# Does Spatial Dependence Depend on Spatial Resolution? – An Empirical Analysis of Organic Farming in Southern Germany

# Ist die räumliche Abhängigkeit von der räumlichen Auflösung abhängig? Eine empirische Analyse des ökologischen Landbaus in Süddeutschland

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## 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 neighbourhood effects and (b) whether results can be confirmed at different spatial resolutions. Explaining the spatial distribution of organic farming in southern Germany (2007) 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 found 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.*

## Key Words

*organic farming; spatial distribution; agglomeration effects; spatial econometrics*

## Zusammenfassung

*Unter der Annahme, dass Agglomerationseffekte im ökologischen Landbau von Bedeutung sind, untersuchen wir (a) die Schwierigkeiten, welche auf die Aggregation von Daten zurückzuführen sind und dann auftreten, wenn Nachbarschaftseffekte statistisch nachgewiesen werden sollen und (b) ob Ergebnisse auf verschiedenen räumlichen Ebenen bestätigt werden können. Wir erklären die räumliche Verteilung des ökologischen Landbaus in Süddeutschland (2007) und vergleichen die entsprechenden Ergebnisse erweiterter autoregressiver Modelle auf zwei räumlichen Ebenen. Die Ergebnisse deuten darauf hin, dass wesentliche Faktoren, die die Umstellungsentscheidung von der konventionellen auf die ökologische Wirtschaftsweise beeinflussen, auf verschiedenen räumlichen Ebenen nachgewiesen werden können. Die Ergebnisse für die geringere räumliche Auflösung werden in diesem Fall nicht künstlich durch den Aggregationsprozess erzeugt, was die Aussagekraft vorheriger Studien stärkt.*

## Schlüsselwörter

*Ökolandbau; räumliche Verteilung; Agglomerationseffekte; räumliche Ökonometrie*

## 1 Introduction

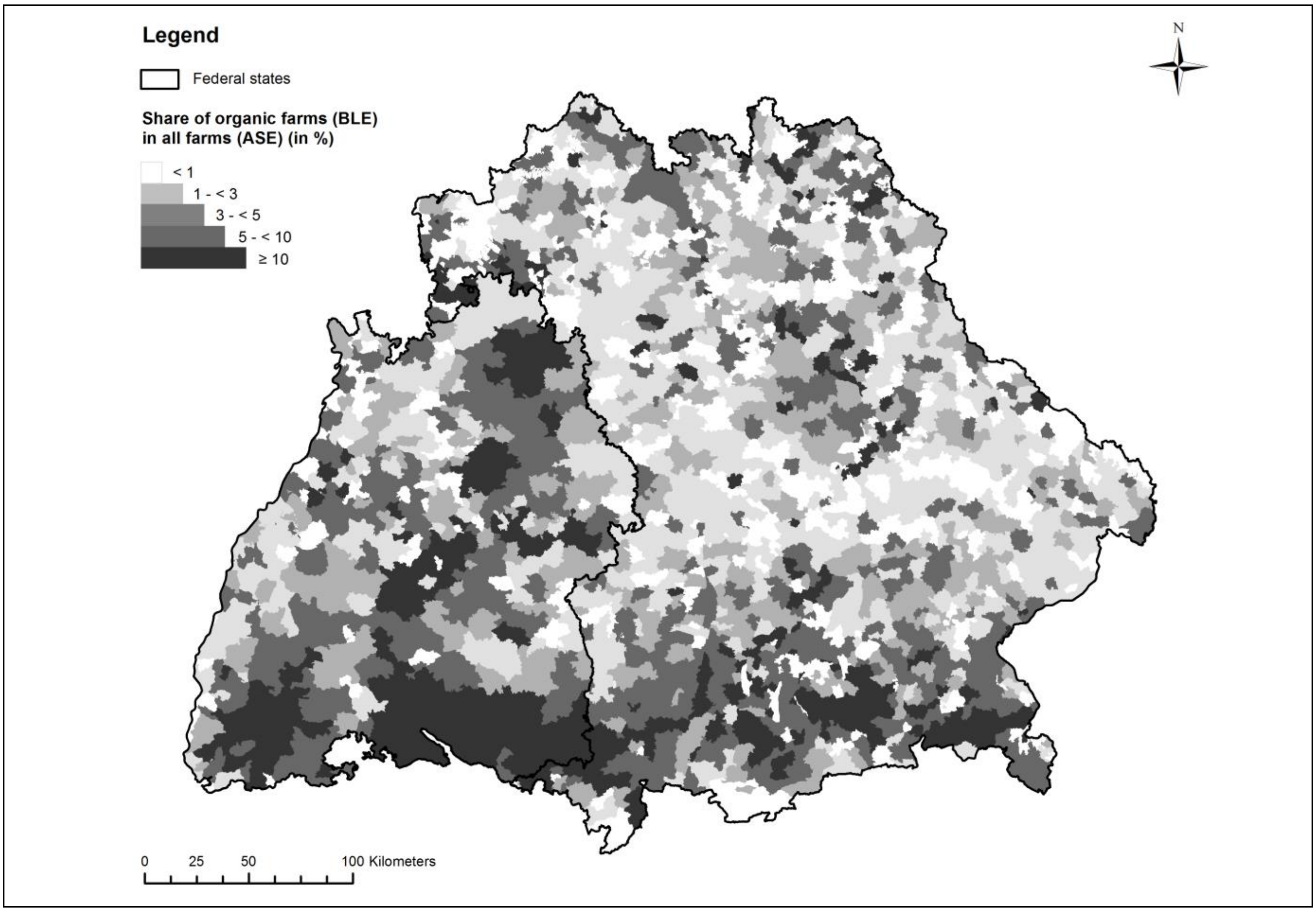
Earlier research has combined common location factors, such as climate and soil, with the concept of agglomeration effects and found – based on aggregated data – that neighbourhood effects may influence the spatial distribution of organic farming (BICHLER et al., 2005, SCHMIDTNER et al., 2012). Background 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.

