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EXPLAINING THE CLIMATE DEPENDET DISTRIBUTION OF CROPS IN SPACE – THE EXAMPLE OF CORN AND CORN-CROB-MIX IN BADEN-WÜRTEMBERG

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Zusammenfassung

Im vorliegenden Beitrag wird die gegenwärtige klimaabhängige räumliche Verteilung von Körnermais und Corn-Cob-Mix in Baden-Württemberg anhand von Landkreis- und Gemeindedaten analysiert. Dabei werden sowohl OLS- als auch räumliche ökonometrische Modelle verwendet, um die Wirkungen verschiedener Klima- und anderer Variablen auf den Anteil von Körnermais und Corn-Cob-Mix an der gesamten LF abzuschätzen. Während die positive Temperaturwirkung mit Hilfe des OLS-Modells nicht aufgedeckt wird, ergibt das angemessene räumliche Fehlermodell einen hoch signifikanten positiven Effekt der jährlichen Durchschnittstemperatur auf Landkreisebene. Darüber hinaus weist dieses Modell ein Temperaturniveau auf, nach dessen Überschreitung ein weiterer temperaturbedingter Anstieg der Körnermaisanteile weniger wahrscheinlich wird. Diese Effekte werden auch durch das multinomiale Logit-Modell auf Gemeindeebene gestützt. Letzteres legt des Weiteren nahe, dass auch die Bodenqualität eine Rolle spielt. Die positive Wirkung der jährlichen Niederschläge ist hingegen nicht eindeutig.

Keywords

Räumliche Verteilung von Mais, Räumliche Ökonometrie, Multinomial Logit, Klimawandel.

1 Introduction

Against the background of ongoing climatic change it is of special interest how crop production and other agricultural activities are distributed in space and how this distribution depends on major climatic factors. The understanding and identification of such dependencies are a prerequisite for predicting how future climate change may affect agricultural production and change agricultural activities in different regions of the world.

Attempts to statistically derive relationships between climate variables and certain land use practices are referred to as structural Ricardian analysis (cf. SEO and MENDELSOHN, 2008b). Such analyses extend the "black box" approach of the traditional Ricardian analysis explaining land value by climate variables (cf. MENDELSOHN et al., 1994; MENDELSOHN, 2007) without revealing which adaptation measures or land use changes are actually behind some observed climate-dependent land value changes[2].

The objective of this paper is to analyse the current spatial distribution of corn (including corn-cob-mix) in Baden-Württemberg by means of cross-sectional spatial statistics in order to compare different approaches used to identify climate influences on land use patterns. Thus, our main motivation for this paper is not to provide for perfectly elaborated statistical models explaining climate dependent spatial distribution of farming activities. Instead, using the example of one specific crop, we want to assess different methods that later shall be used for Ricardian analyses explaining agricultural adaptation to different climatic settings. Here, we

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2 In Germany, the studies by BREUSTEDT and HABERMANN (2011) who included climate variables into their analysis of farms' land rental prices in Lower Saxony and LIPPERT et al. (2009) who explained German average county-level rental prices by climate can be seen as recent examples for the traditional Ricardian approach. Both studies relied on methods from spatial econometrics.

focus on grain maize because from an agronomic point of view we hypothesise that under the moderate and relatively cool climate of Central Europe its distribution is especially dependent on temperature and may also be affected by precipitation. This means that maize cultivated for silage as fodder or as biogas feedstock are not considered in this paper.

In Baden-Württemberg corn production strongly rose since the nineteen-eighties: the corn and corn-cob-mix acreage of this federal state increased by more than 200% from 28,381 hectares in 1979 to 73,735 (64,873) hectares in 2003 (2007) (STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG, 2008; 2011).

In 2007, almost half of the federal state's grain maize was located in the West along the Rhine river (see Figure 1), where the Southern counties of *Ortenau*, *Emmendingen* and *Breisgau-Hochschwarzwald* have been prominent centres of grain maize production. There, late mature corn varieties can be cultivated and corn has become the main crop in many farms to an extent that 1,734 farms even have been completely specialised in its production (HARTMANN, 2010: 37f.)[3]. Thus, corn production in Baden-Württemberg is mainly concentrated in the upper Rhine valley which is characterised by a relatively warm, mild climate (see Figures 1 and 2).

