Universität Hohenheim

Fakultät Agrarwissenschaften
Institut für Landwirtschaftliche Betriebslehre (410a)
Fachgebiet Produktionstheorie und Ressourcenökonomik im Agrarbereich

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Spatial econometric methods in agricultural economics: selected case studies in German agriculture

Kumulative Dissertation

zur Erlangung des Doktorgrades der Agrarwissenschaften der
Fakultät Agrarwissenschaften der Universität Hohenheim

vorgelegt von

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Stuttgart-Hohenheim, 2013

Die vorliegende Arbeit wurde am 18.04.2013 von der Fakultät Agrarwissenschaften der Universität Hohenheim als „Dissertation zur Erlangung des Grades eines Doktors der Agrarwissenschaften“ angenommen.

Tag der mündlichen Prüfung: 10. Juli 2013

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Vorwort

Diese Arbeit wäre nicht ohne die Unterstützung von vielen interessanten und interessierten Personen entstanden.

Ganz herzlich danken möchte ich Prof. Dr. Stephan Dabbert für sein Vertrauen in meine Arbeit, für seine Motivation und Unterstützung sowie für die vielen wertvollen Diskussionen und Denkanstöße.

Mein Dank gilt auch allen Mitarbeitern des Instituts für Landwirtschaftliche Betriebslehre, für die freundliche Arbeitsatmosphäre und die konstruktive Zusammenarbeit. Durch zahlreiche Fachgespräche und Diskussionen entstanden vielen Ideen zur Bearbeitung des Themas. Zum Gelingen dieser Arbeit hat insbesondere Herr Prof. Dr. Christian Lippert beigetragen, der mir stets als kompetenter Ansprechpartner zur Verfügung stand. Herrn Prof. Dr. Tilman Becker danke ich für die Übernahme des Zweitgutachtens.

Ein ganz besonderer Dank gilt meiner Familie und meinen Freunden, die mich seit Jahren begleiten und immer mit Rat und Tat zur Seite stehen.

Eva Schmidtner

Stuttgart-Hohenheim, im Juli 2013

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List of abbreviations and variables used

AIC	Akaike Information Criterion
ASE	agricultural farm census (*German: Agrarstrukturerhebung*)
β	vector containing the regression coefficients for the explanatory variables
BIC	Bayesian Information Criterion
BLE	German Federal Agency for Agriculture and Food (*German: Bundesanstalt für Landwirtschaft und Ernährung*)
CAP	Common Agricultural Policy of the EU
cf.	compare (*Latin: confer*)
CG	Constant Grassland
cm	centimetre
co	conventional
c_t^{ft}	vector of input prices for farming type *ft* in time *t*
$dist_{ij}$	distance between *i* and *j*
DSMW	Digital Soil Map of the World
ε	vector of normally distributed errors
E	expectation operator
e.g.	for example (*Latin: exempli gratia*)
et al.	and others (*Latin: et alii*)
EU	European Union
Eurostat	statistical office of the EU
f.	and the following (pages)
F	production relevant factors
ft	type of farming (*ft* = *or*, *co*)
g	number of explanatory variables
ha	hectare
i	specific location
I	global Moran statistic
I_i	local Moran statistic
I_N	identity matrix
i.e.	that is (*Latin: id est*)
IPCC	Intergovernmental Panel on Climate Change
j	specific location $j \neq i$
k	number of nearest neighbours
K	Kelvin
km	kilometre

km^2	square kilometre
λ	coefficient reflecting the spatial autocorrelation of the residuals u_i
LISA	Local Indicators of Spatial Association
LM	Lagrange Multiplier test
m	meter
MAUP	Modifiable Areal Unit Problem
max	maximum
min	minimum
mm	millimetre
N	number of locations
NASA	U.S. National Aeronautics and Space Administration
NUTS	Nomenclature of Territorial Units for Statistics in the EU
OLS	Ordinary Least Square
or	organic
p	probability
π_t^{ft}	profit of farming type *ft* in time t
p_t^{ft}	vector of output prices for farming type *ft* in time t
pr_t^{ft}	public payments (premiums) for farming type *ft* in time t
q_t^{ft}	vector of produced quantities for farming type *ft* in time t
ρ	spatial lag coefficient reflecting the importance of spatial dependence
r	discount rate
R^2	coefficient of determination
σ^2	variance
SRTM	Shuttle Radar Topography Mission
StdDev	Standard Deviation
t	time
TC_t	(transaction) cost of converting from one type of farming to the other type in time t
tf	point in time in the future
u	vector of the spatially correlated residuals
UAA	Utilisable Agricultural Area
U.S.	United States (of America)
U_t	utility in time t
U_t^{ad}	additional utility or disutility associated with organic farming in time t
v_t^{ft}	vector of input quantities for farming type *ft* in time t
VG	Variable Grassland
W	standardised spatial weight matrix

$W^{(1)}$	first order contiguity neighbourhood matrix
$W^{(2)}$	second order contiguity neighbourhood matrix
$W^{(24nn)}$	neighbourhood matrix identifying the 24 nearest neighbours
$W^{(idw)}$	inverse distance-based neighbourhood matrix
$W^{(idw15)}$	inverse distance-based neighbourhood matrices accounting for neighbours within a radius of 15 km
$W^{(idw30)}$	inverse distance-based neighbourhood matrices accounting for neighbours within a radius of 30 km
w^{ft}	number of products for farming type *ft*
w_{ij}	weights of the spatial neighbourhood matrix
X	matrix containing in every row i the element 1 followed by a set of observations for the g explanatory variables
y	vector containing the observations for a dependent variable, each associated with a specific location i ($i = 1, \ldots, N$)
yl	logit-transformation of y
z	standardized deviation of the variable of interest with respect to the mean
z^{ft}	number of inputs for farming type *ft*
°C	degree Celsius
€	Euro
%	percent

1 Introduction

Johann Heinrich von Thünen (1783-1850), known as the founder of agricultural location theory, was the first economist who explicitly accounted for the importance of space in agricultural economics. Given the fixed location of farms, agricultural location theory analyses the optimal organisation of agricultural activities based on location factors. In Thünen's model of the 'isolated state', different agricultural activities are spatially distributed in a homogenous fertile region based on land rents (Thünen, 1910). Assuming that transportation costs are relevant, agricultural activities (such as crop production, animal husbandry and gardening) are arranged in concentric rings around a central consumers' town, depending on the respective yield, the relative price of agricultural products and the perishability of agricultural goods. Thus, the location of agricultural activities in this case is not set randomly but depends on the spatial location of consumers.

Following Thünen, location theory mainly concentrates on spatial heterogeneity (such as spatial differences in production factors like soil and climate) to explain the occurrence of agricultural activities (see, e.g., Weinschenck and Henrichsmeyer, 1966). In these days, the analysis of spatial dependence[1] was less important. One reason for this might be the limited availability of (spatial) methods and techniques for economic analyses. Currently, common statistical tools such as ordinary least square (OLS) estimation still do not account for the geographic location of attributes. In turn, the failure to use essential spatial information can bias estimation results. Recent advances in analysis techniques now allow spatial aspects to be considered and such biases to be corrected; agricultural economic analyses can now particularly account for spatial heterogeneity and spatial dependence.

There are few studies accounting for spatial effects in analysing economic research questions for Germany's agricultural sector (Bichler et al., 2005, Bichler, 2006, Lippert et al., 2009, Breustedt und Habermann, 2011, Schmidtner et al., 2012). In this dissertation, spatial effects are considered explicitly in selected case studies on the farming sector in Germany. The spatial distribution of German agriculture is analysed from an econometric perspective, and spatial econometric analysis tools are therefore used to account for spatial information.

The next sections will provide background information on spatial econometrics and highlight the prevailing challenges of spatial research approaches[2]. Then, the research objectives of this dissertation are presented and the organisation of the thesis is outlined.

1.1 Development of spatial econometrics

Spatial econometrics is a relatively young and growing field consisting of a subset of econometric methods that account for spatial aspects. The term 'spatial econometrics' was coined by the Belgian

[1] The term 'spatial dependence' is explained in section 1.2.

[2] In agricultural economic publications, it is common practice to generally introduce the research topic. This dissertation is a cumulative thesis, so the introduction to spatial econometrics recurs in part in the text of the thesis.

economist Jean Paelinck in the 1970s to refer to methodological aspects linked to the incorporation of dependence in cross-sectional multiregional econometric models. In the first book completely devoted to spatial econometrics, the following five fundamental characteristics of the subject are outlined (Paelinck and Klaassen, 1979):

(i) the role of spatial interdependence;
(ii) the asymmetry of spatial relations;
(iii) the importance of explanatory factors located in other spaces;
(iv) the differentiation between ex-post and ex-ante interaction and
(v) the explicit modelling of space.

Anselin (1988) further developed these ideas and put them more formally into econometric estimation and specification testing. The need for spatial econometric methods arises because of the specific characteristics of spatial data that limit standard techniques and invalidate corresponding methodological results. OLS regression is a frequently used standard analysis technique; however, an OLS model is not appropriate when basic assumptions are not fulfilled because the OLS estimator will be biased and inconsistent (LeSage, 1999; Backhaus et al., 2011). The presence of spatial autocorrelation, i.e., correlation of error terms, causes statistical problems because it violates the assumption of independence among observations. Spatial heterogeneity of the variables violates the assumption that error terms may show a constant variance (heteroscedasticity). Therefore, alternative methods are required to model spatial data.

The distinction between spatial statistics and spatial econometrics is vague because several methodological aspects are considered in each. To clarify the terminology, Anselin (1988) suggested that spatial econometrics focuses on economic models related to regional and urban economics and the theories behind them, whereas spatial statistics is characterised by data-driven approaches with their primary focus on physical phenomena in biology and geology. Compared to standard econometric methods, spatial econometrics focuses on the specific spatial aspects of data and methods. There is currently a growing interest in spatial econometric techniques that succeed in the presence of spatial autocorrelation. This interest is driven by growing attention within theoretical economics to spatial econometric models and to the increasing availability of spatial data. Thus, spatial econometric techniques are applied in a wide range of empirical investigations, also in agricultural and environmental economics (cf. Anselin, 2003a).

1.2 Spatial effects and agriculture

In this dissertation, two kinds of spatial effects are considered: spatial dependence and spatial heterogeneity (cf. Anselin, 1988). Spatial heterogeneity refers to explanatory variables that differ in space (such as climate or soil), whereas spatial dependence indicates a functional relationship of occurrences at different spatial locations. Spatial dependence results from agglomeration effects.

At first glance, agglomeration effects seem to contradict agricultural production, which is bound to land. The advantages associated with decreasing internal economies of scale and labour pooling (particularly for family farms) might be of little importance. However, assuming positive spillover effects in space between farms, agglomeration effects might be of importance in some agricultural peculiarities such as organic agriculture (Lippert, 2006). To convert a farm from conventional to organic farming is a long-term decision. In addition to purely economic considerations, a variety of factors might influence the decision process. It is assumed that personal communication with organic farmers - as a result of proximity - and a strong nearby institutional and market network can positively influence a farmer's decision to convert from conventional to organic agriculture. Thus, agglomeration in space might be caused by positive agglomeration effects (neighbourhood effects). For example, Osterburg and Zander (2004) found that the proportion of farms that have previously converted from conventional to organic farming in a region positively influences the propensity of additional farms converting. The spatial location of organic production might be influenced by the (spatially uneven) social acceptance of organic farmers. Thus, an uneven distribution of organic farms in space may be caused by spatial heterogeneity (diverse common location factors) and/or by spatial dependence, i.e., by the beneficial (self-enhancing) effects of higher shares of organic farms in all farms. To determine generally whether spatial autocorrelation exists, Moran test statistics can be used. The global Moran's *I* is the regression coefficient of the corresponding OLS regression (cf. Moran, 1948; Anselin, 1988). Equation (1.1) outlines the global version of the Moran's *I*:

$$I = \frac{z'Wz}{z'z} \tag{1.1}$$

where

z = $(y - \bar{y})/\sigma_y$ (with y = column vector of y_i; y_i = dependent variable, e.g., the proportion of organic farms in region i; $\bar{y} =$ arithmetic mean of the y_i; $i = 1, \ldots, N$, σ_y = standard deviation of y) and

W = row-standardised spatial neighbourhood matrix.

The resulting significant values of the global Moran's *I* test suggest spatial autocorrelation for the dependent variable. The average deviations of neighbouring spatial units (Wz) against the deviations of the respective spatial units (z) are presented in a corresponding Moran scatterplot.

By drawing on local indicators of spatial association (LISA) - the local Moran (I_i) - local patterns of spatial associations, such as hot spots of organic farming, may be identified. Using the symbols introduced above, the local version of the Moran test is given by the following equation (cf. Anselin, 1995):

$$I_i = z_i \sum_j w_{ij} z_j \tag{1.2}$$

where w_{ij} are the corresponding elements of the row-standardised contiguity matrix W, z_i and z_j the standardised deviations as defined in equation (1.1) and the summation over j is such that only observations from regions neighbouring the region *i* are included. The corresponding LISA map (cf. Anselin, 2003b) indicates clustering of similar high / low proportions of organic farming in neighbouring spatial units and shows spatial outliers.

1.3 Spatial econometric model

The following equations (1.3) and (1.4) provide the common version of the econometric model (see also Anselin, 1988; LeSage, 1999) that is used for the estimations in this thesis:

$$y = \rho Wy + X\beta + u \tag{1.3}$$

$$u = \lambda Wu + \varepsilon \tag{1.4}$$

with $\varepsilon \sim N(0, \sigma^2 I_N)$

where

y = the vector containing the observations for a dependent variable, each associated with a specific location *i* ($i = 1, \ldots, N$);

X = the design matrix containing in every row *i* the element 1 followed by a set of observations for the *g* explanatory variables;

W = the standardised spatial weight matrix;

I_N = the identity matrix;

u = the vector of spatially correlated residuals;

ε = the vector of normally distributed errors;

β = the vector containing the regression coefficients for the explanatory variables;

ρ = the spatial lag coefficient reflecting the importance of spatial dependence and

λ = the coefficient reflecting the spatial autocorrelation of the residuals u_i.

The parameters to be estimated are the regression coefficients β, the spatial lag coefficient ρ and the spatial error coefficient λ. A significant coefficient ρ suggests that agglomeration effects matter (resulting in spatial dependence). A significant coefficient λ indicates spatial autocorrelation of the residuals u_i, and, therefore, can reflect the potential omission of at least one further spatially correlated explanatory variable (spatial heterogeneity).

In general, there are four different models:

(i) the common OLS model, where $\rho = \lambda = 0$;

(ii) the spatial lag model, where $\rho \neq 0$, $\lambda = 0$;

(iii) the spatial error model, where $\rho = 0$, $\lambda \neq 0$ and

(iv) the spatial mixed model, where $\rho \neq 0$, $\lambda \neq 0$.

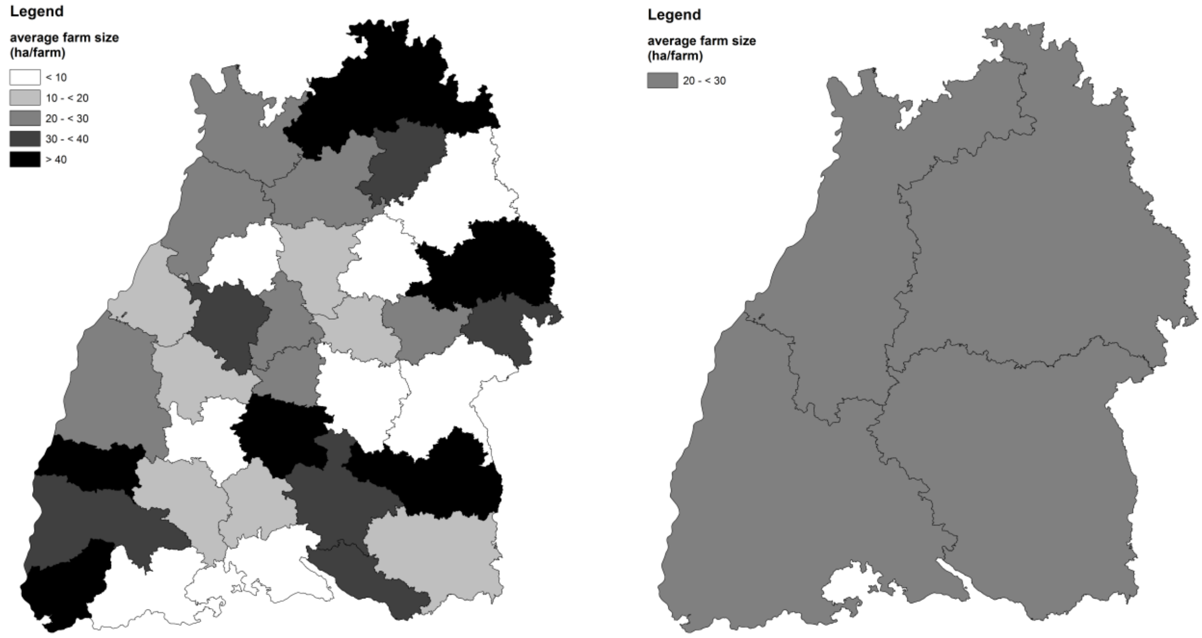
There are several possibilities to determine the appropriate model. First, the model selection can be based on theoretical considerations. If no spatial effects are present, a common OLS model is applied. As discussed above, agglomeration effects might be of importance in certain agricultural specialities, such as the organic farming sector. In this case, a ‘spatial lag model’ might be the appropriate alternative model to account for neighbourhood effects. Due to data restrictions, it is also likely that not all relevant spatially correlated explanatory variables are considered in spatial econometric analyses. The estimations are more efficient in case of a 'spatial error model' than in case of an OLS model. To account for both spatial effects (ρ and λ), a 'spatial mixed model' can be used. However, the effects of the two parameters may act together in a way that makes it rather difficult to interpret them clearly and individually in the mixed model. In addition to theoretical considerations, the model selection procedure can be supported by statistical tests. The (robust) Lagrange Multiplier test (Anselin et al., 1996) can be used to identify which of the two spatial effects (ρ and/or λ) is relevant to the analyses. The Lagrange Multiplier test examines OLS residuals for spatial autocorrelation and statistically determines whether the spatial lag model or the spatial error model is more appropriate to describe the data than a model without any spatial interaction effects. By using the robust versions of the test, the existence of one type of spatial dependence conditional on the other can be identified (cf. Elhorst, 2012). The Moran's *I* test for the residuals of the final model specifications can be used to test whether spatial autocorrelation is relevant.

Spatial econometric research approaches require particular estimation methods in addition to special models. The spatial models (equations 1.3 and 1.4) are estimated using the maximum likelihood method (cf. LeSage and Pace, 2009).

1.4 Challenges in spatial econometrics

Of course, specific estimation methods also entail particular challenges. There are two general challenges within spatial econometrics that will be addressed in this thesis. The first challenge deals with the determination of the appropriate spatial scale for a specific spatial research setting, and the second addresses the associated preferable definition of the spatial neighbourhood matrix. Based on theoretical considerations, both aspects have to be defined a priori, i.e., are taken as exogenously given. Thereby, the availability of data also plays a role.

Depending on data availability, analyses may be conducted at different spatial resolutions. It is often not obvious which of the available options best fits the research approach. However, the choice of the spatial resolution may have essential consequences for an analysis: as framed by the Modifiable Areal Unit Problem (MAUP), the results between analyses may differ or even reverse at different spatial resolutions (Simpson, 1951; Openshaw, 1984). To illustrate the issue of the varying degrees of data aggregation, Figure 1.1 presents a didactic example. Here, an average farm size per spatial unit is presented using two measurement scales. The data are generated by the author. At a high spatial resolution (Figure 1.1a), the average farm size differs considerably in space, whereas no difference in farm size can be observed at a lower spatial resolution (Figure 1.1b). As expected, the aggregation of data reduces the information content. Through the aggregation process, certain information is lost, such as the geographic location of aspects at a more detailed spatial level. This fact could lead to diverging results for spatial econometric analyses and generally questions the relevance of results based on aggregated data. In chapter 3 of this thesis, the determination of the spatial resolution and its consequences for an empirical study in Germany are presented and discussed in more detail.



a) high spatial resolution b) low spatial resolution

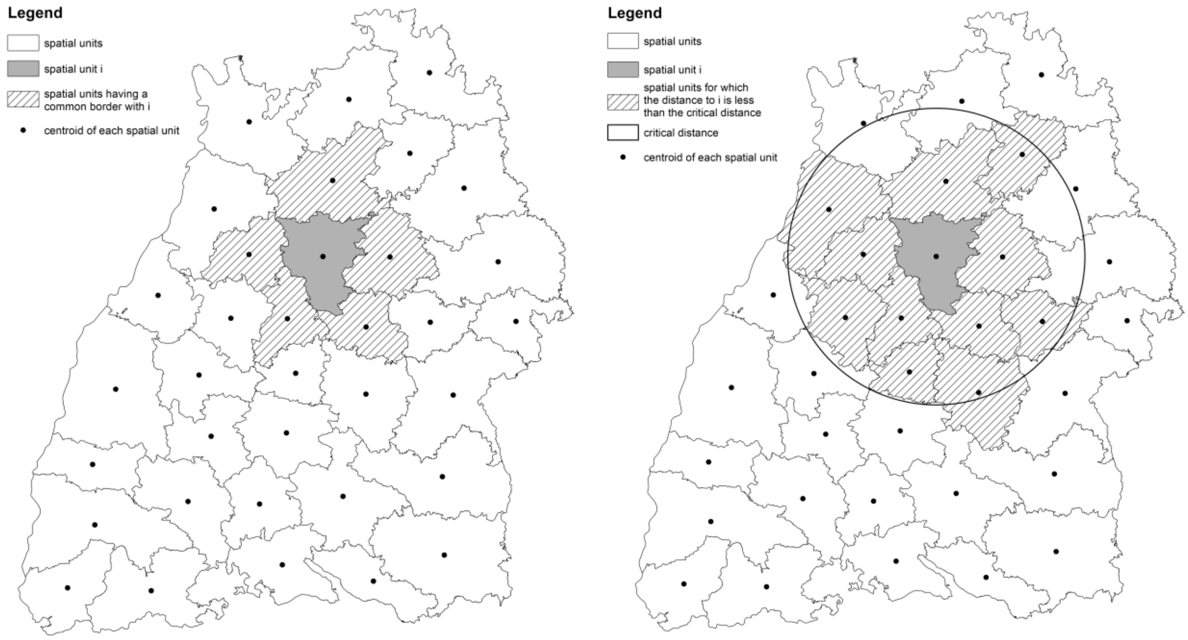
Figure 1.1 Average farm size at two measurement scales
Source: Authors’ own presentation based on data generated by the author and BKG (2010).

To capture spatial aspects and represent spatial relationships, a spatial neighbourhood matrix *W* is used. The neighbourhood matrix displays the proximity and relative position of geographic locations in space. In this thesis, alternative specifications of the spatial neighbourhood matrix *W* are considered to test the stability of estimation results. To determine spatial connectivity, two approaches based on geographical information are used (Anselin, 1988): contiguity-based (also called adjacency) and distance-based spatial neighbourhood matrices. There is often no clear-cut answer regarding the extent of spatial interaction, so the conceptualisation of the spatial relationships of locations in space through neighbourhood matrices remains somewhat arbitrary (Anselin, 2002).

Figure 1.2 shows a didactic example, illustrating the challenge of defining the spatial neighbourhood matrix. Let us consider a dairy processing company that operates in the ‘neighbourhood’. Without additional information, the operational range of the company is unclear. Based on theoretical considerations, the range of action may be approximated. The company might consider all adjoining spatial units *j* to the location of the company (in the spatial unit *i*) as neighbours to be served by the company (Figure 1.2a); location *i* would thus has five neighbours. However, the company may also collect milk from regions within a critical distance. Using a distance-based approach and accounting for all locations within a certain radius (Figure 1.2b), the spatial unit *i* has 11 neighbours[3]. Thus, different definitions of the spatial neighbourhood result in different spatial connectivity of the spatial

[3] The distances are calculated based on the centroid of each spatial unit.

units. If clear information on spatial interactions is unavailable, assumptions have to be made based on theoretical considerations. In the following, alternative spatial neighbourhood matrices are included to test the stability of empirical results with respect to German agriculture.



a) contiguity-based neighbourhood matrix

b) distance-based neighbourhood matrix

Figure 1.2 Connectivity of spatial units based on different definitions of the spatial neighbourhood structure

Source: Authors' own presentation based on BKG (2010).

1.5 Research objectives

The objective of this dissertation is to analyse selected research questions on German agriculture by means of spatial econometric analysis techniques. The thesis focuses on two issues from agricultural economics, the determinants of the spatial distribution of organic farming and the potential impact of climate change on the productivity and profitability of agricultural production while explicitly accounting for different classifications of soil characteristics. In addition to the agricultural research questions, methodological challenges are also assessed.

The specific objectives are to:

- link theoretical considerations to spatial data and current spatial econometric methods, i.e., to
    - select, gather and process appropriate data to conduct spatial analyses;
    - identify current spatial econometric analysis techniques;
    - establish the technical framework to conduct spatial studies;
- conduct an empirical analysis at different measurement scales to assess the effect of data aggregation on the results of estimations;

- assess the effects of alternative specifications of the spatial neighbourhood matrix on the stability of results obtained from selected spatial economic analyses;
- develop a theoretical framework for the conversion from conventional to organic farming;
- analyse the determinants of the spatial distribution of organic farming, with particular emphasis on agglomeration effects and
- analyse the influence of different classifications of soil quality on the results of a Ricardian analysis in Germany.

1.6 Organisation of the thesis

The thesis is written as a cumulative dissertation and is composed of three articles. One of these articles has been published by a peer-reviewed journal; two manuscripts are currently in the review processes of peer-reviewed journals. Chapters 2-4 represent one publication each.

The first article, '*Spatial distribution of organic farming in Germany: does neighbourhood matter?'* (chapter 2), addresses the factors that potentially influence the decision to convert from conventional to organic farming from a theoretical point of view and then implements this theoretical framework into a spatial model for Germany. The paper is published in European Review of Agricultural Economics 39(4) (2012) and may contribute to a better understanding of the factors determining the spatial distribution of German agriculture.

Whether the existence of agglomeration effects in the German organic farming sector can be confirmed at different spatial resolutions is analysed in the second article entitled '*Does spatial dependence depend on spatial resolution? An empirical analysis of organic farming in southern Germany'* (chapter 3). The paper analyses the potential influence of data aggregation on the results of spatial models (as applied to organic farming in Germany) and thus controls for the relevance of the previous study.

The third article, '*Do different classifications of soil quality influence the results of a Ricardian analysis? - A case study for Germany'* (chapter 4), is the result of the DFG-funded research project 'Micro-econometric analysis of climate change effects on the German agriculture: Ricardian analysis and extensions'[4]. This study analyses the effects of different indicators of soil characteristics on the results of spatial models used to explain land rental prices. The results may contribute to a better understanding of the factors determining land rental prices and may help to assess the future climate dependent profitability of agricultural land in Germany.

Following the three articles, the findings of the thesis are discussed and conclusions are drawn in chapter 5. Finally, the thesis is summarised in chapters 6 (English summary) and 7 (German summary).

[4] For further information, please refer to http://uhoh.de/ricardian-analysis

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2 Spatial distribution of organic farming in Germany: does neighbourhood matter?

Authors: Eva Schmidtner, Christian Lippert, Barbara Engler, Anna Maria Häring, Joachim Aurbacher and Stephan Dabbert

This article is published in: European Review of Agricultural Economics 39(4): 661-683; September 2012.

Abstract

The spatial distribution of organic farming can be explained by combining the traditional location factors that account for spatial heterogeneity with the concept of spatial dependence. We present a theoretical model that explains a farmer's decision to convert to organic farming, and this conceptual framework is then implemented in a spatial lag model by using secondary data for Germany at the county level. The results support the assertion that agglomeration effects are important in the organic farming sector. Potential policy implications include a concentration of development measures for organic farming in certain regions.

Keywords: conversion to organic farming, spatial distribution, agglomeration effects, spatial econometrics

JEL classification: C21, O13, R12

Acknowledgements

The authors thank the journal editor, Christoph Weiss, and the anonymous reviewers for valuable comments and suggestions.

2.1 Introduction

The new economic geography (Krugman, 1996; Fujita et al., 1999) is largely concerned with explaining the agglomeration of non-agricultural industries. Its focus is on increasing returns to scale that can be attributed to the advantages associated with labour pooling, decreasing costs of intermediate inputs, technology spillovers and the general advantages resulting from huge local markets (‘backward and forward linkages’). Thus, concentrations of economic activities ‘form and survive because of some form of agglomeration economies, in which spatial concentration itself creates the favourable economic environment that supports further or continued concentration’ (Fujita et al., 1999: 4). Agriculture plays a secondary role in this body of thought.

At first, the term ‘agglomeration’ seems to imply a contradiction with reference to agriculture, which is bound to land as the basis of production. Regarding the whole agricultural sector, this may be true due to natural limitations of production, the low importance of internal economies of scale and a high share of family labour. However, it is assumed that agglomeration effects due to direct communication or - probably more often - resulting from local institutions or markets do indeed play a role for some agricultural specialities, such as organic farming (Lippert, 2006).

