Agricultural rents in econometric Land use models: a spatial analysis

Raja R. Chakir, Anna Lungarska

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Raja CHAKIR Anna LUNGARSKA

UMR Economie Publique, INRA-AgroParisTech, France

Outline

Motivations 1/3

- LU and LUC are the main human derived pressures on the environment (Foley and al., 2005).
- Some LUCs such as deforestation and conversion of permanent pasture, can have adverse effects on the environment such as
  - reduced biodiversity (Sala and al., 2000),
  - carbon release into the atmosphere (Rhemtulla et al., 2009),
  - changes to water cycles (Stevenson and Sabater, 2010)
  - loss of ecosystem services (Schroter and al., 2005).
- Other LUCs such as the establishment of permanent grassland or afforestation, can store carbon in the soil, and thus contribute to the reduction of greenhouse gas (GHG) emissions and preservation of the environment.

Motivations 2/3

- LUC is the result of the complex interaction between changes in economic opportunities in conjunction with the biophysical environment.
- The complexity of LUC is also due to the interaction of decision making at different levels: individual farmers to global drivers
- LUC econometric models are useful because they provide :
    - insights into the driving factors and underlying processes that cause and modify LUC;
    - projections of plausible future LUC trajectories and LU patterns.

  This could help to identify policy measures that efficiently modify or mitigate LUC adverse effects.

Motivations 3/3

- The empirical economic literature on land use has increased significantly in recent years.
- Although each study has particular objectives, data sets and estimation methods, most studies are based on a common economic theory which assumes profit maximization by landowners.
- The optimal land use is determined by comparing the rents associated with each possible use.
- These rents vary depending on land characteristics (fertility: Ricardo, 1817 and location: Von Thünen, 1966).
- Land rent is a rather complex notion and rarely observable,
- It is frequently approximated in the literature (Wu and Segerson, 1995; Plantinga, 1996; Stavins and Jaffe, 1990; Plantinga and Ahn, 2002):
  - Producers' revenues; Land prices; Outputs and/or input prices; Yields; Land quality;

This paper: agri land rents comparison

- Compare land use models based on three different proxies for land rent from agriculture.
  1. Farmers' revenues:
     - The most commonly used in the literature.
     - Directly observed or derived from agricultural census or surveys (Stavins and Jaffe, 1990; Plantinga and Ahn, 2002; Lubowski et al., 2008; Ahn et al., 2000; Chakir and Le Gallo, 2013).
  2. Land price:
     - Generally assumed to be the net present value (NPV) of future land rents (Ricardo, 1817)
     - Ricardian assumption: all expected CC changes are capitalized in land rent value (Mendelsohn,1994).
     - Rarely used in land use literature (Ay et al., 2014).
  3. Land shadow price:
     - Correspond to the marginal productivity of land.
     - Estimated by a mathematical programming model of the European Union agriculture (AROPAj, see Jayet et al., 2015).
     - To the best of our knowledge, it has never been used in econometric land use shares models thus far.

This paper

- We investigate what determines the alternative land use shares using economic, physical, and demographic explanatory variables.
- We estimate a land use share model for France at the scale of a homogeneous (8 km x 8 km) grid.
- We consider five land use classes: (1) agriculture, (2) pasture, (3) forest, (4) urban, and (5) other.
- We model spatial autocorrelation between grid cells, and compare the prediction accuracy as well as the estimated elasticities between different model specifications.
- We simulate the effects of a nitrogen tax on LUC
- We simulate LUC projections for France under two IPCC (Intergovernmental Panel on Climate Change) climate scenarios.

Economic background of LU share models

- Land use share models have been widely employed in the literature (Lichtenberg, 1989; Stavins and Jaffe, 1990; Wu and Segerson, 1995; Plantinga, 1996; Miller and Plantinga, 1999).
- The first step in the modeling procedure assumes that the landowner derives the optimal land allocation from his/her profit-maximization problem: landowner allocates land to the use providing the greatest net present value of the profits.
- In the second step, and following the literature, we aggregate the optimal allocations by individual landowners to derive the observed share of land in the grid cell i in use k, denoted y_{ki}.

$$y_{ki} = p_{ki} + \varepsilon_{ki} \quad \forall i = 1, \ldots, I, \quad \forall, k = 1, \ldots, K, \tag{1}$$

  - y_{ki} is the share of land use k in the grid cell i ;
  - p_{ki} is the the expected share;
  - ε_{ki} is zero mean random factor that accounts for non observed factors.