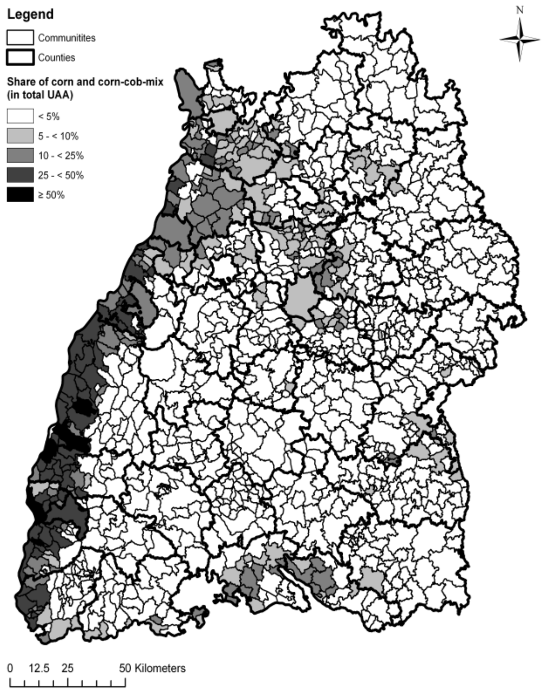
Reasons for the past strong increase in corn cultivation are seen in the current availability of improved coolness tolerant varieties and in the fact that so far maize can be cultivated in uniform crop rotations, and even tolerates monoculture (HARTMANN, 2010: 37). Since 1960, grain maize has shown the highest average yield increases among all cereals in Baden-Württemberg rising from about 3 tons per hectare to more than 10 tons in the past decade (BETZHOLZ, 2010: 32f.).

For the following analysis, we hypothesise that the share of corn and corn-cob-mix in utilised agricultural area (UAA) within a certain administrative unit (county or community) is positively influenced by temperature and precipitation. Also soil quality, grassland share in UAA, livestock and biogas production are supposed to have an influence.

The remainder of this paper is structured as follows: in section 2 we will briefly outline the statistical methods applied. Section 3 deals with the data used. The main estimation results are presented in section 4 and are further discussed in section 5.

[3] Notice that grain maize production in the mentioned counties is limited to the Rhine plain; in the adjacent lower altitudes of the Black Forest maize for producing silage is the only feasible maize cropping system (HARTMANN, 2010: 38).

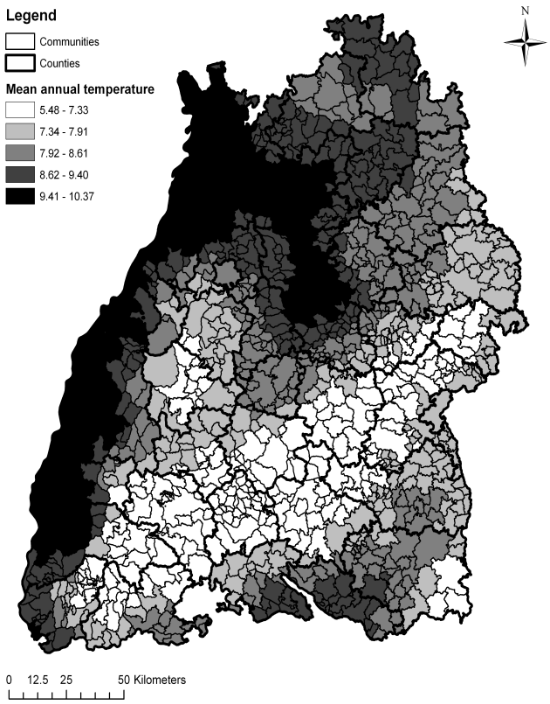
Figure 1: Regional distribution of corn and corn-cob-mix in Baden-Württemberg,



2007

Source: modified from BADER et al. (2010: 9; based on data by Statistisches Landesamt Baden-Württemberg, Agrarstrukturerhebung 2007).

Figure 2: Mean annual temperatures in Baden-Württemberg, averages for 1961-90



Source: own represantation based on DWD(2007).

2 Methods

2.1 Spatial models

In order to get unbiased and efficient estimates when trying to explain the spatial distribution of crop shares in UAA, it may be required to rely on spatial models (cf. ANSELIN, 1988: 34ff.; LESAGE, 1999: 52f.). In our case, the general spatial model is given by:

(1) $y = \rho Wy + X\beta + u$ with $u = \lambda Wu + \varepsilon$ and

y = vector containing transformed shares of corn in UAA in the year 2007 for the 44 counties of Baden-Württemberg ($i = 1, \ldots, 44$);

X = matrix containing for every county the observations for k independent climate and non-climate variables;