We believe that joining the ideas of the new economic geography with traditional concepts used to explain spatial distribution offers an interesting approach to studying the spatial distribution of agricultural production. We hypothesise that in addition to the common factors that determine the location of agricultural production, such as soil and climate, agglomeration effects also exist. The potential causes of agglomeration effects in the agricultural sector might differ from those established by Krugman (1996) for non-agricultural industries. Taking these effects into account might offer a better understanding of the location of certain types of agriculture.

Within the agricultural sector, agglomeration effects clearly have limits; they differ by type of production and may also change over time. For example, based on 1992 data from 71 countries, Antweiler and Trefler (2002: 105) estimated constant returns to scale for agricultural crops, whereas the livestock sector showed an elasticity of scale greater than one. Analysing county-level data from 15 U.S. states, Roe et al. (2002) investigated hog production, an example where considerable concentration is possible, with key limits to further concentration probably coming from environmental concerns, and found significant spatial lag coefficients. Similarly, Isik (2004) estimated a significant spatial lag coefficient for the 1997 U.S. dairy inventories. These results indicate the relevance of agglomeration economies in the corresponding pig and dairy sectors.

In contrast to other agricultural sectors, organic farming is a system that limits specialisation within the farm. Farms with animal husbandry produce most of their forage on the farm, and in general, the aim is to reduce external inputs. Both the intensity of production at the farm level and increasing returns to scale might be more restricted in organic farming than in conventional farming. Agglomeration effects, however, relate to scale economies external to the farm and result from the described linkages, e.g., from local institutions.

Organic farming presents an interesting case because it has only recently developed dynamically in the EU, driven both by market and policy. From 1997 to 2007, organic land area in Europe has more than tripled (Willer and Kilcher, 2009). Despite the dynamic development, however, the organic sector in the EU remains quite small. Organic farming accounts for approximately 4% of all farms in the EU-27 (Willer and Kilcher, 2009) and is distributed quite unevenly throughout Europe and within Germany, the country that is central to this article (Figure 2.1). The uneven spatial distribution in Germany might also reflect the historical development of organic farming. Southern Germany has always been a centre of the organic movement with many institutions, e.g., organic farmers' associations and control bodies, still located there. In Eastern Germany, organic farming mainly developed after the German reunification, driven by subsidies.

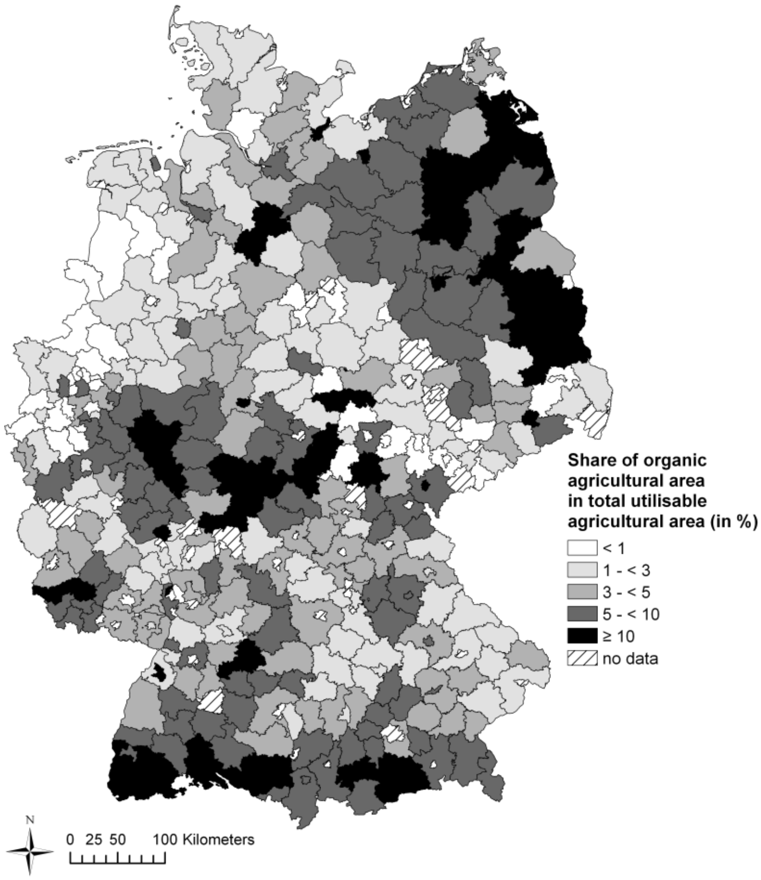

Figure 2.1 Spatial distribution of organic farming in Germany (429 counties) (2007)
Source: Authors' own presentation based on SAeBL (2010).

The key hypothesis underlying this paper is that the spatial distribution of organic farming may be explained by traditional location factors *and* the concept of spatial dependence. The aim of this study is thus to determine whether there is a significant and measurable influence of location factors and agglomeration effects on the spatial distribution of organic farming.

This article extends previous research published in Bichler et al. (2005) and Bichler (2006). Here, we put the empirical estimation in a wider theoretical and conceptual context: we link the approach to economic geography and provide a microeconomic foundation for the spatial econometric model.

Improved data availability has allowed us to add further and more recent variables to the spatial models, thereby integrating additional aspects into the analysis.

Parker and Munroe (2007) also used spatial econometric methods to investigate the spatial distribution of organic farming in a Californian county. The basis of their empirical work is the notion that negative edge-effect externalities, e.g., the negative influences of the pesticides applied on conventional fields adjoining an organic field, exist at a low spatial scale. They estimated a significant spatial lag coefficient at the plot level and showed that the ‘surrounding land uses influence the probability of a given parcel being certified organic’ (Parker and Munroe, 2007: 821). Thus, the notion that external economies of scale can lead statistically to spatial dependence is central to their work.

In contrast to Parker and Munroe (2007), our conceptual background with respect to spatial effects is based on positive network externalities between entire organic farms that are close to each other. The variables in our empirical model were selected based on a theoretical model of the factors influencing the decision to convert to organic farming. Our paper also differs from Parker and Munroe (2007) with respect to the spatial scale used: while they base their analysis on the data of a single county in California with plots as the smallest units, our approach investigates a whole country (Germany) with counties as the smallest units.

Kuminoff and Wossink (2010) have used real options theory to show that sunk costs associated with the conversion to organic farming and uncertainty regarding the future of policy programmes might delay a farmer’s decision to convert and thus decrease the rate of transition to organic agriculture. Using U.S. data at the county level, they illustrated the relevance of this idea empirically. In contrast to Kuminoff and Wossink (2010), we frame our theoretical model to include explicitly a variety of factors that may influence the conversion to organic agriculture. In our empirical model, we additionally account for spatial aspects resulting from possible agglomeration effects.

In the remainder of this article, we first develop a theoretical model linking the decision to convert to organic farming to factors of different spatial characteristics. We then present our econometric model and its specifications. Next, we explain the data used and the construction of our variables. Results are then presented and discussed, and finally, we draw conclusions.

2.2 Why do farmers convert to organic farming?

The decisions to convert from conventional to organic farming can be influenced by a range of factors. There exists a variety of approaches to explain and predict farmers’ decisions to convert (Midmore et al., 2001; Pietola and Oude Lansink, 2001; Padel, 2001; Acs et al., 2007; Kerselaers et al., 2007). For this analysis, it is assumed that all organic farms had already existed as conventional farms before making the transition to organic. The possibility that non-farmers buy farmland to start a career as an organic farmer is neglected because in Germany, non-farmers intending to buy farmland face serious market entry barriers (e.g., by the German law ‘Grundstücksverkehrsgesetz’).

In the context of economic theory, the problem of whether to convert to organic farming can be seen as an investment problem (Dabbert and Madden, 1986; Odening et al., 2004; Mußhoff and Hirschauer, 2008).

In this study, the factors influencing the decision to convert to organic farming are related to two kinds of spatial effects: spatial heterogeneity and spatial dependence (Anselin, 1988). Spatial heterogeneity can most simply be understood as variables (or functional relationships between variables) that differ in space, whereas spatial dependency is best explained as a 'functional relationship of what happens at one point in space and what happens elsewhere' (Anselin, 1988: 11). Based on this conceptual approach we derive hypotheses and proxy variables.

The 'investment problem' underlying the decision to convert or not can be framed as follows: a farmer converts (or continues farming organically) as long as

$$\int_0^\infty E\left[U_t\left(\pi_t^{or} - TC_t\right) + U_t^{ad}\right] e^{-rt} dt \quad - \quad \int_0^\infty E\left[U_t\left(\pi_t^{co}\right)\right] e^{-rt} dt \quad > \quad 0 \tag{2.1}$$

$$\textit{with} \qquad \pi_t^{ft} \; = \; p_t^{ft} \cdot q_t^{ft}\left(v_t^{ft}, F\right) \; - \; c_t^{ft} \cdot v_t^{ft} \; + \; pr_t^{ft}$$

where

t = time;

TC_t = (transaction) cost of converting from one type of farming to the other type (such costs occur at present and in the near future until a point in time $t = tf$);

U_t = utility in time t;

E = expectation operator;

U_t^{ad} = additional utility or disutility associated with organic farming;

ft = type of farming ($ft = or$, co);

or = organic;

co = conventional;

π_t^{ft} = profit of farming type ft in time t;

p_t^{ft} = 1 x w^{ft} vector of output prices (w^{ft} = the number of products for farming type ft);

q_t^{ft} = w^{ft} x 1 vector of produced quantities (q_t^{ft} is a production function of v_t^{ft} and F);

c_t^{ft} = 1 x z^{ft} vector of input prices (z^{ft} = the number of inputs for farming type ft);

v_t^{ft} = z^{ft} x 1 vector of input quantities;

pr_t^{ft} = public payments (premiums) for farming type ft (reflecting the policy environment in which the farmer operates);

F = production relevant factors;

r = discount rate.

The variables p_t^{or}, c_t^{or}, F, U_t^{ad} and TC_t are assumed to be affected by agglomeration effects. Thus, they are assumed to be spatially dependent. TC_t may also capture possible costs due to a loss of flexibility. Odening et al. (2004) have used real options theory to show that under certain assumptions (uncertainty, irreversibility and the possibility of delaying the investment) this implies some disutility attributed to the organic option and takes into account the fact that a decision to convert to organic farming entails a loss in flexibility. A number of reasons for this loss in flexibility may exist (e.g., long-term commitments to stay organic made to receive agri-environmental support or investments in machinery and buildings and knowledge specific to the organic system). The degree of uncertainty to be faced might also influence a farmer's decision to convert (depending on the shape of the farmer's utility function).

Output prices can be spatially heterogeneous - depending, for example, on the location of the farm with respect to a central market, assuming that transportation costs are relevant (von Thünen, 1826). In the case of organic farming, there is some evidence that output prices (p_t^{or}) might also be spatially dependent. Frederiksen and Langer (2004) found, e.g., spatial concentration of organic farming in regions with a high share of milk producers. In the case of milk, a high density of organic farms might lead to a lower cost for the dairy enterprise collecting the milk, thus creating a higher price premium for the farmers. It is assumed that input prices (c_t^{or}) have minor effects on the conversion to organic farming and are more difficult to measure than output prices. Given the limited data availability, input prices will not be further considered in this article.

Differing natural conditions induce different input-output relations: crop production and animal husbandry are thus seen as spatially heterogeneous. However, under certain circumstances some of the production relevant variables (F) can also be spatially dependent, e.g., when an agglomeration of a certain farming system leads to a larger pool of experience that entrepreneurs can draw upon or when the qualification of extension services or their availability increases, both cases that could be relevant for organic farming. Additionally, the amount of surrounding land allocated to farming activities that negatively affect organic farming will influence the output q_t^i and, hence, may lead to spatial dependency (cf. Parker and Munroe, 2007).

The term 'additional utility associated with organic farming' (U_t^{ad}) covers aspects beyond profit that contribute to the utility or disutility of converting to organic farming. These will largely be rooted in the attitudes of farmers with respect to the advantages and disadvantages of the two systems. Such attitudes might be spatially heterogeneous, e.g., for cultural reasons. Other non-monetary benefits, such as acceptance in a social environment, might also influence the decision-making process of converting to organic farming (Mußhoff and Hirschauer, 2008) and might be spatially dependent in part: for example, social acceptability of organic farmers might be higher if many farmers in the vicinity are already organic. An application of network analysis to an Italian case study provides some evidence that local institutions in the organic sector play a role in the diffusion of juridical and technical knowledge (Morone et al., 2006).

For reasons similar to those cited in the case of production relevant factors, the transaction costs of conversion (TC_t) can also be spatially dependent. It is difficult to know whether a disutility associated with the loss of flexibility attributed to the organic option is spatially dependent or heterogeneous because of the difficulty of measuring that concept. It could be argued that the magnitude of such a disutility is correlated with the farming system in question and thus, spatially heterogeneous.

The policy environment is spatially heterogeneous in Europe. In the EU, specifically, there exists a variety of spatially determined restrictions to management in different types of protection zones, and regional development programmes (which also differ between regions) under the Common Agricultural Policy (CAP) offer varying support options. Thus, the policy environment differs on several spatial scales: between European countries, the German federal states and the lower administrative units that, however, do not have to influence agricultural activities directly. However, there are no arguments supporting the spatial dependency of agricultural policy development.

Discount rates are assumed to be spatially homogenous across large areas and our empirical example is concerned with one country, a case where this assumption is reasonable. This variable, then, is assumed to be neither spatially heterogeneous nor spatially dependent.

In conclusion, most variables that potentially determine the conversion from conventional to organic farming are supposed to be spatially heterogeneous, while some may be spatially dependent. For an estimation of an empirical model, this implies that the effect of spatially dependent influences might be captured through one variable representing neighbourhood effects. The variable *neighbourhood (organic agglomeration)* serves as proxy variable for the spatially dependent effect. For the spatially heterogeneous variables, proxy variables were developed from the literature quoted above along with hypotheses on the direction of the effects. They are shown in Table 2.4 (Annex) and will be further explained in section 2.4.

Ideally, an empirical model would account both for spatial dependency and the dynamic nature of the conversion process and thus include spatial and temporal lags. As we only had access to a dataset for one time period (2007) we could not apply a dynamic model but base our empirical model on a cross-sectional approach. The smallest spatial level of agricultural data available for the whole of Germany is at the county level. Thus, rather than modelling individual organic farms and their associated farm neighbours, the empirical model was based on aggregated information. As frequently stated in regional land use modelling (Winter, 2005), we assume that essential aspects, e.g., of the decision to convert to organic farming, are sustained at the aggregated level. The empirical model thus estimates the share of organically farmed land at a given point in time at the county level based on the assumption that in case inequality (2.1) is positive for more farmers (who are heterogeneous regarding their production functions and other profit determining factors), the share of organic agricultural area will increase.

2.3 Econometric model

The following equations (2.2) and (2.3) as well as equation (2.4), which is derived from (2.2) and (2.3), outline the general version of the econometric model (cf. Anselin, 1988: 34ff.; LeSage, 1999: 52ff.) we will use for our estimations:

$$y \;=\; \rho W_L y \;+\; X\beta \;+\; u \tag{2.2}$$

$$u \;=\; \lambda W_E u \;+\; \varepsilon \tag{2.3}$$

with $\varepsilon \sim N(0, \sigma^2 I_N)$

where

y = $N \times 1$ vector containing the observations for a dependent variable, each associated with a specific location i ($i = 1, \ldots, N$);

X = $N \times (g+1)$ design matrix containing in every row i the element 1 followed by a set of observations for the g explanatory variables;

W_L = known $N \times N$ spatial weight matrix;

W_E = another known $N \times N$ spatial weight matrix (W_E may be different from W_L);

I_N = $N \times N$ identity matrix;

u = $N \times 1$ vector of the spatially correlated residuals;

ε = $N \times 1$ vector of normally distributed errors (mean = 0, variance = σ^2);

β = $(g+1) \times 1$ vector containing the regression coefficients for the explanatory variables;

ρ = spatial lag coefficient reflecting the importance of spatial dependence ($0 < |\rho| < 1$);

λ = coefficient reflecting the spatial autocorrelation of the residuals u_i.

In this study, we did not differentiate between the spatial weight matrices W_L and W_E. For the common spatial neighbourhood matrix W, three standardised alternatives are considered: a first order ($W^{(1)}$), second order ($W^{(2)}$) and inverse distance weighted ($W^{(idw)}$) neighbourhood matrix (cf. Anselin, 1988; LeSage, 1999). For $W^{(2)}$, the first and second order neighbours of district i are considered and equally weighted; $W^{(idw)}$ contains the row-standardized inverse distances of each centroid of district $j \neq i$ to the centroid of district i, measured in meters.

Solving equation (2.3) for the vector of the spatially correlated residuals (u) and entering the resulting term into equation (2.2) gives:

$$y \;=\; \rho W y \;+\; X\beta \;+\; \left(I_N - \lambda W\right)^{-1} \varepsilon \tag{2.4}$$

A significant coefficient λ reflects spatial error dependence (cf. Patton and McErlean, 2003: 37), or so-called spatial heterogeneity (i.e., some spatially correlated explanatory variables are omitted), whereas a significant coefficient ρ indicates spatial dependency resulting from agglomeration effects (i.e., one or more explanatory variables correlated with the average of the explained variable in the neighbourhood Wy are omitted).

When neglecting spatial dependency (i.e., $\rho \approx 0$) or assuming that all relevant spatially correlated exogenous variables are taken into account (i.e., $\lambda \approx 0$), equation (2.4) is reduced to

$$y \;=\; X\beta \;+\; \left(I_N - \lambda W\right)^{-1} \varepsilon \;\text{ or} \tag{2.4a}$$

$$y \;=\; \rho W y + X\beta + \varepsilon\,. \tag{2.4b}$$

The general model (2.4) is called the spatial mixed model, while the nested alternatives are referred to as spatial error model (2.4a) and spatial lag model (2.4b). If all relevant explanatory variables are contained in X, both coefficients will be zero and equation (2.4) collapses to the common regression model $y = X\beta + \varepsilon$.

2.4 Data and variable construction

Valid and reliable data for organic farming in Germany is generally not available at the farm-level. Considering the different datasets that are available, the data provided by the official farm census for the year 2007 (SAeBL, 2010) was determined to be the most recent and useful.

The dataset is based on NUTS 3 level (county-level) (NUTS being the Nomenclature of Territorial Units for Statistics, established by Eurostat); mean values for this spatial unit are given. Thus, diversity within spatial units is lost as information, a problem that is exacerbated by the fact that the size of the spatial units differs considerably between units (see Table 2.1). One has to be aware that the data used contains less variation than would a dataset with higher spatial resolution. Our analysis is based on aggregated data at the level of administrative units, and the statistical model does not operate at the same spatial scale as the decision-making and production processes under investigation. However, if inequality (2.1) is positive for more farmers, the share of organic agricultural area will increase.

Table 2.1 Descriptive statistics for variables of interest

Variable	Year	N	Mean	Std Dev	Median	Min.	Max.
Share of organic agricultural area in total UAA (in %)	2007	317	5.28	4.14	4.16	0.16	30.59
Number of organic food stores per 100 ha total land area	2009	317	0.01	0.02	0.01	0.00	0.17
Distance to agglomeration centres (in minutes by car)	2007	317	104.28	26.27	103.40	50.20	194.90
Available household income (in 1000€/ha total land area)	2007	317	4.22	5.91	2.36	0.45	48.20
Soil climate index	2002	317	44.64	10.71	42.60	26.79	78.85
Number of livestock units per ha UAA	2007	317	0.75	0.46	0.64	0.05	3.29
Share of grassland in total UAA 2007 (in %)	2007	317	32.42	21.06	27.19	1.15	99.17
Share of grassland in total UAA 1999 (in %)	1999	317	33.40	21.05	28.72	0.70	99.86
Total annual precipitation (in mm)	1961-1990	317	797.74	200.19	764.65	474.54	1738.40
Share of agricultural area utilised in fulltime farming (in %)	2007	317	74.87	9.23	75.71	48.63	92.24
Share of votes for the green party in all valid votes cast (in %)	2005	317	6.73	2.77	6.32	2.27	19.28
Payment level grassland (in €/ha UAA and year)	1996-2007	317	163.92	37.88	152.00	114.00	226.00
Share of nature conservation areas in total land area (in %)	2007	317	3.14	3.38	2.18	0.02	34.84
Share of water protection areas in total land area (in %)	1999-2010	317	13.91	12.45	9.91	0.00	94.41
Average county size (integrated counties) (in 100 ha)	2007	317	1126.46	517.00	995.41	121.31	3058.21
Average county size (original counties) (in 100 ha)	2007	429	832.37	613.64	776.62	35.71	3058.21

UAA = Utilisable agricultural area

Source: Authors' own calculations based on different sources given in the text.

In Germany, NUTS 3 level data contains 429 counties in the year 2007. Some of the regions are very small, covering only the area of a city. While 27% of all counties are such 'city counties', they only cover 4% of Germany's total land area. In many counties, the regional metropolis is part of the county, whereas in the case of 'city counties', the main city and the surrounding district are artificially separated. However, the main city still belongs to its region. To achieve more spatially uniform units, the number of regions was reduced from 429 (original counties) to 317 (integrated counties). The very small regions were integrated into larger neighbouring counties based on a systematic approach developed by the Federal Agricultural Research Centre (Osterburg, 2005). Missing values were approximated by the corresponding mean value of the counties in the respective federal state before integrating the regions. We believe that, for conceptual reasons, the integrated counties are better suited for statistical analysis, because the approach thus avoids problems associated with the very small counties in the sample, e.g., the fact that they have few (often only one) neighbours and often little agriculture. We check the suitability of the approach later in the paper.

Our study utilises *data on organic and conventional farming*, e.g., in the variable *share of organic agricultural area*, as provided by the German agricultural farm census (SAeBL, 2010).

We try to capture the key factor (output) *prices* by using three proxy indicators: the *number of organic food stores* in a region (bio verlag, 2010), the *distance to agglomeration centres* and the *available household income* (BBR, 2009). This selection was based on the assumption that a favourable accessibility of agglomeration centres and a high number of organic food stores indicate the proximity to and availability of (organic) markets. According to AMI (2010), direct marketing of organic products contributes positively to the development of organic markets. Direct marketing of organic products is widespread in Germany (ZMP, 2003) and usually associated with good marketing possibilities. Accordingly, the proximity to urban areas may lead to a higher share of organic farms (Frederiksen and Langer, 2004). There is also some evidence that the budget share spent on organic food might increase with income (Wier et al., 2003). High incomes might increase demand and the resulting prices for organic products.

Production relevant variables are described by the quality of available natural resources and the kind of farming activities. In Germany, the quality of soil and, therefore, the natural quality of location is described by an estimated soil-index called the *soil climate index* (‘Bodenklimazahl’) (BBR, 2002). The soil climate index was originally designed with a range from 0 to 100. It considers, for example, the slope of the terrain, the water availability, the type of soil and climate and measures the natural yield potential of any location in comparison with the best yield potential (Bauer, 1993). The *share of grassland* is largely determined by natural conditions, such as the total annual precipitation. The *total annual precipitation* will be used as a proxy variable for absolute grassland later. The mean annual sum of precipitation was generated for all counties based on data from Germany's National Meteorological Service for the time period 1961-1990 (DWD, 2007), using an inverse distance weighted interpolation with the power of one and including the five nearest locations. The *number of livestock units* and *share of agricultural area utilised in fulltime farming* (SAeBL, 2010) are used to characterise current farming activities.

The *policy environment* in which farmers operate is described by the magnitude of political support for organic farming, the share of voters of casting ballots for the green party and the proportion of water protection and nature conservation areas. The magnitude of political support for organic farming is approximated by the *payment level grassland*. This variable refers to the average payments for organically farmed grassland within the agri-environmental measures between 1996 and 2007 (based on Nieberg and Kuhnert, 2006; Nieberg, 2007). Every federal state in Germany has its own agri-environmental scheme, and therefore, the subsidies for organic farming can vary between the federal states. We neglected particular payments during the conversion period and based our calculations on the payments received after having fully converted a farm to organic farming. A high *share of votes cast for the green party* is assumed to form a socio-economic environment supporting organic farming (Lakner, 2009). Data are based on the results of the German Bundestag election of 2005 (SAeBL, 2010). As another policy-dependent factor possibly determining the spatial distribution of organic farming, the *share of nature conservation areas* (BfN, 2010) and the *share of water protection areas* in the total area of a county are considered. Data regarding water protection areas was obtained from the responsible authorities of all federal states in Germany.

2.5 Results and discussion

The analysis was conducted for an untransformed (y) and transformed (yl) dependent variable *share of organic farming in total UAA*. Based on Greene (1997), the variable yl was generated using the logit-transformation

$$yl = \ln \frac{y}{1-y} .$$

As explained later in this section, the presented results refer to the integrated counties. Initially, the global and local Moran's I coefficients were calculated to determine whether spatial autocorrelation exists. The *global Moran's I* is the regression coefficient of the corresponding OLS regression (i.e., a regression of Wy on y instead of y on Wy, as in the basic autoregressive equation (2.4b), cf. Anselin, 1988: 102). The global Moran's I is given by the following equation:

$$I = \frac{z'Wz}{z'z} \tag{2.5}$$

where

z = $(y-\overline{y})/\sigma_y$ (with y = vector of y_i; y_i = the share of organically managed land in total agricultural land in region i; $\overline{y}$ = arithmetic mean of the y_i; i = 1, …, 317, σ_y = standard deviation of y);

W = standardised neighbourhood matrix.

For yl, the global Moran's I was calculated correspondingly. Resulting values of the global Moran's I tests (e.g., for the model y, $W^{(1)}$: I = 0.399) suggest spatial autocorrelation for the dependent variable (Table 2.2). The p-value was computed using a normal approximation and is less than 0.01. Therefore, we reject the null-hypothesis 'no spatial dependency and/or heterogeneity' at a very high significance level.

Table 2.2 Diagnostic tests for spatial dependence (n=317)

	$W^{(1)}$		$W^{(2)}$		$W^{(idw)}$	
	y	*yl*	*y*	*yl*	*y*	*yl*
Moran's *I*	0.399 ***	0.403 ***	0.290 ***	0.330 ***	0.057 ***	0.068 ***
LM (spatial error)	23.12 ***	12.94 ***	21.25 ***	21.26 ***	8.16 ***	5.21 **
robust LM (spatial error)	11.10 ***	7.37 ***	8.60 ***	3.14 *	4.53 **	1.05 n.s.
LM (spatial lag)	40.90 ***	26.42 ***	47.27 ***	45.06 ***	14.68 ***	9.48 ***
robust LM (spatial lag)	28.88 ***	20.84 ***	34.62 ***	26.93 ***	11.06 ***	5.32 **

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

y = dependent variable *share of organic agricultural area in total UAA; yl = logit transformation of y: yl = ln(y/(1-y))*

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(idw)}$ = inverse distance weighted neighbourhood matrix

LM = Lagrange Multiplier test

Source: Authors' own calculations based on SAeBL (2010).

The *Moran scatterplot* shows the average deviations of the neighbouring districts (*Wz*) against the deviations of the respective districts (*z*). Figure 2.2 presents the Moran scatterplot for the model *y*, $W^{(1)}$. The positive slope of the regression line (Moran's *I*) indicates that the values of *z* and the associated spatially lagged variables (*Wz*) are positively related. The *Wz*-values seem to disperse less for low and negative *z*-values than they do for positive *z*-values. Neighbouring counties exhibiting similar high proportions of organic farming and few outliers can be observed.

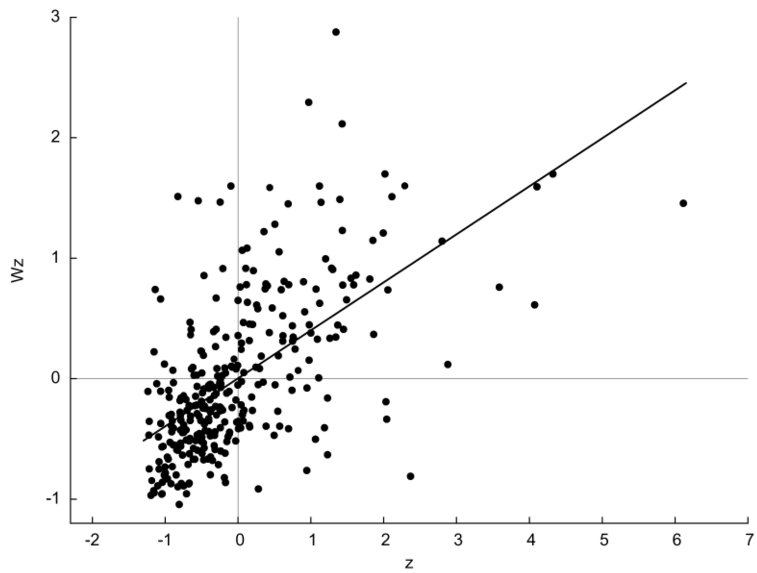

Figure 2.2 Moran scatterplot for the share of organic farming in German counties (2007) (n=317; model *y*, $W^{(1)}$)

Source: Authors' own calculation based on SAeBL (2010).

To identify potential local patterns of spatial associations, such as hot spots of organic farming, a special case of local indicators of spatial association (LISA) - the local Moran (I_i) - was calculated. According to Anselin (1995) and using the symbols introduced above, the local Moran is defined as:

$$I_i = z_i \sum_j w_{ij} z_j \tag{2.6}$$

where the w_{ij} are the corresponding elements of the row-standardised contiguity matrix *W*, z_i and z_j the standardised deviations as defined in equation (2.5) and the summation over *j* is such that only observations from regions neighbouring the region *i* are included.