Econometric model

- We consider a logistic specification for the share functions:

$$p_{ki} = \frac{e^{\beta_k' X_i}}{\sum_{j=1}^{K} e^{\beta_j' X_i}} \tag{2}$$

  - X_i are the explanatory variables and their effects β_k'.

  Applying Zellner and Lee (1965) approximation, y_{Ki} being the land use of reference:

$$\tilde{y}_{ki} = ln(y_{ki}/y_{Ki}) = \beta_k' X_i + u_{ki} \tag{3}$$

Spatial autocorrelation 1/2

- In the context of aggregated land use share models, spatial autocorrelation could result from:
  - a structural spatial relationship among the values of the dependent variable: a fundamental characteristic of spatial processes which are characterized by potentially complex interactions among neighboring values.
  - a spatial autocorrelation among the error terms, due to a spatially correlated error structure. For example, it can arise from data measurement errors involving the boundary of the spatial phenomena differing from the boundaries used for the measurement, or from omitted variables which are spatially correlated

Spatial autocorrelation 2/2

- An econometric model that does not include spatial autocorrelation when the data generating process is spatial, could be adversely affected by this omission:
  - bias in the regression coefficients, inconsistency, inefficiency;
  - masking effects of spillovers;
  - prediction bias.
- Considering spatial autocorrelation in an econometric model can be achieved in different ways by including spatially lagged variables, that is, weighted averages of the observations of "neighbors" of a given observation (Anselin, 1988). These spatially lagged variables can be:
  - the dependent variable (spatial auto-regressive - SAR - model);
  - explanatory variables (spatial cross regressive model);
  - error terms (spatial error model);
  - or any combination of these options.
    (Elhorst, 2010)

Spatial autocorrelation: 2 specifications

- The SAR model is appropriate if the focus of interest is assessment of the existence and strength of spatial interaction:

$$\widetilde{y} = \rho W \widetilde{y} + X\beta + \varepsilon \tag{4}$$

W is an $n \times n$ spatial weight matrix and ρ is the spatial autoregressive parameter that expresses the magnitude of the interaction between grids.

- The SEM takes account of the interactions between non-observed factors that affect the agricultural land use conversion decision:

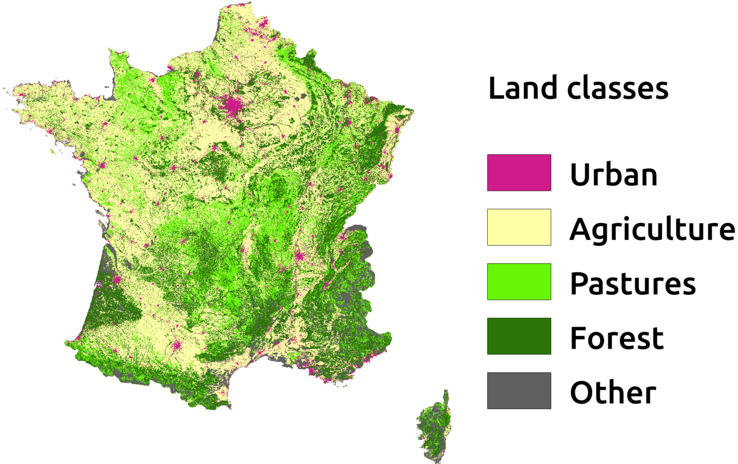
$$\begin{aligned} \widetilde{y} &= X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u \end{aligned} \tag{5}$$

The parameter λ expresses the interaction between residuals and u is an *iid* error term such that $u \sim iid(0, \sigma^2 I)$.

- The spatial neighbourhood matrix, W represent the connectivity between observations.

Data: dependant variable

- **Land use shares** are derived from the Corine Land Cover 2000 database: *agriculture*, *forestry*, *pastures*, *urban* and *other* (used as reference).



