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Spatio-temporal predictions of agricultural land prices. Application to France

Florence Carré¹, David Grandgirard², Vincent Julien³, Blandine Lemerrier⁴

¹ Institute for Environment and Sustainability/ Land Management & Natural Hazards
Unit/ DG JRC/ florence.carre@jrc.it

² Institute for Protection and Security of the Citizens/ Agriculture Unit/ DG JRC/
david.grandgirard@jrc.it

³ SAFER, Paris/ Vincent.Julien@safer.fr

⁴ UMR INRA / AGROCAMPUS OUEST/ Sol Agro et Hydrosystème
Spatialisation/Blandine.Lemerrier@agrocampus-ouest.fr

Abstract. By conditioning uses made on the agricultural land, land market prices have a strong influence on agriculture sustainability. The purpose of the study is to predict spatially and temporally French agricultural land prices. For that, a classification of the land price dynamics is done for the period 1995-2006. Spatial modeling of land price dynamics classes is undertaken following three different approaches: (1) a purely spatial approach on the classes using ordinary kriging, (2) a mixed approach combining regression with kriging. The temporal prediction is done using time-series models. The spatial predictions of land price dynamics classes are done applying the regression-kriging on an independent dataset and temporal prediction is done for 2007. Results show a maximum of 87% of good spatial prediction and only 6% of underestimation of the temporal prediction of the land prices.

1 INTRODUCTION

Agricultural land market prices can have a strong influence on conversion of croplands to urban uses if the price is not affordable for farmers. Land market prices can then contribute a lot to land use and landscape changes and could endanger agriculture sustainability. Thus, it is important to be able to model and/or predict spatially and temporally land market prices. The global aim of the project is to model and predict contemporaneously spatial and temporal agricultural land market price in Europe. This study aims to set up the methodology before applying it to the whole Europe. French Agricultural Administrative Units (AAU), having a size of European NUTS5, are the spatial entities to model from 1995 to 2007. Determinants of agricultural land market prices usually identified are accessibility by road, location, adjacency to state land, date of sale, land use classification, size of parcel, site type, topography, nonlocal buyers (Vrooman, 2006), prices of crops or timber species for agroforest activities (Aronsoon

and Carlen, 2000; Awokuse and Duke, 2006). Relations for modelling agricultural land market prices using these determinants are usually linear (Lourival et al., 2006). In this study, we test the performance of linear relationships between land market prices and the determinants. Since the global aim of the project is to expand the methodology to Europe, the determinants are constrained to be available for Europe and not specific to France. Furthermore, in order to test the spatial specificity of the model, in addition to the linear model which is a non-spatial approach, we test also the relevance of spatial and mixed approaches. After describing the data, the paper then focuses firstly on the spatial modelling, secondly on the temporal prediction.

2 DATA AND METHODS

We describe hereafter the data and the methods used.

2.1 Land market price data

Land market prices are described for each of the 379 French Agricultural Administrative Units (AAU) and for each year between 1995 and 2007. They are prices of transactions of agricultural lands which have been reported to and centralized by the French SAFER Institute which acts as a notary; it assures no bias in the reporting of the land prices. However, agricultural lands which have been sold one year could be not representative of one AAU especially when the number of transactions is low. Unfortunately this information, not available for the moment in the database, will be provided by the SAFER. It will then be integrated in the prediction for correcting the input data due to lack of price information. In order to be able to understand and model land price dynamics, the dataset has been transformed into temporal trends for the period 1995-2006 – 2007 being used for prediction. For that, a fuzzy *k*-means classification (Bezdek, 1981) was processed to segment the AAU into classes of price dynamics. Each AAU is then described by its Euclidian distances to the cluster centroids. The dataset is then divided into two subsets. Three fourths are selected randomly in each classes of price and serve for the spatial modeling; the rest is used for the validation of the prediction.

2.2 The determinants used

The determinants used concern the environmental and economic characteristics of the AAU context. Some are stable over time while others are dynamic. The *stable* determinants in each AAU are the total length of roads (considered with no change in 10 years), the average field size, some landform attributes (relief, slope and hillshade from SRTM data), the area under Natura 2000 program, the percentages of bioclimatic units (Mücher et al., 2003) and of major soil types (from European Soil Database). The last two variables were selected as they condition the potential yield of a crop and the transaction price of the land. The *dynamic* determinants are population density depicting urban pressure, gross domestic product (© Eurostats), organic matter content (French BDAT, INRA). Relative area proportions of 19 land cover classes (Corine Land Cover,

©EEA) and their spatial patterns obtained from FRAGSTATS metrics (McGarigal and Marks, 1995). Dynamics of the determinants is obtained from three years: 1995, 2000 and 2005 and classified as landscape dynamics classes (Grandgirard and Carré, submitted) where each AAU is then described by its distance to each landscape class centroid. Both, individual AAU contexts and landscape dynamics were used as spatial land price dynamic determinant. In order to avoid collinearity of the variables, Principal Component Analysis was performed on the determinants and the 25 first Principal Components (PC) representing 94% of the variability in the dataset were used to model agricultural land prices.