Using the software GeoDa, a LISA cluster map for organic farming in Germany was generated at a significance level of $p \leq 0.05$ for the model y, $W^{(1)}$ (Figure 2.3). Areas with the attributes 'high-high' and 'low-low' indicate clustering of similar high / low proportions of organic farming in neighbouring counties (Anselin, 2003). One can note that a large area in the north-western and north-central part of Germany is characterised by very low shares of organic farming, whereas the north-eastern part and areas in the southern and central regions of Germany indicate the converse situation. Shaded units show spatial outliers.

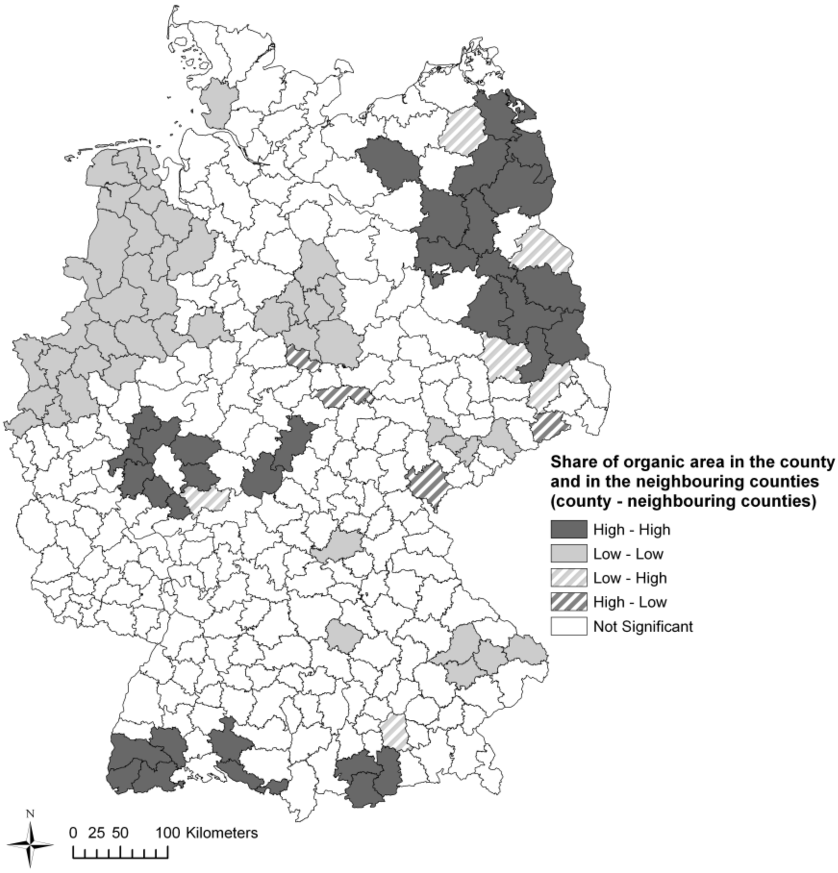

Figure 2.3 LISA cluster map for organic farming in Germany (2007) (n=317; model y, $W^{(1)}$)
Source: Author's own calculation based on SAeBL (2010).

Because the Moran's *I* indicates spatial autocorrelation and the tests for normality (Shapiro-Wilk-test) do not show normally distributed residuals in the OLS models relying on the independent variables introduced above, spatial models were applied to adjust the analysis.

The spatial models (4, 4a, 4b) were estimated by the maximum likelihood method (Jeanty, 2010a). First, we took all independent variables and regional dummy variables into account. We subdivided Germany into three sub-regions that are different in many important respects: *eastern*, *north-western* and *southern Germany* (regional dummy variables). One reason for this is that the farm structure varies significantly between these regions. The southern area is dominated by smaller farms, whereas the eastern part is characterised by much larger farms (the average organic farm size in southern Germany is approximately 40 ha, in eastern Germany approximately 179 ha (Statistisches Bundesamt, 2009)). Based on the Hausman test for endogeneity (Hausman, 1978; Wooldridge, 2009), the variable *share of grassland 2007* turned out to be an endogenous variable and, therefore, was approximated by two variables that are highly correlated with the share of grassland in 2007: *share of grassland 1999* and *total annual precipitation*.

In a second step, only those variables for which a significant influence had been identified were used for the analysis. The variable *north-western Germany* was the most robust regional dummy over all models and therefore kept in the models. The variable *total annual precipitation* (approximating absolute grassland as in Germany, the share of grassland is positively correlated with precipitation) was retained in the model as this natural factor is most likely not endogenous to organic agriculture in the short term. In contrast, organic farming activities in the past could have previously influenced the *share of grassland 1999*. Additionally, four of the explanatory variables were ultimately neglected: *available household income* and *share of agricultural area utilised in fulltime farming* never showed significant influence in the models. Also the variables *payment level grassland* and *share of water protection areas* - both of which are thought to be highly influenced by different political approaches in the German federal states - were taken out of the final models.

To determine the appropriate restricted spatial model, the (robust) Lagrange Multiplier test (Anselin et al., 1996) was conducted (Jeanty, 2010b). The results of the diagnostic tests for spatial autocorrelation in the residuals from OLS for the original counties were heterogeneous (Table 2.5, Annex), whereas the spatial lag model is recommended for all model alternatives of the integrated regions (Table 2.2). Based on that finding and our theoretical considerations regarding the administrative structures in Germany, we will present the analysis only for the integrated counties. We take the spatial lag model (2.4b) as appropriate and preferable specification for considering spatial autocorrelation and testing our hypotheses (Table 2.3). Additional results for the original counties can be found in Table 2.6 (Annex).

The coefficient of determination (R^2) of the OLS and spatial lag models varies between the two specifications of the dependent variable. Regarding R^2, the transformed dependent variable seems to be better explained by the selected independent variables than the untransformed variable *y*. To further analyse the performance of the different models, we calculated the Akaike information criterion (AIC) and Bayesian information criterion (BIC). The models explaining *yl* show smaller AIC and BIC values and, therefore, seem to perform better than the models for the untransformed dependent variable. According to Raftery (1995), a BIC difference of at least 10 provides strong evidence that one model fits the data better than another. Based on Raftery's guidelines and the coefficient of determination (R^2), the model explaining the transformed dependent variable using the second order neighbourhood matrix (*yl*, $W^{(2)}$) was determined as the preferable model.

Table 2.3 Results of the retained OLS and spatial lag models (n=317)

	OLS		Spatial lag model					
	-		$W^{(1)}$		$W^{(2)}$		$W^{(idw)}$	
	y	*yl*	*y*	*yl*	*y*	*yl*	*y*	*yl*
Number of organic food stores	69.766 **	16.355 ***	56.489 **	13.823 **	56.678 **	13.253 **	65.925 **	15.568 ***
Distance to agglomeration centres	0.010 n.s.	0.003 *	0.005 n.s.	0.002 n.s.	0.004 n.s.	0.002 n.s.	0.009 n.s.	0.003 *
Available household income	-0.132 *	-0.035 **	-0.105 n.s.	-0.027 *	-0.100 n.s.	-0.024 *	-0.121 n.s.	-0.032 **
Soil climate index	-0.123 ***	-0.027 ***	-0.082 ***	-0.019 ***	-0.087 ***	-0.019 ***	-0.116 ***	-0.025 ***
Number of livestock units	-2.437 ***	-0.607 ***	-1.585 ***	-0.451 ***	-1.495 ***	-0.388 ***	-2.200 ***	-0.564 ***
Total annual precipitation	0.003 ***	0.001 ***	0.003 **	0.001 ***	0.003 ***	0.001 ***	0.003 **	0.001 ***
Share of votes cast for the green party	0.140 n.s.	0.067 ***	0.064 n.s.	0.046 **	0.051 n.s.	0.036 *	0.109 n.s.	0.055 ***
Share of nature conservation areas	0.222 ***	0.036 ***	0.127 **	0.027 **	0.123 **	0.024 **	0.195 ***	0.033 ***
Dummy north-western Germany (=1)	-1.686 ***	-0.399 ***	-0.823 n.s.	-0.237 **	-0.535 n.s.	-0.129 n.s.	-1.205 **	-0.272 **
Constant	7.503 ***	-3.092 ***	4.432 **	-2.034 ***	3.599 *	-1.303 ***	3.100 n.s.	-0.449 n.s.
Spatial dependence ρ			0.442 ***	0.356 ***	0.594 ***	0.585 ***	0.854 ***	0.808 ***
R^2	0.270	0.347	0.307	0.375	0.311	0.384	0.277	0.351
adjusted R^2	0.249	0.328						
F	12.64	18.1						
Prob > F	0.00	0.00						
Likelihood Ratio chi^2			36.40	23.46	33.23	33.53	10.05	7.47
Prob > chi2			0.00	0.00	0.00	0.00	0.00	0.01
AIC			1687.04	684.73	1690.21	674.67	1713.40	700.73
BIC			1732.15	729.84	1735.32	719.77	1758.50	745.84

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

y = dependent variable *share of organic agricultural area in total UAA; yl = logit transformation of y: yl = ln(y/(1-y))*

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(idw)}$ = inverse distance weighted neighbourhood matrix

AIC = Akaike information criterion; BIC = Bayesian information criterion

Source: Authors' own calculations.

The direction of influence of the explanatory variables is consistent over all models. This can be taken as indication that the variables tested interact in the same manner in different model specifications. However, the parameter estimates from the OLS and the spatial lag models have to be interpreted differently (LeSage and Pace, 2009). To exemplify that aspect, we calculated the effects of a change in the explanatory variable *share of nature conservation areas* for the model *yl*, $W^{(2)}$. To interpret the impacts in an adequate way, the average direct impact (0.0247), average total impact (0.0575) and average indirect impact (0.0328) can be considered. According to LeSage and Pace (2009), averaging over the direct impact associated with all observations is basically similar to the interpretation of the OLS coefficients. In the presented example, the average direct impact is nearly 4% higher than the corresponding coefficient of the spatial lag model (0.0238) due to the effect of feedback loops.

The factor *spatial dependence* seems to have a relevant influence on the spatial distribution of organic farming: the coefficient ρ varies between 0.36 (model *yl*, $W^{(1)}$) and 0.85 (model *y*, $W^{(idw)}$) and is highly significant, regardless of the specification of the spatial weight matrix and the transformation of the dependent variable. The positive sign of the spatial lag coefficient implies that the share of land already managed organically in one county positively influences the share of organic agricultural area in neighbouring counties. The coefficient ρ, depicting the existence of agglomeration effects between regions, has to be interpreted as follows (e.g., for the model *y*, $W^{(1)}$: ρ = 0.44): if *ceteris paribus* the mean of the share of organically managed land in the neighbouring regions increases by one percentage point, then the estimated share of organically managed land in the considered region will rise by 0.44 percentage points in the first step.

The variable *number of organic food stores* shows a significant influence on the share of organically managed land. The availability of organic markets seems to favour proximate organic production. The *distance to agglomeration centres* is slightly significant in only one spatial model, the *available household income* only for the models explaining *yl*. However, for the latter, the estimations did not yield the expected signs.

It is remarkable that the production relevant variables *soil climate index*, *number of livestock units* and *total annual precipitation* (approximating absolute grassland) were significant at a high level in all models calculated. This may be due to the fact that organic farms have a reduced stocking density and higher share of grassland compared to conventional farms (Häring et al., 2003). According to Pietola and Oude Lansink (2001), the conversion to organic farming is more likely on farms with low-intensity livestock production. Regarding the influence of the soil climate index, farms located in low-yield regions seem to be more likely to convert to organic farming than farms in more fertile areas. This is traced back to the fact that converting a farm to organic methods in these areas has fewer consequences concerning the farm organisation than it is the case for a conversion in advantageous regions (Dabbert and Braun, 1993; Loibl, 1999). In disadvantaged regions, conventional agriculture is usually organised quite differently from conventional agriculture in intensive regions. Grasslands tend to be more important than arable land, and less fertiliser is used on farmland. Extensive forms of animal husbandry, such as cattle or sheep production, tend to play a major role in these regions, whereas intensive animal production systems, such as poultry or pig production, are rarely found. If a conventional farmer both relies heavily on feedstuffs - especially roughage - produced on his own farm to feed the animals and uses low amounts of pesticides and synthetic fertilisers, then the changes the farm has to undergo to convert to organic agriculture tend to be small (Dabbert et al., 2004). However, the selected factors do not fully capture the effects of the physical environment on the conversion decision. There might be some other natural factors that make an area particularly suitable for organic farming and thus, can also influence the spatial distribution of organic farming. The impact of not explicitly considered variables can increase the estimated coefficient ρ, which measures the spatial dependence.

For the models explaining the transformed dependent variable, the factor *share of votes cast for the green party* has a significant and positive influence on the share of organic farming. It is assumed that voters of the green party are in general interested in alternative forms of environmental resource management and, consequently, are likely to support alternative ways of agriculture like organic farming.

The analysis of the influence of the *share of nature conservation areas* on the spatial distribution of organic farming also shows a positive regression coefficient in all cases, despite the fact that implementation strategies of nature conservation areas might differ between federal states (e.g., restrictions on farming activities).

The dummy variable *north-western Germany* has a significantly negative influence on the proportion of organically farmed land in three spatial lag models. As presented in the LISA cluster map (Figure 2.3), wide associated areas in the north-western part of Germany are characterised by very low proportions of organic agriculture, a point that is in accordance with the negative influence of the dummy variable found in the retained models.

2.6 Conclusions

Organic farming activities are regionally agglomerated to a certain degree; regions with high shares of organic farming tend to be close to other regions with high shares of organically farmed land. Scale economies external to the farm seem to exist in organic farming. Our results show that several factors may contribute to a high share of organic land area, e.g., poor soil quality, low livestock density and a high share of protected nature areas. In addition, a high share of organically managed land in a region seems to be an ideal precondition for the decision of a farmer to convert to organic production. Available technical and juridical knowledge in a region (Morone et al., 2006), as well as positive external effects at the plot level (Parker and Munroe, 2007), might increase the diffusion of organic farming as an innovation (Padel, 2001). These aspects lead to the conclusion that incentives to stimulate clusters of organic farming could support the exploitation of economies of scale external to the farm.

For this analysis, we used aggregated, secondary data at the county level with mean values, and therefore, we could not interpret diversity within the regions. It is likely that the data used contains less variation than a dataset with higher spatial resolution. Thus, a promising avenue of research might be to acquire data on organic farming and analyse neighbourhood effects at a lower spatial scale. Another aspect that could not be sufficiently addressed due to the lack of data is the time lag effect. Accounting also for time series would certainly deepen the understanding of causalities and contribute to further discussions. Further analyses might also include a formalised selection procedure of the spatial neighbourhood matrix, e.g., as presented in Holloway and Lapar (2007). Our statistical model does not operate at the same scale as the production and decision-making processes. Some variables that would have been of interest (e.g., the exact physical environment) could not be tested. Using secondary data also precluded the use of variables like the personal attitude of farmers in the analysis. Focusing on areas with a high positive association of organic farming (such as counties in southern Bavaria and Baden-Württemberg or in Brandenburg) and gathering additional variables, such as the share of organic farmers belonging to an organic farmers' association, would bring the econometric model closer to the actual decision model. Additionally, spatial structures such as proximity to processors or certification bodies might also influence the location of organic farming and should therefore be explicitly considered.

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2.8 Annex

Table 2.4 shows a summary of the arguments presented in section 2.2 with regard to the spatial characteristics of the variables that are important for equation (2.1) along with hypotheses on the direction of the effects.

Table 2.4 Proxy variables used for hypothesis testing and their spatial characteristics

Key factors influencing the decision to convert to organic farming	**Spatial characteristic of key factors**	**Proxy variable for spatially heterogeneous effect**	**Proxy variable for spatially dependent effect**
Prices (p_t^{or}, c_t^{or})	Spatially heterogeneous, spatially dependent	Number of organic food stores (+) Distance to agglomeration centres (-) Available household income (+)	Neighbourhood (organic agglomeration) (+)
Transaction costs of conversion (TC_t)	Spatially heterogeneous, spatially dependent	No data	Neighbourhood (organic agglomeration) (+)
Production relevant factors (F)	Spatially heterogeneous, spatially dependent	Natural quality of location (-) Number of livestock units (-) Share of grassland (+) Share of agricultral area utilised in fulltime farming (-)	Neighbourhood (organic agglomeration) (+)
Non-monetary benefits (U_t^{ad})	Spatially heterogeneous, spatially dependent	No data	Neighbourhood (organic agglomeration) (+)
Policy environment (contained in pr_t^i)	Spatially heterogeneous	Share of votes cast for the green party (+) Share of water protection areas (+) Share of nature conservation areas (+) Magnitude of political support for organic farming (+)	-
Costs from loss of flexibility (contained in TC_t)	Spatially heterogeneous	No data	-

(+) = the hypothesis is that the proxy variable positively influences the proportion of organic farming in a region.

(-) = the hypothesis is that the proxy variable negatively influences the proportion of organic farming in a region.

Source: Authors' own presentation.

Table 2.5 shows the results of the diagnostic tests for spatial dependence for the 429 original counties. The global Moran's *I* tests indicate a positive and highly significant spatial autocorrelation of organically managed land at the original county level, regardless of the specification of the spatial neighbourhood matrix. However, the results of the (robust) Lagrange Multiplier test are heterogeneous; they vary between the untransformed (spatial lag model) and transformed (no spatial model) depending variable. This is one reason to present and interpret the results of the spatial models only for the integrated counties in the article. A second important reason for using the integrated counties for the analysis is based on theoretical considerations explained in section 2.4 of the article.

Table 2.5 Diagnostic tests for spatial dependence (original counties, n=429)

	$W^{(1)}$		$W^{(2)}$		$W^{(idw)}$	
	y	*yl*	*y*	*yl*	*y*	*yl*
Moran's *I*	0.118 ***	0.063 ***	0.128 ***	0.038 ***	0.036 ***	0.013 ***
LM (spatial error)	1.85 n.s.	0.18 n.s.	7.76 ***	0.10 n.s.	3.60 *	0.07 n.s.
robust LM (spatial error)	3.00 *	0.61 n.s.	4.33 **	0.23 n.s.	4.92 **	0.65 n.s.
LM (spatial lag)	3.27 *	0.37 n.s.	13.69 ***	0.26 n.s.	6.96 ***	0.00 n.s.
robust LM (spatial lag)	4.43 **	0.81 n.s.	10.26 ***	0.39 n.s.	8.28 ***	0.58 n.s.

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

y = dependent variable *share of organic agricultural area in total UAA; yl = logit transformation of y: yl = ln(y/(1-y))*

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(idw)}$ = inverse distance weighted neighbourhood matrix

LM = Lagrange Multiplier test

Source: Authors' own calculations based on SAeBL (2010).

The results of the retained OLS and spatial lag models for the original counties are presented in Table 2.6. Partly, the results are similar to the results for the integrated counties. The tests for normality (Shapiro-Wilk-test) also do not show normally distributed residuals in the OLS for the original counties. According to the (robust) Lagrange Multiplier test the spatial lag model is the appropriate model type for the models explaining the untransformed dependent variable *y*. However, no spatial model seems to be preferable for the models explaining the transformed depending variable *yl*. Correspondingly, the spatial lag coefficient ρ is not significant for those models. While the direction of influence of the explanatory variables is consistent over all models for the integrated regions, this is not true for the original counties. One reason for this might be the fact that some counties of the original data set are very small. Due to historical reasons, the sizes of the counties and the connectivity to neighbouring counties differ between the federal states. In some regions (especially in eastern Germany), the administrative units were restructured in the last years. Thereby, very small counties were merged or integrated into neighbouring counties. In other regions, this had not been done. Furthermore, and probably most important, in many regions the regional metropolis is part of the county. However, in case of the very small 'city counties' the main city and the surrounding district are separated artificially. Nevertheless, the main city still belongs to its region. Thus, it does not seem to make sense to explicitly consider very small urban 'city counties' in regions where they exist, whereas comparable cities belong to the surrounding rural area in other regions. Accordingly, the integration of the counties for the analysis may help to adjust the counties all over Germany and assist to better represent the real (agricultural) structures of the regions.

Table 2.6 Results of the retained OLS and spatial lag models (original counties, n=429)

	OLS		Spatial lag model					
	-		$W^{(1)}$		$W^{(2)}$		$W^{(idw)}$	
	y	*yl*	*y*	*yl*	*y*	*yl*	*y*	*yl*
Number of organic food stores	57.095 ***	41.068 **	55.680 ***	41.142 **	51.841 **	40.913 **	52.805 **	41.071 **
Distance to agglomeration centres	0.037 **	-0.002 n.s.	0.035 **	-0.003 n.s.	0.030 *	-0.004 n.s.	0.029 *	-0.003 n.s.
Available household income	0.002 n.s.	-0.315 ***	0.007 n.s.	-0.311 ***	0.014 n.s.	-0.312 ***	0.012 n.s.	-0.315 ***
Soil climate index	-0.125 ***	-0.076 **	-0.109 ***	-0.074 **	-0.096 **	-0.074 **	-0.111 ***	-0.076 **
Number of livestock units	-3.065 ***	-1.228 n.s.	-2.730 **	-1.226 n.s.	-2.386 **	-1.221 n.s.	-2.701 **	-1.229 n.s.
Total annual precipitation	-0.001 n.s.	0.004 *	-0.001 n.s.	0.004 *	0.000 n.s.	0.004 *	0.000 n.s.	0.004 *
Share of votes cast for the green party	-0.046 n.s.	0.322 **	-0.054 n.s.	0.310 **	-0.050 n.s.	0.308 **	-0.040 n.s.	0.322 **
Share of nature conservation areas	0.351 ***	0.030 n.s.	0.319 ***	0.027 n.s.	0.289 ***	0.032 n.s.	0.322 ***	0.030 n.s.
Dummy north-western Germany (=1)	-2.587 **	0.151 n.s.	-2.236 **	0.210 n.s.	-1.851 *	0.206 n.s.	-2.337 **	0.152 n.s.
Constant	9.540 ***	-3.994 n.s.	8.070 **	-3.764 n.s.	6.099 *	-3.584 n.s.	4.772 n.s.	-3.966 n.s.
Spatial dependence ρ			0.185 **	0.056 n.s.	0.401 ***	0.076 n.s.	0.705 ***	0.004 n.s.
R^2	0.131	0.124	0.135	0.124	0.144	0.124	0.135	0.124
adjusted R^2	0.112	0.105						
F	6.99	6.58						
Prob > F	0.00	0.00						
Likelihood Ratio chi^2			4.92	0.50	12.40	0.31	5.47	0.00
Prob > chi2			0.03	0.48	0.00	0.58	0.02	0.99
AIC			3009.60	2950.67	3002.12	2950.86	3009.04	2951.17
BIC			3058.34	2999.41	3050.86	2999.60	3057.78	2999.91

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

y = dependent variable *share of organic agricultural area in total UAA; yl = logit transformation of y: yl = ln(y/(1-y))*

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(idw)}$ = inverse distance weighted neighbourhood matrix

AIC = Akaike information criterion; BIC = Bayesian information criterion

Source: Authors' own calculations.

3 Does spatial dependence depend on spatial resolution? - An empirical analysis of organic farming in southern Germany

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This manuscript is submitted to: European Review of Agricultural Economics; date of submission: 02.05.2012, date of re-submission (major revisions): 12.12.2012.

Abstract

Assuming that agglomeration effects do matter in organic farming we analyse (a) the difficulties due to data aggregation arising when trying to statistically verify such effects and (b) whether results can be confirmed at different spatial resolutions. Drawing on secondary data we compare results of spatial lag models at two measurement scales. The results suggest that essential factors determining the decision to convert from conventional to organic farming are the same at different spatial resolutions. The results at the lower spatial resolution are not artificially generated through the aggregation process in this case, strengthening the relevance of previous studies.

Keywords: organic farming, spatial distribution, agglomeration effects, spatial econometrics

JEL classification: C21, O13, R12

3.1 Introduction

Earlier research has established - based on aggregated data - that agglomeration effects are likely to play an important role in explaining the spatial distribution of organic farming. Bichler et al. (2005) and Schmidtner et al. (2012) combined common location factors, such as climate and soil, with the concept of agglomeration effects and found that neighbourhood effects might influence the spatial distribution of organic farming at the county level in Germany. Background to these finding was economic theory: Schmidtner et al. (2012) developed a theoretical model linking the decision to convert from conventional to organic farming to factors of different spatial characteristics.

The decision-making and production processes are assumed to operate at the farm-level. Thus, an analysis at a high spatial resolution such as the farm-level would be preferable. Until now the data availability restricted the spatial analyses to the county level. This article extends previous research published in Bichler et al. (2005) and Schmidtner et al. (2012). Improved data availability allows us to analyse data at a higher spatial resolution, the community association level, and to compare the results to another measurement scale, the county level. We hypothesize that agglomeration effects become manifest at both measurement scales and that results at a lower spatial resolution are not merely artificially generated through the aggregation process but can be supported by a comparable analysis at a higher spatial resolution for the organic farming sector.

The issue of scale is a fundamental aspect of spatial analyses. Most geographers agree that ‘scale matters’. However, the conception of geographic scale varies across disciplines and research objectives. While using and comparing results at different spatial resolutions are common practices in the geosciences (Taylor, 2004), a comparable systematic approach is hardly to be found in agricultural economics, particularly for the organic farming sector. Goodchild and Proctor (1997) state that the term ‘scale’ is often ambiguously used to refer to two aspects of geographic information: the level of detail and the extent of geographic coverage. While Gibson et al. (2000) generally use the term to refer to the spatial dimension used to measure any phenomenon, Atkinson and Tate (2007) refer to the scales of spatial variation that are present in data and result from measurement. Lam (2004) established a classification of scale ‘types’ including, for example, the observational scale (referring to the spatial extent of a study area), the measurement scale (the resolution) and the operational scale (referring to the spatial extent where geographical processes take place). According to Smith (2004), the scale of spatial units can be seen as naturally given or as a methodological aspect of research. The latter aims at defining the appropriate spatial scale for a research problem or comparing results at different spatial resolutions. Another issue, called the Modifiable Areal Unit Problem (MAUP), is that results can differ between analyses at different spatial resolutions (Openshaw, 1984; see also Wong, 2009). Even more, the results may reverse in some cases, such as spatial examples of Simpson’s Paradox (Simpson, 1951). Thus, the actual relevance of results based on aggregated data is arguable.

In this study, we treat scale as a methodological aspect of research. To see whether our results still hold when the data is less aggregated, we will conduct an empirical analysis at two different measurement scales using the terminology introduced by Lam (2004).

Organic farming is an interesting case as it is distributed quite unevenly within Germany and the southern federal states of Bavaria and Baden-Württemberg, which are central to this study (Figure 3.1).

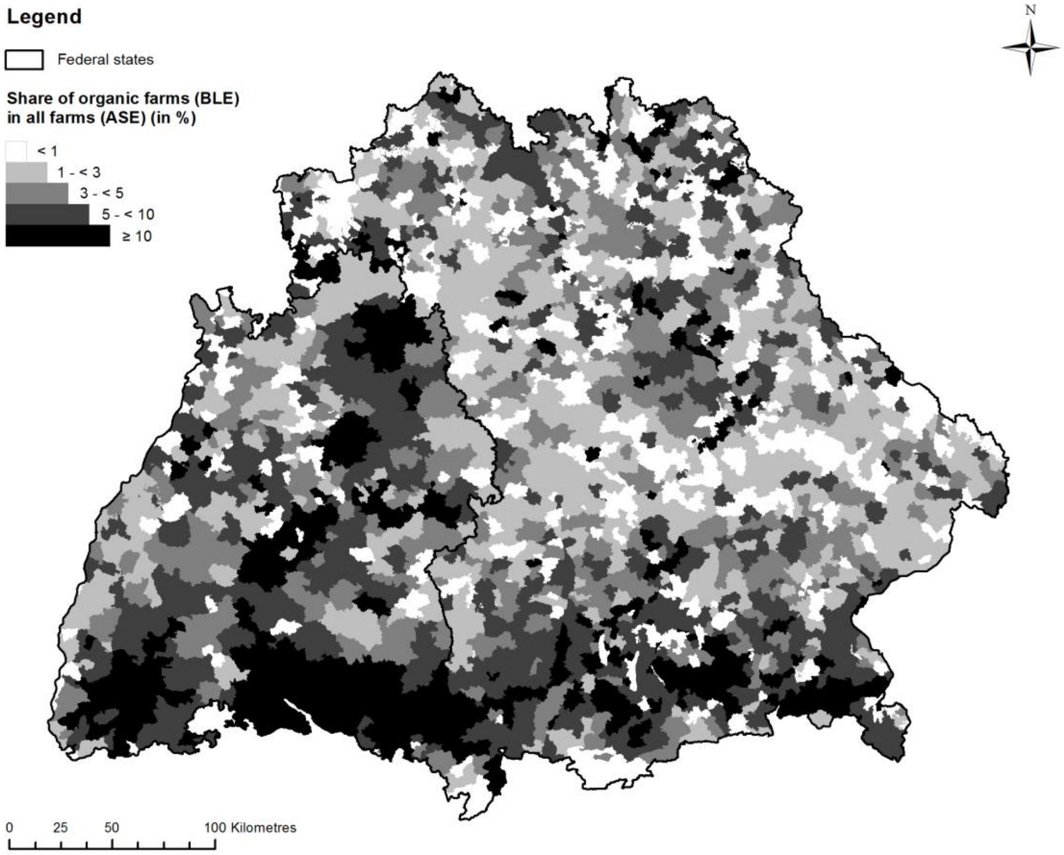

Figure 3.1 Spatial distribution of organic farming in Bavaria and Baden-Württemberg at the community association level (2007)

Source: Authors' own presentation based on BKG (2010), BLE (2009), SAeBL (2010).

