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Municipality disaggregation of German's agricultural sector model Raumis

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Abstract

Since several decades the RAUMIS modelling system is applied for policy impact assessments to measure the impact of agriculture on the environment. A disaggregation at the municipality level with more than 9.000 administrative units, instead of currently used 316 counties, would tremendously improve the environmental impact analysis. Two sets of data are used for this purpose. The first are geo-referenced data, that are, however, incomplete with respect its coverage of production activities in agriculture. The second set is the micro census statistic itself, that has a full coverage, but data protection rules (DPR) prohibit its straightforward use. The paper show how this bottleneck can be passed to obtain a reliable modelling data set at municipality level with a complete coverage of the agricultural sector in Germany. We successfully applied a Bayesian estimator, that uses prior information derived a cluster analysis based on the micro census and GIS information. Our test statistics of the estimation, calculated by the statistical office, comparing our estimates and the real protected data, reveals that the proposed approach adequately estimates most activities and can be used to fed the municipality layer in the RAUMIS modelling system for an extended policy analysis.

Keywords: Highest Posterior Density estimator (HPD), RAUMIS, Down scaling

JEL classification: C11, C61, C81, Q15.

1. INTRODUCTION

Frequently, the impact of agricultural activities on the environment can only be properly assessed if the underlying distribution is well-covered. For instance, the likely impact of new pests such as the western corn rootworm (*Diabrotica virgifera ssp. virgifera* LeConte), which is relevant to the debate on bT-maize, depends on the share of maize in the crop rotation. Namely, if the share of maize exceeds 50%, western corn rootworm may have a serious impact (CARRASCO et al., 2009). If we analyse the cultivated area in 2007 at the county level (316 regions in Germany) the results indicate that the cultivation of maize in Germany should barely be affected by the rootworm (FDZ, 2010). However, if we conduct the same analysis on the municipality level, almost 13% of the maize cultivating areas would be affected by the rootworm. Thus, because agricultural land use and its dynamics are site-dependent, the utilisation of wider regional averages to model specific situations can be misleading (e.g., OSTERBURG *et al.*, 2009, p. 40 ff.).

The agricultural and environmental modelling and information system RAUMIS (HENRICHSMEYER *et al.*, 1996) is a mathematical programming, modelling and information platform used to cover Germany's agricultural sector. RAUMIS is used to analyse agricultural and agri-environmental policy instruments and currently operates at the county level. Similar to other economic models such as CAPRI (BRITZ and WITZKE, 2008), the RAUMIS model simulates an aggregate over all farms in a particular region. To overcome problems related to data aggregation, the underlying heterogeneity of farming patterns must be represented. Thus, several different approaches have been applied to disaggregate regional models. For example, a specifically tailored component in the CAPRI model has been used to disaggregate crop shares, stocking densities and fertilizer application rates from about 250 administrative regions across Europe into clusters of 1x1 km grid cells (LEIP et al., 2008) that are based on homogeneous spatial mapping units (KEMPEN *et al.*, 2005). Other downscaling approaches of agricultural statistical data with the help of geographical and/or remote sensing data are presented by DENDONCKER et al., (2006), VERBURG et al. (2006), YOU and WOOD, (2006). However, the resulting resolution with respect to animal and crop categories is very limited and therefore less useful in modelling agricultural decision process. Also if the results are spatially disaggregated into clusters of grid cells, the borders of the clusters do not necessarily coincide with administrative boundaries. Alternatively, a disaggregation of regional production levels into farming groups such as done by GOCHT and BRITZ (2010) is an option. However, this approach also has serious disadvantages because of the missing territorial representation which in turn does not allow spatially geo-referenced data to be linked, an important feature for regional models as RAUMIS.

Alternatively and in the focus of this study, county data are disaggregated to the municipality level using Agricultural Census data and GIS data. However, the provision of data is limited by legal constraints. In particular, many production activities at the municipality level fall under the data protection regulation (DPR) and are not reportable because the number of observations is limited. Currently, the DPR is by censoring data if they are derived from less than three observations or if a one or two observations dominate the result (primary confidentiality) (EUROSTAT, 2009). In Germany a result is viewed as being dominated if a single observation contributes more than 80% to the aggregate (FDZ, personal communication). Furthermore, additional aggregates are censored to ensure that data censored in step one cannot be retrieved from the published data (secondary confidentiality). As result, the likelihood that the data will be censored increases with increasing resolution.