BICHLER et al. (2005) and SCHMIDTNER et al. (2012) both operated at the German county level, an administrative unit covering different areal sizes, number of farms and utilized agricultural areas (UAA). The agricultural decision-making and production processes, however, are assumed to operate at the farm-level. Thus, an analysis at a high spatial resolution such as the farm-level would be preferable in the context of analysing potential agglomeration effects in organic farming. Until now the data availability restricted the spatial analyses to the county level. Improved data availability now 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 (based on the same original data). Thereby, we intend not only to adjust the analysis but also to critically question the previous results based on spatial entities as we believe that deepening scientific research is only possible while continuously testing the appropriateness of the basic scientific approach and data used. 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.

In 2007, nearly half of the approximately 375 000 German farms are located in Bavaria and Baden-Württemberg (the two southern federal states which are central to this study), managing about 25 per cent of the 17 million hectares UAA in Germany. With an average farm size of about 25 ha per farm the southern farms are relatively small (German average: 48 ha per farm). The southern farms are characterized by a relatively high grassland share in total UAA; in Baden-Württemberg, the share of permanent crops (like wine) in total UAA is above the German average. On arable land, cereals like wheat and barley are dominant; in Bavaria also fodder crops such as silage maize are important. Regarding animal husbandry, Bavaria is characterised by a high number of cattle (especially dairy cows) per UAA. Some regions in Baden-Württemberg (like the county Schwäbisch Hall) have a high density of pigs, especially breeding sows (SAEBL, 2010). Organic farming is an interesting case as it is distributed quite unevenly within Germany and the southern federal states of Bavaria and Baden-Württemberg (Figure 1). About 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 in 2007. 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 'every

**Figure 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) and ASE according to SAEBL (2010) thing 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). Agglomeration effects result in spatial dependence. In the following we suppose positive spillover effects in space between farms; we expect these effects to overcompensate possible negative spillovers like competition for special inputs. 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, agglomeration effects also 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. 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).

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 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 4, we introduce the data used and variables constructed. Next, we present and discuss the results, and finally, we draw conclusions.

## 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 emissions 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 positive 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[1] is facilitated if organic farms that want to commonly use machinery 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, 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).

