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

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Abstract The aim of this paper 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 analyze 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 analyzing 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.

1 Introduction

Climate change is expected to affect agriculture very differently in different parts of the world (Parry et al. 2004). Many studies have analyzed the influence of climate and climate

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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 (a) moderate potential damages, (b) take advantage of emerging opportunities, and/or (c) 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 adapt 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 paper we analyzed 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 Methodology

2.1 Conceptual basis for analyzing 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 (Fig. 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 2.3). Farm characteristics may also change as a result of regional impacts on farm performance, which, however, is not further addressed in this paper. As different crops respond differently to

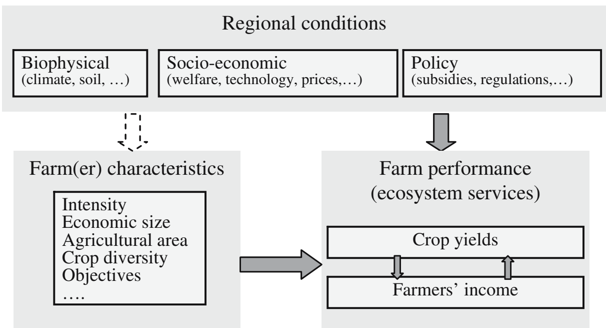

Fig. 1 The investigated relationships (represented by the *block arrows*). Potential impacts of climate conditions are influenced by other regional conditions and farm characteristics, which determine adaptive capacity

climatic conditions, yields of five important crops (wheat, grain maize, barley, potato and sugar beet), were analyzed.

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 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 Fig. 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% of all farms, i.e. 20,936 farms, crop production is the main activity, i.e. when more than 66% 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% 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. 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

[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.

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 characteristics of the land. More variables were available, but variables needed to be selected to reduce multi-collinearity (see Sections 2.3.2 and 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.

Climatic effects were analyzed using data from the ATEAM project[4] based on New et al. (2002). Averages from the 30-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 $10' \times 10'$. 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 6 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). In Table 1 a description is given of all variables used in the analysis.

[4] ATEAM (Advanced Terrestrial Ecosystem Analysis and Modelling), http://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.

Table 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	26,609	50,478
Fnv/ha	Farm net value added/hectare (€)	1	906	1,761
Farm characteristics				
Irr_perc*	Irrigated percentage of utilized agricultural area (%)	1	15	31
Fert/ha*	Costs of fertilizers and soil improvers per hectare (€)	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 monthly temperature (°C) of first half year	2	9.1	2.5
Pmean*	Mean monthly 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	14,145	5,181
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 €1,200.

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

[g] Lfa = Less-favoured area.

2.3 Statistical analysis

2.3.1 Multilevel modelling

The effect of climate and management on farm performance is analyzed 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 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 analyzing within region effects of farm characteristics on yields and income. In Fig. 2 this is depicted graphically.

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.

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

In Eq. 1, y_{ij} is the dependent variable, β_{0j} is the intercept estimate, β_{qj} is the coefficient estimate of the variable x_{qj}, 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 Eqs. 1 and 2.

$$\beta_{0j} = \beta_0 + \mu_j \tag{2}$$

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

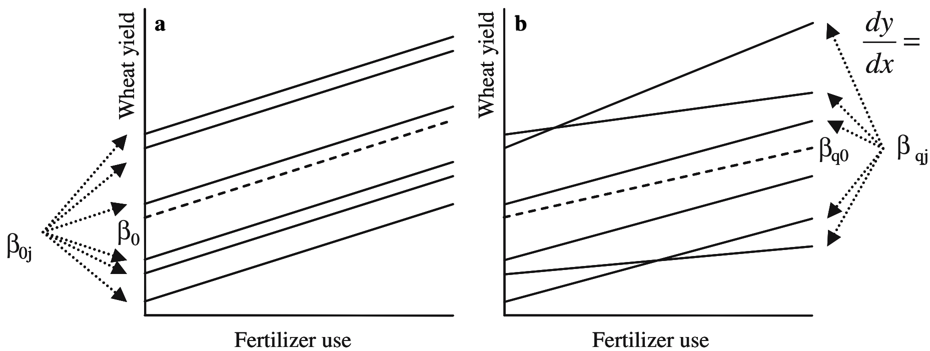

Fig. 2 Graphical example of a multilevel model with **a** random intercept β_{0j} and **b** random intercept β_{0j} and slopes β_{qj}. Each *solid line* represents the effect of fertilizer use on wheat yield in a specific region j, whilst the *dotted line* represents the mean (fixed) relationship across 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's the average of the relationships per region. See Section 2.3.1 for further explanation

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 Eqs. 1, 2 and 3.

$$\beta_{qj} = \beta_{q0} + u_{qj} \tag{3}$$

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 3).