Data: explanatory variables

- **Forestry rents** are estimated by the FFSM++ partial equilibrium model (Lobianco et al., 2014) for the administrative region.
- **Urban rent** is approximated by the population density and revenues for the *commune* (INSEE).
- **Agricultural rent**:
  1. *Farmers' revenues*: provided by Agreste at the scale of the administrative region (NUTS 2).
  2. *Land prices*: Agreste/SAFER, available for the (group of) small agricultural regions.
  3. *Land shadow price*: estimated by an agricultural supply-side model at the scale of the administrative region (NUTS 2).
- **Soils and land slope** are represented by soils' texture class (Panagos et al., 2012), and the slope derived from a Digital Elevation Model.

Summary statistics

Variable	Description	Mean	St. dev.	Min	Max
Land use					
s_{ag}	Share of agricultural use	0.438	0.276	0	1
s_{pa}	Share of pastures	0.181	0.181	0	0.94
s_{fo}	Share of forests	0.262	0.22	0	0.989
s_{ur}	Share of urban	0.053	0.097	0	0.99
s_{ot}	Share of other uses	0.065	0.133	0	1
	Source: CLC 2000				
	Scale: aggregated at 8 km x 8 km				
Shadow price	Land shadow price (k€/ha)	0.576	0.197	0	1.029
	Source: AROPAj v.2 (2002)				
	Scale: NUTS 2				
Agri revenue	Farmers' revenues (k€/ha)	0.651	0.153	0.19	0.975
	Source: FADN, mean 1995-1999				
	Scale: NUTS 2 scale				
Land price	Price for arable land (k€/ha)	3.035	1.485	0	20.256
	Source: Agreste, mean 1995-2000				
	Scale: Small agricultural region or*département*				
For revenue	Forestry revenues (€/ha)	65.295	34.279	0	133.915
	Source: FFSM++, 2006				
	Scale: NUTS 2 scale				
Pop revenues	Households' revenues (k€/ year/ household)	12.424	3.213	0	44.642
	Source: INSEE, 2000				
	Scale: French *commune*				
Pop density	Households density (households/ ha)	5.541	2.973	2.75	140.131
	Source: INSEE, 2010				
	Scale: 200 m x 200 m grid				
Slope	Slope (%)	4.363	6.211	0	44.2
	Source: GTOPO 30				
	Scale: 30 arc sec $\sim$ 1 km				
TEXT	Soils' texture classes	*1*	*2*	*3*	*4*
	Number of cells	1180	4258	2859	525
	Source: JRC, Panagos et al. (2012)				
	Scale: 1:1000000				

Elasticities of agricultural land with respect to different agricultural rent proxies

$$\frac{\partial s_{ag}}{\partial Agr\ rent} * \frac{Agr\ rent}{s_{ag}} = \beta_{agr\_rent} * Agr\ rent \quad (6)$$

Agr rent	Model	Min.	1st Qu.	Median	Mean	3rd Qu.	Max	St.Dev
Shadow price	OLS	0	0.3166	0.3558	0.4183	0.4949	0.7478	0.143
Shadow price	SEM	0	0.3766	0.4232	0.4975	0.5886	0.8895	0.170
Shadow price	SAR	0	0.2164	0.2432	0.2859	0.3382	0.5111	0.098
Land price	OLS	0	0.0976	0.1255	0.1381	0.168	0.8198	0.065
Land price	SEM	0	0.1676	0.2156	0.2372	0.2884	1.408	0.111
Land price	SAR	0	0.2835	0.3647	0.4014	0.488	2.382	0.188
Agri revenue	OLS	0.07943	0.2338	0.2563	0.2715	0.3161	0.407	0.064
Agri revenue	SEM	0.09455	0.2783	0.3051	0.3232	0.3763	0.4846	0.076
Agri revenue	SAR	0.01576	0.04639	0.05085	0.05387	0.06272	0.08076	0.013

Predictions

For the models ignoring spatial autocorrelation, estimated by OLS, the predictor for the ith cell for equation k is simply:

$$\hat{\tilde{y}}_{ik}^{OLS} = X_{ik}\hat{\beta}_{k,OLS} \tag{7}$$

where X_{ik} is the matrix of data for observation i in equation k and $\hat{\beta}_{k,OLS}$ is the pooled OLS estimator obtained for equation k.
In case of the SEM model allowing for spatial autocorrelation of error terms, the predictor is similar as follows:

$$\hat{\tilde{y}}_{ik}^{SEM} = X_{ik}\hat{\beta}_{k,SEM} \tag{8}$$

where $\hat{\beta}_{k,SEM}$ is the SEM estimator obtained for equation k.
In case of the SAR model the predictor is as follows:

$$\hat{\tilde{y}}_{ik}^{SAR} = (I - \hat{\rho}_k W)^{-1} X_{ik}\hat{\beta}_{k,SAR} \tag{9}$$

where $\hat{\beta}_{k,SAR}$ is the SAR estimator and $\hat{\rho}_k$ is the estimated autocorrelation coefficient for equation k.