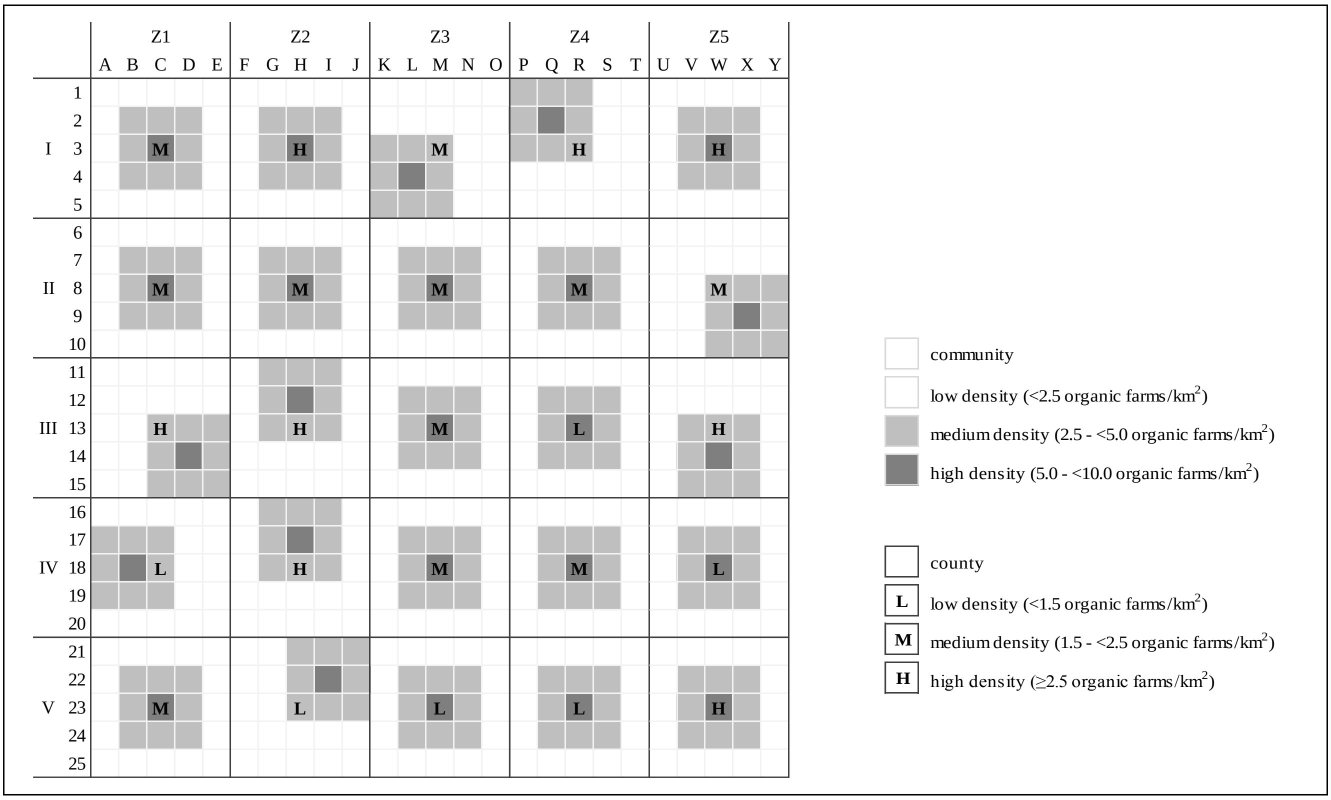
Considering the various factors potentially causing agglomeration of organic farming, it is challenging to assess the importance of particular agglomeration patterns. Neighbourhood effects may not only differ but also span spatial measurement scales. An associated problem is the availability of data that 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 A1 in the Annex). Another didactic example to illustrate one challenge arising for spatial analyses is presented in Figure 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 us. It is further assumed that no significant spatial concentration of organic farms can be found at the

[1] 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.

**Figure 2. Spatial distribution of the density of organic farms at two measurement scales**




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

lower spatial resolution (county level), but rather, is found within particular counties (at the higher spatial resolution, the community level).[2] 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. The global Moran's *I* (ANSELIN, 1988) is calculated to determine whether spatial autocorrelation of organic farms exists. As presented in Table 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 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.

To conclude, the two examples support the concerns about the relevance of results based on aggregated data. To address that issue, we compare results at different spatial measurement scales.

## 3 Spatial Resolution and Spatial Neighbourhood Matrix Determination

There exist 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.[3] In the year 2007, Bavaria and Baden-Württemberg were organized into 1 886 community associations and 140 counties. However, some counties are very small, covering only the area of a city (Table 2 in section 5).

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

[3] Thus, the dataset is based on NUTS 3 level (county-level) (NUTS being the Nomenclature of Territorial Units for Statistics, established by Eurostat).

**Table 1. Descriptive statistics and diagnostic test for spatial dependence for the number of organic farms per km$^2$ (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 |

*The data relate to the fictitious example presented in Figure 2.

Source: authors' own calculations based on data generated by the authors

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, 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 (cf. ANSELIN, 2002). 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 row-standardized (see ANSELIN, 1988) for all approaches by the following weighting scheme:

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

with

$i$ = a spatial unit,

$j$ = another spatial unit,

$N = N_i = N_j$ = number of spatial units.

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 criterion. 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:

$$w_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ have a common border or vertex} \\ 0, & \text{otherwise} \end{cases} \qquad (2)$$

We consider first and second order neighbours.[4] In the case of the first order neighbourhood matrix $W^{(1)}$, the weights are assigned according to Condition (2). For $W^{(2)}$, the first and second order neighbours of district $i$ are considered and treated equally. A schematic integration of small city counties into neighbouring counties (integrated counties) results in a much more uniform neighbourhood matrix than the matrix for the original counties. 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 ab-

[4] First order neighbours have a common border with the respective district. Second order neighbours have a common border with the first order neighbours (except the respective district itself).

sent 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:

$$w_{ij} = \begin{cases} \dfrac{1}{\text{dist}_{ij}}, & \text{if the distance } (\text{dist}_{ij}) \\ \text{between } i \text{ and } j \text{ is less} \\ \text{than a critical distance} \\ 0, & \text{otherwise} \end{cases} \qquad (3)$$

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

$$w_{ij} = \begin{cases} 1, & \text{if } j \text{ is one of } i\text{'s nearest neighbours,} \\ \text{where } k > 0 \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

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. The first order contiguity-based 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 26,320 m. The distances are calculated based on the geographical centroid of each spatial unit and measured in meters. We now base the selection of relevant distances on at least some plausibility: we draw on the spatial characteristics like connections to other regions and distance between two adjacent communities. Thus, we use 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 (rounded up from 26.32 km) and an unrestricted inverse distance-weighted neighbourhood matrix ($W^{(idw)}$). The matrix $W^{(idw)}$ 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 A2 (Annex), 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. 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.