2.3.2 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 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 analyzed, for income models only farms where crop production was dominating were considered (see Section 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[7]). 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

$$M = \left(\widetilde{\beta} - \widehat{\beta}\right)'\left(\widetilde{V} - \widehat{V}\right)\left(\widetilde{\beta} - \widehat{\beta}\right) \tag{4}$$

where $\widetilde{\beta}$ is the parameter vector resulting from the model based on IV estimates for the possible endogenous variables and $\widehat{\beta}$ is the parameter vector of the model with the observed values. $\widetilde{V}$ and $\widehat{V}$ are the variance-covariance matrices of $\widetilde{\beta}$ and $\widehat{\beta}$, respectively. This test has a χ^2 distribution with N degrees of freedom (N is the number of parameters). The null

[7] A full list of variables used in the instrumental variables regression can be obtained from the corresponding author.

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 analyzed 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.

3 Results

3.1 Spatial variability in yield and income variables

In Fig. 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) 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 northwest 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.

3.2 Selection of variables affecting crop yield and 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) 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 $r^2=0.467$, suggesting that *prot/ha* may be a good predictor of wheat yield and should be included in the multilevel model.

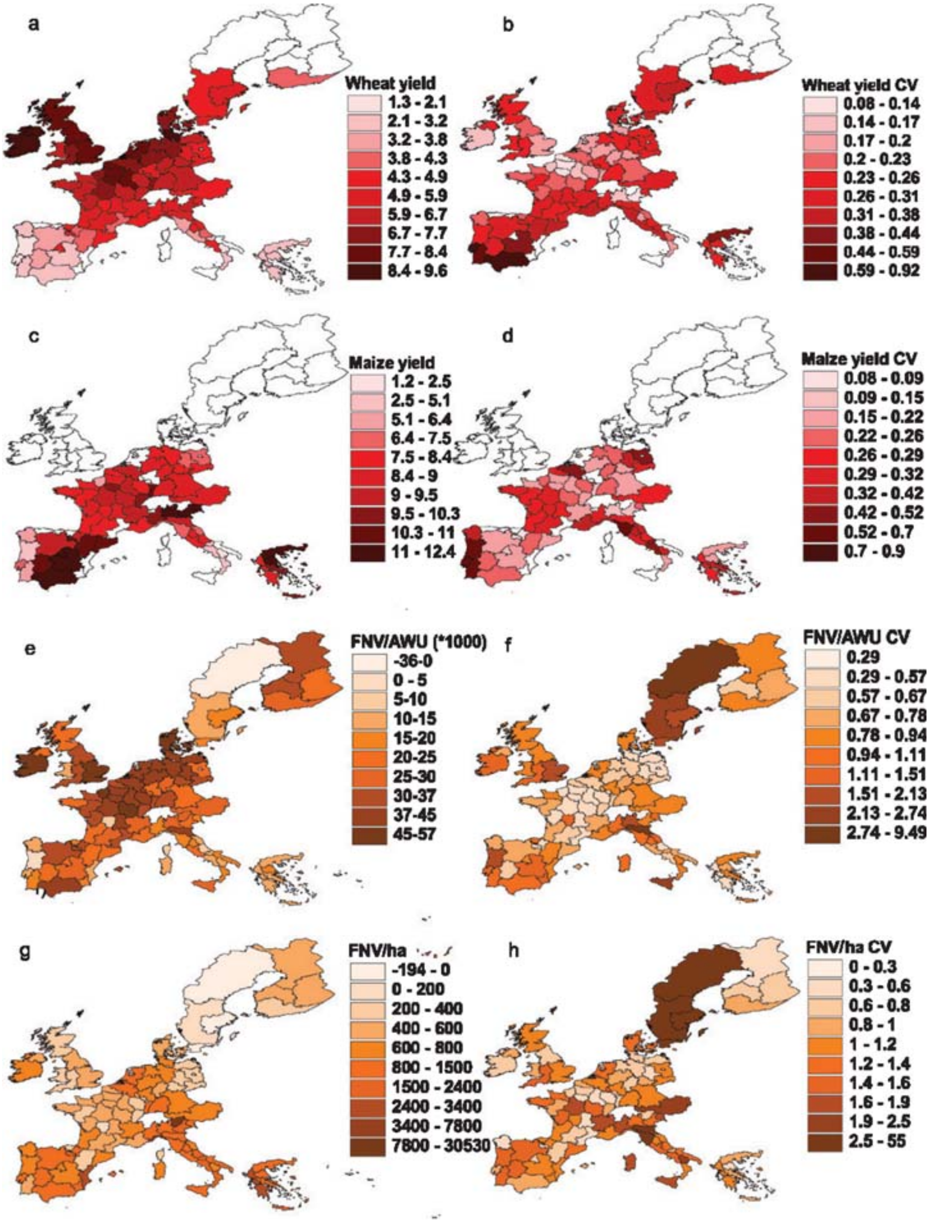

Fig. 3 Spatial variability of crop yields (tons/ha) and income variables (€) in 2000 between and within HARM regions for **a** average wheat yield, **b** CV of wheat yield, **c** average maize yield, **d** CV of maize yield, **e** average of farm net value added/annual work unit (*fnv/awu*), **f** CV 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

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

Table 2 Partial correlation matrix of selected variables in 2000 for farms with crop production as the main farming activity

	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**

Pearson's correlation coefficients (r^2) in bold are significant. Names of crops refer to actual yields. Other variables are described in Section 2.2 and Table 1.

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*.

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 61,744 for a model with fixed effects only, to 57,104 ($p<0.001$) when a random intercept was included, to 55,735 ($p<0.001$) 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 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*) suggests 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 $p<0.10$,