W = standardised spatial weights matrix reflecting spatial neighbourhood between the counties;

u = vector of spatially correlated residuals, and

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

The regression coefficients β for the k independent variables and if relevant the spatial lag coefficient ρ as well as the coefficient λ reflecting spatial autocorrelation of the residuals u_i are the parameters to be estimated. According to theoretical considerations both coefficients could matter: a significant parameter λ (i.e., spatial heterogeneity) suggests one or more spatially correlated omitted explanatory variables; a significant parameter ρ (i.e., spatial dependence) indicates the existence of agglomeration effects. Since it cannot be inferred a priori which of these two effects is relevant in case of regional corn distribution or whether even both effects matter a (robust) Lagrange multiplier test for spatial autocorrelation of OLS residuals (ANSELIN et al., 1996) is used to establish which model is most adequate. In principle, there are four possibilities:

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

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

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

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

Estimations are done using Stata along with additional routines for Moran's I statistics and the spatial models (1) as well as for the mentioned (robust) Lagrange multiplier test. These routines were provided by JEANTY (2010a, b, c). Two alternative row-standardised spatial weights matrices are used: a first order contiguity matrix (W1) and an inverse distance based matrix (Wdist). The distances are calculated based on the centroid of each spatial unit and are measured in meters. These matrices were generated using the software GeoDa and the Stata modules spwmatrix (JEANTY, 2010d) and spatwmat (PISATI, n.a.).

2.2 Multinomial choice model

Unfortunately, for data privacy reasons the analysis outlined in section 2.1 could only be done with counties as smallest spatial units. However, since we could obtain a map displaying corn and corn-cob-mix classes at the lower spatial scale of communities (see Figure 1) we also perform a multinomial logit analysis at this level. In principle, such an approach corresponds to structural Ricardian modelling put forward by SEO and MENDELSOHN (2008a, b).

Choosing the share of a crop is a decision accounted for intrinsically by farmers. As a series of other farm decisions in cross-sectional studies, the choice of a crop share can reveal farmers' adaptation to current climate conditions. In this context, a multinomial logit regression analysis can be deemed fruitful in estimating the link between the choice of corn share in total UAA and exogenous climate and soil variables. Such a model could be thought of as a synchronous estimation of many binary logit models in order to compare the effects of given regressors on different outcomes simultaneously (CAMERON and TRIVEDI, 2009; LONG, 1997)[4]. The formal statement of the multinomial logit model is given by formula (2):

$$(2) \qquad \Pr(s = m \mid x) = \frac{\exp(x\beta_{m|b})}{\sum_{j=1}^{J} \exp(x\beta_{j|b})}.$$

Let s be the response variable "share of corn and corn-cob-mix in total UAA" consisting of the categories of Figure 1 (i.e., $J = 5$). The left hand side term of formula (2), then, translates the probability of observing the corn share class m given some values for the explanatory variables and a base (i.e., the most frequent) category b, whose β parameters are set to 0. Since the effects of the exogenous variables are allowed to differ for each outcome, the coefficient for the effect of a specific variable might differ for each corn share category. Clearly, the model ensures that the probabilities are non-negative and sum up to 1.

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[4] Whereas any multinomial equivalent could have been used instead, crop shares were not obtained in the form of unambiguous data, but were extracted from Figure 1. Moreover, our interest lies for the moment in a descriptive context and not in predicting crop share probabilities. For these reasons, this paper follows a comprehensible, unordered multinomial technique that conceptually corresponds to a structural Ricardian regression of climate and edaphic factors on different crops

3 Data

The 2007 county level data on UAA, permanent grassland, livestock units and number of farms with crops for biogas production as the main use are taken from STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG (2008). Corn and corn-cob-mix hectares in 2007 were communicated by STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG (2011). The shares of corn and corn-cob-mix in overall agricultural land (variable "corn share") are calculated by dividing the corresponding acreage by the respective UAA of each county.

For data privacy reasons, 2007 corn and corn-cob-mix acreage is lacking for two counties in the administrative district ("Regierungsbezirk") of Freiburg. However, since the overall acreage for the entire district is known as well as the acreage of the remaining counties of this district, we assign the corresponding difference (933 hectares) to the two counties with lacking data (i.e., *town county of Freiburg* and *Schwarzwald-Baar county*) and distribute this acreage to both, according to the known share of their common corn acreage in 2003.