If we want to overcome this and disaggregate the county data for the RAUMIS model to the municipality level using Agricultural Census data we need a method to extract additional information from official statistical offices without violating DPR. In contrast to GOCHT and ROEDER (2010) who apply a method based on locally weighted averages and only restricted to a specific region in Germany, we propose an algorithm that recovers local information with the help of the activities' median at the municipality level German wide. These medians are calculated for clusters of similar municipalities. The aim of the present study is to develop an algorithm that is capable to depict the distribution of agricultural land use with the spatial resolution of municipalities. We evaluate the estimated results with respect to both relative intensities (i.e. shares in the crop rotation and stocking levels) and absolute values (i.e. ha or livestock units (LU)). To our knowledge no attempt has been made so far at this coverage and administrative resolution, which results in a public and not traceable dataset for policy impact assessment.

The remainder of the paper is organized as follows. Section 2 highlights some key characteristics of the data. In Section 3, we describe the applied data manipulation algorithms and introduce the estimation framework. Lastly, Section 4 presents the results, and we conclude in a final section.

2. METHODS

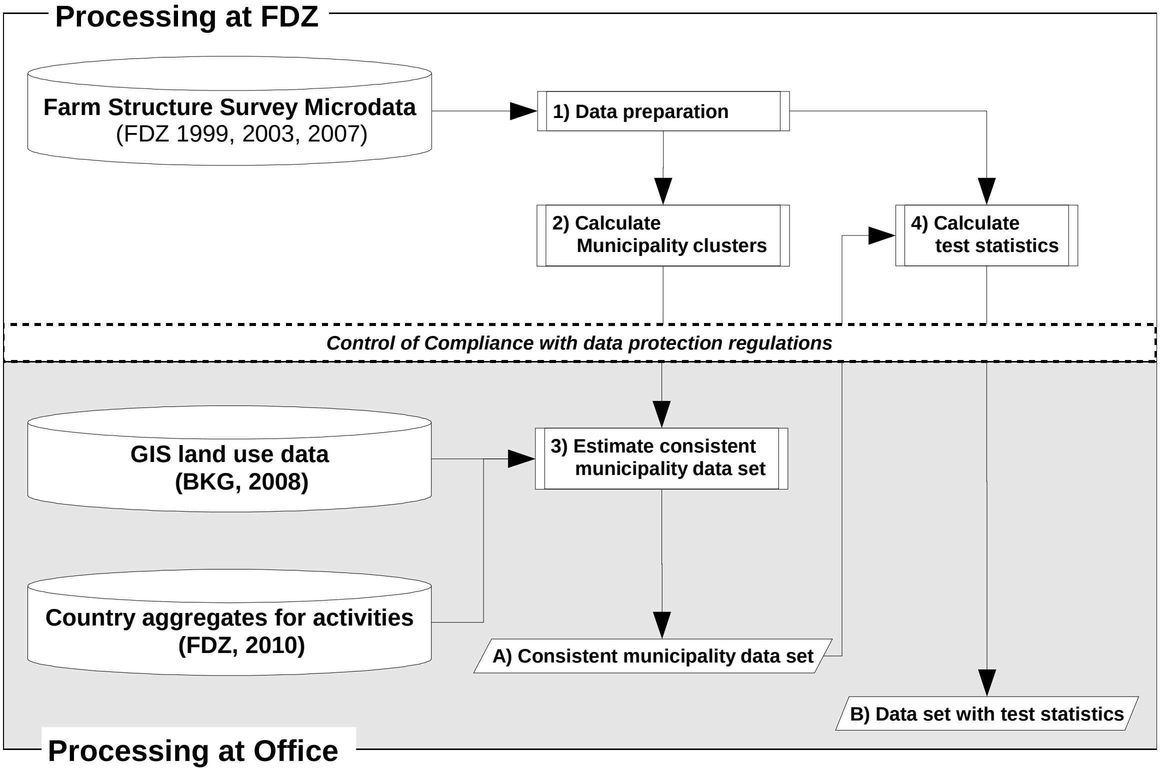
The section starts with explaining the preparatory steps necessary to overcome inconsistent data definitions between the statistical data bases and the RAUMIS model definition, before we describe the estimation framework and we finalize introducing the test statistic used to evaluate our estimates.

Figure 1 presenting the consecutive processing steps in order to facilitate the understanding of the data processing and handling. It distinguishes between two data processing environments. Processing at the **Research data centre** (FDZ) is done via sending data processing algorithm of standard statistical packages to the FDZ and because a researcher has never direct access to the micro data, one is forced to construct the processing algorithm virtually blind, knowing only the data structure and definition of the data. These conditions are rather uncomfortable because a validation whether a result is an observed trend or just a phenomena resulting from mapping or definition errors is difficult. Also the situation that economic simulation models are rarely realized in a standard statistical package makes the direct processing in the FDZ environment very cumbersome, and often impossible for economic policy evaluation. However, the big advantage is to have the opportunity to use the high resolution micro data shown in Figure 1 with the AFiD-Panel Agriculture database, to derive indicators. The Panel provides extensive information on the agricultural activities of farms in a four year interval for all farms in Germany.