## 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):

$$y = \rho W y + X\beta + u \qquad (5)$$

$$u = \lambda W u + \varepsilon \qquad (6)$$

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

and

- $y$ = vector containing the *share of organic farms within all farms* in the selected administrative units in Bavaria and Baden-Württemberg;
- $X$ = matrix containing the observations for *m* independent variables for every administrative unit;
- $W$ = row-standardized spatial weight matrix;
- $I_N$ = identity matrix;
- $u$ = vector of the spatially correlated residuals;
- $\varepsilon$ = vector of normally distributed errors (mean = 0, variance = $\sigma^2$);
- $\beta$ = vector containing the regression coefficients for the explanatory variables;
- $\rho$ = spatial lag coefficient reflecting the importance of spatial dependence;
- $\lambda$ = coefficient reflecting the spatial autocorrelation of the residuals *u*.

As we use row-standardized spatial weighting matrices $W$ the estimated coefficients $\rho$ and $\lambda$ will usually lie between -1 and 1 (theoretically, the lower bound of $\rho$ could be less than 1 also in case of row standardization, see ANSELIN, 1999: 7f.). A significant spatial lag coefficient $\rho$ indicates the possible existence of agglomeration effects resulting in spatial dependence, whereas a significant coefficient $\lambda$ hints at spatial autocorrelation of the residuals $u$ (spatial heterogeneity). We do not know from theoretical considerations which spatial effects influence the spatial distribution of organic farming in southern Germany. However, previous studies such as BICHLER et al. (2005) and SCHMIDTNER et al. (2012) indicated that neighbourhood effects are very likely to influence the spatial distribution of organic farming at the county level in Germany. Thus, we strongly assume spatial lag effects to be also relevant in our research setting.

Generally, there are four possibilities (resulting in different models):

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

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

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

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

Next to the theoretical considerations above 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 (cf. ELHORST, 2012).

## 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 10 934 certified organic farms and 3 104 organic processors in Bavaria and Baden-Württemberg (BLE, 2009). Unfortunately, the precise location of the farms and processors is also not available. However, the provided residential postal code is used to assign the location of the organic farms and processors to the community associations (DEUTSCHE POST DIREKT, 2010).

As described in section 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 (using several data sources) 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*[5]*) in all farms (ASE*[6]*)*. We need to rely upon this farm related 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 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 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 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.

To capture the availability of and proximity to (organic) markets the *number of residents per km$^2$*, the *average distance to the next three agglomeration centres*[8] (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 result-

[5] Data source: Federal Agency for Agriculture and Food (*Bundesanstalt für Landwirtschaft und Ernährung, BLE*) (BLE, 2009).

[6] Data source: official German farm census (*Agrarstrukturerhebung, ASE*) (SAEBL, 2010).

[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.*

[8] This variable refers to the average travel time in minutes by car to the next 3 out of 36 agglomeration centres as defined by the BBR (2009).

**Table 2. Descriptive statistics for variables of interest at different measurement scales**

| Variable | Year | Mean: Community associations | Mean: Counties[a)] | Min: Community associations | Min: Counties[a)] | Max: Community associations | Max: 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 km$^2$ UAA | 2007 | 4.23 | 3.94 | 0.00 | 2.33 | 38.74 | 8.70 |
| Total annual precipitation (in cm) | 1961-1990[b)] | 91.80 | 92.96 | 57.08 | 63.00 | 203.01 | 173.12 |
| Mean annual temperature (in °C) | 1961-1990[b)] | 7.89 | 7.83 | 5.59 | 6.32 | 10.37 | 9.80 |
| Soil-Index | 1981, 1986[c)] | 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[d)] | 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 |