To avoid negative corn share (s) estimates and since we expect some kind of temperature threshold below which corn production is hardly feasible, the regression analysis outlined in section 2.1 is done with a transformed variable s. As it is also impossible to exceed a share of 1 and since for high corn shares a saturation effect is supposed to occur no matter how beneficial certain corn increasing factors may be, we use logit-transformed shares as dependent variable y:

$$(3) \qquad y = \ln\left(\frac{s}{1-s}\right).$$

For the purpose of this study, it is important to have a variable that reflects mere soil quality without incorporating climate influences like the German Soil climate index ("Bodenklimazahl"). Hence, we use the soil index ("Bodenzahl") kindly communicated by FORSCHUNGSZENTRUM JÜLICH (2009). The original data was on a 3 km grid resolution and was resampled to a 200 m grid using the value of the nearest neighbour of the original data. The resulting cell values have been aggregated on community and county level by calculating arithmetic means.

Historic weather data regarding temperature and precipitation from 1961 to 1990 were taken from Deutscher Wetterdienst (DWD, 2007). These data had been spatially explicit for 475 observation stations for precipitation and 132 stations for temperature in Baden-Württemberg. After creating temporal averages, the data were spatially interpolated using the inverse distance weighting method to create a 200m grid (exponent: 1, 5 neighbouring observations included). The resulting grid values were again aggregated at the community and county level using arithmetic averages. All spatial calculations have been carried out in the projection UTM 32 N.

Corn share classes for the communities of Baden-Württemberg (see Figure 1) were derived from BADER et al. (2010). For the soil, temperature and precipitation variables, quadratic terms are also considered.

Grassland share (permanent grassland per hectare of UAA), livestock density (livestock units per hectare of UAA) and biogas farm density (number of farms with crops for biogas per hectare of UAA) are negatively correlated with mean annual temperature (in °C). Moreover, there are correlations between grassland share and both annual precipitation sums (in mm) and livestock density. Livestock density is also correlated with biogas farm density. Soil index is negatively correlated with annual precipitation as well as with grassland share. All mentioned correlation coefficients are significant at the 5% level.

4 Results

4.1 Results from spatial regression models

As already suggested by Figure 1, a Moran's I test yields a highly significant spatial autocorrelation of logit-transformed corn shares in Baden-Württemberg (I=0.3125, $p<0.002$). Spatial concentration of corn production may result from obvious spatial autocorrelation of presumed explanatory variables like mean annual temperature (see Figure 2). The full OLS model yields only one significant variable. However, there is strong spatial autocorrelation in the residuals; the corresponding (robust) Lagrange multiplier test suggests estimating a spatial error model instead of applying OLS (LM=9.34, p=0.002). The results from the spatial error model are shown in Table 1.

Table 1: Full spatial error model for logit-transformed corn shares in the 44 counties of Baden-Württemberg, 2007 (spatial weight: first order contiguity matrix)

N = 44, LR chi2(1) = 10.614, P > chi2 = 0.001, Var. ratio = 1.037, R2corr = 0.55, logL = -62.059, σ = 0.92
Dependent variable: logit-transformed corn share

	Coef.	Std. Err.	z	P > |z|	[95% Conf. Interval]	
Mean annual temperature	12.5297	3.3948	3.69	0.000	5.8759	19.1834
(Mean annual temperature)^2	-0.6054	0.2063	-2.94	0.003	-1.0097	-0.2012
Mean annual precipitation	-0.0064	0.0087	-0.74	0.460	-0.0234	0.0106
(Mean annual precipitation)^2	0.0000	0.0000	0.63	0.531	-0.0000	0.0000
Soil index	0.1824	0.2038	0.90	0.371	-0.2171	0.5819
(Soil index)^2	-0.0023	0.0020	-1.14	0.252	-0.0063	0.0016
Town county (1=yes)	-0.7361	0.4825	-1.53	0.127	-1.6818	0.2096
Grassland share in UAA	0.8747	1.9322	0.45	0.651	-2.9123	4.6617
Livestock density	-0.1028	0.9704	-0.11	0.916	-2.0048	1.7993
Biogas farm density	235.2389	163.2828	1.44	0.150	-84.7894	555.2673
Constant	-65.9138	15.0535	-4.38	0.000	-95.4181	-36.4094
Lambda (λ)	0.7187	0.1253	5.74	0.000	0.4731	0.9643

Wald test of lambda = 0: $chi^2(1)$ = 32.896 (0.000), LR ratio test of lambda = 0: $chi^2(1)$ = 10.614 (0.001)

Source*:* own calculations based on data from STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG (2008; 2011); DWD (2007) and FORSCHUNGSZENTRUM JÜLICH (2009).

In the spatial error model, the coefficients of mean annual temperature and squared mean annual temperature are highly significant as well as the coefficient λ.