All routines to be processed at the FDZ will be checked and results leave the FDZ only when they are in compliance with the DPR, presented in Figure 1 as the dotted rectangle between the two processing environments. Figure 1 also shows the processing at office environment, which is the researcher's office. Here we can use the outcome of the FDZ, which is anonymous not traceable and in compliance with the DPR for further analysis and applications. In Figure 1 step 3 illustrates the setup of an estimation framework, in which we use GIS data together with the FDZ information to obtain a consistent municipality data set.

We now explain step 1 until 3 in more detail: The data preparation in ***Step 1*** comprise the usual preparatory data work, mainly harmonizing definitions. As we need for RAUMIS a consistent data set at municipality level for several years from 1999 onwards we had to adjust and map regional definitions. As example, municipalities merged, split or exchanged and hence significant amounts of land. After harmonizing we remained with 9,679 time consistent municipality units. We had to aggregate some statistical codes to be in line with our 36 RAUMIS agricultural production activities.

Figure 1: Information flow in the estimation procedure



Source: Own elaboration

As the DPR prevent a direct retrieval of RAUMIS production activities at municipality level, we developed in ***Step 2*** a processing algorithm that complies with the DPR. We clustered the 9,679 regional units into 180 clusters based on several indicators for general land use, arable land use and animal density given in Table 1. For the three groups we independently applied the kMeans-algorithm (Witten & Frank, 2005). The algorithm was sent to the FDZ and applied to the micro data.

Table 1: Indicators obtained from each cluster

Indicator group	Unit	Indicators
General land use	% of utilized agricultural area (UAA)	Arable land, cereals, root crops, vegetables, main forage area, fruits, grassland, rough pastures
Arable land use	% of arable land	winter wheat, summer barley, rye, other winter cereals, other cereals, grain maize, rape seed, potatoes, sugar beet, green maize, other forage crops on arable land, other crops, set aside
Livestock husbandry	Livestock units (LU) per ha of UAA	Suckler cows, dairy cows, heifers, bulls, calves, sheep, horses, poultry, pig fattening, pig breeding

Source: Own elaboration

For each cluster, and hence the municipalities belonging to it, we obtained median and standard deviation of the respective indicators from the FDZ. In ***Step 3*** we setup an estimation framework with the aim to estimate the municipality production structure of our 36 RAUMIS production activities. We setup the model per county. Hence we have to solve 316 models. With each model we estimate the maximum 36 possible production activities for all municipalities in a county the number of municipalities per county ranges from 6 to 159 with a median of 25. In addition, the estimation algorithm uses GIS information on the extent of five land use types (utilized agricultural area (UAA), arable land, grassland, wine yards and orchards) and the agricultural production statistic at the country level, which is public available.

The cluster median for each indicators is interpreted as a priori information in the Bayesian sense, whereas the data information consists of the given county production values, sum of production activities over the municipalities is equal to the county level, and the constraint that the estimated activity levels add up to observed land use type, observed in GIS data GOCHT and ROEDER (2010).

Our Bayesian Highest Posterior Density estimator (HPD) maximizes the log of the joint posterior density (see HECKELEI et al., 2008), i.e. it searches for the most probable deviations from the cluster median fitting our data information on country activity level and the land type GIS information. Without knowledge about the exact distribution of the error terms in the clustered data, normally distributed errors with a co-variance of zero between the different medians and the obtained variance from FDZ are assumed.

The constraints alone do not allow a unique solution to be identified because there are too many unknown vectors of estimated cropping hectares and livestock herd sizes, exceeding the number of data constraints from GIS and country level statistic. Therefore, prior information must be included in combination with a penalty function. Generalised maximum entropy (GOLAN *et al.*, 1996) has frequently been applied to this end. However, we used the HPD estimation, which allows a direct and transparent formulation of prior information and reduces the computational complexity of the model (HECKELEI ET AL., 2008).

After we applied the estimation we obtained absolute and relative shares for all RAUMIS activities. In ***Step 4***, we calculate test-statistics to verify our findings by comparing the obtained estimates with the micro census data. We had to use the virtually blind approach, sending the estimates together with the routines to the FDZ and obtained the test statistics. We evaluated the distribution of the differences between estimated and observed cropping shares and livestock densities weighted with the respective local production level to assess the overall quality of the results.

The following software was used for the analysis at the FDZ: SAS 9.1 for regression and cluster analysis and the Conopt3-solver in GAMS 23.5 for the Bayesian minimisation problem.