As 56% of all German organic farms are located in Bavaria and Baden-Württemberg (BLE, 2009), we conduct the empirical analysis for these two federal states. Due to data availability, we apply a cross-sectional approach at the selected measurement scales. Thus, the empirical model analyses the share of organic farms in all farms at a given point in time and at two different spatial resolutions.

Spatial data has special characteristics, such as the multi-directional relationship of spatial units, so we account for spatial effects in our analysis. Probably the most famous definition of spatial effects is given by the first law of geography in which 'everything is related to everything else, but near things are more related than distant things' (Tobler, 1970: 236). Thus, strong relationships are expected among variables that are located nearby. Anselin (1988) distinguishes two kinds of spatial effects: spatial heterogeneity and spatial dependence. While the term 'spatial heterogeneity' refers to (explanatory) variables that differ in space (like soil or climate conditions), the term 'spatial dependence' specifies a functional relationship between events at different places in space (for a more detailed discussion see also LeSage and Pace, 2009). Spatial dependence results from agglomeration effects. In the following we suppose positive spillover effects in space between farms. These effects can be direct (e.g., because of direct communication between farmers) or indirect (e.g., due to local institutions or markets that are brought about or improved when many neighbouring actors have the same business). Our hypothesis is that in addition to the classical factors that determine the location of agricultural production also agglomeration effects influence the spatial distribution of agricultural activities like organic farming. In other words: different incidences of organic farms in space may be caused by different natural and other location factors (i.e., spatial heterogeneity) and/or by the beneficial (self-enhancing) effects of higher shares of organic farms (i.e., spatial dependence).

Beyond that, Anselin and Getis (2010) note that spatial effects can also be due to the structure of spatial measurement units, i.e., the size, shape and configuration of spatial units may influence the probability of spatial dependence in nearby units. To analyse the spatial distribution of organic farming in an appropriate way, we account for spatial heterogeneity and dependence through implementing spatial econometric methods.

Another issue that might affect an empirical analysis of organic farming is the conceptualization of the spatial relationships of spatial units through spatial neighbourhood matrices. According to Anselin (2002), the determination of such matrices is also somewhat arbitrary. Recently, there have been various approaches to specifying the spatial weights matrix (see, e.g., Getis and Aldstadt, 2004; Aldstadt and Getis, 2006; Fernandez-Vazquez and Rodriguez-Valez, 2007; Kostov, 2010). Nevertheless, there is no formal guidance for selecting the 'correct' spatial neighbourhood matrix (Lee, 2008). As the real spatial interdependences and interaction structures of organic farms are not known, we analyse, compare and discuss different specifications of the spatial neighbourhood matrix. These specifications are based on the data and theoretical considerations regarding the structure of spatial dependence in the organic sector.

In the remainder of the article, we frame the concept of agglomeration effects in organic farming. Then, we explain the utilization of different spatial resolutions and neighbourhood matrices in the context of our study. After presenting our econometric model in section 3.4, we introduce the data used and variables constructed. Next, we present and discuss the results, and finally, we draw conclusions.

3.2 Concept of agglomeration effects in organic farming

In the new economic geography (Krugman, 1996; Fujita et al., 1999), factors such as labour pooling, technology spillovers and backward and forward linkages in production may increase external economies of scale and, thus, favour the concentration of economic activity. While some of these factors causing agglomeration, such as knowledge spillovers or natural advantages, may take place only at a narrow operational scale, others, such as input and output linkages, may operate at a wider spatial extent (Giacinto and Pagnini, 2008). Thus, the adoption of organic farming practices could be due to different agglomeration patterns, depending on the operational scale.

We assume that easy interaction with organic farmers due to local proximity and a strong institutional and market network positively influence the propensity of conventional farmers to convert to organic farming. Besides, also negative edge-effect externalities like imissions of pesticides or genetically modified pollen from neighbouring conventional fields (cf. Parker and Munroe, 2007) are likely to be less frequent in case of a high share of organic farmers within a certain region which may facilitate the conversion to organic farming for further farmers. Such neighbourhood effects (positive agglomeration effects) may be one reason for organic agglomeration in space. Generally, the decision to convert to organic farming can be seen as an investment problem. Beyond the expected profit, this decision is influenced by issues such as the transaction costs of converting from one farming type to another and possibly by the additional utilities associated with organic farming (cf. Schmidtner et al., 2012).

Analysing organic land conversion in Greece, Genius et al. (2006) suggest that the provision of information has an important influence on the adoption of organic farming. At a high spatial resolution such as the community level, direct communication between farmers may be one essential source of knowledge exchange. The attitudes of farmers towards alternative agriculture and the resulting acceptance of organic farmers in the social environment might determine the location of organic production in space. It is also likely that the common use of machinery such as combine harvesters[5] is facilitated if cooperating organic farms are located nearby. At a lower spatial resolution such as the county level, other factors might be of importance. Analysing the Danish pig sector, Larue et al. (2011) state that spatial technical externalities may arise from the diffusion of information and knowledge through, for example, farmers' associations. Also, pecuniary externalities may affect the geographic location of production through the transmission of price effects to individual farms. Thus, the availability of input and output markets as well as the associated infrastructure may be relevant to the geographic concentration of organic farming in Germany assuming that transportation costs are relevant (Thünen, 1826). In addition, extension services of the German organic farmers' associations or veterinary services might work on a large scale. Furthermore, proximate organic processors, such as organic dairy enterprises, may facilitate the selling and further processing particularly of perishable organic products like milk (Bichler, 2006). However, competition in input and output markets, such as access to agricultural land, could have a dispersal effect on agglomeration (Larue et al., 2011).

Considering the various factors potentially causing agglomeration of organic farming, it is challenging to assess the importance of particular agglomeration patterns. Neighbourhood effects may not only differ but also span spatial measurement scales. An associated problem is the availability of data that

[5] Due to the relatively small farm sizes in Germany, machinery such as combine harvesters are quite often shared and used by several farmers. An organic farmer using a harvester previously used on a conventional field risks to 'contaminate' his crop with pesticide residues as combine harvesters are difficult to clean.

is, in our case, bound to administrative units. Thus, we can only approximate the situation of single farms by using available aggregated data at the selected spatial levels.

One reason of the differing effects of explanatory factors at varying degrees of data aggregation can be Simpson's paradox (cf. the corresponding example and Figure 3.5 in the Annex). Another didactic example to illustrate one challenge arising for spatial analyses is presented in Figure 3.2 which shows the spatial distribution of the density of organic farms, i.e., the number of organic farms per square kilometre for a constructed region and two measurement scales. For this example we assume that there are not any relevant explanatory variables but positive agglomeration effects in the closer vicinity (indicated by a first order neighbourhood matrix). The underlying data has been generated and classified into categories by the authors. It is further assumed that no significant spatial concentration of organic farms can be found at the lower spatial resolution (county level), but rather, is found within particular counties (at the higher spatial resolution, the community level).[6] Such a spatial pattern could be due to important benefits such as the common use of machinery or other assets but little or no beneficial spillover effects at the spatial scale of the counties.

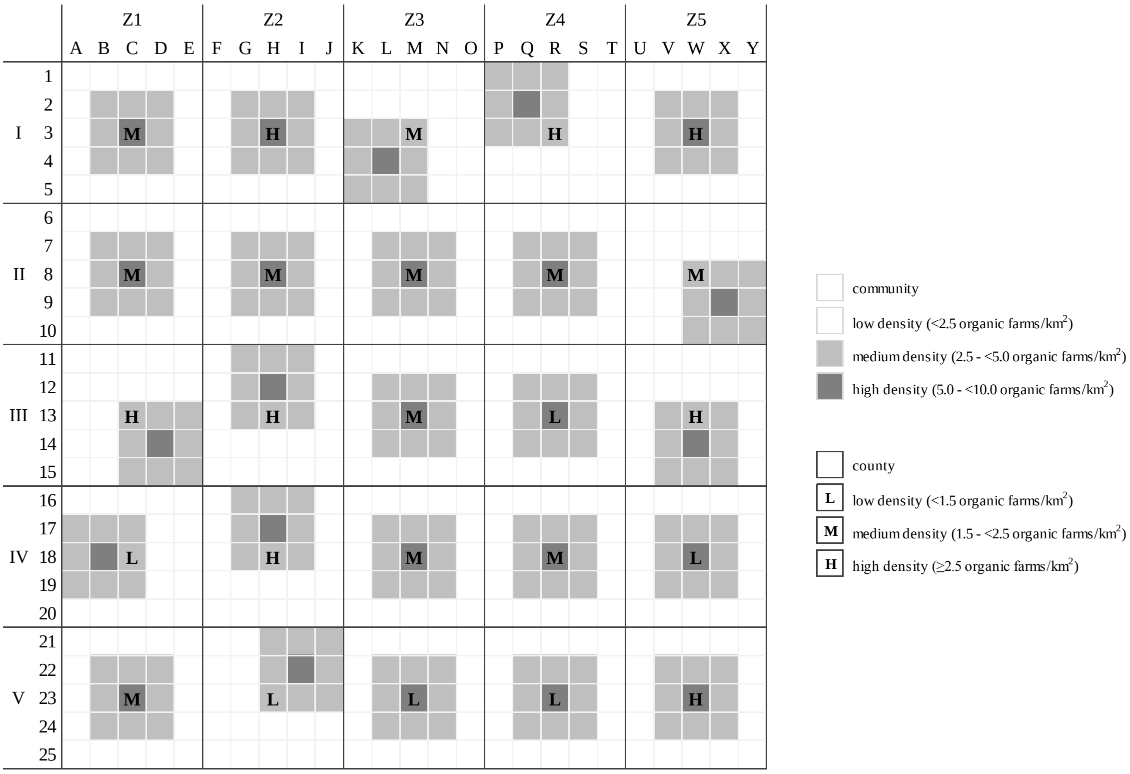

Figure 3.2 Spatial distribution of the density of organic farms at two measurement scales

Source: Authors' own presentation based on data generated by the authors.

The global Moran's *I* (Anselin, 1988) is calculated to determine whether spatial autocorrelation of organic farms exists. As presented in Table 3.1, the global Moran's *I* test indicates a positive and highly significant spatial autocorrelation only at the community level. At the county level, no spatial autocorrelation is indicated and, thus, no first-order spatial autoregressive model could be estimated at

[6] The example could also be translated to other issues such as the density of residents or firms.

this spatial level. Hence, the uneven spatial concentration of organic farms in the communities cannot be taken into account in the analysis at the county level. This points us to a general problem: while using aggregated data, information like the spatial distribution of aspects at a higher spatial resolution is lost.

Table 3.1 Descriptive statistics and diagnostic test for spatial dependence for the density of organic farms (spatial weight: first order contiguity matrix $W^{(1)}$)

	N	Mean	Std Dev	Median	Min	Max	Moran's *I*	p-value
Community level	625	2.19	1.63	1.80	0.05	9.80	0.37	0.00
County level	25	2.19	0.59	2.18	1.27	2.96	0.00	0.36

Source: Our own calculations based on data generated by the authors.

To conclude, the two examples above support the concerns about the relevance of results based on aggregated data. To address that issue, we test our analysis by comparing results at different spatial measurement scales.

3.3 Spatial resolution and spatial neighbourhood matrix determination

There are some studies on the organic sector that use spatial econometrics to analyse the spatial distribution of organic farming (cf. Bichler et al., 2005; Parker and Munroe, 2007; Schmidtner et al., 2012). However, to our best knowledge, there is no study in the field of spatial econometrics that analyses the spatial distribution of organic farming at different aggregation levels. As results might differ between different spatial resolutions (Openshaw, 1984), we aim to analyse spatial effects at different measurement scales. The lowest spatial resolution that offers sufficient explanatory variables for the analysis is the community association level. We additionally account for a lower spatial resolution (the county level) that consists of several community associations. In the year 2007, Bavaria and Baden-Württemberg were organised into 1886 community associations and 140 counties. However, some counties are very small, covering only the area of a city (Table 3.2). While 24% of all counties are such 'city counties', they only cover 3% of Bavaria's and Baden-Württemberg's total land area. In the case of the city counties, the regional metropolis and its surrounding districts are separated artificially, while in other regions the regional metropolis is part of the county. Additionally, the city counties often have only one neighbour (the surrounding district) and little agriculture. To avoid the problems associated with very small counties and to obtain more spatially uniform units (see also Figure 3.6, Annex), the city counties are integrated into larger neighbouring counties based on a systematic approach developed by the Federal Agricultural Research Centre (Osterburg, 2005). Thereby, the number of counties is reduced from 140 (original counties) to 106 (integrated counties, further on just called 'counties').

To capture spatial aspects and represent spatial relationships at the two measurement scales, a spatial neighbourhood matrix W is used that indicates the relative position and proximity of spatial units. To determine the spatial connectivity we draw on two approaches based on geographical information: contiguity (adjacency) and distance-based neighbourhood matrices (Anselin, 1988). The latter includes inverse distance-based neighbourhood matrices and matrices identifying the *k*-nearest neighbours. Because it is impossible to estimate the spatial neighbourhood matrix *W*, we take it as exogenously given. To examine the stability of the estimation results we try out different specifications of *W*.

The spatial neighbourhood matrix is an *N* x *N* matrix with the weights w_{ij}. To facilitate the interpretation of the estimated coefficients, the neighbourhood matrix *W* is standardized (see Anselin, 1988) for all approaches by the following weighting scheme:

$$w_{ij}* = \frac{w_{ij}}{\sum_{j=1}^{N_j} w_{ij}} \quad (3.1)$$

Probably the most common approach in spatial econometrics is to derive a contiguity-based neighbourhood matrix from the administrative units given, i.e., adjoining spatial units are defined as neighbours. We determine spatial neighbours according to the queen criteria. Thus, spatial units that share a common border or a vertex are treated as neighbours. The weights of the contiguity-based neighbourhood matrix are defined as follows:

$$w_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ have a common border or vertex} \\ 0, & \text{otherwise} \end{cases} \quad (3.2)$$

In the case of the first order neighbourhood matrix $W^{(1)}$, the weights are assigned according to Condition (3.2). For $W^{(2)}$, the first and second order neighbours of district *i* are considered and treated equally. Figure 3.6 (Annex) presents three connectivity maps for the first order neighbourhood matrix at different measurement scales. Regarding the community associations (a), it appears that cities, such as the federal states' capitals Stuttgart and Munich, are surrounded by a high number of relatively small administrative units. The resulting high number of spatial neighbourhood connections in such regions might be one influencing factor in the model. A schematic integration of small city counties into neighbouring counties (integrated counties) results in a much more uniform neighbourhood matrix (c) than the matrix for the original counties (b). This is another reason to use the integrated counties for the analysis.

The *distance-based approach* of defining a spatial neighbourhood matrix includes inverse distance-based neighbourhood matrices and matrices identifying the k-nearest neighbours. It is assumed that the strength of the spatial relationship declines as distance increases between spatial units (Getis, 2010). Both approaches share the challenge of determining the appropriate distance or number of neighbours to ensure that every district $i \neq$ j has at least one neighbour. Otherwise, the spatial neighbourhood matrix would be incomplete and information of artificially generated 'island units' could not be considered in the analysis.

According to Lee (2008), the critical distance approach is appropriate when spatial interactions are expected to decrease with distance until they are absent beyond a certain critical distance. By defining a critical distance, an area of influence ('moving window') is imposed.

The distance-based neighbourhood matrix is defined as:

$$w_{ij} = \begin{cases} \dfrac{1}{\mathrm{dist}_{ij}}, & \text{if the distance } (\mathrm{dist}_{ij}) \text{ between } i \text{ and } j \text{ is less than a critical distance} \\ 0, & \text{otherwise} \end{cases} \quad (3.3)$$

The neighbourhood matrix identifying the *k*-nearest neighbours is based on the following condition:

$$w_{ij} = \begin{cases} 1, & \text{if } j \text{ is one of } i\text{'s nearest neighbours, where } k > 0 \\ 0, & \text{otherwise} \end{cases} \quad (3.4)$$

We assume that interactions between farmers decline with increasing distance. However, there is no theoretical evidence for a certain critical distance for our research problem. Negreiros (2009) notes that the distance-based neighbourhood approach is blind to obvious natural neighbours and suggests combining it with the contiguity-based neighbourhood approach to identify direct neighbours. To tackle that point, we evaluate the first order contiguity-based neighbourhood matrix and use the information gained to establish a framework determining the distance-based neighbourhood relationships. To compare the effects of different neighbourhood matrices we intend to cover the contiguity matrix of the community associations with the distance-based approaches. The first order neighbourhood matrix of the community associations shows an average number of links of 5.8; the most connected region has 24 links. The largest distance between two adjacent community associations is 26.32 km. The distances are calculated based on the centroid of each spatial unit and measured in meters. Based on this information, we draw on several matrices at the community association level: a neighbourhood matrix identifying the 24 nearest neighbours ($W^{(24nn)}$), a restricted inverse distance weighted neighbourhood matrix ($W^{(idw30)}$) considering distances up to 30 km and an unrestricted inverse distance weighted neighbourhood matrix ($W^{(idw)}$). $W^{(idw)}$ contains the row-standardized inverse distance of each centroid of district $j \neq i$ to the centroid of district i. As the maximum distance of 26.32 km between two community associations exists only in one case, a lower critical distance ($W^{(idw15)}$) is also analysed. As presented in Figure 3.3, the definition of different critical distance bands results in quite different spatial connectivities of the community associations. For the counties, only the first order, second order and inverse distance weighted neighbourhood matrices are considered.

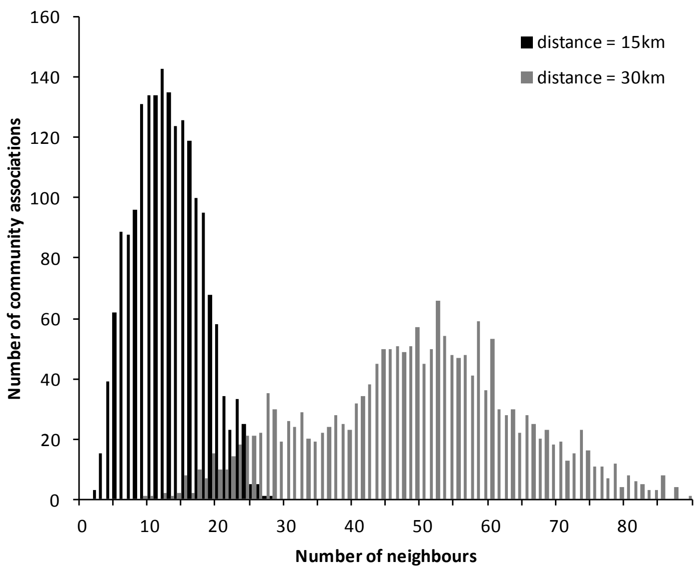

Figure 3.3 Connectivity of community associations at different distance bands
Source: Authors' own calculations based on BKG (2010).

Using the *k*-nearest neighbours approach ensures that every spatial unit has the same number of neighbours, regardless of the size of the spatial units. However, the corresponding weighting matrix is asymmetric (Anselin, 2002). That means if *j* is a neighbour of *i*, *i* does not have to be a neighbour of *j* depending on the distances to other neighbouring units. Thus, the *k*-nearest neighbour approach would be especially useful to account for specific aspects such as trade relationships in the organic sector. Even if corresponding data is not available, we use the *k*-nearest neighbours approach as an alternative way of representing spatial relationships based on distance.

3.4 Econometric model

The alternative specifications of the spatial neighbourhood matrix *W* are implemented in the econometric model we use for our analysis. As also described in Schmidtner et al. (2012), the general version of our model is given by the following equations (cf. Anselin, 1988; LeSage, 1999):

$$y = \rho Wy + X\beta + u \tag{3.5}$$

$$u = \lambda Wu + \varepsilon \tag{3.6}$$

with $\varepsilon \sim N(0, \sigma^2 I_N)$

and

y = vector containing the *share of organic farms* in the selected administrative units in Bavaria and Baden-Württemberg;

X = matrix containing the observations for *g* independent variables for every administrative unit;

W = row-standardized spatial weight matrix;

I_N = identity matrix;

u = vector of the spatially correlated residuals;

ε = vector of normally distributed errors (mean = 0, variance = σ^2);

β = vector containing the regression coefficients for the explanatory variables;

ρ = spatial lag coefficient reflecting the importance of spatial dependence;

λ = coefficient reflecting the spatial autocorrelation of the residuals u_i.

As we use row-standardized spatial weighting matrices W the estimated coefficients ρ and λ will usually lie between -1 and 1 (theoretically, the lower bound of ρ could be less than 1 also in case of row standardization, see Anselin, 1999, p.7f.). A significant spatial lag coefficient ρ indicates the possible existence of agglomeration effects resulting in spatial dependence, whereas a significant coefficient λ reflects spatial autocorrelation of the residuals u_i, i.e., spatial heterogeneity. We do not know from theoretical considerations which spatial effects influence the spatial distribution of organic farming in southern Germany. Generally, there are four possibilities (resulting in different models):

(i) $\rho = \lambda = 0$ (common OLS model);

(ii) $\rho \neq 0, \lambda = 0$ (spatial lag model);

(iii) $\rho = 0, \lambda \neq 0$ (spatial error model) and

(iv) $\rho \neq 0, \lambda \neq 0$ (spatial mixed model).

Thus, we draw on the (robust) Lagrange Multiplier test for spatial autocorrelation in the residuals from OLS (Anselin et al., 1996) to identify which of the two effects are relevant in our analysis.

3.5 Data and variable construction

Previous studies such as Bichler et al. (2005) and Schmidtner et al. (2012) draw on agricultural data from the official farm census, which are partly restricted due to data protection legislation and are only available at the county level for organic farming. Due to an improved database, we now have access to information on all 10934 certified organic farms and 3104 organic processors in Bavaria and Baden-Württemberg (BLE, 2009). The provided residential postal address is used to geo-reference the location of organic farms and processors (Deutsche Post Direkt, 2010).

As described in section 3.3, the analysis is conducted at two measurement scales: the community association and county level. Due to the data availability the spatial level of community associations is the lowest administrative unit at which our analysis can be performed. To test the robustness of spatial models, different specifications of the spatial neighbourhood matrix are considered.

The analysis is conducted for the dependent variable *share of organic farms (BLE) in all farms (ASE).* We need to rely upon this variable because we do not know the share of organically farmed land at the community association level. However, trying to explain the share of organic farms makes also sense from a theoretical point of view as several supposed agglomeration effects result from interactions (communication) between farmers.[7] The share of all certified organic farms as provided by the Federal Agency for Agriculture and Food (BLE, 2009) is calculated from the total number of agricultural

[7] Furthermore, at least at the county level there is a strong correlation between the *share of organic farms in all farms* and the *share of organically farmed land in overall farmed land.*

farms reported by the official farm census (SAeBL, 2010). However, the official farm census has some data restrictions; for example, it accounts only for farms with more than 2 ha utilised agricultural area (UAA) and a certain number of animals. Thus, only farms fulfilling these restrictions are represented in the official farm census, whereas all organic farms are provided by BLE (2009). As shown in Table 3.2, this results in the fact that the maximum share of organic farms (BLE) in all farms (ASE) exceeds 100% at the community association level. This applies to two community associations and is a statistical artefact of the database. At the integrated county level, the bias is reduced through averaging across the counties.

Table 3.2 Descriptive statistics for variables of interest at different measurement scales

Variable	Year	Mean		Min		Max	
		Community associations	Counties[a)]	Community associations	Counties[a)]	Community associations	Counties[a)]
Share of organic farms (BLE) in all farms (ASE) (in %)	2007	5.63	6.60	0.00	1.19	122.58	42.12
Number of residents per km^2	2007	259.01	236.59	0.00	70.68	4,216.20	1,661.29
Average distance to the next 3 agglomeration centres (in min. by car)	2007	107.84	106.66	49.60	58.80	172.80	164.40
Number of organic processors per 10 km^2	2007	0.33	0.31	0.00	0.04	7.54	2.36
Share of UAA in the total area (in %)	2007	44.23	43.58	0.00	15.08	158.54	68.48
Number of farms (ASE) per km^2	2007	1.74	1.67	0.00	0.77	14.75	3.06
Number of farms (ASE) per 100 km^2 UAA	2007	4.23	3.94	0.00	2.33	38.74	8.70
Total annual precipitation (in cm)	1961-1990	91.80	92.96	57.08	63.00	203.01	173.12
Mean annual temperature (in °C)	1961-1990	7.89	7.83	5.59	6.32	10.37	9.80
Soil-Index	1981, 1986	47.92	47.73	14.39	27.34	87.00	65.59
Share of water protection areas in the total area (in %)	2007	8.25	9.91	0.00	0.65	99.84	86.72
Share of nature conservation areas in the total area (in %)	2007	1.80	2.17	0.00	0.03	99.32	34.82
Share of votes cast for the Green Party in all valid votes cast (in %)	2005, 2009	8.16	9.14	0.00	4.16	27.35	19.86
Average size of the community associations (in km^2)	2007	56.38		1.77		339.07	
Average size of the integrated counties (in km^2)	2007		1,003.20		323.96		2,071.27
Average size of the original counties (in km^2)	2007		759.56		35.45		1,971.48

Community associations: N = 1886

[a)] All values refer to the integrated counties (N = 106) with the exception of the variable *average size of the original counties* (N = 140)

Source: Authors' own calculations based on BBR (2009), BfN (2010), BLE (2009), BLSD (2011), BLU (2010), DWD (2007), Forschungszentrum Jülich (2009), LUBW (2009), SAeBL (2010), SLBW (2010).

To capture the availability of and proximity to (organic) markets the *number of residents per km^2*, the a*verage distance to the next three agglomeration centres* (BBR, 2009) and the *number of organic processors per 10 km^2* (BLE, 2009) are considered. Generally, the location of (potential) consumers might influence the location of organic producers. It is assumed that a high population density indicates a high demand potential for (organic) food that might increase resulting prices for organic products. The proximity to urban regions (associated with good marketing possibilities) is approximated by the distance to the next three agglomeration centres and may lead to a high share of organic farms (Frederiksen and Langer, 2004). The existence of organic processors may facilitate the selling and further processing of organic products (Bichler, 2006). We assume that organic processors in the wider vicinity, e.g., in neighbouring community associations, are important for organic farmers. Therefore, we account for spatially lagged variables of the number of organic processors per 10 km^2 using different spatial neighbourhood matrices.

The agricultural structure is approximated by the variables *share of UAA in the total area*, *number of farms (ASE) per km^2 UAA* and *number of farms (ASE) per km^2* (SAeBL, 2010). We assume that a high density of farms and organically managed land facilitates knowledge exchange between farmers and positively influences the propensity of conventional farmers to convert to organic farming. In Germany, the agricultural farm census is based on the *principle of the farm location* ('Betriebssitzprinzip'), i.e., all agricultural activities (e.g., UAA, animal husbandry) are attributed to the location of the farm, even if the activities are located in other administrative units. This results in the shares of UAA in the total area being higher than 100% at the community association level (Table 3.2). Unfortunately, this bias also cannot be corrected.

The policy environment in which organic farmers operate is described by the *share of water protection areas in the total area* (BLU, 2010; LUBW, 2009), the *share of nature conservation areas in the total area* (BfN, 2010) and the *share of votes cast for the Green Party in all valid votes cast* (BLSD, 2011; SLBW, 2010). For the latter, the mean values of the German Bundestag elections in 2005 and 2009 are generated. The restrictions on management in water protection areas and nature conservation areas may favour less-intensive forms of agriculture like organic farming. As agricultural activities are not allowed in the central catchment area of water protection areas, we only account for the wider catchment area (zone 3) of water protection areas. To consider the different political frameworks for organic farmers in the two federal states, such as the designation of and regulations on water protection areas, we also generate a regional *dummy variable Bavaria*.

The *total annual precipitation* and *mean annual temperature* are used as natural production factors. These data are generated based on data from Germany's National Meteorological Service for the time period 1961-1990 (DWD, 2007), using an inverse distance weighted interpolation with the power of one and including the five nearest locations when assigning a value to a specific point in space. The resulting grid is used to calculate zonal statistics and assign corresponding mean values to the spatial units. Additionally, the German *soil-index* ('Bodenzahl') is considered as a measure of the productivity of agricultural land (Forschungszentrum Jülich, 2009).

The estimations are done using the programs GeoDa, R and STATA along with additional routines provided by Keitt et al. (2010), Hothorn et al. (2010), Jeanty (2010a, b, c, d), Pebesma and Bivand (2011), Bivand (2011) and Pisati (n.a.). The spatial models according to the equations (3.5) and (3.6) are estimated using the maximum likelihood method.

3.6 Results and discussion

To determine if spatial autocorrelation of the dependent variable exists, the local and global Moran´s *I* of the variable *share of organic farms (BLE) in all farms (ASE)* are calculated (cf. Anselin, 1988: 102). The global Moran's *I* tests indicate a positive and highly significant spatial autocorrelation for the dependent variable at all measurement scales. The Moran's *I* varies between 0.306 ($W^{(1)}$) and 0.041 ($W^{(idw)}$) (both community associations) and is highly significant regardless of the specification of the spatial neighbourhood matrix.