Staying with the spatial error approach, a stepwise backwards selection of variables was carried out. Whereas the significance of other variables changes depending on the variables removed, only the linear and quadratic temperature terms remain highly significant, and their magnitude is more stable. Our preferred restricted spatial error model is shown in Table 2.[5]

[5] Whereas the model suffers from high collinearity between the linear and quadratic variables, centering the linear terms before squaring reduces collinearity but produces very similar results.

Table 2: Restricted spatial error model for logit-transformed corn shares in the 44 counties of Baden-Württemberg, 2007 (spatial weight: first order contiguity matrix)

N = 44, LR chi2(1) = 12.837, P > chi2 = 0.000, Var. ratio = 0.922, R2corr = 0.53, logL = -66.024, σ = 1.02

Dependent variable: logit-transformed corn share

	Coef.	Std. Err.	z	P > |z|	[95% Conf. Interval]	
Mean annual temperature	12.2416	3.3290	3.68	0.000	5.7170	18.7663
(Mean annual temperature)^2	-0.6213	0.1958	-3.17	0.002	-1.0051	-0.2376
Constant	-62.2698	14.0743	-4.42	0.000	-89.8550	-34.6846
Lambda (λ)	0.6443	0.1335	4.83	0.000	0.3827	0.9059

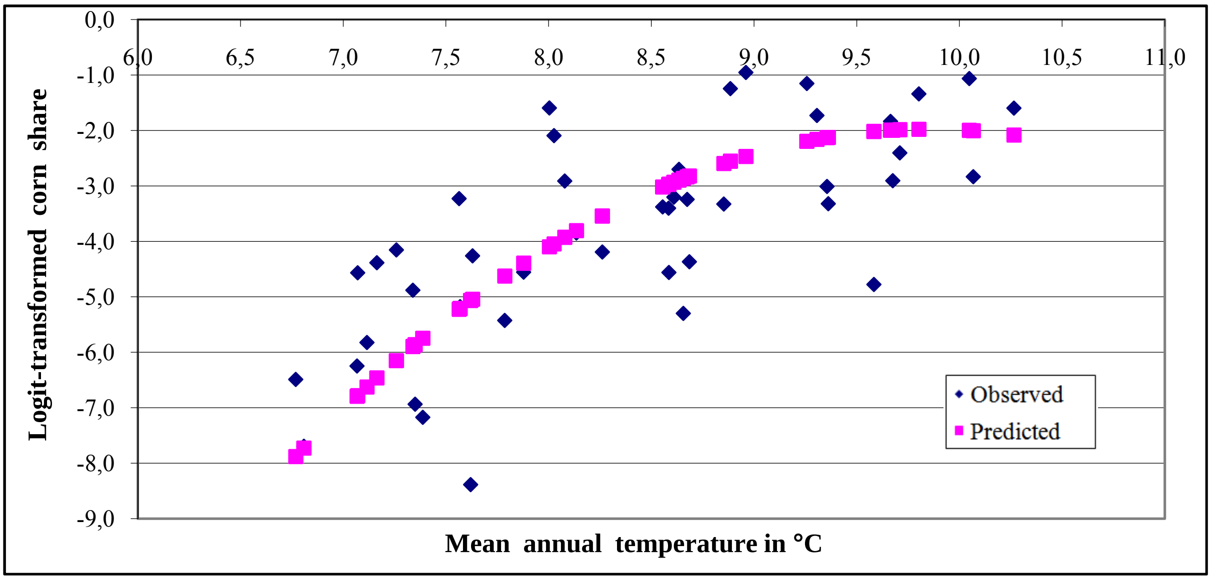
Wald test of lambda = 0: chi^2(1) = 23.307 (0.000), LR ratio test of lambda = 0: chi^2(1) = 12.837 (0.000)

Source: own calculations based on data from STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG (2008; 2011) and DWD (2007).

For the restricted version in Table 2, we also estimate a simple OLS model followed by a (robust) Lagrange multiplier test for spatial autocorrelation in the residuals. Again, this test suggests to rely on a spatial error model (LM=21.55, p=0.000). Using an inverse distance based matrix still leads to very similar significant effects as those shown in Table 2, but this time at lower significance levels.

Hence, the finally retained model (see Table 2 and Figure 3) yields a quadratic relationship between mean annual temperature and logit-transformed corn shares. Notice that the differences between observed and predicted values in Figure 3 correspond to the uncorrected errors u_i in equation (1).