3. RESULTS

In section 3.1 we analyse the overall fit of the model using the weighted differences between observed and estimated cropping shares and livestock densities. Afterwards we compare for selected activities the real intensity gradient at municipality level with the ones resulting from our estimation approach and a distribution obtained by a naive break down of "county shares" using to the municipality in a county. We finish this section with a detailed analysis of the distribution and development of maize production in Germany to illustrate the potential of high resolution data.

3.1. Error Distribution

Table 2 shows that for nearly all analyzed livestock activities the estimated livestock densities deviate from the observed ones by less than 0.1 LU per ha. For cattle, sheep and horses roughly 90% of the stock is located in municipalities where the density is estimated with an accuracy of ± 0.1 LU per ha. The distribution of granivores is covered worse. Here, especially for laying hens the density is partly significantly underestimated. However, this is not surprising as especially egg and poultry production pronounced local concentrations are typical.

Table 2: Distribution of the differences between the estimated and observed livestock densities at municipality level (in LU per ha) (differences weighted with respective local level)

		Quantile of the error distribution				
RAUMIS	**Description**	5%	25%	50%	75%	95%
KALB	Calves	-0.11	-0.04	-0.01	0.01	0.12
BULL	Male cattle > 6 month; stock bulls	-0.10	-0.03	0.00	0.04	0.11
FAER	Heifers	-0.16	-0.02	0.01	0.04	0.11
MIKU	Dairy cows	-0.12	-0.02	0.01	0.04	0.10
AMMU	Suckler and fattening cows	-0.09	-0.03	-0.01	0.01	0.05
SCHA	Sheep	-0.13	-0.04	-0.02	0.00	0.04
SOTI	Other livestock (horses)	-0.09	-0.03	-0.01	0.01	0.05
SAUH	Sows for piglet production	-0.30	-0.06	-0.01	0.03	0.11
SMAS	Pig fattening	-0.24	-0.04	0.01	0.07	0.27
LEHE	Laying hens	-3.46	-0.15	-0.05	0.00	0.32
SOGE	Poultry fattening (broiler, turkeys, etc.)	-0.69	-0.21	-0.07	0.00	0.27

Source: FDZ, own calculation.

Also for the cropping shares the local shares are generally well met (table 3). For cropping activities generally 50% of the production is located in municipalities where the respective share on the UAA is estimated with accuracy above ± 3%. The algorithm hardly overestimates the cropping share at the local level. Especially, the share of wheat, rye, rape seed, the grassland activities, fruits, vegetable, set aside and fallow is severely underestimated in some areas. The large differences for rape seed, set aside, and rye might be linked to their concentration in Eastern Germany. Here, the farms are rather large in comparison to the municipalities so the difference between the land use in the cadastre for the municipality and the actual land use of the farms in this municipality might be rather large. For the three grassland activities the difference might be explained by a mutual exchange of activities in particular meadows and pastures. In addition in particular the location of the rough grazing reported in the cadastre is likely to differ significantly from the distribution according to the Agricultural Census as not all these areas are managed by farms or where included in the definition of agricultural area. The last argument might also explain the problems observed in fruits, vegetables and fallow.

Table 3: Distribution of the differences between estimated and observed cropping shares at municipality level (in % of UAA) (differences weighted with respective local level)

		Quantile of the error distribution				
RAUMIS	**Description**	**5%**	**25%**	**50%**	**75%**	**95%**
WWEI	Winter wheat, spelt	-0.40	-0.02	0.02	0.04	0.08
SWEI	Summer wheat, durum wheat	-0.07	-0.02	-0.01	0.00	0.01
WGER	Winter barley	-0.11	-0.02	0.00	0.02	0.05
SGER	Summer barley	-0.06	-0.02	0.00	0.02	0.06
ROGG	Rye, and winter cereal mixes	-0.20	-0.03	0.00	0.04	0.10
HAFE	Oats and summer cereal mixes	-0.05	-0.02	-0.01	0.00	0.03
KMAI	Grain maize (including CCM)	-0.07	-0.03	0.00	0.03	0.11
SGET	Other cereals, triticale	-0.07	-0.03	-0.01	0.01	0.05
RAPS	Rape and turnip rape	-0.21	-0.02	0.01	0.03	0.06
HUEL	Pulses	-0.07	-0.03	-0.01	0.00	0.05
SHAN	Other oilseeds and industrial crops (hops, tobacco, etc.)	-0.09	-0.04	-0.01	0.00	0.04
SKAR	Potatoes	-0.06	-0.03	-0.01	0.02	0.07
ZRUE	Sugar beet	-0.08	-0.02	0.00	0.02	0.05
SHAC	Other root crops (fodder beet, etc.)	-0.03	-0.01	0.00	0.00	0.00
SMAI	Green and silage maize	-0.09	-0.02	0.00	0.03	0.07
FEGR	Grass on arable land (including all other fodder on arable land)	-0.09	-0.03	-0.01	0.02	0.06
WIES	Meadow	-0.20	-0.03	0.00	0.03	0.09
WEID	Pasture	-0.27	-0.08	-0.02	0.01	0.11
HUTU	Rough pastures	-0.19	-0.05	-0.02	0.00	0.05
FLST	Set aside	-0.15	-0.08	-0.06	-0.04	-0.02
GEMU	Vegetables, strawberries	-0.15	-0.06	-0.02	0.00	0.05
SOPF	Other plant production (flowers, nurseries, etc.)	-0.09	-0.02	-0.01	0.00	0.03
OBST	Fruits (without strawberries)	-0.16	-0.03	-0.01	0.00	0.03
REBL	Wine	-0.10	-0.03	0.00	0.02	0.07
FALL	Fallow	-0.52	-0.03	-0.01	0.00	0.01