2.3 The spatial prediction of land price trends

2.3.1 The spatial approach or ordinary kriging

The spatial approach is done by applying classical ordinary kriging (Wackernagel, 1995) on the distances between each AAU and each cluster centroid. The AAU dataset which is a polygon shape file has been transformed into a 10*10 km gridcell nodes leading to 4743 spatially georeferenced points. This resolution of 10km is the best for detecting the smallest AAU polygons in France. It allows for having at least 3 points per polygon and to integrate the different shapes of the polygons. The ordinary kriging approach takes into account the spatial autocorrelation of the distances. The spatial autocorrelation could be interpreted in that case as the influence that nearby land prices have on the land price of the specific location. The modeling is based on the following equation:

$$D_{o,j}(z_o) = \sum_{v=1}^N \lambda_v D_{v,j}(z_v) \quad \text{Eq. (1)}$$

Where λ_i are the kriging weights, $D_{v,j}(z_v)$ the measurements at location z_v and $D_{o,j}(z_o)$, the prediction of the distance between cluster centroid j and AAU at location z_o , N the number of locations taken into account for the calculation. The ordinary kriging is run for each land price cluster.

2.3.2 The mixed model or regression-kriging

The regression-kriging model is a Multiple Linear Regression between $D_{i,j}$ (the distances between the i^{th} AAU and the j^{th} land price cluster centroid) and the k^{th} PC followed by an ordinary kriging of the residuals to the regression (see Eq. 2):

$$D_{i,j} = \alpha_{o,j} + \sum_{k=1}^{25} \alpha_{k,j} PC_{i,k} + \varepsilon_{i,j} \quad \text{Eq.(2)}$$

Where α_{oj} is the intercept of the regression for the cluster j , $\alpha_{k,j}$ are the coefficients of the regression of the 25 PC and $\varepsilon_{i,j}$ are the regression residuals of i^{th} AAU for the regression of the j^{th} cluster. There are as many regressions as land price clusters. To estimate the quality of the predictions, the 3 models are applied on the validation dataset. The minimal distance and the corresponding cluster are assigned to each validation AAU. We then calculate the percentage of concordance between predicted and observed land price dynamic cluster as criteria of performance of the models.

2.4 The temporal prediction of land prices

The temporal prediction of land prices is done on the year 2007 using the centroids of the land price dynamics clusters. On each centroid, an Auto-Regressive (AR) model (Eq.3) is tested and applied on the year 2007.

$$X_t = \varepsilon_t + \varphi * X_{t-1} \quad \text{Eq. (3)}$$

Where X_t is the land price at time t , ε_t is the white noise a time t , φ is the regression coefficient. The quality of the predictions is estimated from the average residual error percentage.

3 RESULTS

3.1 The land price dynamics cluster

The classification of the land price dynamics leads to 7 clusters. Figure 1a shows the price evolution of the 7 cluster centroids. Figure 1b shows the spatial distribution of the 7 clusters.

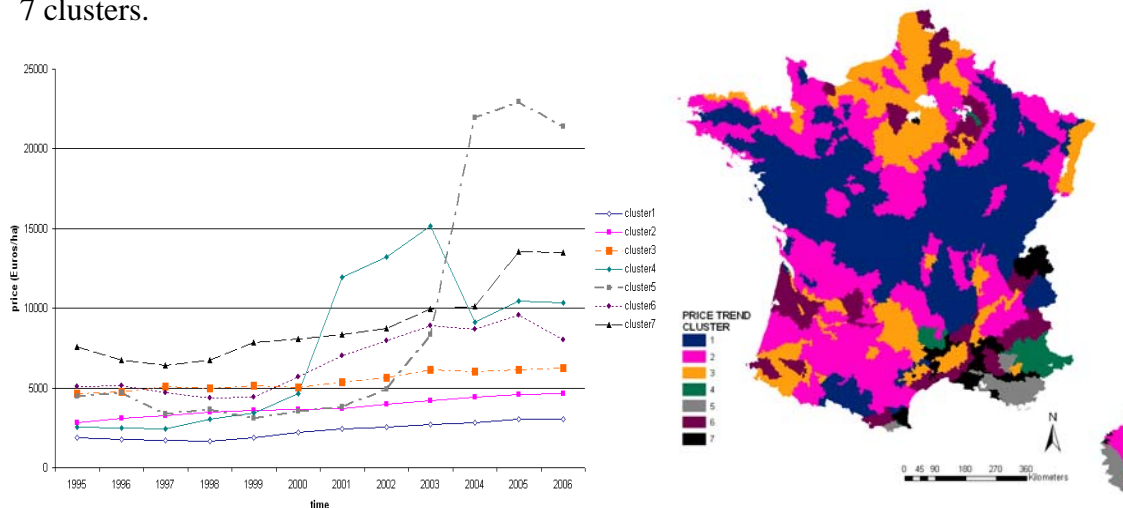


Figure 1- Temporal evolution of the prices of each cluster (a) and cluster mapping (b)