The local Moran's I is calculated to identify potential hot spots of organic farming or regions with a relatively low share of organic farms. Figure 3.4 shows the local indicators of spatial association of organic farms (LISA) for the first order neighbourhood matrix of the community associations at a significance level of $p \leq 0.05$. Regions with the attributes 'High-High' and 'Low-Low' indicate clustering of similar high / low shares of organic farms in neighbouring community associations. Shaded units show spatial outliers. Large areas in the southern and north-eastern parts of Baden-Württemberg are characterised by clusters with a very high share of organic farms, whereas regions in northern Bavaria and north-western Baden-Württemberg indicate the converse situation. In addition, for the counties, the local Moran's I highlights clusters with high shares of organic farms in southern Baden-Württemberg and clusters with low shares in northern Bavaria (see Figure 3.7, Annex).

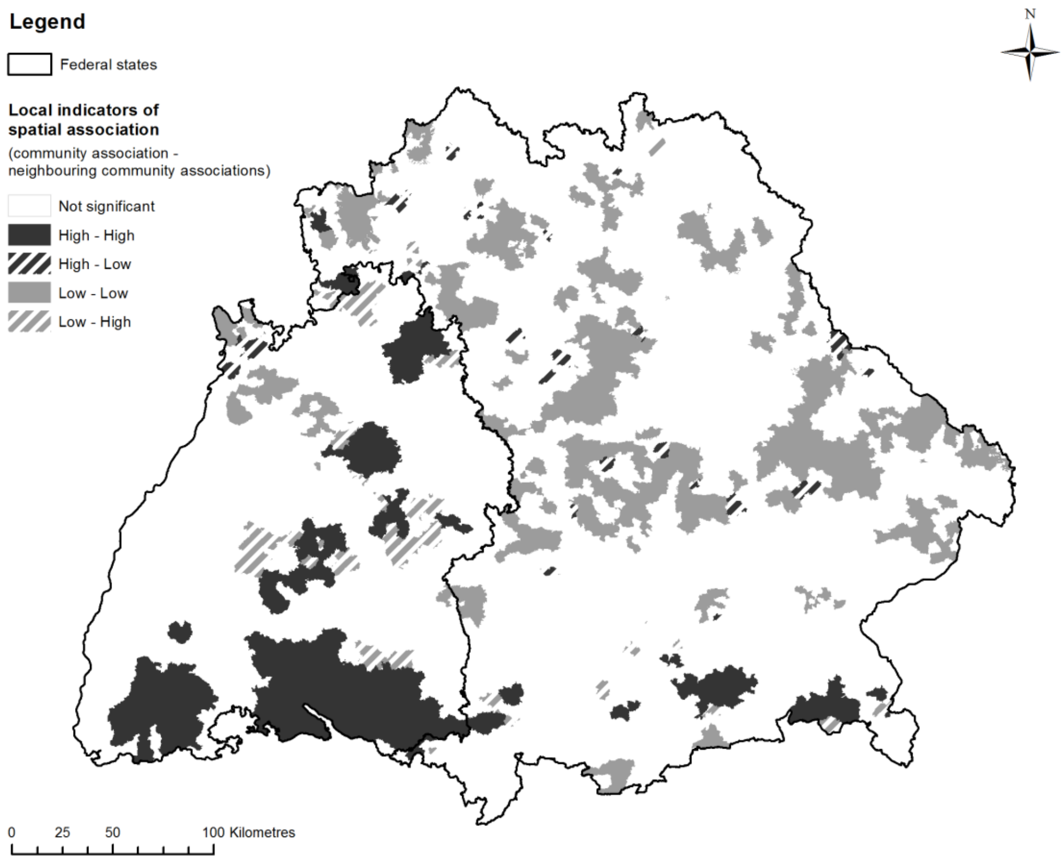

Figure 3.4 LISA cluster map for the share of organic farms at the community association level (spatial weight: first order contiguity matrix $W^{(1)}$)

Source: Authors' own calculations based on BKG (2010), BLE (2009), SAeBL (2010).

Spatial models are applied to adjust the analysis. First, all explanatory variables and the regional dummy variable are taken into account and analysed for the community associations. The final models are obtained by a step-wise selection procedure applied to the spatial models. Those variables lacking significant influence are step-by-step taken out of the spatial models (identified by the Lagrange Multiplier test, respectively). At the same time, the Morans's I of the residuals of each model is calculated to determine whether spatial autocorrelation is of relevance. The natural production factors *total annual precipitation* and the *soil-index*, the political proxy variables *share of water protection* *areas* and *share of nature conservation areas* as well as the variables *share of UAA in the total area* and *number of farms per km^2 UAA* are removed from the analysis. Also, the *dummy variable Bavaria* and the *spatially lagged variables for the number of organic processors per 10 km^2* do not show significant influence on the models. For the retained model, the (robust) Lagrange Multiplier test (Anselin et al., 1996) suggests estimating spatial mixed models or spatial lag models for nearly all model alternatives (Table 3.3). A spatial error model would be better for only two specifications of the inverse distance weighted neighbourhood matrices at the community association level ($W^{(idw30)}$, $W^{(idw)}$). However, a spatial lag model also makes sense. Based on our hypothesis that there are agglomeration effects in the organic sector, we draw on the spatial lag model in further analyses. The Morans's I of the corresponding residuals indicate that spatial autocorrelation is of relevance (e.g., for the community associations and the first order contiguity matrix $W^{(1)}$: I = 0.2417, p = 0.00). After determining the final model at the community association level, the retained explanatory variables are also analysed for the lower spatial resolution. The aim of this procedure is to analyse whether similar results can be found at the county level using the same database as for the community associations. The (robust) Lagrange Multiplier test recommends using the spatial lag model for the lower spatial resolution.

Table 3.3 Diagnostic tests for spatial dependence

	Community associations						Counties		
	$W^{(1)}$	$W^{(2)}$	$W^{(24nn)}$	$W^{(idw15)}$	$W^{(idw30)}$	$W^{(idw)}$	$W^{(1)}$	$W^{(2)}$	$W^{(idw)}$
LM (spatial error)	255.30 ***	280.80 ***	267.94 ***	318.65 ***	405.68 ***	159.81 ***	6.11 **	1.57 n.s.	1.95 n.s.
robust LM (spatial error)	1.22 n.s.	14.99 ***	21.18 ***	3.77 *	45.77 ***	40.44 ***	0.00 n.s.		
LM (spatial lag)	270.35 ***	290.52 ***	272.44 ***	341.06 ***	390.12 ***	139.62 ***	8.69 ***	4.00 **	5.20 **
robust LM (spatial lag)	16.27 ***	24.70 ***	25.67 ***	26.18 ***	30.21 ***	20.25 ***	2.59 n.s.		
LM (spatial error and lag)		305.51 ***	293.61 ***	344.83 ***	435.90 ***	180.06 ***			

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(24nn)}$ = neighbourhood matrix identifying the 24 nearest neighbours;

$W^{(idw15)}$ and $W^{(idw30)}$ = inverse distance weighted neighbourhood matrices considering distances up to 15 km and 30 km, respectively

$W^{(idw)}$ = inverse distance weighted neighbourhood matrix

LM = Lagrange Multiplier test

The test results refer to the variables used in the models displayed in Table 4.

Source: Authors' own calculations based on BBR (2009), BLE (2009), BLSD (2011), DWD (2007), SAeBL (2010), SLBW (2010).

Table 3.4 presents the results of the spatial lag models for the community associations and the counties. The spatial lag coefficient ρ shows a significant influence on the models regardless of the neighbourhood specification and measurement scale. For the first order neighbourhood matrix of the community associations (ρ = 0.439), this implies that *ceteris paribus*, if the share of organic farms in the neighbouring regions increases by one percentage point, then the estimated share of organic farms in the region will rise by 0.439 percentage points in the first step. If one considers potential feedback loops, the average direct impact of ρ (0.457) is slightly higher (LeSage and Pace, 2009). Thus, spatial dependence seems to influence the spatial distribution of organic farms in the southern federal states of Germany.

The explanatory variables exhibit significant influence on the share of organic farms with consistent directional influence for all model alternatives. One variable that is not significant for all neighbourhood matrices is the variable *number of organic processors per 10 km²*. For the counties, the *mean annual temperature* also does not have a significant impact.

A larger *distance to agglomeration centres* and lower *population density* seem to influence the share of organic farms positively. This could be due to the low availability of agricultural land near agglomeration centres and the importance of other factors for the distribution channels of organic products, such as the existence of supra-regional organic discounters.

A high density of farms does not seem to influence the share of organic farms positively. This could be due to the importance of consultants of organic farmers' associations in the conversion process and the agricultural farm structures. As the average size of organic farms in Bavaria and Baden-Württemberg (approx. 32 ha) is larger than farms in general (approx. 26 ha) (Statistisches Bundesamt, 2008), organic farms might tend to be located in regions with lower farm density. However, the availability of organic processors like organic dairy enterprises seems to influence the share of organic farms positively.

The climate variable *mean annual temperature* has a highly significant and negative influence at the community association level. According to our data, cold regions like the Alpine regions have a high level of precipitation and a high share of grassland. Such grassland areas are often used less intensively for animal husbandry and, thus, facilitate the conversion to alternative forms of agriculture like organic farming (Dabbert et al., 2004).

The *voters for the Green Party* variable shows a highly significant influence on the share of organic farms. It is assumed that voters for the Green Party are interested in sustainable resource management and non-monetary benefits for farmers, such as acceptance in the social environment, may favour the conversion to organic farming (Musshoff and Hirschauer, 2008).

To identify the model that performs best in our research approach, we draw on the Akaike information criterion (AIC) and Bayesian information criterion (BIC). As a BIC difference of at least 10 provides strong evidence that one model fits the data better than another (Raftery, 1995), the model using the inverse distance weighted neighbourhood matrix $W^{(idw15)}$ is the preferred model at the community association level.

In a further analysis, we ignore the results of the community associations and merely consider the spatial distribution of organic farms at the county level (analyses II, see Tables 3.6 and 3.7 in the Annex). Table 3.6 (Annex) presents the corresponding results of the diagnostic tests for spatial dependence. Again, the number of variables is reduced stepwise until only significant explanatory variables remain in the models (see Table 3.7, Annex). Based on the (robust) Lagrange Multiplier test, spatial lag models are used to adjust the analysis. Compared to the results presented in Table 3.4, fewer variables remain in the model. This might be due to lower variability at the county level (Table 3.2). The spatial lag coefficient ρ is significant for all specifications of the spatial neighbourhood matrix. As expected, the agglomeration effects are weaker at the lower spatial resolution than at the community association level. Compared with the results found by Schmidtner et al. (2012), our models for the counties show slightly lower spatial lag coefficients (Table 3.5). This might be because we do not analyse the spatial distribution of organic farming for all German counties but just focus on the southern federal states.

The results show that spatial dependence influences the spatial distribution of organic farms at the county level. Thus, the county level seems to be an appropriate approach for our research objective.

Table 3.4 Results of the retained spatial lag models at different spatial levels

	Community associations						Counties		
	$W^{(1)}$	$W^{(2)}$	$W^{(24nn)}$	$W^{(idw15)}$	$W^{(idw30)}$	$W^{(idw)}$	$W^{(1)}$	$W^{(2)}$	$W^{(idw)}$
Number of residents per km^2	-0.0017 **	-0.0017 **	-0.0017 **	-0.0015 **	-0.0017 **	-0.0022 **	-0.0152 **	-0.0170 ***	-0.0168 ***
Average distance to the next 3 agglomeration centres (in min. by car)	0.0242 **	0.0236 **	0.0244 **	0.0215 **	0.0223 **	0.0328 ***	0.0777 **	0.0852 ***	0.0862 ***
Number of organic processors per 10 km^2	0.6315 *	0.6110 n.s.	0.5929 n.s.	0.5582 n.s.	0.5619 n.s.	0.7003 *	7.9506 n.s.	9.4306 *	9.3891 *
Number of farms (ASE) per km^2	-0.6779 ***	-0.7138 ***	-0.7131 ***	-0.6150 ***	-0.6407 ***	-0.8201 ***	-2.8018 ***	-2.9927 ***	-2.9049 ***
Mean annual temperature (in °C)	-0.7828 ***	-0.7301 **	-0.6223 **	-0.7474 **	-0.6306 **	-0.9789 ***	0.6967 n.s.	0.5300 n.s.	0.4537 n.s.
Share of votes cast for the Green Party in all valid votes cast (in %)	0.7050 ***	0.6775 ***	0.6807 ***	0.6702 ***	0.6350 ***	0.8860 ***	1.2875 ***	1.3575 ***	1.3733 ***
Constant	2.3740 n.s.	1.7532 n.s.	0.6455 n.s.	2.0302 n.s.	0.7360 n.s.	-0.9554 n.s.	-15.4121 n.s.	-14.9789 n.s.	-17.2817 *
ρ	0.439 ***	0.538 ***	0.561 ***	0.529 ***	0.643 ***	0.959 ***	0.355 ***	0.313 *	0.687 **
AIC	12888	12942	12958	12870	12919	13044	657	662	661
BIC	12937	12992	13007	12920	12969	13094	681	686	685

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(24nn)}$ = neighbourhood matrix identifying the 24 nearest neighbours;

$W^{(idw15)}$ and $W^{(idw30)}$ = inverse distance weighted neighbourhood matrices considering distances up to 15 km and 30 km, respectively;

$W^{(idw)}$ = inverse distance weighted neighbourhood matrix

AIC = Akaike information criterion; BIC = Bayesian information criterion

dependent variable: *share of organic farms (BLE) in all farms (ASE) (in %)*

Source: Authors' own calculations based on BBR (2009), BLE (2009), BLSD (2011), DWD (2007), SAeBL (2010), SLBW (2010).

Table 3.5 Spatial lag coefficient resulting from different spatial analyses of organic farming in Germany

	Community associations			Counties II[a)]			Schmidtner et al. (2012)					
	$W^{(1)}$	$W^{(2)}$	$W^{(idw)}$	$W^{(1)}$	$W^{(2)}$	$W^{(idw)}$	$W^{(1)}$		$W^{(2)}$		$W^{(idw)}$	
	y	*y*	*y*	*y*	*y*	*y*	*ys*	*ysl*	*ys*	*ysl*	*ys*	*ysl*
Number of residents per km^2	x	x	x	x	x	x						
Average distance to the next 3 agglomeration centres	x	x	x	x	x	x	n.s.	n.s.	n.s.	n.s.	n.s.	x
Number of organic processors per 10 km^2	x	n.s.	x									
Number of farms (ASE) per km^2	x	x	x	x	x	x						
Mean annual temperature	x	x	x									
Share of votes cast for the Green Party in all valid votes cast	x	x	x	x	x	x	n.s.	x	n.s.	x	n.s.	x
Density of organic food stores							x	x	x	x	x	x
Available household income							n.s.	x	n.s.	x	n.s.	x
Soil climate index							x	x	x	x	x	x
Density of livestock units							x	x	x	x	x	x
Total annual precipitation							x	x	x	x	x	x
Share of nature conservation areas							x	x	x	x	x	x
Dummy north-western Germany (=1)							n.s.	x	n.s.	n.s.	x	x
Constant	n.s.	n.s.	n.s.	x	x	x	x	x	x	x	n.s.	n.s.
ρ	0.439 ***	0.538 ***	0.959 ***	0.360 ***	0.310 *	0.688 **	0.442 ***	0.356 ***	0.594 ***	0.585 ***	0.854 ***	0.808 ***

x indicates statistically significant explanatory variables; *, ** and *** indicate statistical significance of ρ at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

y = dependent variable: *share of organic farms (BLE) in all farms (ASE)*; *ys* = dependent variable *share of organic agricultural area in total UAA; ysl* = logit transformation of *ys: ysl = ln(ys/(1-ys))*

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(idw)}$ = inverse distance weighted neighbourhood matrix

a) Here, we use the full set of variables just at the county level to find the preferable model. These results at the county level (now called 'counties II') are not dependent on the analysis at the community association level.

Source: Authors' own presentation based on BBR (2009), BLE (2009), BLSD (2011), DWD (2007), SAeBL (2010), Schmidtner et al. (2012), SLBW (2010).

3.7 Conclusions

Our study suggests that agglomeration effects do play a role in the organic sector and, hence, supports the findings by Bichler et al. (2005) and Schmidtner et al. (2012). The analysis yields similar results at two spatial resolutions, the community association and county level. The use of aggregated information does not influence the results of the spatial analysis in this case; the results at the lower spatial resolution are not artificially generated through the aggregation process. The study indicates that essential aspects of the decision to convert from conventional to organic farming are sustained at the county level and, thus, strengthen the relevance of the previous studies. To bring the models even closer to the real decision processes of farmers, a promising research approach would be to further increase the spatial resolution and conduct an analysis at the farm level. However, data restrictions do not allow this yet.

The results indicate that certified organic farms are often located in rural areas with low farm density, low mean annual temperature and a high share of voters for the Green Party. The agricultural structure in disadvantaged regions seems to facilitate the conversion to organic agriculture (Dabbert et al., 2004). A favourable social environment might also encourage the decision to convert to organic farming. Institutional, market and communication networks might additionally support the transmission of knowledge about organic farming.

Our case study applies for Bavaria and Baden-Württemberg, where the majority of German organic farms are located. To generalize the conclusions on spatial effects at different spatial resolutions, further analyses have to be conducted.

One issue that could not be considered explicitly is that the varying size of the spatial units might also influence the spatial dependence of neighbouring units (Anselin and Getis, 2010). A promising avenue for future research might be to use uniform raster cells and corresponding aggregated measurement scales as spatial units. At the moment, those data are not available for all explanatory variables used in this study. However, this approach could be implemented in a theoretical study using artificially generated datasets simulating the spatial distribution of organic farming and its explanatory variables.

Our study uses different specifications of the spatial relationship of administrative units. Regarding the determination of the spatial neighbourhood matrix, it would be interesting to take into account additional information such as social network structures or the infrastructure. The selection of the spatial neighbourhood matrix could also be based on a formalized selection procedure as presented in Aldstadt and Getis (2006), Fernandez-Vazquez and Rodriguez-Valzez (2007) and Kostov (2010). According to Kostov (2009) specifying the models by dropping insignificant variables is arguable. Further analyses might also include a formal model comparison as developed by Chib (1995) and Chib and Jeliazkov (2001) and exploit recent advances in Bayesian estimation and model comparison as presented in Holloway and Lapar (2007).

Generally, the consideration and implementation of a time series would deepen the analysis and enable discussions of policy implications on the spatial distribution of organic farming.

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3.9 Annex

Table 3.6 Diagnostic tests for spatial dependence at the county level

	Counties II[a]		
	$W^{(1)}$	$W^{(2)}$	$W^{(idw)}$
LM (spatial error)	7.32 ***	0.97 n.s.	1.72 n.s.
robust LM (spatial error)	0.01 n.s.		
LM (spatial lag)	9.74 ***	4.29 **	5.50 **
robust LM (spatial lag)	2.42 n.s.		

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(idw)}$ = inverse distance weighted neighbourhood matrix

LM = Lagrange Multiplier test

The test results refer to the variables used in the models displayed in Table A2

[a] Here, we use the full set of variables just at the county level to find the preferable model. These results at the county level (now called 'counties II') are not dependent on the analysis at the community association level.

Source: Authors' own calculations based on BBR (2009), BLE (2009), BLSD (2011), SAeBL (2010), SLBW (2010).

Table 3.7 Results of the retained spatial lag models at the county level

	Counties II[a)]		
	$W^{(1)}$	$W^{(2)}$	$W^{(idw)}$
Number of residents per km^2	-0.0059 **	-0.0063 **	-0.0062 **
Average distance to the next 3 agglomeration centres (in min. by car)	0.0728 ***	0.0852 ***	0.0876 ***
Number of farms (ASE) per km^2	-1.9541 **	-2.1171 **	-2.0626 **
Share of votes cast for the Green Party in all valid votes cast (in %)	1.4300 ***	1.5392 ***	1.5540 ***
Constant	-11.9182 ***	-13.5673 ***	-16.5645 ***
ρ	0.3605 ***	0.3101 *	0.6875 **
AIC	656	662	661
BIC	674	680	679

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

$W^{(1)}$ = first order neighbourhood matrix; $W^{(2)}$ = second order neighbourhood matrix; $W^{(idw)}$ = inverse distance weighted neighbourhood matrix

AIC = Akaike information criterion; BIC = Bayesian information criterion

dependent variable: *share of organic farms (BLE) in all farms (ASE) (in %)*

[a)] Here, we use the full set of variables just at the county level to find the preferable model. These results at the county level (now called 'counties II') are not dependent on the analysis at the community association level.

Source: Authors' own calculations based on BBR (2009), BLE (2009), BLSD (2011), SAeBL (2010), SLBW (2010).

Figure 3.5 shows a constructed example of Simpson's paradox similar to the one presented in Fotheringham et al. (2002). The relationship of the share of votes cast for the Green Party in all valid votes cast and the share of organic farms in all farms is expected to be positive due to positive agglomeration effects. It is assumed that voters for the Green Party are generally interested in alternative forms of environmental resource management. A high share of votes cast for the Green Party may form a positive socio-economic environment that supports alternative methods of agriculture such as organic farming (Lakner, 2010). However, Figure 3.5 illustrates that results may reverse, depending on the measurement scale used. While in the example the share of organic farms is positively related to the share of voters for the Green Party if one considers two locations separately, the converse situation results for the aggregated data of both locations, i.e., for aggregated information at a lower spatial resolution.

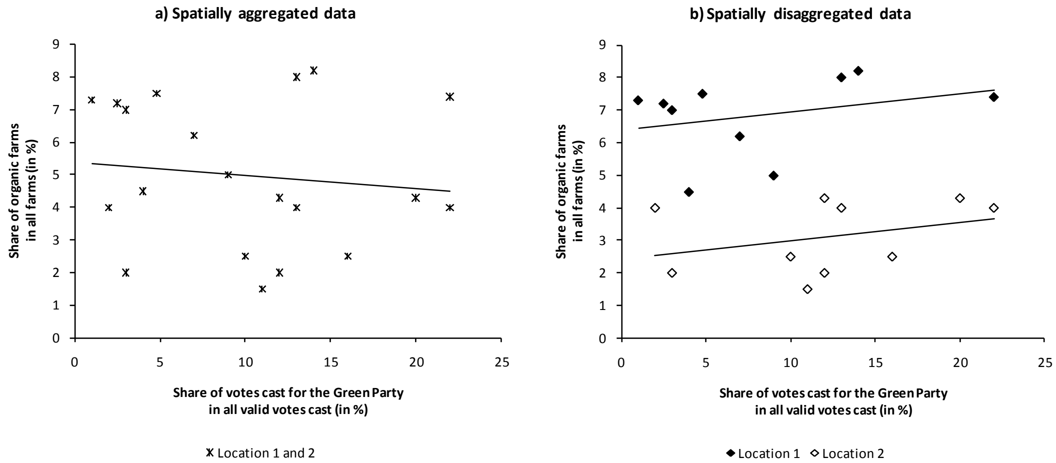

Figure 3.5 Spatial example of Simpson's Paradox

Source: Authors' own presentation based on data generated by the authors.

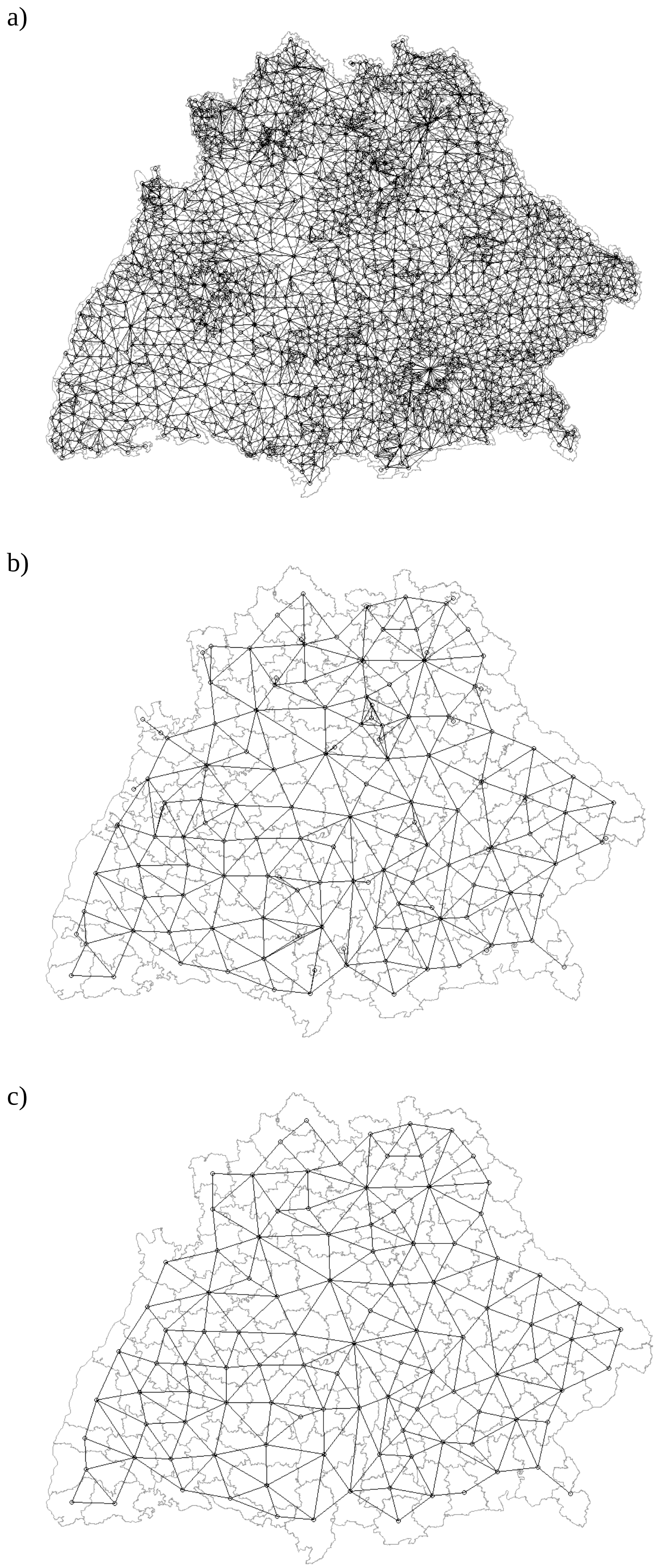

Figure 3.6 Connectivity maps for the first order neighbourhood matrices of a) community associations, b) original counties and c) integrated counties

Source: Authors’ own presentations based on BKG (2010).

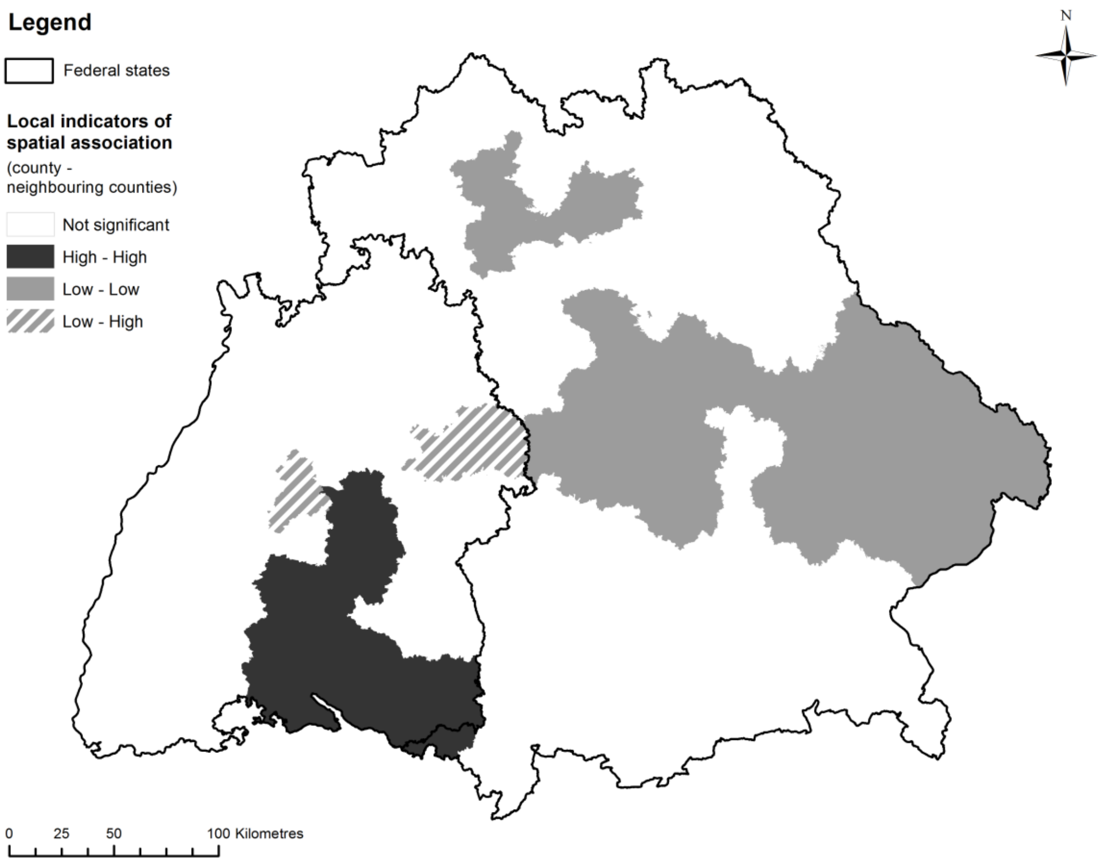

Figure 3.7 LISA cluster map for the share of organic farms at the county level (spatial weight: first order contiguity matrix $W^{(1)}$)

Source: Authors’ own calculations based on BKG (2010), BLE (2009), SAeBL (2010).

