillen van de potentiële effecten, welke gebaseerd zijn op simulaties van potentiële en water gelimiteerde gewasopbrengsten, **hebben gewasmodellen verbeteringen nodig zodat ze werkelijke gewasopbrengsten kunnen simuleren**. De verschillen worden bepaald door management en adaptatie, welke afhankelijk zijn van regionale omstandigheden, bedrijfs- en gewas karakteristieken. Informatie over deze factoren kan verkregen worden via andere modellen (zoals economische modellen of landgebruiksmodellen), maar dit vergt adequate koppelingen.

Hoewel het mechanisch modelleren van alle processen die gewasopbrengsten beïnvloeden, en de hieraan gerelateerde prestaties van landbouwbedrijven, op dit moment niet mogelijk is; voor betrouwbare voorspellingen wat betreft de effecten van klimaatverandering op de landbouw zijn er modellen nodig die de werkelijke situatie beter uitbeelden. **Boeren passen zich continu aan**, en dit heeft zowel invloed op de huidige situatie als op de toekomstige effecten. Daarom zouden we adaptatie niet meer moeten zien als een laatste stap die eventueel genomen kan worden in een kwetsbaarheidanalyse, maar **als een geïntegreerd onderdeel van de modellen** die gebruikt worden om gewasopbrengsten en andere ecosysteemdiensten die door de landbouw geleverd worden te simuleren.

Curriculum Vitae

Pytrik Reidsma was born on the 12th of February 1980 in Koudum, the Netherlands, and from 1987 to 1997 she lived in the Frisian village Ysbrechtum. From 1991 to 1997 she followed secondary education, gymnasium, at the Bogerman in Sneek. After a year of traveling and working, she started in 1998 with the study Natural Sciences and Innovation Management at Utrecht University. After obtaining her propaedeuse (1st year degree) she continued her studies in Environmental Sciences at the same university. She finished this study in 2003 with a specialization in Environment and Land Use and an internship at Alterra (Wageningen University and Research Centre). In 2003 she started her PhD project at the Plant Production Systems Group (WUR) on agricultural adaptation to climate change in Europe. This project was in collaboration with the Netherlands Environmental Assessment Agency (MNP) in Bilthoven. After finishing this PhD thesis she continued her work as a post-doc at the Plant Production Systems Group in Wageningen, in the LUPIS project (Land Use Policies and Sustainable Development in Development Countries) and the SEAMLESS project (System for Environmental and Agricultural Modelling: Linking European Science and Society).

PE&RC PhD Education Certificate

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities).

Review of Literature (5.6 credits)
- Climate change, impacts and adaptation (2003)

Post-Graduate Courses (7 credits)
- Integrated assessment of vulnerable ecosystems under global change; AVEC (PIK-Potsdam) (2003)
- GIS application in land use resources and land use studies; PE&RC (2004)
- Modelling techniques and system engineering; PE&RC (2004)
- Simulation of complex systems: agent-based modelling and natural resource management; PE&RC (2006)

Deficiency, Refresh, Brush-up and General Courses (2.8 credits)
- Quantitative analysis of land use systems; PPS 30304 (2004)

Discussion Groups / Local Seminars and Other Scientific Meetings (7 credits)
- Statistics, maths and modelling in production ecology and resource conservation (2003-2007)
- The link between socio-economic and natural sciences (2004)

PE&RC Annual Meetings, Seminars and the PE&RC Weekend (1.5 credits)
- PE&RC introduction weekend (2003)
- PE&RC science day: global change and biodiversity (2003)
- PE&RC science day: biological disasters (2004)

International Symposia, Workshops and Conferences (7.2 credits)
- Annual ATEAM (Advanced Terrestrial Ecosystem Analysis and Modelling) meeting; EU-funded project, Evora, Portugal (2003)
- Annual ATEAM (Advanced Terrestrial Ecosystem Analysis and Modelling) meeting; EU-funded project, Annot, France (2004)
- Integrated assessment of the land use system: the future of land use; Amsterdam, The Netherlands (2004)
- Adaptation of crops and cropping systems to climate change; NJF seminar 380, Copenhagen, Denmark (2005)
- New visions for rural areas: changing European farming systems for a better

future; 7th European IFSA symposium, Wageningen, The Netherlands (2006)
- IX congress of the European society for agronomy; Warsaw Agricultural University (WAU), Poland (2006)
- 2nd LaSys workshop: Danish network for land system science; Copenhagen, Denmark; key note (2006)
- Global environmental change: regional challenges: an earth system partnership global environmental change open science conference; Beijing, China (2006)
- Farming systems design. An international symposium on methodologies for integrated analysis of farm production systems; Catania, Sicily (2007)

Courses in Which the PhD Candidate Has Worked as a Teacher
- Ecology I; Nature Conservation & Plant Ecology Group, WUR, 2.5 days
- Integrated assessment of vulnerable ecosystems under global change; AVEC, PIK-Potsdam, 13 days

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