In general land prices in France present a small but regular yearly increase (see clusters 1, 2 and 3). Central France has usually lower prices (cluster 1) than extreme North (cluster 2 and 3) and South (clusters 2, 3, 4, 5, 6, 7). In South, prices can be extremely high and vary over time (clusters 4, 5, 6 and 7) because of higher human settlement pressure and land speculation.

3.2 The agricultural landscape dynamics classes

The classification of the landscape dynamics leads to 13 classes. Figure 2 shows the spatial distribution of the classes. More information can be found in Grandgirard and Carré (submitted).

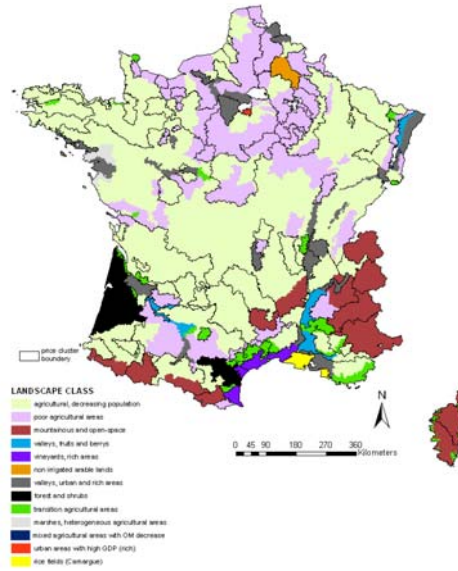


Figure 2- Spatial distribution of the 13 dynamic landscape classes

3.3 The spatio-temporal prediction of the land price dynamics

For the spatial prediction of land price trends (clusters), the variograms of the distances to the land price clusters showed non-stationarity probably due to the spatial trend of the landscape dynamics effects (see Figure 3 (a) for class 1 of the land price). When removing the spatial trend by using regression-kriging, the variogram of the residuals to the regression, showed two nested spatial exponential structures (one under 200 km and the other one after). We applied then the regression-kriging for a spatial neighbor of 150 km and tested its performance on the validation dataset. The average adjusted coefficient of determination on the distances to the land price class centroid is 0.97 meaning that this method is very relevant for predicting the distances to the centroids. When assigning the land price classes and assuming that the land prices are not correlated (which is wrong), regression-kriging leads to 53.1% of concordance between modeled classes and observed classes. When taking into account the similarity coefficient (S_c) between two classes i and j (or degree of confusion) equals to:

$$S_{ij} = 1 - \left(\frac{d_{ij}}{D_{max}} \right) \quad \text{Eq. (4)}$$

Where d_{ij} is the distance between classes centroid i and centroid j and D_{max} is maximum distance between the centroids, the percentage of concordance reaches 89.6% meaning a good prediction of the land price classes.

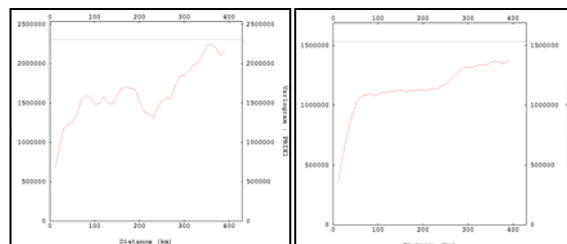


Figure 3- Variograms of the distances to class 1 (a) of price trends and to residuals to the regression of class 1 (b)

For the temporal modeling, land prices of 2007 are underestimated 6.1% with the AR model meaning that this method is also very efficient for predicting the land prices based on previous time-series dataset.

4 CONCLUSIONS

Dynamic of French land prices has been spatially modeled using a regression-kriging approach on environmental and socio-economic determinants. Since spatial autocorrelation of land price dynamics is significant, geostatistical approaches lead to better results than linear regression. In that context, spatial autocorrelation can be seen as the neighboring influence of land market speculation. Temporal prediction of 2007 land prices was well performed using an Auto-Regressive model. This methodology which is promising for French land prices prediction should be applied to Germany for testing its transferability to other European countries.

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