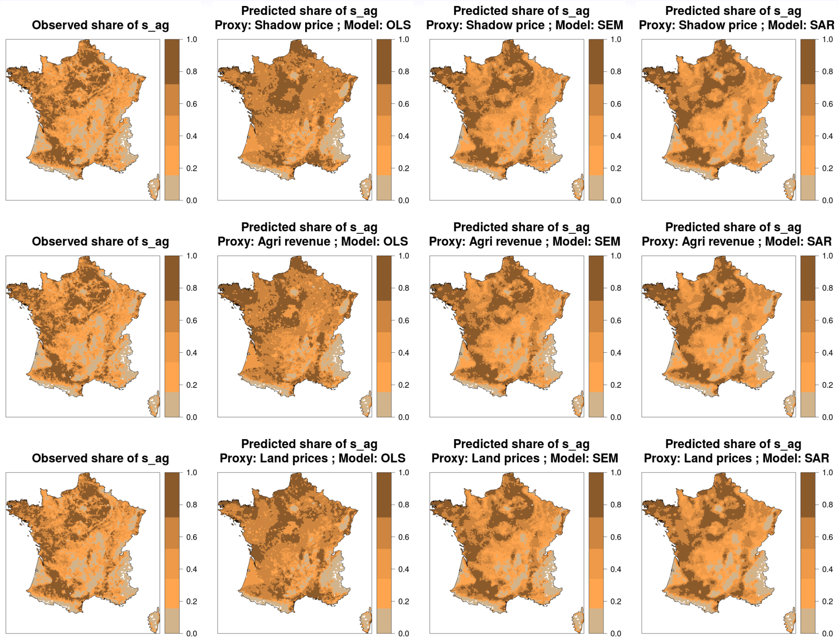
Quality of predictions: Normalized root-mean-square errors

Formula for the (Normalized) Root-mean-square error, (N)RMSE:

$$\text{RMSE}_k = \sqrt{\frac{\sum_{i=1}^{n} \left(\hat{y}_{ik} - y_{ik}\right)^2}{n}}$$

$$\text{NRMSE}_k = \frac{\text{RMSE}}{y_k^{max} - y_k^{min}}$$

Land	Shadow price			Land price			Agri revenue		
use k	*OLS*	*SEM*	*SAR*	*OLS*	*SEM*	*SAR*	*OLS*	*SEM*	*SAR*
s_ag	0.2265	0.1221	0.1268	0.2223	0.1206	0.1252	0.2232	0.1215	0.1260
s_fo	0.1891	0.1125	0.1169	0.1872	0.1116	0.1155	0.1911	0.1125	0.1168
s_ot	0.0978	0.0647	0.0643	0.0995	0.0647	0.0646	0.0998	0.0648	0.0646
s_pa	0.1906	0.0885	0.0884	0.1888	0.0876	0.0882	0.1909	0.0882	0.0886
s_ur	0.0632	0.0470	0.0504	0.0624	0.0474	0.0504	0.0614	0.0470	0.0503