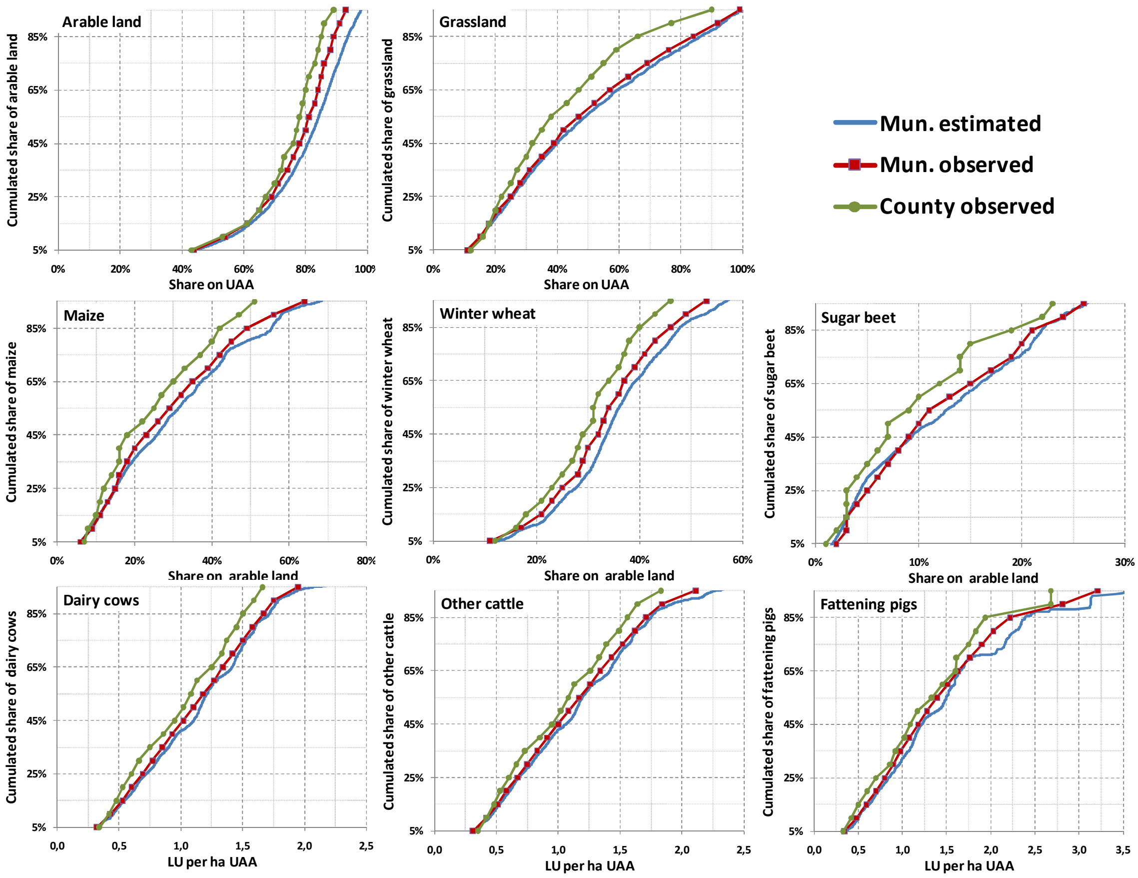
Source: FDZ, own calculation.

3.2. Fit of the estimate

Figure 2 compares for different production activities the cumulative density distribution observed at the municipality level (red curve = *Municipality observed*) with the outcome of the estimation procedure described above (blue curve = *Municipality estimated*) and a distribution calculated naively on the county shares (green curve = *Municipality taken over from county shares*). Note, we do not present the tails of each curve as the extreme values of the observed distribution at municipality levels are censored due to DPR. For a better comparability all curves are truncated to the available interval that ranges from the 5% to 95% quantile.