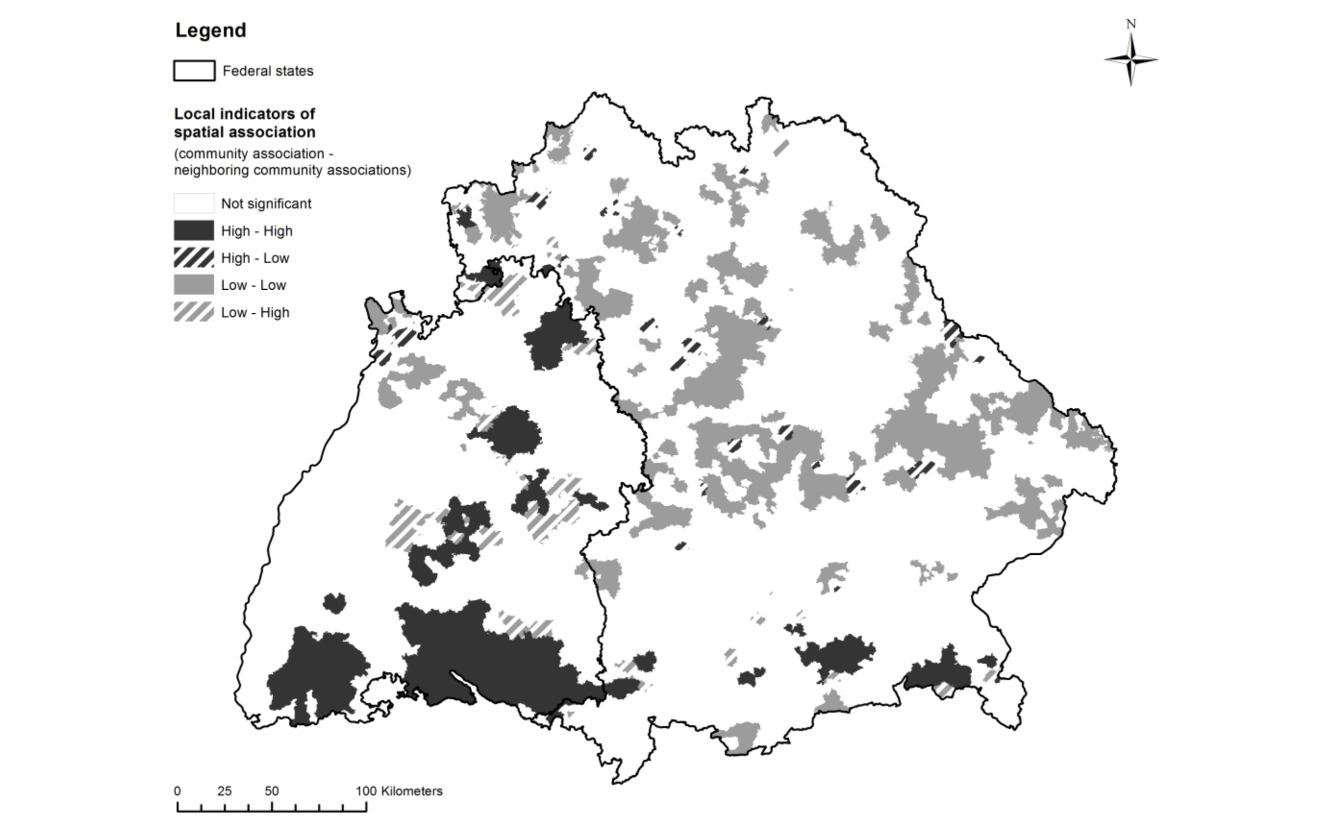
Community associations: N = 1886
[a)] All values refer to the integrated counties (N = 106) with the exception of the variable *average size of the original counties* (N = 140)
[b)] average of 1961-1990
[c)] soil data for eastern Germany refer to the year 1981, soil data for western Germany to 1986 (further explanations in the text)
[d)] average of 2005 and 2009
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) and SLBW (2010). More details are given in the text.

ing 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 also 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 facilitates knowledge exchange between farmers. A high number of organic farms in an area might positively influence 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 maximum shares of UAA in the total area being higher than 100% at the community association level (Table 2). Unfortunately, this bias 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 calculated. 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

**Figure 3. 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) and SAEBL (2010)

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')[9] 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 (5) and (6) are estimated using the maximum likelihood method.

## 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 shows the local indicators of spatial association (LISA) of

[9] The index ranges from 7 (lowest yield potential) to 100 (best yield potential) and is generated based on the observed grain structure of the soil material, geological development and the state of development of the parent material of the soils (cf. SCHACHTSCHABEL et al., 1984).