Table 3 Fixed effects of multilevel models of 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***	3,3728^{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†	2,285^{a}	0.96
Org=2	−1.52***	−1.42^{ab}	−4.96**	−15.07*	−1.02***	−5,482	622***
Org=3	−0.79**	−1.36	−3.75†	−4.49	−0.73***	−1,391	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***	−15,055***	713†
Grass/uaa	−0.59***	−0.25^{a}	−1.57^{ab}	−4.99*	−0.24**	−27,936***	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}	−2,425*	39.3
Alt=3	−0.30**	−0.55*	0.27^{a}	−0.09$^{ab(+)}$	−0.11^{a}	−1,786$^{a(+)}$	161*
Lfa=2	−0.32***	−0.38**	−1.95*	−3.08**	−0.22***	−2,298*	−0.72$^{ab(+)}$
Lfa=3	−0.47***	−0.77***	−3.82***	−2.41^{ab}	−0.22**	−2,150†	399***
Tmean	0.43***	−0.18†	1.45*	6.15*	0.37***	2,515†	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***	44,729**	−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 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.

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 a 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) 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.

3.4 The influence of climate and management on income variables

3.4.1 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*.

3.4.2 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). 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 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.

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 (Fig. 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

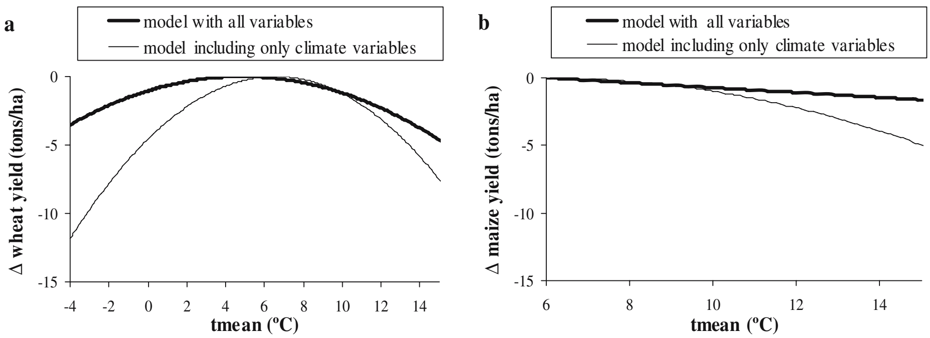

Fig. 4 The effect of *tmean* (°C) on **a** wheat yield (tons/ha) and **b** maize yield (tons/ha), based on the full multilevel model, including climate variables and farm characteristics (*thick line*) and a model only including climate variables. A value of *zero* represents no reduction in yield and 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 attributed to *tmean*. The difference between both lines indicates the amplifying effect of farm characteristics on the impact of *tmean* on crop yields

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.

For maize, the effects of climatic conditions were not significant (Table 3). Nevertheless, we can also draw the relationship between *tmean* (including the quadratic term) and maize yield. Fig. 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 13°C 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.

4 Discussion

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. (2004) 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.

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 Fig. 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 analyzed 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 Reidsma et al. (in review) for analysis of temporal variability. As mentioned in Section 3.5, maximizing crop yields is not the only objective of farmers and adaptation may be focussed 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.

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 impact on agriculture.

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