The first row presents the shares of arable land and grass land on UAA. The second row depicts production activity shares for maize, winter wheat and sugar beet on arable land and the last row visualizes the distribution for dairy cows, other cattle and fattening pigs. Each of the curves is a cumulated density distribution, it depicts how much of a certain activity level (y-axes) can be represented by a certain range of shares from zero up to the indicated share of the curve on the x-axes.

Figure 2: Cumulated density plots for selected agricultural activities in 2007



Source: FDZ, and own calculation.

In all figures, the county shares are on the left side of the observed shares. This is not surprising as we lose the heterogeneity of shares across municipalities by the aggregation of the observed municipality level (red line) to county shares and their re-assignment to all municipalities of a county. The green line presents the current resolution of the RAUMIS modelling system, for which we assume that shares for production activities at county level equal those in the municipalities. This does not hold as differences between county and observed municipality exists, as presented in Figure 2.

We also can observe that the steeper the curve is for a given activity the smaller is the heterogeneity of production shares range in which the majority of the production can be found. As example for grassland: 45% of Germany's total grassland is located in municipalities where the share of grassland on UAA is below 40% and roughly 18% of the grassland is located in municipalities where the respective share is above 80% (red curve). If the shares are calculated on a county base instead more than 55% of Germany's grassland is located in counties where the share is below 40% and roughly 10% is located in counties where the grassland share exceeds 80% (green curve). One can see that the blue curve (the estimated values at municipality level) follow the red (the observed distribution) quite closely. The green curve (if county averages are taken as a proxy for the local situation) is far left of the red one. As indicated before, this implies that in particular the proportion of grassland in areas with a grassland share of 25% to 60% is greatly overestimated. The distribution of arable land differs quite significantly from the one for grassland. Only 10% of Germany's arable land is located in counties or municipalities where the arable land accounts for less than 50% of the UAA. At municipality level for arable land the fit between the estimated and observed distribution is lower than for grassland. In tendency the difference between the observed distribution at municipality level and the estimated at municipality on the one hand and the county averages is comparable. While the county averages locate more arable land in areas with lower shares of arable land (underestimate the specialisation). Our estimation approach is overspecialised compared to the observed distribution at municipality level. This result might be explained by the fact that there exists a difference of nearly 2 million ha (~ 30% of the grassland according to the census) between the grassland areas reported in the Agricultural Census and the cadastre. If this error is not randomly distributed a slight systematic underestimation of the grassland share in municipalities with high shares of arable land will lead due to the large lever of the grassland share to a significant right shift of the curve (Taking a municipality of 1,000 UAA and a share of arable land of 10% an underestimation of 1% (= error of 10 ha grassland) will relocate 910 ha of arable land to the right (to areas with higher shares of arable land)).The tendency to overspecialize is found in other production activities, particular with high shares as winter wheat. Another reason for the overspecialisation might be the fact that for most activities the standard deviation, which we use as an indicator for the confidence we have in the appropriateness of a cluster median for a designated municipality is strongly positively with cluster median. This implies that larger shares are intrinsically associated with a lower confidence in the value and a deviation from the prior information is less punished in our HPD estimation framework.