Figure 3: Observed and predicted temperature dependent logit-transformed corn shares in the 44 counties of Baden-Württemberg, 2007



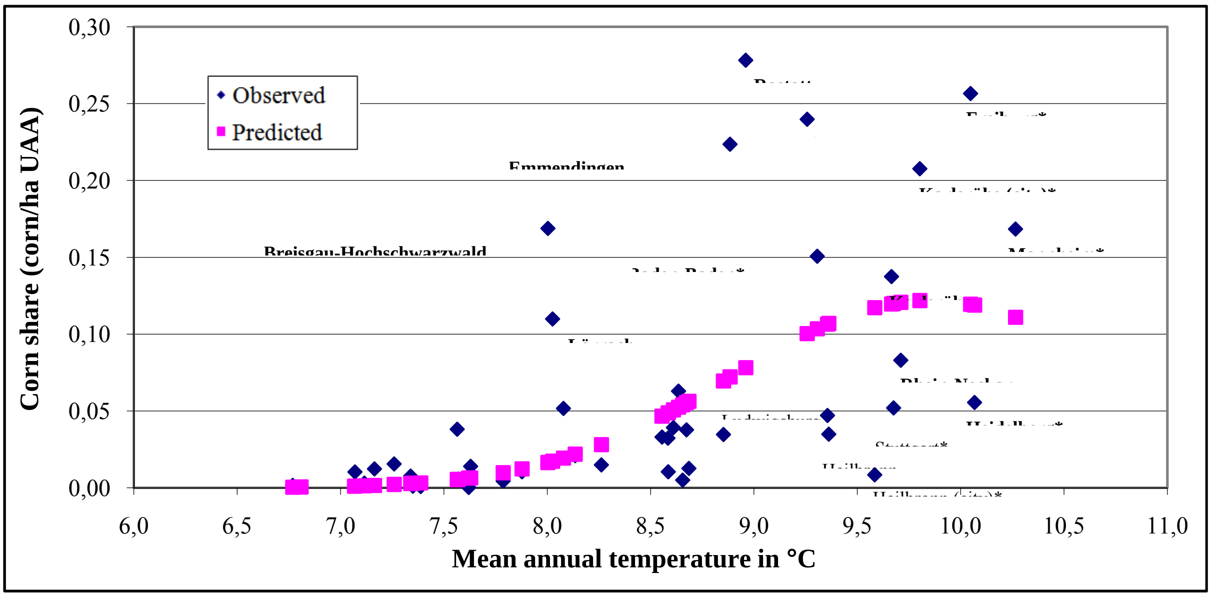
Source: own representation; data and estimations based on data from STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG (2008; 2011) and DWD (2007).

According to this model the retransformed relationship between mean annual temperature (T) and a county's corn share (s) is given by

$$(4) \qquad s = \frac{1}{1+e^{-(cons+b_1 T+b_2 T^2)}} = \frac{1}{1+e^{(62.270-12.242\,T+0.621\,T^2)}}.$$

Figure 4 shows the predicted temperature dependent corn shares along with the corresponding observed values. Clearly, the temperature point at which the curve levels off, is well within the range of the observed data. In the figure counties located along the navigable part of the Rhine river are highlighted by bold letters (not astonishingly, the cities in the Rhine valley are among the warmest places).

Figure 4: Observed and predicted temperature dependent corn shares in the 44 counties of Baden-Württemberg, 2007



Bold letters: counties along or (like Freiburg and Heidelberg) quite close to navigable Rhine river. *Town county.

Source: own representation; data and estimations based on data from STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG (2008; 2011) and DWD (2007).

4.2 Results from the multinomial logit model

The results above are supported by the multinomial logit analysis at the community level. First, a pentanomial logit regression of the 30-year temperature and precipitation normals, and soil index on the corn share classes of Figure 1 was done. Rejection of the null hypothesis of pairwise indistinguishability between categories 2-3 and 4-5 by means of the respective Wald tests (cf. LONG and FREESE, 2001: 184) allows us to get more efficient estimates by combining these outcomes into a trinomial model (see Table 3 on the next page).

The trinomial model passes both the Hausman and Small-Hsiao tests of the restrictive assumption of independence of irrelevant alternatives. The results indicate failure to reject the null hypothesis that the ratio of probabilities between two outcomes remains constant irrespective of the choice made (for details, cf. LONG and FREESE, 2001: 189; HAUSMAN and McFADDEN, 1984: 1226).

The overall fit of the trinomial model is seemingly relatively poor, however the regressors are jointly statistically significant at the 1% level with a high LR chi2(12) value. Three out of the four temperature coefficient estimates are significant at the 1% level but, since such a result would vary with the omitted outcome, the joint significance of temperature in the model should be tested. As such, both the corresponding LR and Wald test results suggest that mean annual temperature has a highly statistically significant effect on corn share. Similarly, both tests portray a joint statistical significance for soil index at the 5% level. Mean annual precipitation, nonetheless, is jointly statistically significant at the 5% level only by means of the LR test.