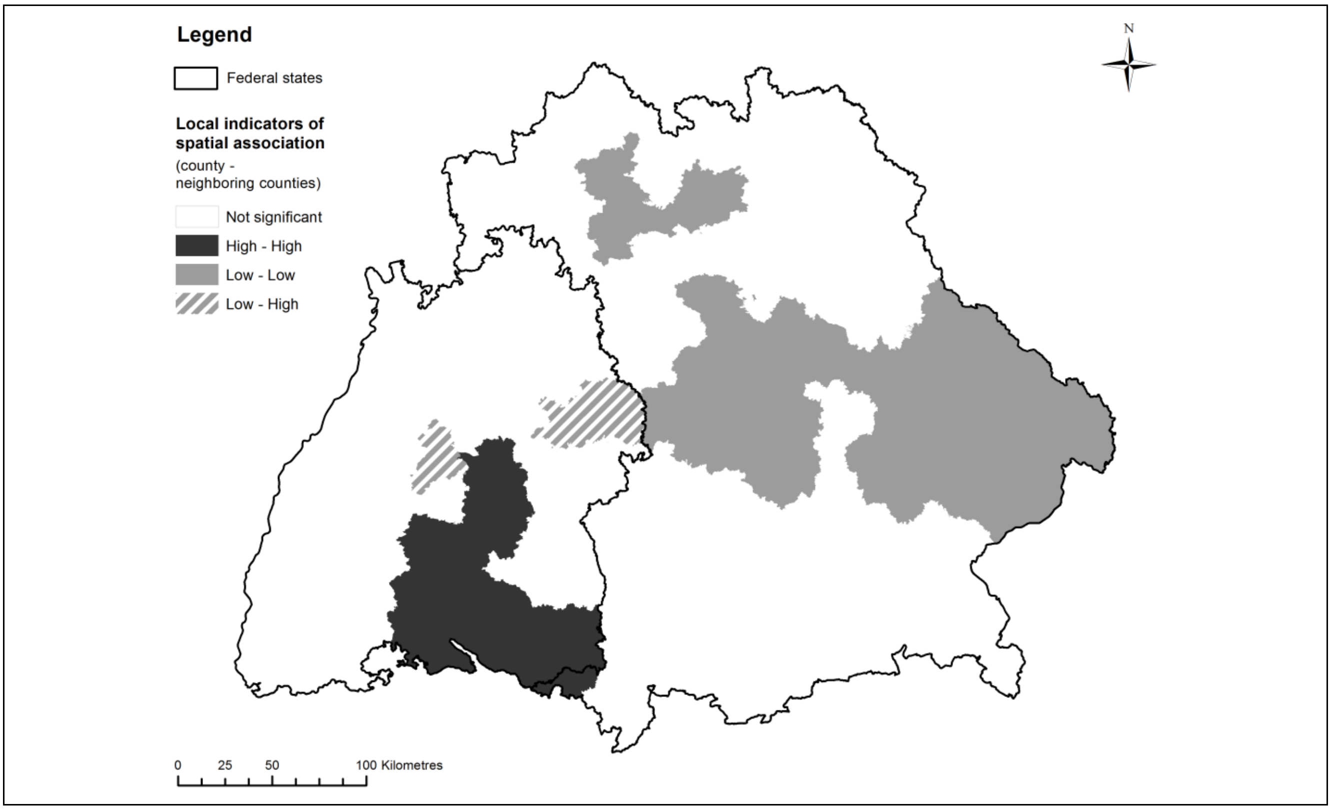
organic farms for the first order neighbourhood matrix of the community associations at a significance level of $p \leq 0.05$. Regions with the attributes 'High-High' and 'Low-Low' indicate clustering of similar high / low shares of organic farms in neighbouring community associations. Striped units show regions with the attributes 'High-Low' or 'Low-High' indicating clustering of dissimilar shares of organic farms in neighbouring community associations. Large areas in the southern and north-eastern parts of Baden-Württemberg are characterized by clusters with a very high share of organic farms, whereas regions in northern Bavaria and north-western Baden-Württemberg indicate the converse situation. 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 and central Bavaria (see Figure 4).

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.

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. Again, the number of variables is reduced stepwise until only significant explanatory variables remain in the models. 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.

For the retained models, the (robust) Lagrange Multiplier test (ANSELIN et al., 1996) suggests estimating general spatial models or spatial lag models for nearly all model alternatives, respectively (Table 3).

**Figure 4. 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) and SAEBL (2010)

**Table 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 *** | 7.32 *** | 0.97 n.s. | 1.72 n.s. |
| robust LM (spatial error) | 1.22 n.s. | 14.99 *** | 21.18 *** | 3.77 * | 45.77 *** | 40.44 *** | 0.01 n.s. | 0.86 n.s. | 1.19 n.s. |
| LM (spatial lag) | 270.35 *** | 290.52 *** | 272.44 *** | 341.06 *** | 390.12 *** | 139.62 *** | 9.74 *** | 4.29 ** | 5.50 ** |
| robust LM (spatial lag) | 16.27 *** | 24.70 *** | 25.67 *** | 26.18 *** | 30.21 *** | 20.25 *** | 2.42 n.s. | 4.18 ** | 4.97 ** |
| LM (spatial error and lag) | 271.57 *** | 305.51 *** | 293.61 *** | 344.83 *** | 435.90 *** | 180.06 *** | 9.74 *** | 5.15 * | 6.69 ** |

*, ** 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 models of which the regression coefficients are given in Table 4.

Source: authors' own calculations based on BBR (2009), BLE (2009), BLSD (2011), DWD (2007), SAEBL (2010) and SLBW (2010)

A spatial error model is suggested for only two specifications of the inverse distance-weighted neighbourhood matrices at the community association level ($W^{(idw30)}$, $W^{(idw)}$).

Based on our hypothesis that there are agglomeration effects in the organic sector and to allow for comparability with previous results, we draw on the spatial lag model (suggested in most Lagrange Muliplier tests) 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 $W^{(1)}$: $I = 0.2417$, $p = 0.00$).

Table 4 presents the results of the spatial lag models for the community associations and the counties. The spatial lag coefficient $\rho$ 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 ($\rho = 0.439$), 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, i.e. without taking further feedback loops into account. If one considers potential feedback loops, the average direct impact of $\rho$ (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 agglomeration effects are weaker at the lower spatial resolution than at the community association level. As positive agglomeration effects result from interaction between farmers this finding makes sense intuitively.

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 in every case is the variable *number of organic processors per 10 km$^2$*. For the counties, the *mean annual temperature* does not have a significant impact, too. The fewer number of variables remaining in the model at the lower spatial resolution might be due to lower variability at the county level (Table 2).