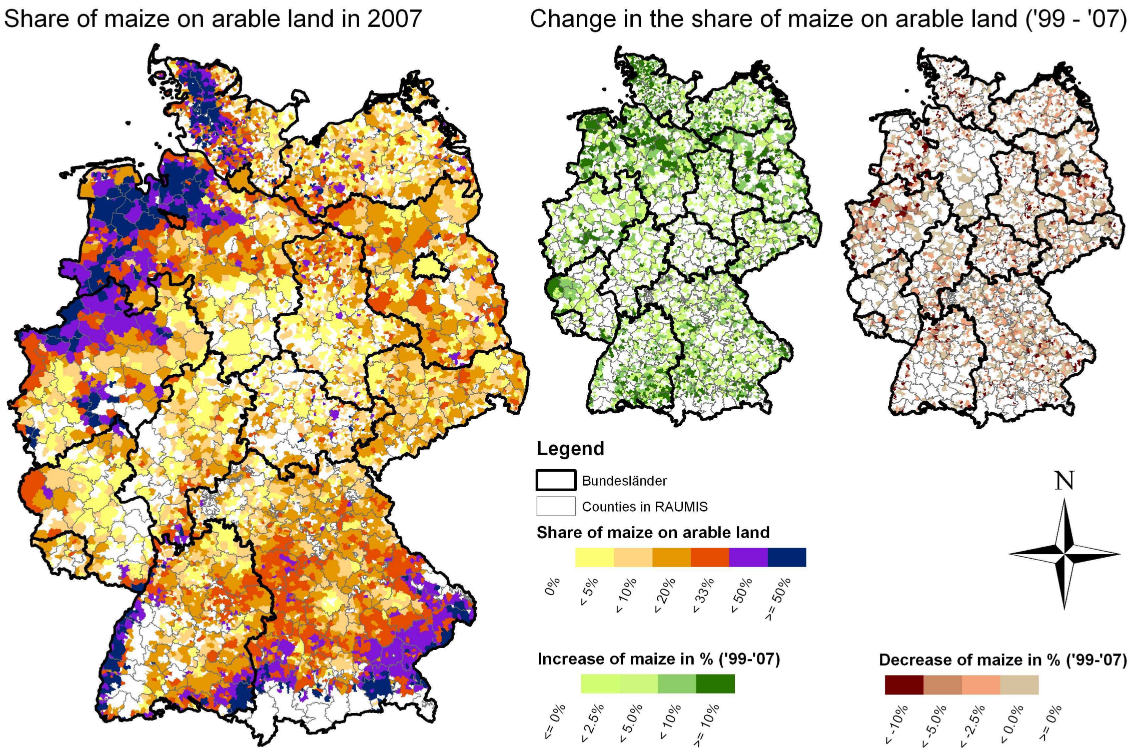
To summarize Figure 2 the municipality based estimator outperforms the county based approach especially for activities that are of smaller overall importance and locally concentrated like rough grazing, sugar beet, wine, potatoes, or poultry.

3.3. Local distribution and development and cultivation of maize in Germany

After we evaluated the quality of the estimation, we will use of the obtained results to analyse the distribution and development of maize shares in Germany at municipality levels, to gain more insight into possible phytosanitary problems. To our knowledge, such an exercise is done for Germany for the first time with such a resolution.

Figure 3 depicts the estimated distribution on municipality level of maize (grain and green) in Germany for 2007. Despite the fact that maize was grown only on 16% of Germany's arable land, maize covers more than 33% of the respective arable land in a couple of areas. One centre regarding the cultivation of maize lies in north-western Germany between the Ruhrgebiet and Rhine in the south-west and the Elbe in the north-east. Regarding the cultivation of maize a second large hot spot is located in south-eastern Bavaria east of the Inn and between the Alps and the Bavarian Forest. Smaller areas with high shares of maize (beyond 33%) can be found in the Geest (Schleswig Holstein), the Upper Rhine valley (Baden-Württemberg), the foothills of the Allgäu (Baden-Württemberg and Bavaria) and the Sauerland (Northrhine-Westphalia). Maize reaches, hence, in several areas quite critical levels regarding phytosanitary issues when the distribution is analysed at municipality level.