Table 3: Trinomial logit regression for corn share in Baden-Württemberg, 2007

N = 1110, LR $chi^2(12) = 478.42$, $P > chi^2 = 0.000$, Pseudo-$R^2 = 0.311$, logL = -530.359

Corn share category	**Coef.**	**Std. Err.**	**z**	**P > |z|**	**[95% Conf. Interval]**	
1 (base outcome)						
2+3						
Mean annual temperature	1.5568	0.1686	9.23	0.000	1.2264	1.8872
(Mean annual temperature)^2	-0.0122	0.1325	-0.09	0.927	-0.2719	0.2475
Mean annual precipitation	0.0007	0.0007	1.01	0.315	-0.0007	0.0021
(Mean annual precipitation)^2	0.0000	0.0000	-0.99	0.321	0.0000	0.0000
Soil index	0.0402	0.0084	4.76	0.000	0.0236	0.0567
(Soil index)^2	-0.0010	0.0005	-2.16	0.030	-0.0019	-0.0001
4+5						
Mean annual temperature	11.9882	2.9669	4.04	0.000	6.1733	17.8032
(Mean annual temperature)^2	-3.5013	1.1098	-3.15	0.002	-5.6765	-1.3261
Mean annual precipitation	0.0014	0.0015	0.91	0.362	-0.0016	0.0044
(Mean annual precipitation)^2	0.0000	0.0000	-1.98	0.048	0.0000	0.0000
Soil index	0.0132	0.0136	0.97	0.330	-0.0134	0.0398
(Soil index)^2	-0.0018	0.0008	-2.21	0.027	-0.0034	-0.0002
Constant	-9.1701	1.9640	-4.67	0.000	-13.0195	-5.3207

Note: 1 = up to 5% of the UAA, 2+3 = between 5 and 25% of the UAA, 4+5 = at least 25% of the UAA. The linear terms were centered before computing the quadratic ones.

Source: own calculations based on BADER et al. (2010: 9; data from Statistisches Landesamt Baden-Würtemberg, Agrarstrukturerhebung 2007); DWD (2007); FORSCHUNGSZENTRUM JÜLICH (2009).

En masse, mean annual temperature and soil quality are two factors affecting the intrinsic corn share decision in the same way: as the linear term parameters are positive, a ceteris paribus increase in any of these factors is more likely to lead to a higher corn share in total UAA. The negative quadratic parameters, however, provide evidence for the existence of temperature and soil quality cut-off points after which corn share is less likely to rise.

5 Discussion

With respect to grain maize, we did not find any other spatial statistical analyses at the county or community level that we could use to compare our results with.

The results of the two different statistical approaches show a similar relationship between temperature and corn share. However, in contrast to the multinomial logit analysis a significant effect of soil quality could not be found in the spatial error model.

Figure 4 and the functional relationship of the underlying estimated equation (4) indeed suggest that a certain minimum temperature is required for the cultivation of grain maize. Obviously, corn production is linked to a warmer climate.

The relevance of spatial error models established by the Lagrange multiplier tests hints at at least one further spatially correlated explanatory variable that determines the incidence of corn besides temperature. For instance, such a factor could be the access to markets or low transportation cost in case of near river ports. Also omitted topographic variables like average slope of UAA could matter in this context. Given the huge underestimation of corn shares in most of the highlighted counties in the Rhine valley, in these places there seems to be a further factor beyond relatively warm climate that is beneficial for the cultivation of grain maize. On the other hand, the lower than - due to the high temperature - expected corn shares in the Northwest of Baden-Württemberg (especially *Kraichgau*) may also be explained by the fact that this region is characterised by very good soils suitable for sugar beet production. Moreover, different distributions of precipitation over the year may matter: e.g., in field trials grain maize varieties harvested in Ladenburg (in the Rhine valley) had always a higher dry matter in 2010 than those harvested in *Kraichtal* located in the *Kraichgau* (BECHTOLD et al., 2010: Tab. 7).

The outliers *Breisgau-Hochschwarzwald* and *Lörrach* (see Figure 4) illustrate a general problem of trying to analyse climate dependent land use at a relatively high spatial scale: both counties reach from the Rhine valley to the top of the Black Forest mountain range. Hence, their aggregated annual temperature is relatively low; nevertheless, due to the huge amount of maize in the valley they show important overall corn shares (see also the distribution of corn shares at the community level in Figure 1).