A larger *distance to agglomeration centres* influences the share of organic farms positively. This could be due to the low availability of agricultural land near agglomeration centres. A low *number of residents per km$^2$* also positively influences the share of organic farms maybe due to the importance of other factors for the distribution channels of organic products. For example, direct marketing has been very important in organic farming, requiring a spatial proximity of producers and consumers. Now, supra-regional organic discounters become more important and the spatial location of production and consumption of organic products is increasingly separated.

A high density of farms influences the share of organic farms negatively. We assumed that a high density of farms facilitates knowledge exchange between farmers; a high number of organic farms in an area then positively influences the propensity of conventional farmers to convert to organic farming.

However, other factors like the support of consultants of organic farmers' associations in the conversion process or the agricultural farm structures might also be important now. The average size of organic farms in Bavaria and Baden-Württemberg (approx.

## Table 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 ** | -0.0059 ** | -0.0063 ** | -0.0062 ** |
| Average distance to the next 3 agglomeration centres (in min. by car) | 0.0242 ** | 0.0236 ** | 0.0244 ** | 0.0215 ** | 0.0223 ** | 0.0328 *** | 0.0728 *** | 0.0852 *** | 0.0876 *** |
| 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 * | | | |
| Number of farms (ASE) per km$^2$ | -0.6779 *** | -0.7138 *** | -0.7131 *** | -0.6150 *** | -0.6407 *** | -0.8201 *** | -1.9541 ** | -2.1171 ** | -2.0626 ** |
| Mean annual temperature (in °C) | -0.7828 *** | -0.7301 ** | -0.6223 ** | -0.7474 ** | -0.6306 ** | -0.9789 *** | | | |
| 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 *** | 1.4300 *** | 1.5392 *** | 1.5540 *** |
| 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. | -11.9182 *** | -13.5673 *** | -16.5645 *** |
| $\rho$ | 0.439 *** | 0.538 *** | 0.561 *** | 0.529 *** | 0.643 *** | 0.959 *** | 0.3605 *** | 0.3101 * | 0.6875 ** |
| AIC | 12888 | 12942 | 12958 | 12870 | 12919 | 13044 | 656 | 662 | 661 |
| BIC | 12937 | 12992 | 13007 | 12920 | 12969 | 13094 | 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; $W^{(24nn)}$ = 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) and SLBW (2010)

## Table 5. Spatial lag coefficient resulting from different spatial analyses of organic farming in Germany (SCHMIDTNER et al. (2012) vs. current analysis)

| | Community associations | | | Counties | | | 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 centers | 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. |
| $\rho$ | 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 $\rho$ 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

Source: authors' own presentation based on BBR (2009), BLE (2009), BLSD (2011), DWD (2007), SAEBL (2010), SCHMIDTNER et al. (2012) and SLBW (2010)

32 ha) is larger than all farms' average (approx. 26 ha) (STATISTISCHES BUNDESAMT, 2008). Large 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 in some models at the community association level.

The climate variable *mean annual temperature* has a highly significant and negative influence at the community association level. According to our data, relatively 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 positive 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 models that perform 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 (the model using the first order neighbourhood matrix $W^{(1)}$ at the county level).

Compared to the results found by SCHMIDTNER et al. (2012), the models at the county level show slightly lower spatial lag coefficients (Table 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 differences between the dependent variables in the two studies could be another reason.

However, the results indicate that spatial dependence influences the spatial distribution of organic farms at the county level.

## 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 the county level. The use of aggregated information does not distort the results of the spatial analysis; the results at the lower spatial resolution are not artificially generated through the aggregation process. Thus, spatial dependence does not depend on spatial resolution in this case. The study indicates that essential aspects of the decision to convert from conventional to organic farming are also relevant at the county level. Beyond the scientific intention of checking the appropriateness of former analyses the relevance of the previous studies are strengthened by the results. To bring the analysis 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 (given data availability).

The results indicate that certified organic farms are often located in rural areas with low farm density and low mean annual temperature. The characteristics of (climatically) disadvantaged regions seem to facilitate the conversion to organic agriculture. This is in accordance with the literature (e.g., DABBERT et al., 2004). A favourable social and political environment like a high share of voters for the Green Party 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. Generally, the consideration and implementation of a time series could deepen the analysis and enable discussions of policy implications on the spatial distribution of organic farming.

To conclude, spatial dependence does not depend on spatial resolution in the case of organic farming in southern Germany.