Figure 3: Dynamic of estimated maize shares on arable land 2007 compared to 1999



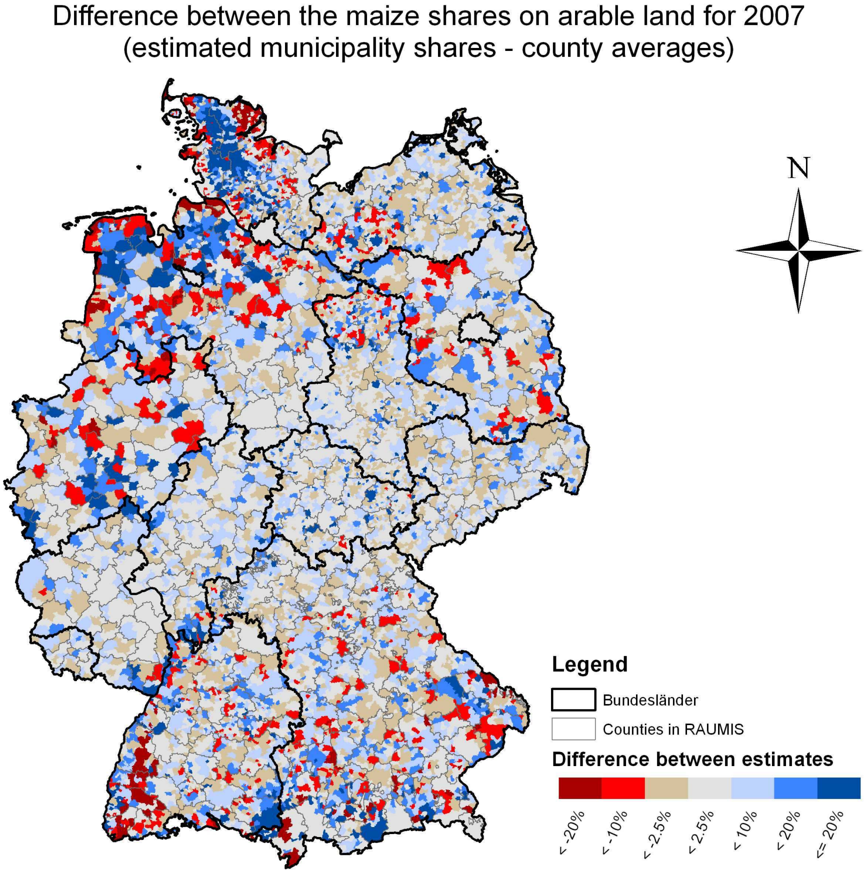
Source: Own estimation

In the following section we analyze the development of maize shares depicted by the small maps in Figure 3. The area cultivated with maize expanded by 300,000 ha between 1999 and 2007 resulting in a moderate increase of maize's share on total arable land from 13.3% to 15.9%. However, these aggregate figures cover a quite significant dynamic on the local level that we now are able to analyze with the outcome of the estimation. In large parts of North-Western Germany, in the Geest, and in the vicinity of mountain ranges (Eifel, Sauerland, Allgäu, Alps and Bavarian forest) maize's share on arable land increased by more than 10%.

Till 2002 the cultivation of maize was strongly linked to arable forage cropping in particular dairy farming and bull fattening. This explains the high shares of maize in areas with high cattle densities (e.g. along the North Sea and in the foothill of the alps). Grain maize including corn-cob mix was important in the Upper Rhine Valley, along the border between Northrhine-Westphalia and Lower Saxony and in south east of Bavaria. While the area of grain maize remained nearly constant over the last decade the area of green maize declined parallel to the declining cattle stock till 2002. From 2002 till 2007 the maize area expanded by more than 360,000 ha due to the promotion of biogas production based on silage maize (BMELV, various years). While the cultivation of maize declined in the north-western part of Northrhine Westphalia, the eastern part of Bavaria and the northern part of Baden-Württemberg. This development is critical for two reasons. First, maize cultivation is expanded in areas where maize is already the dominant crop, increasing phytosanitary risks. Second, the cultivation of maize in mountain ranges induces a high risk of erosion, as in these areas the precipitation is high, the terrain is fairly undulated and maize is developing a protective vegetation cover late in the year.

Figure 4 compares the result obtained from the estimation approach and the county averages for the share of maize on arable land. In large parts of Germany the county averages are a reasonable estimate for the municipality shares (e.g. Rhineland-Palatine, Hesse, Thuringia, and Saxony). However, the county averages underestimate drastically the relevance of maize in the Geest of Schlewig-Holstein and Lower Saxony, and in the foothills of the Alps, the Bavarian Forst and the Odenwald. On the other hand the relevance of maize is overestimated for large parts of the Black forest, the marsh land of Lower Saxony and the north eastern part of Schleswig-Holstein.

Figure 4: Difference between the estimated share of maize on arable land for 2007 (estimated municipality shares – county averages)



Source: Own estimation

4. CONCLUSIONS AND OUTLOOK

The proposed method of disaggregation, which combined the highest posterior density (HPD) and a cluster analysis improved land use estimates at the municipality level and complied with the data protection rules (DPR) at the FDZ.

The correlation between the observed and predicted values was analysed for the entire data set in German, and the results indicated that the proposed approach can adequately depict the spatial and density distribution of most RAUMIS activities while complying with the DPR.

Not surprisingly the described procedure greatly improves the mapping quality for activities whose distribution shows are clear spatial pattern that does not coincidence with the county borders e.g. the distribution of rough pastures or the distribution of maize in Schleswig-Holstein and Baden-Württemberg. If an activity is widespread and dominant the advantage of the estimated results versus a naive downscaling of the county shares is less clear.

For most activities the described procedure generally covers well the intensity gradient present in Germany's agriculture. However, it has slight tendency for an overspecialisation. In principle, there are three reasons why our estimated results on the municipality level deviate from the observed levels:

1. The reference area and therefore the plot is not recorded in the same municipality as the farmstead. In the FSS the UAA is attributed to a municipality according to the locality of the farmstead, while in the cadastre the plot the situs principle is applied.
2. Agricultural used areas are wrongly recorded in the cadastre or Agricultural Census. To illustrate the importance of this fact, one has to keep in mind that the agricultural area reported in the cadastre exceeds the one of the FSS by nearly 2 million ha or 10%.
3. False attribution of activities on the municipality level (in step 3). This can be due to several reasons. First, the fact that the median is not a suitable estimator for the activity level in a given municipality. Second, the assumption of a normal error distribution is oversimplifying. Third, the weighting of the different parts of the error term is inappropriate.

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