By means of the county data analysis, we could not identify an upper corn share limit to which observed corn shares converge ("saturation")[6]. Anyway, Figure 1 shows that in certain communities shares of more than 50% are reached which is much more than the highest corn shares at the county level. The model underlying Figure 4 simply suggests that from a certain temperature on, further temperature increases do not matter. Then, other driving forces seem to be more important when explaining the extent of grain maize cultivation.

For ecological reasons it is very likely that in the long run there will be a maximum share above which corn cultivation cannot be increased sustainably. Probably, the limits of sustainable corn production are already exceeded in the upper Rhine valley: high maize shares led to increased pest pressures and recently the quite harmful Western corn rootworm ("Maiswurzelbohrer", *Diabrotica virgifera*) appeared in this region for the first time which entailed the prohibition of maize monocultures in the counties of *Ortenau* and *Emmendingen* (HARTMANN, 2010: 38). The European corn borer ("Maiszünsler", *Ostrinia nubilalis*) is another propagating pest linked to intensive maize cultivation (ERHARDT, 2011: 19).

Whether grain maize acreage will increase in other regions of Baden-Württemberg or Germany due to future climate warming also depends on the then available maize varieties as well as on the means to cope with the mentioned pests and possible new phytosanitary problems linked to high corn shares.

In the long run, there may also be limits to corn production due to reduced precipitation in summer time (predicted by climate modelling for Southwestern Germany, cf. SCHALLER and WEIGEL, 2007: 29f.) as maize is a crop that still needs some water when other main crops like barley are already harvested[7]. Consequently, a more detailed analysis of climate dependent maize frequencies at the community level should also include summer precipitation among the regressors. In this context, also (future) irrigation possibilities matter.

Comparing Alsace in France and Baden - two neighbouring regions both located in the upper Rhine valley - differences in irrigation practices are striking: whereas in 2006 in the French district *Haut-Rhin* half of the grain maize area of 59,000 hectares was irrigated (MINISTÈRE DE L'AGRICULTURE ET DE LA PÊCHE, 2008), in the counties of *Ortenau* and *Emmend-*

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[6] As some farmers accomplish maize monocultures (see section 1) at present this upper limit is probably close to one. A spatial error model again with temperature and squared temperature as only independent variables but explaining $\ln(s)$ instead of $\ln(s/(1-s))$ yields almost the same coefficients as the model in Table 2 which means that these coefficients are determined by relatively small corn shares s in the exponentially increasing area of function (4).

[7] The trinomial logit model displayed in Table 3 yielded a significant (at the 5% level) effect of mean annual precipitation at the low spatial scale of communities, between outcomes 1 and 4+5**.**

ingen only about 0.7% of the overall UAA was irrigated in the year 2002 (STATISTISCHES LANDESAMT BADEN-WÜRTTEMBERG, 2010; more recent data were not available). Probably, this huge difference can be explained by different local irrigation policies. For drier climates it has been pointed out that it is important to distinguish between irrigated and non-irrigated agricultural area to get unbiased parameter estimates in Ricardian analysis (HANEMANN, 2000: 578). In case of a future drier summer climate this aspect may also matter for Germany.

In all, besides climatic and other ecological factors used to explain and predict climate driven land use changes also policy variations need to be considered. Agricultural policy directly influences the regional distribution of land use practices by locally different subsidies (e.g., natural handicap payments in less favoured areas) or varying command-and-control measures like the above mentioned prohibition of maize monocultures or irrigation authorisations.

The main result of our exemplary statistical analysis, i.e., corn and corn-cob-mix incidence is to a large extent explained by the transgression of a certain temperature level, for sure is not surprising for an agronomist. However, one main purpose of this paper is to outline and critically assess statistical methods that may be used to predict future climate driven land use patterns. Our results clearly indicate that issues of spatial autocorrelation have to be taken into account in order to get efficient parameter estimates: in the county level analysis, we would not have detected the significant temperature effect by means of simple OLS estimation. Moreover, for climate and land use data, an analysis at a relatively low spatial scale should be preferred as well as a wider study area (e.g., the entire Germany instead of only Baden-Württemberg) in order to obtain more observations and capture more climate variability.

In case exact crop shares had been known -which was not the case for our community level data- multinomial choice models would not have been necessary. So far, existing multinomial logit approaches have got the disadvantage not to account for spatially correlated errors, which would distort estimation results in case a spatial error model was adequate.

Besides examining the spatial distribution of single key crops, also structural Ricardian analyses explaining the regional frequency of farm types (e.g., dairy or specialised crop farms) need to be done to better understand how farming systems change with climate. This can only be done relying on multinomial choice models that at best incorporate also spatial features.

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