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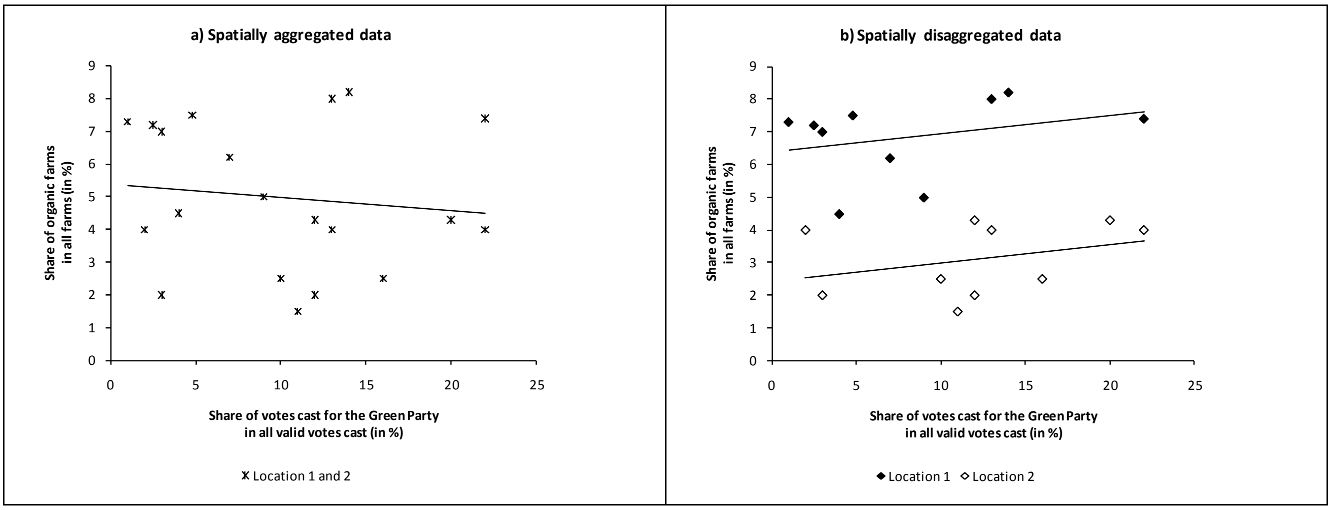
## Annex

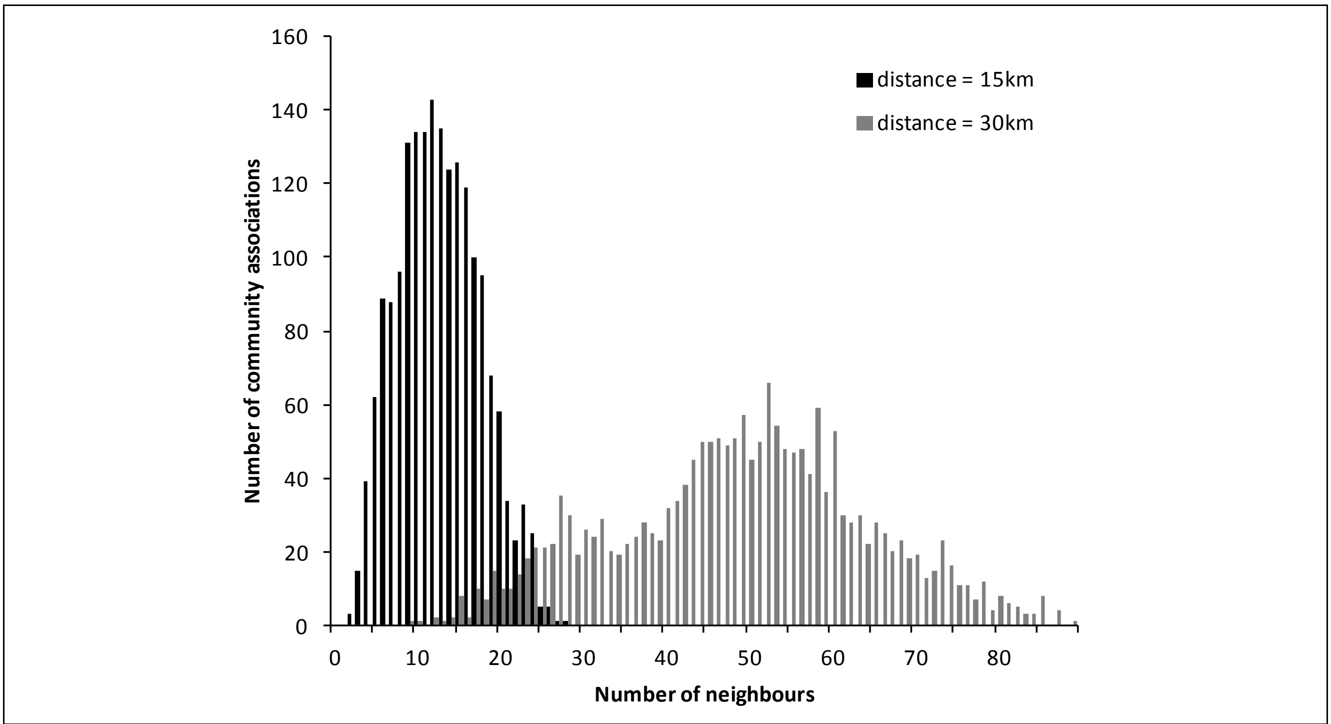
Figure A1 shows a constructed example of Simpson's paradox similar to the one presented in FOTHERINGHAM et al. (2002). The relationship of the share of votes cast for the Green Party in all valid votes cast and the share of organic farms in all farms is expected to be positive due to positive agglomeration 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 A1 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 A1. Spatial example of Simpson's Paradox**




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

**Figure A2. Connectivity of community associations at different distance bands**




Source: authors' own calculations based on BKG (2010)