4 Do different classifications of soil quality influence the results of a Ricardian analysis? - A case study for Germany

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This manuscript is submitted to: Ecological Economics; date of submission: 12.12.2012.

Abstract

This study assesses the potential impact of future climate change on agricultural land rents in Germany using a Ricardian approach. In addition to including common explanatory variables, we focus on the effects of different indicators of soil characteristics when explaining land rental prices. The analysis is based on data from the official farm census 1999, weather data from the German National Meteorological Service and different soil data bases at the county level. The results of spatial error models indicate higher land rental prices for locations with more productive soils and higher mean annual temperatures. Also a lower land slope, a smaller share of rented land and (in some cases) less spring precipitation increase land rental prices. The method of measuring soil quality does not influence the results of the spatial analysis in our study. To estimate the effects of changing climatic conditions on future land rents, we draw on data from the regional climate model REMO for 2011-2040. Our models show an average land rent increase of 10-17% resulting from the expected changes in temperature and spring precipitation. According to our results future climate change will have an overall positive but spatially heterogeneous impact on the agricultural income in Germany.

Keywords: climate change, land rents, Ricardian analysis, spatial econometrics

Acknowledgement

This publication was generated as part of the DFG-funded research project *'Micro-econometric analysis of climate change effects on the German agriculture: Ricardian analysis and extensions'.* The authors thank Joachim Aurbacher for valuable support in climate data processing.

4.1 Introduction

The increasing concentration of greenhouse gases in the atmosphere due to natural and anthropogenic causes will change the climate around the world. This climate change will especially impact climate-sensitive systems, such as agriculture, and thus affect the productivity and the profitability of agricultural production. The IPCC (Intergovernmental Panel on Climate Change) expects an increase in the mean temperature of Europe of 2.1°C to 5.3°C by the end of the 21st century and an increase in precipitation in northern Europe (IPCC, 2007a). As shown in Figure 4.1, the predicted changes in the mean annual temperature and the spring precipitation are distributed unevenly within Germany, the country analysed in this study.

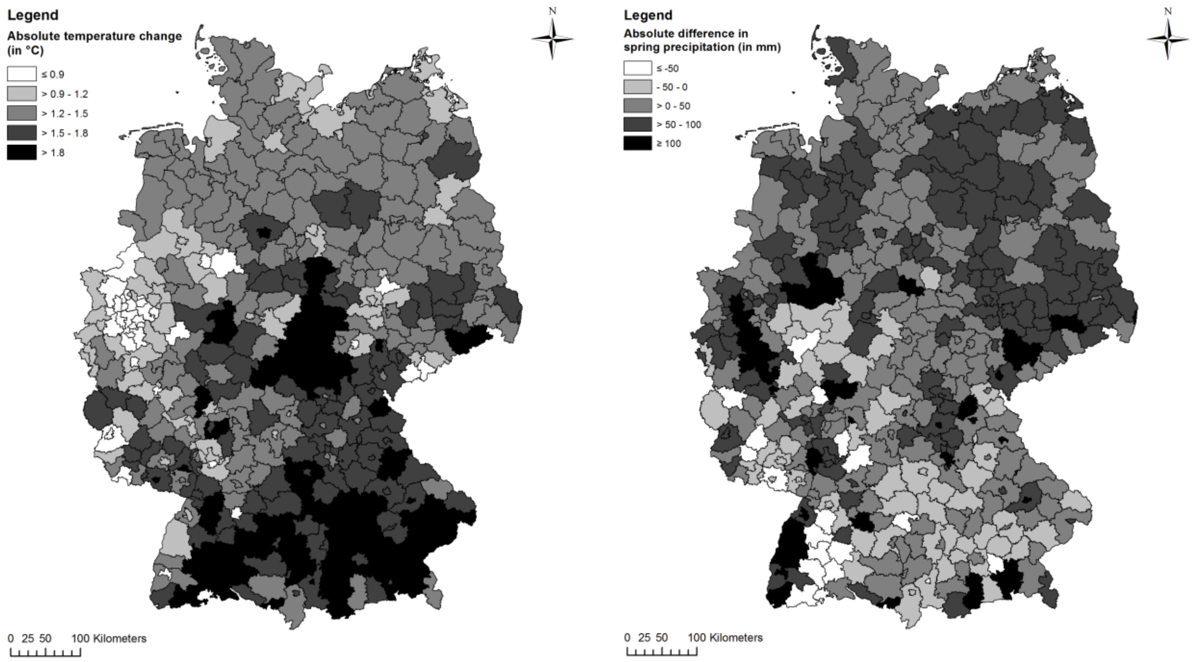


Figure 4.1 Predicted changes in mean annual temperature and spring precipitation 2011-2040 (IPCC scenario A1B), compared to mean annual temperature and spring precipitation 1961-1990[8]

Source: Authors' own presentation based on BKG (2010), DWD (2007), MPI on behalf of the Umweltbundesamt (2006).

Because the projected climate change will not be evenly distributed in space, the agronomic and economic impacts of the projected change will vary across regions depending on the existing climatic, agronomic and political conditions (Henseler et al., 2009). For example, Supit et al. (2010) found that changing climatic conditions, such as temperature and radiation, increased the yield potential of several crops in the UK and some regions in northern Europe over the time period 1976-2005, but potential crop yields in southern central Europe decreased. To assess the potential impact of future climate change on the value of agricultural land in Germany, we use a Ricardian approach (Mendelsohn et al., 1994).

The Ricardian approach is a cross-sectional approach named after the English economist David Ricardo (1772-1823), who stated that the net productivity of farmland is reflected by land rents

[8] for detailed information on underlying data and data processing see section 4.4

(Mendelsohn and Reinsborough, 2007). Corresponding to the hedonic pricing of environmental attributes, the Ricardian approach is used to explain the impact of climate and other variables on the value of agricultural land (cf. Mendelsohn et al., 1994; Mendelsohn and Reinsborough, 2007; Polsky, 2004; for applications for Germany: Lang, 2007; Lippert et al., 2009). In response to changing climatic conditions, farmers can adapt their agricultural activities by cultivating different crops or changing livestock species (Seo and Mendelsohn, 2008; Seo et al., 2010). Thus, '[...] spatial variations in climate result in varying land uses and consequently land values' (Polsky and Easterling, 2001:135). In Germany, land rental prices are distributed unevenly in space (see also Figure 4.2a). High rental prices for agricultural land can be found in the north-western and the south-eastern parts of Germany, whereas regions in eastern Germany are characterised by low land rental prices (cf. Doll, 2001; Magrarian, 2008). In addition to common factors that determine agricultural production, such as climate and soil, several other factors influence farmland rental prices. Feichtinger and Salhofer (2011) defined two major groups of influencing factors: internal (agricultural) variables and external variables. In addition to the common agricultural production factors, Feichtinger and Salhofer (2011) refer to governmental payments, such as the direct payments from the Common Agricultural Policy (CAP), as internal variables that affect the rental prices of farmland. As external influencing factors, they consider variables describing the market (e.g., farm density), macroeconomic factors and urban pressure indicators (e.g., population density) (cf. Feichtinger and Salhofer, 2011). Furthermore, a high density of livestock increases land rental prices in Germany (Breustedt and Habermann, 2011; Habermann and Ernst, 2010). Nowadays, nearby biogas plants also have a positive influence on land rental prices (Habermann, 2009; Plumeyer and Emmann, 2010).

Two studies use a Ricardian approach to analyse land rents in Germany. Lang (2007) estimated the economic impact of global warming on agriculture with a panel data set for the time period 1990-1994 that includes weather data and information on farmers in western Germany. He found that '[...] German farmers will be winners of climatic change in the short run, with maximum gains occurring at a temperature increase of +0.6°C against current levels' (Lang, 2007: 423). He predicted a negative impact on the agricultural sector in the event of a future temperature increase greater than 1°C. Lippert et al. (2009) implemented a spatial error model to assess the economic impact of climate change on German agriculture. They draw on 1999 data from the agricultural farm census and German weather data and found increasing land rental prices in regions with a rising mean temperature and declining spring precipitation (the latter except for eastern Germany). The results of simulations under three IPCC scenarios suggest that the land rental prices will increase, so German agriculture will benefit from climate change. However, the extent of such benefits is distributed unevenly in space.

Lang (2007) and Lippert et al. (2009) both indicate a positive impact of climate change on German agriculture but neglect important production factors, such as the quality of the soil. We intend to advance these previous Ricardian approaches. In addition to the explanatory variables used previously, we compare the effects of different classification systems of soil quality on the land rental prices and consider a land slope variable. We use the original micro data of the German agricultural census of 1999 provided by the FDZ der Statistischen Ämter des Bundes und der Länder (2000) for our analysis and thus do not need to estimate the missing values for several German counties, as in Lippert et al. (2009). Furthermore, we implement additional tests, such as the (robust) Lagrange Multiplier test for spatial autocorrelation in the residuals from the OLS model. We additionally define two different neighbourhood structures to examine the stability of our results. Thus, compared to Lang (2007) and Lippert et al. (2009), we account for additional factors of agricultural production, such as the average soil characteristics (including farmland slope), and implement refined econometric methods to deepen the understanding of future climatic impacts on the profitability of agricultural land in Germany.

4.2 Theoretical considerations

In this study, we assess the effects of different methods of accounting for soil quality in a Ricardian analysis of German land rental prices. Controlling for soil quality is of particular relevance because the existence of any correlation between an omitted variable and one of the variables explaining land value will lead to biased results. For example, if soil quality is positively correlated with temperature but not considered as explanatory variable, the effect of the former explanatory variables on the land rent will be overestimated. Thus, we include soil quality and land slope as explanatory variables in our analysis.

Several indicators of soil quality are available. We use three approaches to control for soil quality and test the appropriateness of different soil data bases for an analysis at a relatively high spatial resolution, such as the county level. One source of global soil information is the Digital Soil Map of the World (DSMW) (cf. FAO, 2003), which is frequently used by scientists all over the world. However, its original low spatial resolution (1:5 million scale) may not be suitable for all analyses, such as those at a more detailed spatial scale. In contrast, a unique regional classification system for the productive capacity of the agricultural land in Germany is available at a relatively high spatial resolution. The quality of farmland was defined all over Germany starting in 1934 to harmonise taxation in the former German empire (‘Reichsbodenschätzung’). The resulting soil index (‘Bodenzahl’) represents a measure of the productivity of agricultural land. The index ranges from 7 (lowest yield potential) to 100 (best yield potential) and was generated based on the geological development and the state of development of the parent material of the soils. As a third data source, we consider the German soil database (‘Bodenübersichtskarte’) that indicates the parent materials of the soils. Additionally, the slope of the farmland plays a role in terms of land cultivation, as a steep land slope can hamper the use of heavy machinery or sometimes exclude the cultivation of certain crops, such as maize.

The basic assumption of the Ricardian approach is that climatic factors, such as temperature or precipitation, influence the rental price of farmland. In Germany, spring precipitation between March and June affects the main growth phase of arable crops and thereby strongly determines the yield and quality of agricultural production. Late precipitation during the harvesting season is less important and is therefore not considered in our analysis.

Lippert et al. (2009) implemented a dummy variable east indicating two aspects that differ between eastern and western German: the agricultural structure such as the share of rented land and the natural production conditions such as precipitation (see also Table 4.1). In eastern Germany the share of rented land is relatively high, so (ceteris paribus) lower land rental prices are expected in eastern regions due to theoretical considerations. On the other hand, the effect of precipitation in eastern Germany is supposed to be positive because of large areas with sandy soils. When using the dummy variable east, these two aspects cannot be interpreted separately.

To separately account for the unequal agricultural structures between the German regions, we consider the share of rented land. The amount of rented land in a region might affect the land rental price. If only a low share of farmland is rented, the shadow prices of the land (marginal land rental prices) can be paid by the tiller, neglecting the fixed costs of the farm. Furthermore, given a low farm density and large farm size, which is often the case in eastern Germany, the demand for rented farmland might be determined by only a few farmers. In some regions, this could lead to a nearly monopsonistic situation in the land rental market. The effect of precipitation in relatively dry regions is explicitly considered by means of specific dummy variables (see supplementary analyses in section 4.5).

Some studies (Breustedt and Habermann, 2011; Habermann and Ernst, 2010) indicate that a high density of livestock increases German land rental prices. However, animal husbandry may be one opportunity to adapt to future climate change, so we do not include a corresponding proxy variable in our analysis.

4.3 Econometric model

An analysis of the spatially heterogeneous impact of climate change on land rental prices may require spatial models (cf. Anselin, 1988:34ff.; LeSage, 1999:52f.) to obtain unbiased and efficient estimates. The general version of our model is given by

$$y = \rho W y + X\beta + u \tag{4.1}$$

$$u = \lambda W u + \varepsilon \tag{4.2}$$

with $\varepsilon \sim N(0, \sigma^2 I_N)$

and

y = vector containing the land rental prices in the year 1999 for the 440 German counties ($i = 1, \ldots, 440$);

X = matrix containing the observations for g independent climate and non-climate variables at the county level (cf. section 4.4);

W = standardised spatial weight matrix;

I_N = identity matrix;

u = vector of spatially correlated residuals;

ε = vector of errors assumed to be normally distributed;

β = vector containing the regression coefficients for the explanatory variables;

ρ = spatial lag coefficient reflecting the importance of spatial dependence;

λ = coefficient reflecting the spatial autocorrelation of the residuals u_i.

The regression coefficients β and, if considered relevant, the spatial lag coefficient ρ and the spatial error coefficient λ are the parameters to be estimated. A significant spatial lag coefficient ρ indicates spatial dependency; a significant spatial error coefficient λ reflects the existence of one or more spatially correlated omitted explanatory variables (i.e., spatial heterogeneity).

In principle, there are four possibilities:

(i) $\rho = \lambda = 0$ (common OLS model);

(ii) $\rho \neq 0$, $\lambda = 0$ (spatial lag model);

(iii) $\rho = 0$, $\lambda \neq 0$ (spatial error model) and

(iv) $\rho \neq 0$, $\lambda \neq 0$ (mixed spatial model).

Theoretical considerations indicate that the spatial error coefficient λ may be more important for the regional distribution of land rental prices. Due to data restrictions, it is likely that we do not consider all relevant explanatory variables. If at least one omitted explanatory variable is correlated with different locations in space this will result in spatial autocorrelation of the residuals. In this context, direct payments from the CAP or the distance to markets might matter. The hypothesis that agglomeration effects (capture by a spatial lag coefficient), e.g., due to direct communication between farmers play a role for land rental prices appears to be of less importance. However, we draw on the (robust) Lagrange Multiplier test (Anselin et al., 1996) to statistically determine the importance of the two effects.

To examine the stability of the estimation results under different specifications of the relationship of spatial units, two alternative spatial neighbourhood matrices are used: a first order contiguity matrix ($W^{(1)}$) and an inverse distance-based matrix ($W^{(idw)}$) (cf. Anselin, 1988; LeSage, 1999). For $W^{(1)}$, all adjoining counties are considered; $W^{(idw)}$ contains the row-standardised inverse distances of each centroid of county $j \neq i$ to the centroid of county i measured in meters. For the analysis we use the programs GeoDa and Stata along with additional routines provided by Jeanty (2010a, b, c, d) and Pisati (n.a.).

4.4 Data and variable construction

The analysis is conducted at the NUTS 3 level (NUTS being the Nomenclature of Territorial Units for Statistics, established by Eurostat). Information on agriculture is obtained from the official German farm census (FDZ der Statistischen Ämter des Bundes und der Länder, 2000). To control for soil quality, different soil data bases (BGR, 2007a; FAO, 2003; Forschungszentrum Jülich, 2009) are used. The slope of the land is generated based on digital elevation data (Jarvis et al., 2008). We describe climatic conditions by drawing upon weather data from the German National Meteorological Service for the time period 1961-1990 (DWD, 2007) and data from the regional climate model REMO for the time period 2011-2040 (MPI on behalf of the Umweltbundesamt, 2006). Detailed information on the data and the variables used is given below.

Of all the different agricultural data sources available, the data provided by the official German farm census is the most useful. We base our analysis on the original data from the farm census in 1999 (FDZ der Statistischen Ämter des Bundes und der Länder, 2000). The 1999 data are the most recent available to us; more recent data from 2010 will be available in the future. Generally, the farm census contains information on all German farms that are above certain thresholds. The farm census from 1999 includes, for example, only farms managing more than 2 hectares of utilised agricultural area (UAA) and a certain number of animals. For the year 1999 information on 471,960 German farms managing more than 17 million hectares is available. As we do not have detailed spatial information on single farms (we only know the county in which each farm is located), we aggregate the data to a lower spatial resolution, the county level. Thus, the analysis is conducted with the mean values for the 440 German counties.

As dependent variable, we use the average (acreage-weighted) *land rental price* per hectare (FDZ der Statistischen Ämter des Bundes und der Länder, 2000) calculated for farms with rental farmland. In 1999, the average land rental price was approximately 183 € per ha UAA. Rental prices tend to be lower for grassland compared to arable land, so we account for the s*hare of grassland* in the total UAA.

The proxy variable *share of rented land* (FDZ der Statistischen Ämter des Bundes und der Länder, 2000) is used as indicator of the demand for and resulting prices of rental farmland. As shown in Table 4.1, the share of rented farmland differs considerably between western and eastern Germany.

Table 4.1 Mean values for variables of interest at the county level

	year	Germany (N=440)	western Germany (N=327)	eastern Germany (N=113)
land rental price (in € / ha UAA[a])	1999	183.02	212.06	98.99
soil index	1981, 1986	46.11	46.96	43.66
land slope (in %)	2008	1.75	1.85	1.48
spring precipitation (in mm)	1961-1990	269.62	287.18	218.83
spring precipitation scenario A1B (in mm)	2011-2040	314.14	326.70	277.80
spring precipitation scenario A2 (in mm)	2011-2040	325.49	341.23	279.95
spring precipitation scenario B1 (in mm)	2011-2040	301.99	314.96	264.45
mean annual temperature (in °C)	1961-1990	8.42	8.51	8.17
mean annual temperature scenario A1B (in °C)	2011-2040	9.86	9.93	9.66
mean annual temperature scenario A2 (in °C)	2011-2040	9.97	10.04	9.73
mean annual temperature scenario B1 (in °C)	2011-2040	9.82	9.90	9.59
share of rented UAA in UAA[a]	1999	0.58	0.47	0.88
share of grassland in UAA[a]	1999	0.32	0.35	0.23

Due to data protection legislation minimum and maximum values of the variables cannot be presented.

[a] UAA = utilised agricultural area

Source: Authors' own calculations based on BGR (2007a), DWD (2007), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Jarvis et al. (2008), MPI on behalf of the Umweltbundesamt (2006).

We consider indicators of soil quality and the mean slope of the land within the counties, as these variables are expected to have an influence on land rents. We use three approaches to control for soil quality. The natural soil quality is described by different proxy variables: the *soil index* (kindly provided by Forschungszentrum Jülich, 2009), a dummy variable for the parent materials of the soils given in the German soil database (BGR, 2007a), and two dummy variables derived from the Digital Soil Map of the World (DSMW) (FAO, 2003). Using zonal statistics, the mean value of the soil index is assigned to each county. For the German soil database and the DSMW, the dominant soil class is assigned to each county; only information on agriculturally managed land, as indicated by the German soil database (BGR, 2007b), is considered. From the German soil database, we select the *dummy variable loess*, as loess tends to develop into highly productive soils. From the DSMW, we account for the two most frequent soil classes at the county level in Germany: *dystric cambisols*, representing less productive soils, and *orthic luvisols*, indicating land with good soil quality. Figure 4.4 (Annex) shows the spatial distribution of soil quality based on the different data sources. All three maps indicate that highly productive soils are located in central and south-eastern Germany; orthic luvisols are additionally found in north-eastern Germany. The variable *land slope* (expressed as a percentage) is generated based on altitudes given by the SRTM (Shuttle Radar Topography Mission) digital elevation data (Jarvis et al., 2008) originally produced by NASA. Again, only information on agricultural land (BGR, 2007b) is considered. The resulting grid is used to calculate zonal statistics and assign corresponding mean values to the counties.

For this analysis, we use weather data from the German National Meteorological Service for the time period 1961-1990 (DWD, 2007). We assume that the weather stations located on mountains are above the agricultural area of the region and, thus, do not reflect the conditions for agriculture; therefore, we neglect all weather stations with an altitude above 1,500 m. As a result, 4,742 stations for precipitation and 663 stations for temperature are used to interpolate the observations spatially. The mean annual *temperature* and average sum of *spring precipitation* (March - June) are generated for all counties using an inverse distance weighted interpolation with the power of one and including the five nearest locations at an output raster cell size of 200 m. The corresponding mean values are then assigned to the county level using zonal statistics. We additionally consider the quadratic terms of the two climate variables in our analysis.

To estimate the potential impact of climate change on future land rents, we draw on IPCC data from the regional climate model REMO (MPI on behalf of the Umweltbundesamt, 2006), which is used for weather forecasting and climate simulation (Jacob, 2001; UBA, 2006). We consider three storylines representing different demographic, social, economic, technological and environmental developments (IPCC, 2007b). The IPCC storyline A1B describes a future world with rapid economic growth, a global population that peaks in the middle of this century and a balanced use of fossil and non-fossil energy resources. The A2 storyline describes a very heterogeneous future world: the global population increases continuously, and economic development is primarily regionally oriented. Per capita economic growth and technological change in this storyline are slower than in other storylines. Storyline B1 describes a convergent future world with the same global population growth as in A1B and a rapid change in economic structures towards a service and information economy with a reduction in material intensity and the introduction of low-emission, resource-efficient technologies. To allow for comparability with previous studies, we replicate the data processing method for the scenario period 2011-2040, as described in Lippert et al. (2009). We include all data points below 1,000 m and generate mean values of mean annual *temperature* and sum of *spring precipitation* (March - June) for all counties at a raster cell size of 1,000 m using an inverse distance weighted interpolation with the power of two and including the twelve nearest locations (cf. Lippert et al., 2009).

4.5 Results and discussion

In this section, we present the results for the first order neighbourhood matrix $W^{(1)}$; the corresponding main results for the distance-based neighbourhood matrix $W^{(idw)}$ are shown in the Annex.

As presented in Table 4.4 (Annex), our data show significant correlations between the grassland share and the following variables: spring precipitation (0.61), mean annual temperature (-0.36) and land rental prices (-0.28). Furthermore, some of the indicators of soil quality are significantly correlated with climate variables. Thus, we determine two models considering either spring precipitation (model I) or the share of grassland (model II) as explanatory variables. Additionally, there are three specifications of both models (a, b, c) that account for the three data sources of soil quality.

The spatial models (equations 1 and 2) are estimated using the maximum likelihood method. The quadratic terms of temperature and spring precipitation never show significant influences in our analysis and are removed from the models. For the retained explanatory variables considered in the models I and II (see Table 4.2), the results of the Lagrange Multiplier test suggest using spatial lag or spatial error models as appropriate models. Based on our theoretical considerations regarding the importance of spatial effects in the case of German land rental prices, the spatial error model is preferable for considering spatial autocorrelation and testing our hypotheses. However, the residuals of the spatial models do not pass a Shapiro-Wilk test for normal distribution which may be partly due to outliers (see Figure 4.5 in the Annex).

Table 4.2 (see also Table 4.5, Annex) presents the results of the spatial error models. Regarding R^2, the models using the soil index as an independent soil variable perform the best. To further analyse the performance of models considering different definitions of the spatial neighbourhood structure, we calculate the Bayesian information criterion (BIC). The models using the first order neighbourhood matrix ($W^{(1)}$) show smaller BIC values than the models using the inverse distance-based neighbourhood matrix ($W^{(idw)}$). A BIC difference of at least 10 provides strong evidence that one model fits the data better than another (Raftery, 1995), so the models accounting only for adjoining neighbours ($W^{(1)}$) are the preferable models.

Table 4.2 Results of the spatial error models (spatial neighbourhood matrix: $W^{(1)}$)

	models[a]					
	Ia	Ib	Ic	IIa	IIb	IIc
soil index	2.30 ***			1.73 ***		
dummy loess (=1)		26.07 ***			14.22 ***	
dummy dystric cambisol (=1)			-16.83 ***			-13.64 **
dummy orthic luvisol (=1)			17.72 ***			12.61 **
land slope (in %)	-17.10 ***	-17.68 ***	-15.32 ***	-10.46 ***	-10.70 ***	-8.94 **
spring precipitation (in mm)	-0.12 n.s.	-0.20 **	-0.23 ***			
temperature (in °C)	22.14 ***	25.92 ***	23.89 ***	12.50 ***	14.88 ***	12.87 ***
share of grassland				-141.28 ***	-160.29 ***	-164.65 ***
share of rented land	-220.40 ***	-198.61 ***	-210.73 ***	-216.43 ***	-199.35 ***	-206.41 ***
constant	77.47 n.s.	155.01 **	188.20 ***	187.48 ***	242.65 ***	264.96 ***
lambda	0.78 ***	0.84 ***	0.82 ***	0.82 ***	0.85 ***	0.84 ***
R^2	0.67	0.54	0.56	0.66	0.56	0.59
BIC	4625.51	4671.27	4678.32	4556.63	4593.40	4591.77

[a] Either spring precipitation (model I) or the share of grassland (model II) is considered to be an explanatory variable.
Additionally, there are three specifications of both models (a, b, c) accounting for three different data sources of soil quality.
*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant
R^2 = square of the correlation coefficient between the observed and predicted data values without adjustment of the error term
BIC = Bayesian information criterion

Source: Authors' own calculations based on BGR (2007a), DWD (2007), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Jarvis et al. (2008).

It is remarkable that the spatial error coefficient is highly significant for all the model alternatives. This indicates the possible existence of at least one variable that is correlated with different locations in space and determines land rental prices besides the significant variables shown in Table 4.2. For instance, such factors could be direct payments from the CAP or distances to input and output markets. Unfortunately, the corresponding data are not available for this analysis.

With the exception of the dummy variables orthic luvisol and dystric cambisol (model IIc, $W^{(1)}$), all soil indicators show highly significant results. As expected, productive soils, such as loess or soils with a higher soil index, increase the land rental prices significantly, whereas less productive soils, such as dystric cambisols, show a negative influence. The different definitions of soil quality do not influence the results of the spatial analysis in this case. Furthermore, as expected, an increasing average slope of a county's farmland decreases land rental prices.

A high share of rented land shows a significant negative influence in our models. We assume that an increased share of rented land indicates higher competition for farmland.

Regarding the climate variables as well as the variable share of grassland, all models indicate similar results. Increasing spring precipitation (models I) or grassland share (models II) reduces the rental prices for agricultural land. Rental prices tend to be lower for grassland compared to arable land, so it is likely that the variable share of grassland is an endogenous variable. In Germany, a decline in spring precipitation and an increase in temperature both reduce the grassland share. The models I implicitly allow for the adaptation of the grassland share. The transformation of grassland to arable land is currently restricted by the cross-compliance requirements that farmers must fulfil to receive direct CAP payments. However, this restriction might be changed in the future.

When comparing these findings to the study by Lippert et al. (2009), accounting for soil quality and land slope does not remarkably influence the results. The effect of spring precipitation is slightly lower in our models. This effect might be due to the in our case not included slope dummy variable east that indicated a positive influence of spring precipitation in eastern Germany (Lippert et al., 2009).

To estimate the effects of changing climatic conditions on future land rents, we draw on the climate data from the IPCC scenarios. The three selected scenarios (A1B, A2, B1) assume different future climatic conditions. Scenario B1 presents the lowest increase in average temperature (+1.40°C) and in spring precipitation (+32 mm), and scenario A2 describes large changes in climate variables (temperature: +1.55°C; spring precipitation: +56 mm) at the county level (see Table 4.1). A moderate climatic development is characterised by scenario A1B. Table 4.3 shows the estimated additional land rents, which increase in all scenarios and model alternatives. With the exception of model Ic the highest increase in total land rent can be found in scenario A2, which shows the highest increase in temperature and spring precipitation. The effect of spring precipitation is less clear when comparing different models; the agricultural profit mainly depends on the temperature increase. Our models show that the weighted average rent increase amounts to 10-17% of the average land rent in 1999. Under a moderate development scenario (scenario A1B) with an average temperature increase of 1.44°C, land rent will rise by 18-31 €/ha UAA and lead to an additional 316-533 million € of land rent. Our results suggest an overall positive impact of climate change on German agriculture, similar to the results in Lippert et al. (2009).

Table 4.3 Estimated additional land rent

		Total additional land rent (in million €)[a]			Weighted average rent increase (€ / ha)[b]		
		A1B	A2	B1	A1B	A2	B1
VG	model Ia	478.93	496.12	479.12	27.92	28.93	27.93
	model Ib	521.93	532.72	531.94	30.43	31.06	31.01
	model Ic	451.11	453.87	467.83	26.30	26.46	27.28
CG	model IIa	316.02	336.73	304.61	18.43	19.63	17.76
	model IIb	376.31	400.98	362.72	21.94	23.38	21.15
	model IIc	325.58	346.92	313.83	18.98	20.23	18.30
VG	Lippert et al. (2009)	611.90	597.81	623.14	35.66	34.84	36.32
CG	Lippert et al. (2009)	568.59	599.17	527.21	33.14	34.92	30.73

[a] Total estimated land rent increase for Germany = Σ_i (UAA_i × (difference between the estimated land rent after climate change and the estimated land rent in 1999) for the 440 German counties (i = 1, ..., 440)), for models I and II using the spatial neighbourhood matrix $W^{(1)}$ cf. Table 2

[b] The utilisable agricultural areas (UAA_i) of the counties are used as weights

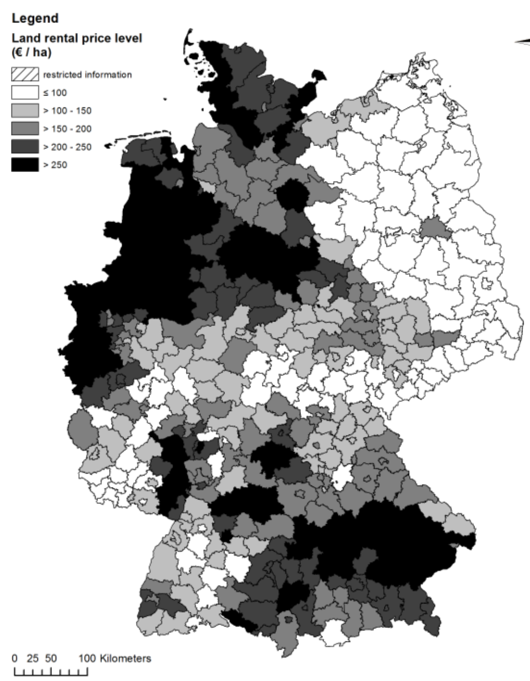
VG = variable grassland: grassland is allowed to be converted into arable land

CG = constant grassland: shares of grassland are to be kept constant

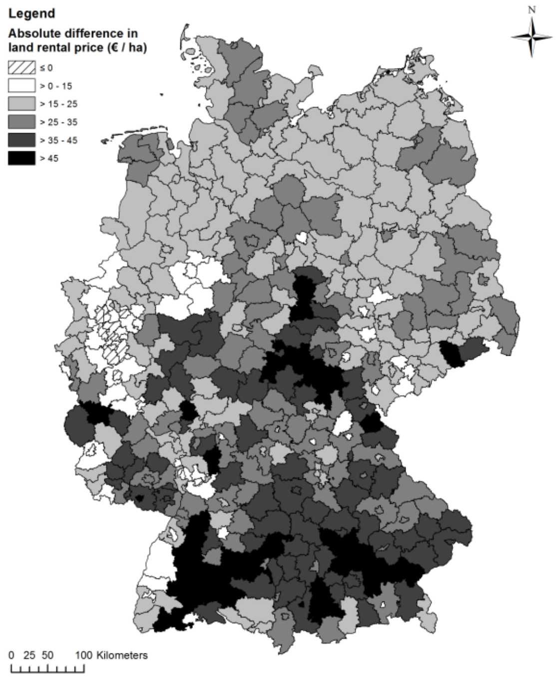
Source: Authors' own calculations based on BGR (2007a), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Lippert et al. (2009), Jarvis et al. (2008), MPI on behalf of the Umweltbundesamt (2006).

The spatial distribution of land rent changes is shown in Figures 4.2b-d and 4.3b-d. These figures present the differences between the estimated future land rents and the estimated land rents in 1999, considering the soil index as indicator of soil quality (models Ia and IIa). Both models indicate that the land rental prices increase from northern to southern Germany, particularly in model I due to the predicted future temperature increase, which shows the same geographic tendency (see Figure 4.1). For some western regions with a high increase in spring precipitation, model I shows decreasing land rents. Thus, we support the spatially heterogeneous findings by Lippert et al. (2009). However, not accounting for a dummy variable east, our models do not indicate a strong increase in rental prices in eastern Germany. Due to the presently unfavourable climatic water balance, a rise in spring precipitation (see Figure 4.1) could have a positive impact on the land rents in eastern Germany. Thus, we consider additional dummy variables indicating extreme precipitation (extreme dry conditions) or low spring precipitation and less productive soils in supplementary analyses. However, these model alternatives do not yield significant results. This is probably due to an insufficient number of corresponding observations.

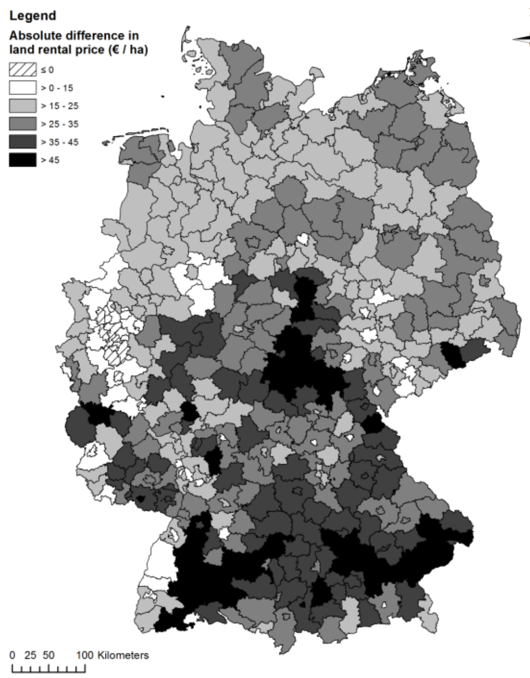
To analyse the dispersion of land rents at the county level, we calculate the coefficient of variation using the unweighted average of farms' land rental prices by county (Figure 4.6, Annex). In large parts of northern and south-eastern Germany, the prices for rental farmland are similar within a county. However, other regions show the opposite situation. To account for such heterogeneous land rental prices within a county, an increase in the spatial resolution would certainly deepen the analysis. Unfortunately, such data are not available for this study.



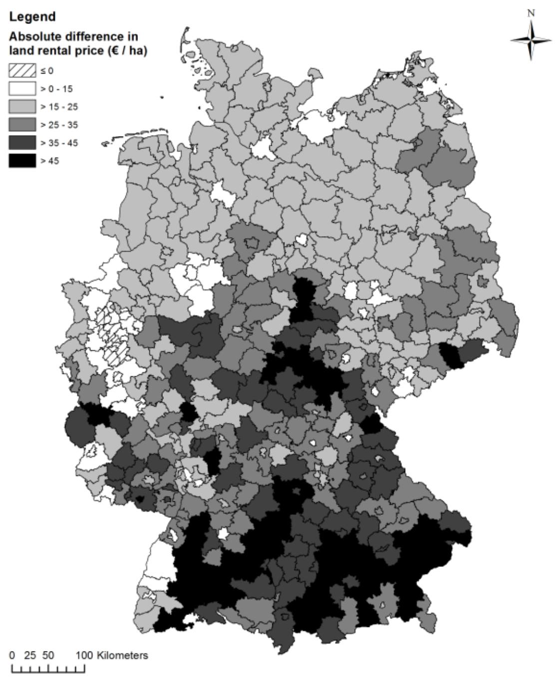
a) Reference: Average land rents (1999)



b) Average land rent changes (scenario A1B)



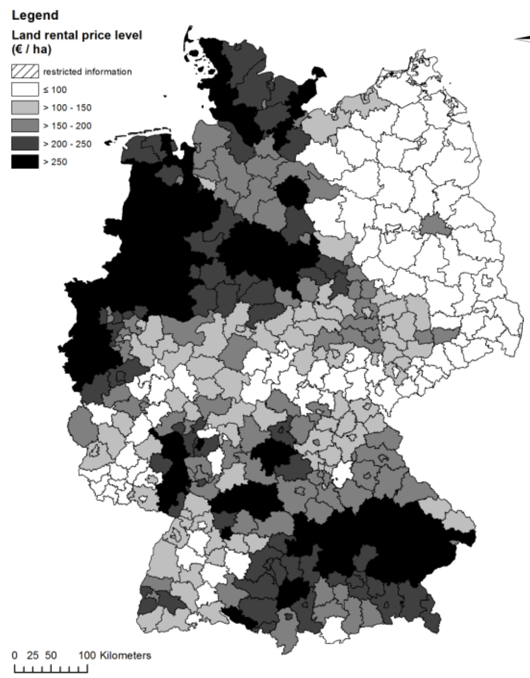
c) Average land rent changes (scenario A2)



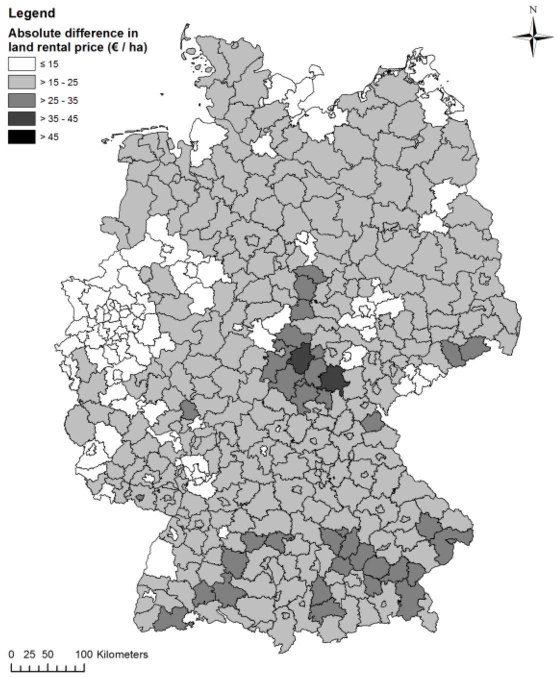
d) Average land rent changes (scenario B1)

Figure 4.2 Average land rents in 1999 and predicted land rent changes for three IPCC climate scenarios (2011-2040) by county (model Ia, spatial neighbourhood matrix: $W^{(1)}$)

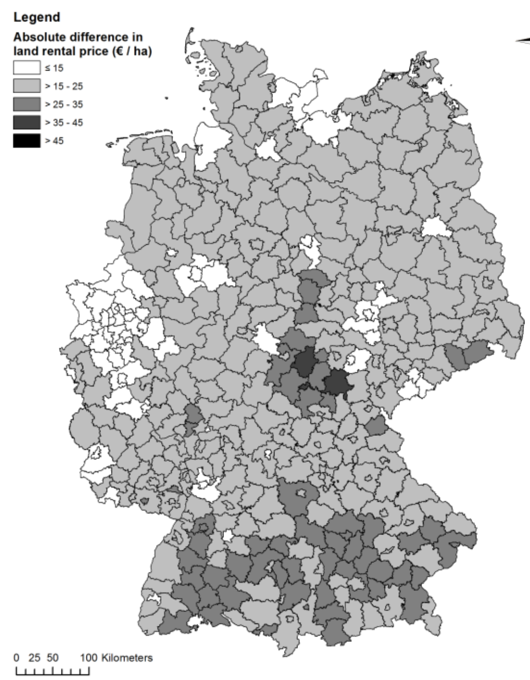
Source: Authors' own presentations based on BGR (2007a), BKG (2010), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Jarvis et al. (2008), MPI on behalf of the Umweltbundesamt (2006).



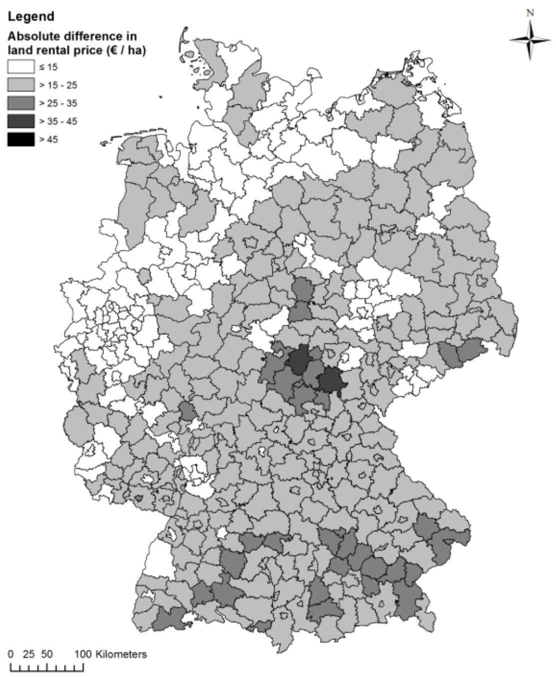
a) Reference: Average land rents (1999)



b) Average land rent changes (scenario A1B)



c) Average land rent changes (scenario A2)



d) Average land rent changes (scenario B1)

Figure 4.3 Average land rents in 1999 and predicted land rent changes for three IPCC climate scenarios (2011-2040) by county (model IIa, spatial neighbourhood matrix: $W^{(1)}$)

Source: Authors' own presentations based on BGR (2007a), BKG (2010), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Jarvis et al. (2008), MPI on behalf of the Umweltbundesamt (2006).

4.6 Conclusions

In Germany, the rental prices for agricultural land are determined by climate and non-climate factors. Natural production factors, such as soil quality, land slope, spring precipitation and temperature, show significant influences on the land rental prices in our models. Additionally, the agricultural structure, such as the share of rented land, which is distributed quite unevenly within Germany, plays a role. The use of different data sources for soil quality (including worldwide soil data at a low spatial resolution and unique German soil data at a more detailed spatial resolution) and spatial neighbourhood matrices yield similar results. Thus, the definitions of the spatial neighbourhood matrices tested here and the method to account for soil quality do not influence the results of the Ricardian analysis in this case. The relevance of spatial error models established by the Lagrange multiplier test hints at a minimum of one additional explanatory variable that is correlated with different locations in space and determines land rental prices in addition to the significant variables found here. In this context, livestock density, direct CAP payments or distances to markets might matter. As indicated by the coefficient of variation, the land rental prices are quite heterogeneous within counties. Thus, an increase in the spatial resolution would certainly deepen the understanding of future climatic effects on agriculture. Unfortunately, such data are not available for this study. Furthermore, a new German agricultural census has been conducted in the year 2010. These new data will be a promising area for research, particularly for repeating our estimation.

To project the future impact of climate change on agricultural productivity, we draw on three IPCC scenarios for the time period 2011-2040. The future climatic conditions for agricultural production will vary by geographic location. Our models show a weighted average increase in land rents of 10-17% compared to the reference situation in 1999 and indicate an increase in land rents. The increments of land rental prices will increase from northern to southern Germany. Thus, we support the findings of Lippert et al. (2009) that indicate that future climate change will have an overall positive but spatially heterogeneous impact on the income from agricultural land in Germany. As also indicated by Lang (2007), German farmers will gain from climate change in the short run. However, in the event of more severe climatic changes and a higher frequency of extreme weather events, income losses for German farmers cannot be excluded.

In response to changing economic and environmental conditions, farmers usually make adaptations (Mendelsohn et al., 1994). We do not consider adjustments, such as the introduction of new technologies. This omission leads to an underestimation of the real development of rental prices for agricultural land. German farmers may additionally benefit from increasing world market prices due to increasingly unfavourable production conditions in other regions of the world. In contrast, our models may overestimate the real development of land rental prices because farmers will have adjustment and transaction costs due to climate change adaptation.

Nowadays, irrigation is of little importance in German agriculture, so our estimations apply to rain fed farmland. However, irrigation might be used to mitigate climate change damages in increasingly dry districts in the future. Then, different regression equations should be considered for irrigated areas and non-irrigated farmlands (see e.g., Schlenker et al., 2005; Fleischer et al., 2008).

4.7 References

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4.8 Annex

Table 4.4 Correlation matrix for variables of interest

	land rental price	soil index	dummy loess (=1)	dummy dystric cambisol (=1)	dummy orthic luvisol (=1)
land rental price	1				
soil index	0.4952 *	1			
dummy loess (=1)	0.2644 *	0.5992 *	1		
dummy dystric cambisol (=1)	-0.4427 *	-0.4091 *	-0.2285 *	1	
dummy orthic luvisol (=1)	0.3060 *	0.4304 *	0.3255 *	-0.4313 *	1
land slope	-0.3274 *	-0.0764	-0.0131	0.3144 *	-0.1445
spring precipitation	0.0240	0.0539	-0.1196	-0.0158	0.2268
mean annual temperature	0.3724 *	0.2104 *	0.1445 *	-0.1030	0.0811
share of grassland	-0.2788 *	-0.2660 *	-0.3814 *	0.1553 *	-0.1039
share of rented land	-0.5160 *	-0.0538	0.1147	0.2145 *	-0.1032

	land slope	spring precipitation	mean annual temperature	share of grassland	share of rented land
land slope	1				
spring precipitation	0.5040 *	1			
mean annual temperature	-0.4378 *	-0.3244 *	1		
share of grassland	0.3466 *	0.6105 *	-0.3602 *	1	
share of rented land	-0.1452 *	-0.5161 *	0.1014	-0.3004 *	1

* indicates statistical significance at the 1 per cent significance level

Source: Authors' own calculations based on BGR (2007a), DWD (2007), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Jarvis et al. (2008).

Table 4.5 Results of the spatial error models (spatial neighbourhood matrix: $W^{(idw)}$)

	models[a]					
	Ia	Ib	Ic	IIa	IIb	IIc
soil index	3.02 ***			2.53 ***		
dummy loess (=1)		55.16 ***			39.09 ***	
dummy dystric cambisol (=1)			-35.56 ***			-29.84 ***
dummy orthic luvisol (=1)			31.72 ***			21.12 ***
land slope (in %)	-20.74 ***	-24.07 ***	-13.70 ***	-19.20 ***	-20.06 ***	-13.49 ***
spring precipitation (in mm)	-0.18 ***	-0.10 n.s.	-0.25 ***			
temperature (in °C)	17.90 ***	23.74 ***	25.16 ***	12.72 ***	16.76 ***	17.59 ***
share of grassland				-108.80 ***	-118.01 ***	-134.85 ***
share of rented land	-274.15 ***	-278.12 ***	-263.65 ***	-276.02 ***	-287.57 ***	-266.59 ***
constant	122.73 *	176.30 **	162.50 n.s.	185.62 ***	265.26 ***	232.77 **
lambda	0.95 ***	0.96 ***	0.97 ***	0.96 ***	0.97 ***	0.97 ***
R^2	0.67	0.59	0.58	0.69	0.63	0.63
BIC	4790.29	4870.29	4880.78	4742.93	4819.67	4818.14

[a] Either spring precipitation (model I) or the share of grassland (model II) is considered to be an explanatory variable.

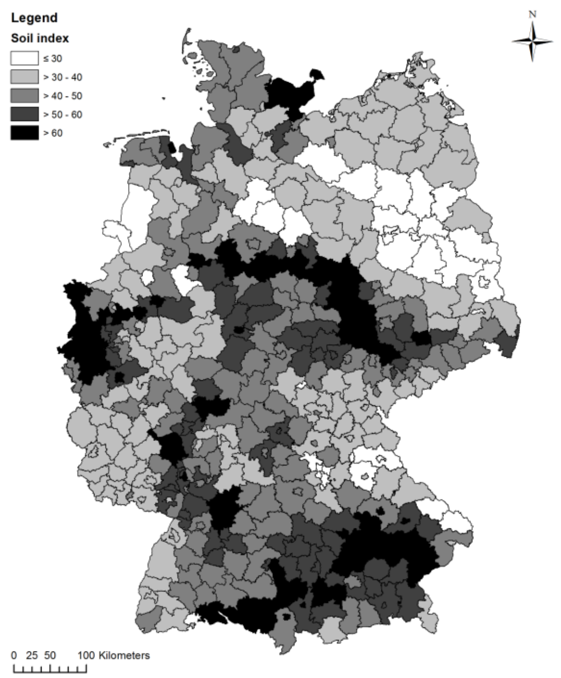
Additionally, there are three specifications of both models (a, b, c) accounting for three different data sources of soil quality.

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent significance level, respectively; n.s. indicates not significant

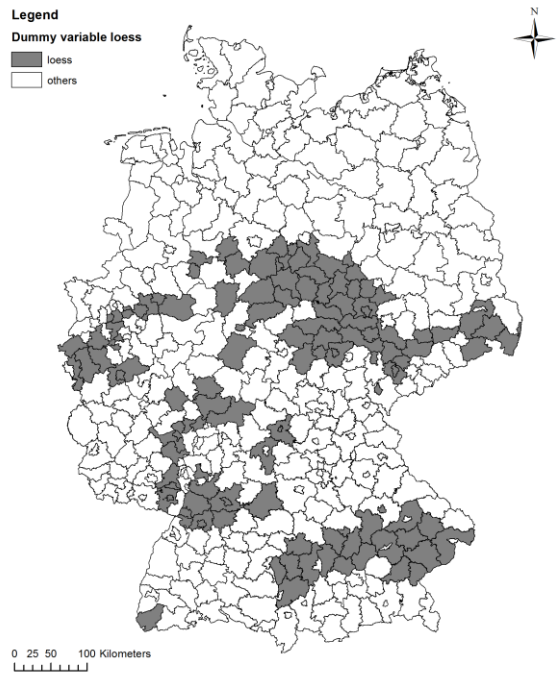
R^2 = square of the correlation coefficient between the observed and predicted data values without adjustment of the error term

BIC = Bayesian information criterion

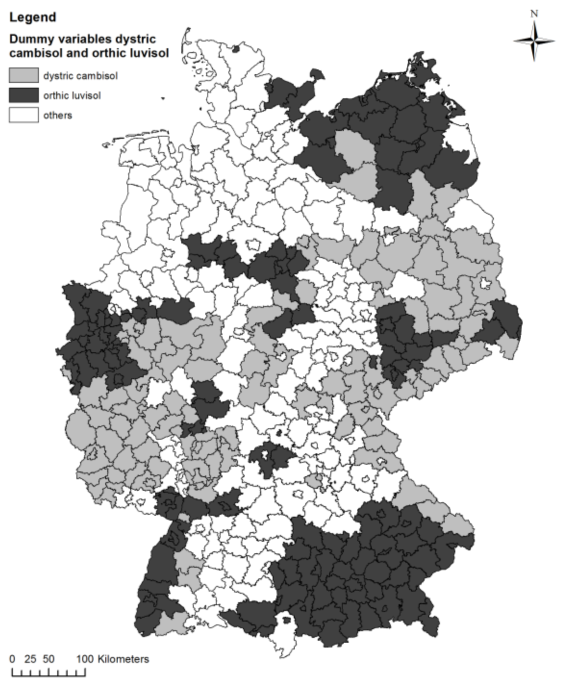
Source: Authors' own calculations based on BGR (2007a), DWD (2007), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Jarvis et al. (2008).



a) Soil index



b) Dummy variable loess

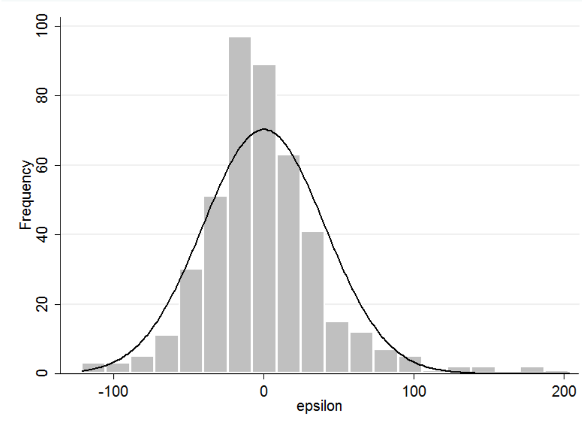


c) Dummy variables dystric cambisol and orthic luvisol

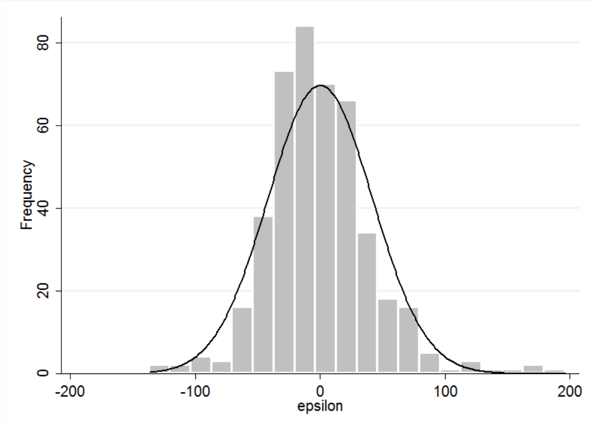
Figure 4.4 Spatial distribution of soil quality at the county level using different indicators

Source: Authors' own presentations based on BGR (2007a), BKG (2010), FAO (2003), Forschungszentrum Jülich (2009).

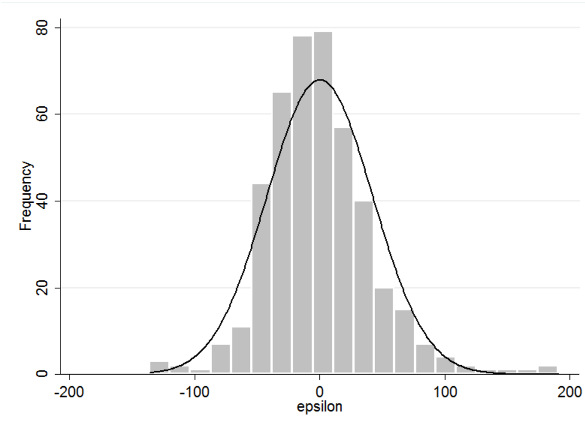
a) model Ia



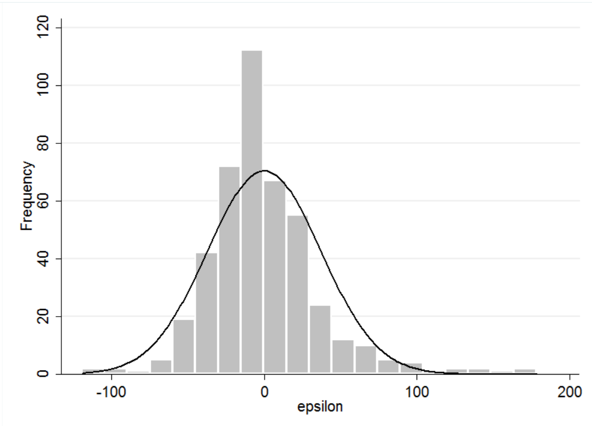
b) model Ib



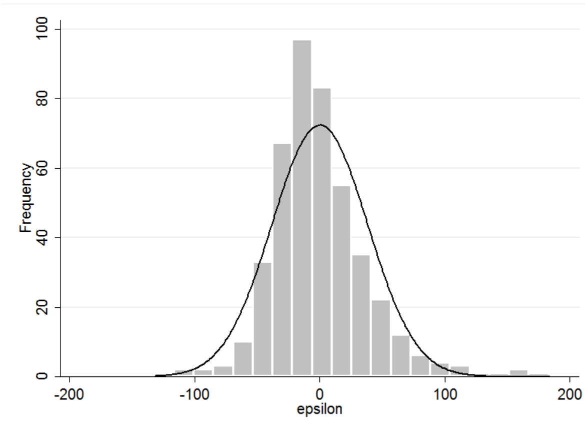
c) model Ic



d) model IIa



e) model IIb



f) model IIc

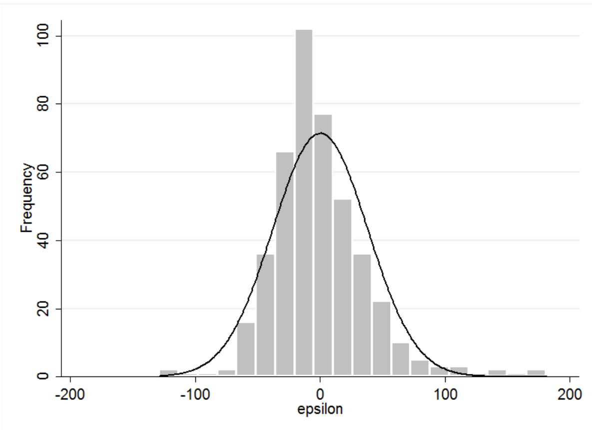


Figure 4.5 Histograms for the residuals of the finally retained spatial error models and the first order spatial neighbourhood matrix $W^{(1)}$

Source: Authors' own calculations based on BGR (2007a), DWD (2007), FAO (2003), FDZ der Statistischen Ämter des Bundes und der Länder (2000), Forschungszentrum Jülich (2009), Jarvis et al. (2008).

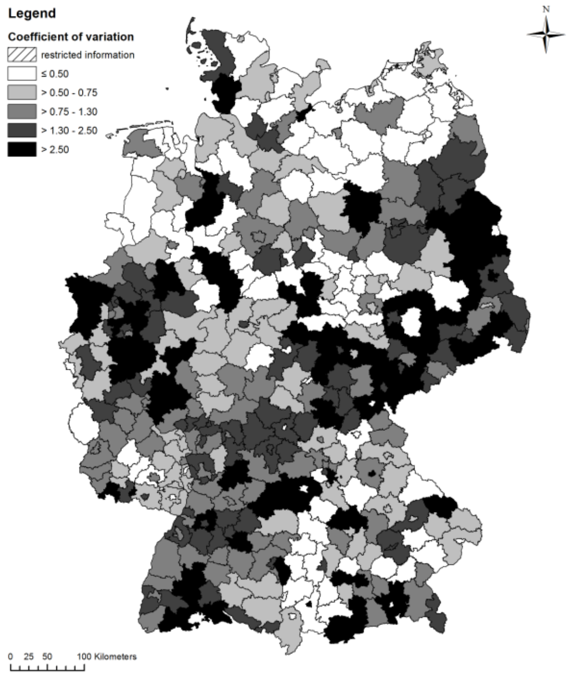


Figure 4.6 Coefficient of variation using the unweighted average of farms' land rental prices by county

Source: Authors' own presentations based on BKG (2010), FDZ der Statistischen Ämter des Bundes und der Länder (2000).

5 Synthesis and outlook

The following conclusions refer to the research questions raised in the introduction and are highlighted in the text of this chapter. In the first part, the methodological approach is critically addressed with particular emphasis on the technical analysis tools, the data used and the relevance of spatial resolutions and spatial neighbourhood matrices in spatial econometric applications. Then, experiences gained in the analysis of organic farming and Ricardian studies are discussed. This chapter concludes with an outlook on research suitable to extend the current work.

5.1 Spatial econometric methods

Spatial econometric methods form the methodological basis of all three articles presented. The analyses draw on spatial econometric indicators and models as well as on non-spatial statistical methods such as Pearson's correlation coefficient. The diagnostic tests for spatial dependence (the Morans' *I* test and the Lagrange Multiplier test) indicate that spatial models are appropriate for all three research approaches. This is consistent with the theoretical considerations. Thus, the application of spatial econometric methods assists in avoiding problems associated with non-compliance of the assumptions of basic models such as the assumption of independent errors in the OLS model.

For an agricultural economist, there are several practical challenges when dealing with spatial data. First of all, features from different disciplines have to be combined. In this instance, spatial data analysis, econometric techniques and agricultural economic theories are linked.

To analyse spatial data from an agricultural econometrics point of view, an appropriate ***technical framework has to be established***. Therefore, ***recent spatial econometric analysis techniques are identified and technically implemented***. Regarding the estimation procedure there are several limiting factors such as the availability of estimation routines, programs and computers that are powerful enough to conduct the estimations. The technical framework of the analyses is discussed in more detail below.

In a first step, appropriate analysis techniques have to be identified. The applied spatial analysis depends on the availability and the quality of estimation routines. Respective information about and sources for the implementation of spatial analysis tools are gathered by diverse publications (e.g., Bivand et al., 2008) and manuals of spatial analysis programs and routines. Considering all alternatives available, the programs ArcGIS, GeoDa, R and Stata - along with additional routines provided by Keitt et al. (2010), Hothorn et al. (2010), Jeanty (2010a, b, c, d), Pebesma and Bivand (2011), Bivand (2011) and Pisati (n.a.) - are determined to be the most recent and useful. Nevertheless, a variety of alternatives including programs such as Matlab, would be suitable for these analyses. One challenge is that not all programs and routines are compatible with one another. For example, a spatial neighbourhood matrix may be generated in different (spatial) programs. However, not all resulting matrix formats match all estimation routines. This limits the flexible application of pre-built analysis routines. For the targeted analyses, compatible spatial tools are identified and implemented. Additionally, the data, matrices and estimation processes are complex. To control for the results, different programs (R and Stata) and estimation procedures are compared at the beginning of the analyses. For example, the spatial neighbourhood matrix is visualised in the program R (see Figure 3.6). This assists in controlling for potential misspecifications due to island situations or inappropriate distance-bands. The results of similar spatial estimations are compared in R and Stata, which confirms the estimation procedure. However, implementing an advanced and systematic model comparison would certainly broaden the current research approach.

Depending on the spatial resolution and spatial extent of the research approach, characteristics such as the spatial neighbourhood matrix require large working memory. For example, there are 1886 community associations in Baden-Württemberg and Bavaria entailing an 1886 x 1886 spatial neighbourhood matrix. Depending on the working and storage process, this will produce up to 3.5 million values for one matrix. For an ordinary working computer, this is a demanding requirement. In the case presented, the technical resources available limit the analysis at the community association level to the spatial extent of the two southern federal states of Germany.

In the field of agricultural economics, similar research settings have utilised spatial econometric methods (Roe et al., 2002; Isik, 2004; Bichler, 2006; Lang, 2007; Parker and Munroe, 2007; Lippert et al., 2009). Here, spatial lag and error models are calculated at two spatial resolutions, the German community association level and the county level. Spatial econometrics is used to tackle new and specific empirical research questions for the German agricultural sector. Next to spatial econometric models, other approaches, such as logistic regression models, may be of interest. For example, the probability of being certified organically could be estimated at the farm level by using data on farms and farm production; however, single farm data were not available for the analysis. Given an improved data base, spatial panel analysis (e.g., considering the development of conversions from conventional to organic farming and vice versa over time) would extend the current research. For further research, additional estimation methods, such as the general method of moments (GMM) (Hansen, 1982; for an agricultural application, see Parker and Munroe, 2007), may be suitable, depending on the research setting and resources available.

5.2 Data sets used

The cross-sectional analyses presented in this dissertation are based on secondary data. Before testing theoretical considerations by current spatial econometric methods, ***appropriate data have to be selected, gathered and processed to conduct spatial analyses***. An essential step for all analyses is the identification of variables that approximate theoretically identified factors.

The data used in this dissertation are selected according to theoretical considerations and features, such as reliability, regional differentiation, covered attributes and accessibility. Most of the information is not surveyed continually, so data are available from different points in time. However, many factors (like soil quality) change very little in the mid-term; corresponding variables measured in different years should not adversely affect the analyses. The agricultural data refer to one single year (per analysis). Thus, a common analysis of data from different years seems to be reasonable in the case studies presented. Some data, such as information on water protection areas, are collected and published only locally, e.g., by the federal states. However, not all institutions have an identical mode of data publication. This influences the large-scale availability and quality of data for scientific research and may also affect data processing.

Regarding the processing of data, there are several characteristics of data that have to be brought together to permit the joint analysis of variables. For example, data have different formats. In this thesis, raster data (e.g., the soil index) and vector data (e.g., information for all administrative units) are used. Within administrative units, there are various ways of defining spatial units (such as communities and postal code areas). Administrative units are defined according to features such as area and numbers of inhabitants that lead to administratively reasonable spatial units. For an agricultural research approach, the use of administrative units might bias the results. Administrative units do not reflect natural conditions, so actual continuous natural zones such as areas of arable land or forests are artificially divided. The different data formats imply particular ways of data processing (e.g., spatial interpolation or data aggregation) to generate data for a common analysis. This may lead to a certain (spatial) impreciseness of estimation results.

For all analyses, mean values are used. This precludes modelling single farm activities. In general, some variables that would have been of interest, such as direct CAP payments, could not be tested. Using secondary data also precluded the use of variables such as the personal attitude of farmers. Gathering additional explanatory variables would certainly bring the econometric models closer to the real (decision) models. Further research might focus on a smaller spatial extent (e.g., one county) and survey and analyse more detailed information to advance the current study.

The agricultural data used are discussed in detail below. The data source best describing the agricultural situation in Germany is the official farm census. For the analyses, two years (the complete census in 1999 and a partial census in 2007) are selected (FDZ, 2000; SAeBL, 2010). The agricultural census has certain data restrictions; only farms fulfilling these restrictions are represented in the official farm census. However, it is assumed that all full-time farms are displayed by the census. The German agricultural farm census draws on the principle of the farm location (‘Betriebssitzprinzip’). All agricultural attributes (such as UAA and animal husbandry) are assigned to the location of the farm, even if the activities are located in other administrative units. This type of data assessment may lead to incorrect interpretations of estimation results. Unfortunately, this bias cannot be corrected. Furthermore, the census is not conducted in annual intervals. The measurement limits and attributes are adapted to the current agricultural situation. For example, the threshold related to farm size increased from 2 hectares UAA (2007) to 5 hectares UAA (2010) because of changes in the agricultural structure. This reduces the comparability of results relating to different years.

For the Ricardian analysis, the original census data (1999) are provided jointly by the Research Data Centers of the Federal Statistical Office and the statistical offices of the German states (FDZ, 2000). These data refer to all (more than 400,000) individual farms. Analyses at the county level are performed at the guest scientist workstation of the Statistical Office of Stuttgart. The contract with the Statistical Office is accompanied by restrictions in terms of software and data analysis, meaning that only certain programs and estimation routines can be used for the analysis. The contract also regulates the time period of data use. In terms of long-term availability and reproducibility of results, time-restricted availability of data is not desirable. For example, new aspects on estimations may arise during a review process, including new calculations; however, this is restrained by the time-limited use of local data at the Statistical Office.

The second analysis on the effects of data aggregation (chapter 3) draws on information about organic farms that is provided by the Federal Agency for Agriculture and Food (BLE, 2009). By contrast to the agricultural census, the BLE-data set represents all certified organic farms in Germany and has no threshold. For purposes of this thesis, the BLE-data are suitable; all farms that are certified according to organic standards are represented. However, the BLE-data are provided by different private control bodies that do not apply standardized data measurement and collection procedures. For a more detailed research approach, such as one concerning the organic certification system (Zorn et al., 2012), the lack of common definitions of variables might limit further (spatial) analysis.

The use of data sets additionally included in the analyses is discussed in the respective sections of the articles (chapters 2-4).

5.3 Data aggregation and spatial resolutions

One target of the study is to ***conduct an empirical analysis at different measurement scales to assess the effect of data aggregation on the results of estimations*****.** Whether spatial dependence is based on spatial resolution is tackled in the second article (chapter 3). The organic farming sector in Germany is analysed from a spatial econometrics point of view. Results at different spatial measurement scales are compared to test whether the results a) can be found to be similar at different spatial resolutions and b) remain constant at different levels of data aggregation.

When using secondary data sources, information is available for certain spatial units. However, the resolution of data does not necessarily fit the theoretical considerations. In this case, spatial effects are assumed between farmers, but data are available only for community associations and previously only for counties. Mean values at different spatial units are considered that might not reflect the real decision model. Moreover, results may be different or even reversed at different measurement scales (see also section 1.4). Thus, the relevance of results based on aggregated data is questionable. This is a general problem present in nearly all econometric research approaches.

In this case, the models yield similar results at two measurement scales; the results at the lower spatial resolution are not artificially generated through the aggregation process, strengthening the relevance of the previous study (chapter 2). Hence, for this research topic, the findings indicate no major problems as a result of data aggregation. But naturally, the appropriateness of spatial measurement scales has to be analysed separately for other research settings.

5.4 Spatial neighbourhood matrix

The next methodological research question attempts to ***assess the effects of alternative specifications of the spatial neighbourhood matrix on the stability of results obtained from selected spatial economic analyses*.**

The spatial neighbourhood matrix *W* indicates the relative position of observations in geographic space. In all studies presented in this dissertation, different specifications of the spatial neighbourhood matrix are used to test the stability of results. The definition of the spatial neighbourhood matrix is defined a priori, i.e., it is taken as exogenously given and based on theoretical considerations. However, there are several problems related to the connectivity of spatial units: the approaches presented do not account for natural conditions influencing the connectivity of locations in space. This means that there may be insurmountable barriers (such as mountains) or enhancing factors (such as highways) between spatial units that are not considered in defining the spatial neighbourhood matrix. Thus, spatial connectivity could be assumed for spatial units not connected (in reality). Gathering corresponding data would entail detailed information on local conditions and connectivity. Furthermore, the size of the administrative units differ, which may affect the spatial dependence of units that are located nearby. To address this problem, spatial units that are relatively similar in size (e.g., the integrated counties) are selected for the analyses.

Another challenge is that spatial units without an assigned neighbour cannot be considered in the spatial estimations, and information is therefore lost, which may bias the results. To avoid no-neighbour entities, a critical distance that secures at least one neighbour for every spatial unit is selected (Bivand et al., 2008). Specific cases of no-neighbour problems are islands; islands do not have a common border with other spatial units. Thus, spatial relationships are assigned artificially, potentially leading to biased results. Here, there is only one case tackled by the island-problem at the county level: the island 'Rügen'. The determination of neighbours of the island Rügen is based on access to the mainland via bridges and ferries. Because there is a real interaction between the island and the mainland, the biases (resulting from the artificial assignments of neighbours) are assumed to be of minor importance in this case.

Due to lack of information, the potential asymmetry in spatial relations (Paelinck and Klaassen, 1979) is not represented in the selected spatial neighbourhood matrices. For an analysis accounting for the demand of (agricultural) products this issue might be of importance. Without additional information, this feature cannot be implemented in the analysis.

5.5 Agglomeration effects in the organic farming sector

One target of the studies on organic farming is to ***develop a theoretical framework for the conversion from conventional to organic farming*.** In this context, a farmer's decision to convert or continue farming organically is treated as an 'investment problem' and framed in a theoretical model (cf. section 2.2). Various potential ***determinants of the spatial distribution of organic farming are presented*** in sections 2.2 and 3.2 ***and analysed with a particular emphasis on agglomeration effects*.**

The theoretical model includes factors potentially influencing the decision to convert to organic farming. Different variables characterising (organic) farming are considered, such as output prices, production relevant natural and spatial factors and the policy environment in which farmers operate. Beyond that, spatial characteristics of variables and potential direction of effects are also specified. Thus far, this is the first spatial econometric approach to the organic farming sector that links factors determining the conversion decision to spatial effects in a formal theoretical model. However, certain variables that would have been of interest (such as the proportion of organic farmers belonging to an organic farmers' association) could not be tested in the empirical model. Further analyses might advance the approach and consider additional explanatory variables (see also section 5.2).

The results support the assertion that organic agriculture and agglomeration do not seem to contradict one another. Positive neighbourhood effects seem to play a role in organic farming. However, path dependency might also be of importance for organic agglomeration in space (Krugmann, 1996; Bichler, 2006). The historical development of agglomeration arising a) because of favorable location factors or b) as random occurrence (cf. Lippert, 2006) may have led to advantages in knowledge and resulting positive agglomeration effects. Organic movements and institutions such as organic farmers' associations and control bodies are located in southern regions of Germany since the early beginnings of organic farming (cf. Vogt, 2000; Willer et al., 2002). By contrast, the development of organic agriculture in eastern Germany was mainly driven by governmental payments after the German reunification (Köhne and Köhn, 1998). This might have affected the heterogeneous distribution of organic agriculture in Germany. Unfortunately, detailed data on organic farming in Germany (such as the official farm census) are not available before 1999, so an initial spark of organic farming cannot be identified statistically.

5.6 Different indicators of soil quality and their effects in a Ricardian analysis

The thesis also aims at ***analysing the influence of different classifications of soil quality on the results of a Ricardian analysis in Germany.*** In general, variables that are important from a theoretical point of view are frequently not available for a particular analysis because of data restrictions, which may lead to biased estimation results. In this case study (chapter 4), previous research is advanced by considering additional important explanatory variables in a Ricardian analysis, such as soil quality and land slope. There are diverse concepts of measuring soil quality; therefore, different data bases describing the quality of soil are compared. The classification systems and spatial resolutions differ between the data sets. Some data, such as those of the DSMW (Digital Soil Map of the World) (FAO, 2003), are available for regions all over the world, while other data bases cover only Germany. Information on soil quality at a low spatial resolution might not be suitable for this analysis, which is conducted at a detailed spatial scale. However, the results do not support this concern. The three selected indicators of soil quality show similar effects in all analyses.

Generally, the results indicate that climate change will have an overall positive but spatially heterogeneous impact on the productivity and the profitability of agricultural production. The basic assumption of the Ricardian approach is that climatic factors, such as temperature or precipitation, influence the rental price of farmland. In the analysis, interpolated climatological means are used to represent average climatic conditions in German counties. This interpolation of climate values might be subject to certain prediction errors, particularly in mountainous regions. Furthermore, the quadratic terms of temperature and spring precipitation do not show significant influences in the models. One reason for this could be the low variability of climatic factors in Germany.

The research approach presented performs a rough estimate on the potential effect of climate change on German agriculture. One assumption in the models is that agricultural agents react identically to climate change. This is most likely not consistent with reality. By contrast, dynamic agent-based models aim at analysing the influence of climate change on short-term farm managing by simulating annual and day-to-day farm management decisions. For example, Aurbacher et al. (2012) coupled an economic and management model with a plant growth model. Thus, the model can implement farmers' responses and adaptations to changing economic and environmental conditions. However, due to the complexity of those models, an analysis covering large regions is difficult to implement. Jointly interpreting the experiences gained from both research approaches might lead to more reliable conclusions on future climatic impacts on German agriculture.

5.7 Outlook

Returning to Thünen's theory on the location of agricultural activities, space might be of importance in various agricultural research settings. Spatially heterogeneous concentrations of agricultural activities may be caused by spatial heterogeneity (e.g., spatially differing traditional location factors) and/or spatial dependence (e.g., by the beneficial effects of these activities themselves). In this dissertation agricultural production is analysed by means of spatial econometric techniques in three different research settings. The results of the diagnostic tests for spatial dependence support the (theoretically assumed) appropriateness of spatial models in all three cases. In addition to the organic farming sector, agglomeration effects might be relevant in other agricultural specialties such as hog husbandry, viticulture and hop production (Lippert, 2006). For these farming specialties, spatial econometrics might be an interesting analysis approach. This may also have political implications: if there are economies of scale external to the farm, development measures might stimulate corresponding clusters of agriculture specialities.

Due to data restrictions, cross-sectional analyses were conducted. An interesting avenue of research would be to account for spatial panels, e.g., to consider the development of conversions from conventional to organic farming and vice versa over time. This could facilitate the analysis of time-delayed effects of organic subsidies and thereby enhance the reliability of such subsidies, which might improve the basis of farmers' planning. Additionally, using different and more recent variables would certainly strengthen the results. In this context, considering variables, such as the distance to markets or the proportion of farmers belonging to farmers' associations, could bring the models closer to reality. Additionally, a new farm census was conducted in 2010 and weather data now are available for more recent years. Accounting for such data may lead to a promising way of research. Depending on the research setting, further specifications of spatial econometric models, such as the spatial Durbin model (Anselin, 1988) that accounts for spatially lagged explanatory variables, might also be appropriated.

The traditional Ricardian analysis explains land values by climate variables (Mendelsohn et al., 1994; Mendelsohn, 2007). One approach that attempts to statistically derive relationships between climate variables and certain land use practices is the structural Ricardian analysis (cf. Seo and Mendelsohn, 2008). Current research could be advanced by conducting structural Ricardian analyses for different farm types or crops. Adaptation to climate change could thus be explored in terms of farm type or crop choice.

Further analyses could also include data at a higher spatial resolution to allow for spatially more differentiated conclusions, which would enhance the local relevance of results. In cooperation with the Research Data Centers of the Federal Statistical Office and the Statistical Offices of the German federal states, analyses at a higher spatial resolution such as the community level could be performed through a controlled data analysis ('Datenfernverarbeitung').

Concluding, this dissertation illustrates the potential application of spatial econometrics to selected empirical research questions on German agriculture. In all cases, spatial econometric methods are appropriate tools of analysis. The idea that strong relationships are expected among variable values in spatial units that are located nearby can be of relevance in various agricultural economic research settings. The examples presented might assist future analysis to rely on an approach involving spatial econometrics.

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6 Summary

The location of agricultural activities is determined by location factors that are spatially heterogeneous, such as climate and soil; for the spatial distribution of some agricultural specialties, spatial dependence, i.e., beneficial and self-enhancing effects resulting from a concentration of these agricultural activities, might also play a role. Thus, the dimension ‘space’ might be of importance in analysing agricultural research settings. This cumulative dissertation consists of three articles addressing current research questions on the spatial distribution of agricultural activities and agricultural profitability in Germany. The spatial distribution of organic farming and the potential impacts of climate change on German agriculture are analysed from an econometric perspective. The failure to implement essential spatial information can cause biased estimation results. To account for the geographic location of attributes, spatial econometric analysis tools are used. First, the technical framework for a spatial analysis is established; appropriate spatial econometric analysis techniques and spatial data are identified and processed. Then, three case studies are conducted.

The first article addresses the determinants of the uneven spatial distribution of organic farming in Germany. In addition to traditional location factors, positive agglomeration effects might also influence the spatially heterogeneous concentration of organic agriculture. Conventional farmers might be more likely to convert to organic farming given an easy communication with organic farmers located nearby and a geographically close and strong institutional network. First, a theoretical model explaining the decision of a farmer to convert from conventional to organic agriculture is established. Next, secondary data at the German county level are analysed by using spatial lag models. Data on organic farming refer to the year 2007. The results suggest that agglomeration effects matter in organic agriculture. Further clustering of organic farming might be stimulated by governmental incentives, such as development measures for organic agriculture concentrated in certain regions.

For the previous analysis, aggregated data at a relatively low spatial resolution are used, which might lead to results that are artificially generated through the process of data aggregation. The second article addresses the question whether results can be confirmed at different spatial levels, assuming that agglomeration effects are important in organic farming. The results of spatial lag models are compared at two measurement scales, the German counties and community associations. Secondary data are also used in this analysis; for the organic sector, 2007 data are considered. The analysis indicates that essential factors determining the decision to convert from conventional to organic farming are sustained at different spatial resolutions. The results at the lower spatial resolution are shown to be not artificially generated through the aggregation process in this case, which strengthens the relevance of the previous study.

The third publication assesses the effects of different indicators of soil characteristics on the estimation results of a Ricardian analysis. The study draws on data from the official farm census conducted in 1999 and on weather data from the German National Meteorological Service at the county level for the time period 1961-1990. Additionally, different soil data bases are considered to control for soil

quality. The results of spatial error models suggest that rental prices are determined by climate and non-climate factors. Accounting for different methods of measuring soil quality does not influence the results of the analysis. To estimate the effects of changing climatic conditions on future land rents, data from the regional climate model REMO for the time period 2011-2040 are used. The models show that projected temperature and precipitation levels will lead to an increase in land rents of approximately 14 percent compared to the 1999 reference situation. According to the projections future climate change will have an overall positive but spatially heterogeneous effect on the income from agriculture in Germany.

The empirical analyses presented illustrate that spatial econometrics can offer appropriate tools for analysing agriculture. In all three cases theoretical considerations and diagnostic tests for spatial dependence suggest using spatial analysis techniques. The use of alternative specifications of the spatial neighbourhood matrix further supports the stability of results.

Future studies might be based on even more detailed data (e.g., farm-level data over time) and rely on different approaches, such as spatial panel or logistic regression analyses. Such data bases and methods would allow for analysing the decision making of individual farmers on the conversion process from conventional to organic farming. As a first step, this could also be realised for a small spatial area (such as one German county). The influence of climate change on specific farm types or crops could be analysed by conducting structural Ricardian analyses.

The general approach and methods used could be translated to other issues in agricultural economics such as potential agglomeration effects in hog production or the future impact of climatic factors on the spatial distribution of viticulture. Thus, spatial econometrics might offer an interesting approach to various spatial research questions in agricultural economics, in addition to the applications that were selected for this thesis.

7 Zusammenfassung

Die räumliche Verteilung landwirtschaftlicher Aktivitäten wird durch (räumlich heterogen verteilte) Standortfaktoren wie Klima und Boden bestimmt. Für die räumliche Verteilung einiger landwirtschaftlicher Ausprägungen spielt möglicherweise auch räumliche Abhängigkeit eine Rolle, also positive und sich selbst verstärkende Effekte, die durch eine Konzentration dieser landwirtschaftlichen Aktivitäten entstehen. Dies bedeutet, dass die Dimension „Raum“ in landwirtschaftlichen Forschungsansätzen durchaus von Bedeutung sein kann. Die vorliegende kumulative Dissertation besteht aus drei Artikeln, die aktuelle Fragestellungen hinsichtlich der räumlichen Verteilung landwirtschaftlicher Tätigkeiten und landwirtschaftlicher Profitabilität in Deutschland behandeln. Die räumliche Verteilung des ökologischen Landbaus und mögliche Auswirkungen des Klimawandels auf die deutsche Landwirtschaft werden ökonometrisch analysiert. Wenn wesentliche räumliche Informationen unberücksichtigt bleiben, können Schätzergebnisse verzerrt sein. Um die geographische Lage von Merkmalen berücksichtigen zu können werden räumlich ökonometrische Analysewerkzeuge eingesetzt. Zunächst wird der technische Rahmen für eine räumliche Analyse geschaffen indem geeignete räumlich ökonometrische Analysetechniken und räumliche Daten identifiziert und aufbereitet werden. Anschließend werden drei Fallstudien durchgeführt.

Der erste Artikel untersucht die Bestimmungsgründe der ungleichen Verteilung des ökologischen Landbaus in Deutschland. Neben klassischen Standortfaktoren beeinflussen möglicherweise auch positive Agglomerationseffekte die räumlich heterogene Konzentration des ökologischen Landbaus. Konventionelle Landwirte stellen ihren Betrieb eventuell eher auf die ökologische Wirtschaftweise um, wenn der Austausch mit benachbarten ökologischen Landwirten vereinfacht und ein nahe gelegenes starkes institutionelles Netzwerk gegeben ist. Zu Beginn wird ein theoretisches Modell entwickelt, dass die Entscheidung eines Landwirtes, von der konventionellen auf die ökologische Wirtschaftsweise umzustellen, abbildet. Anschließend werden Sekundärdaten auf Ebene der deutschen Landkreise unter Verwendung erweiterter autoregressiver Modelle (spatial lag models) analysiert. Die Daten zum ökologischen Landbau beziehen sich auf das Jahr 2007. Die Ergebnisse deuten darauf hin, dass Agglomerationseffekte im ökologischen Landbau von Bedeutung sind. Eine weitere Cluster-Bildung im ökologischen Landbau könnte durch staatliche Anreize wie die Konzentration von Entwicklungsmaßnahmen für den ökologischen Landbau in bestimmten Regionen gefördert werden.

In der ersten Analyse werden aggregierte Daten mit einer relativ geringen räumlichen Auflösung verwendet, sodass die Ergebnisse möglicherweise künstlich durch den Aggregationsprozess generiert sind. Unter der Annahme, dass Agglomerationseffekte im ökologischen Landbau von Bedeutung sind, untersucht der zweite Artikel die Fragestellung, ob Ergebnisse auf verschiedenen räumlichen Ebenen bestätigt werden können. Die Ergebnisse erweiterter autoregressiver Modelle werden auf zwei räumlichen Ebenen verglichen, den deutschen Landkreisen und Gemeindeverbänden. Für die Analyse werden erneut Sekundärdaten verwendet; für den ökologischen Sektor werden Daten aus dem Jahr

2007 berücksichtigt. Die Analyse deutet darauf hin, dass wesentliche Faktoren, die die Umstellungsentscheidung von der konventionellen auf die ökologische Landwirtschaft beeinflussen, auf verschiedenen räumlichen Ebenen erhalten bleiben. Die Ergebnisse für die geringere räumliche Auflösung werden in diesem Fall nicht künstlich durch den Aggregationsprozess erzeugt, was die Aussagekraft der vorangegangenen Studie stärkt.

Die dritte Veröffentlichung untersucht die Effekte verschiedener Bodenqualitätsmaße auf die Schätzergebnisse einer Ricardischen Analyse. Es werden Daten der Landwirtschaftszählung 1999 und Daten des Deutschen Wetterdienstes für den Zeitraum 1961-1990 auf Ebene der Landkreise genutzt. Als Maß für die Bodenqualität werden zusätzlich verschiedene Datenquellen berücksichtigen. Die Ergebnisse räumlicher Fehlermodelle (spatial error models) deuten darauf hin, dass Pachtpreise durch klimatische und nicht-klimatische Faktoren bestimmt werden. Die Berücksichtigung verschiedener Bodenqualitätsmaße hat keinen Einfluss auf die Ergebnisse der räumlichen Analyse. Um Auswirkungen eines künftigen Klimawandels auf Bodenrenten abschätzen zu können, werden Daten des regionalen Klimamodells REMO für den Zeitraum 2011-2040 genutzt. Die Schätzergebnisse zeigen dass die vorhergesagten Temperatur- und Niederschlagswerte einen Anstieg der Bodenrenten um etwa 14 Prozent im Vergleich zur Referenz-Situation im Jahr 1999 bedeuten würden. Ein künftiger Klimawandel hätte demnach einen insgesamt positiven aber räumlich heterogenen Einfluss auf das landwirtschaftliche Einkommen in Deutschland.

Die vorgestellten empirischen Studien zeigen, dass die räumliche Ökonometrie geeignete Analysewerkzeuge für eine Untersuchung der Landwirtschaft bereit hält. In allen drei Fällen deuten theoretische Überlegungen und Diagnosetests auf räumliche Abhängigkeit darauf hin, räumliche Analysetechniken einzusetzen. Ferner bekräftigt die Verwendung alternativer Spezifikationen der räumlichen Nachbarschaftsmatrix die Stabilität der Ergebnisse.

Zukünftige Studien könnten noch differenziertere Daten (z.B. auf Betriebsebene und für verschiedene Jahre) verwenden und unterschiedliche Ansätze wie räumliche Panel-Analysen oder logistische Regressionsanalysen einbeziehen. Die Verwendung solcher Datensätze und Methoden würde es ermöglichen, die Entscheidung einzelner Landwirte bezüglich des Umstellungsprozesses von konventionellen auf ökologischen Landbau zu untersuchen. Dies könnte zunächst auch für ein kleines räumliches Gebiet (wie einen Landkreis) realisiert werden. Der Einfluss des Klimawandels auf spezielle landwirtschaftliche Betriebstypen oder Kulturen könnte durch eine strukturelle Ricardische Analyse untersucht werden.

Der vorgestellte Ansatz und die angewandten Methoden könnten auch auf andere agrarökonomische Fragestellungen wie mögliche Agglomerationseffekte in der Schweinehaltung oder die künftige Auswirkung klimatischer Faktoren auf die räumliche Verteilung des Weinbaus übertragen werden. Somit könnte die räumliche Ökonometrie nicht nur für die hier ausgewählten Anwendungen sondern auch für vielfältige räumliche Fragestellungen in der Agrarökonomie einen interessanten Ansatz darstellen.