Observed share of s_ag
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Proxy: Shadow price ; Model: OLS
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Predicted share of s_ag
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Observed share of s_ag
Predicted share of s_ag
Proxy: Agri revenue ; Model: OLS
Predicted share of s_ag
Proxy: Agri revenue ; Model: SEM
Predicted share of s_ag
Proxy: Agri revenue ; Model: SAR
Observed share of s_ag
Predicted share of s_ag
Proxy: Land prices ; Model: OLS
Predicted share of s_ag
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Predicted share of s_ag
Proxy: Land prices ; Model: SAR
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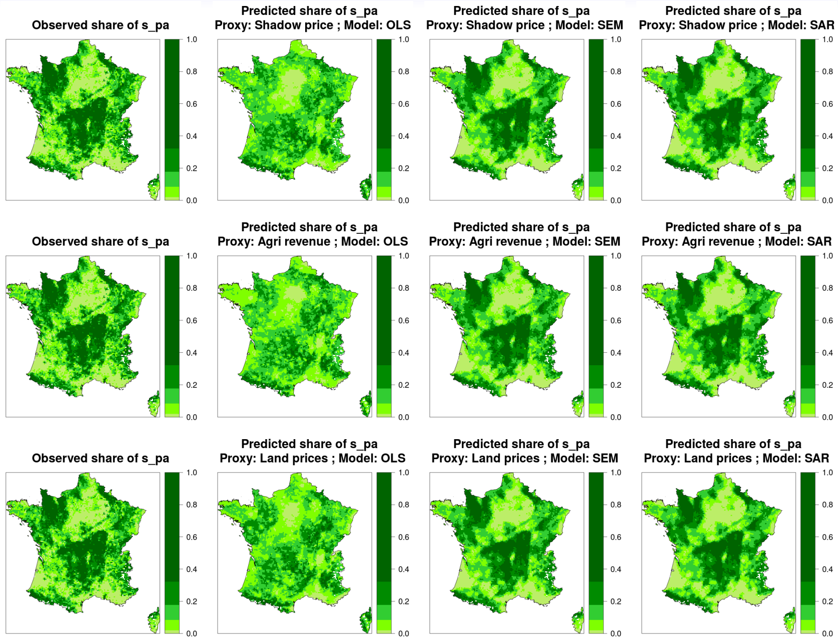
Observed share of s_pa
Predicted share of s_pa
Proxy: Shadow price ; Model: OLS
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Predicted share of s_pa
Proxy: Shadow price ; Model: SAR
Observed share of s_pa
Predicted share of s_pa
Proxy: Agri revenue ; Model: OLS
Predicted share of s_pa
Proxy: Agri revenue ; Model: SEM
Predicted share of s_pa
Proxy: Agri revenue ; Model: SAR
Observed share of s_pa
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Proxy: Land prices ; Model: OLS
Predicted share of s_pa
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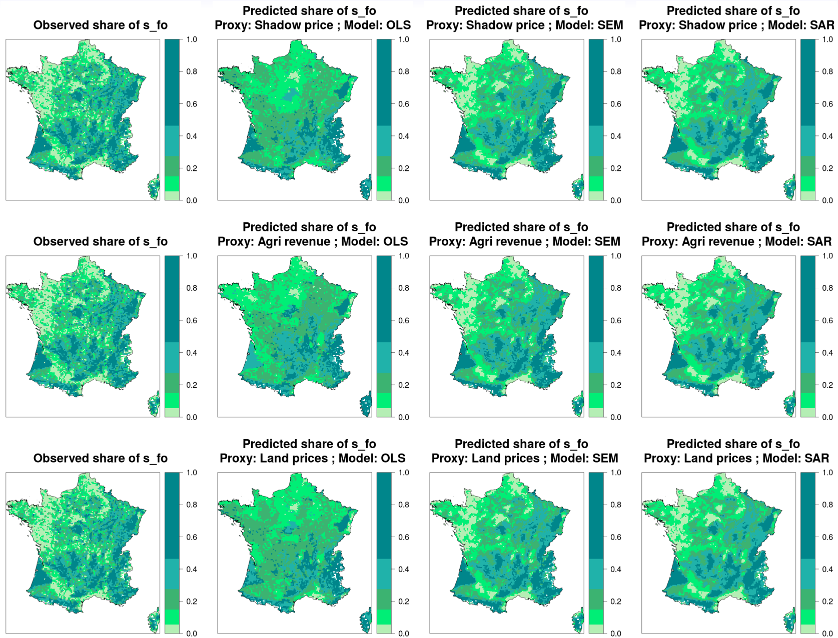

Observed share of s_fo
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Proxy: Shadow price ; Model: OLS
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Predicted share of s_fo
Proxy: Shadow price ; Model: SAR
Observed share of s_fo
Predicted share of s_fo
Proxy: Agri revenue ; Model: OLS
Predicted share of s_fo
Proxy: Agri revenue ; Model: SEM
Predicted share of s_fo
Proxy: Agri revenue ; Model: SAR
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Proxy: Land prices ; Model: OLS
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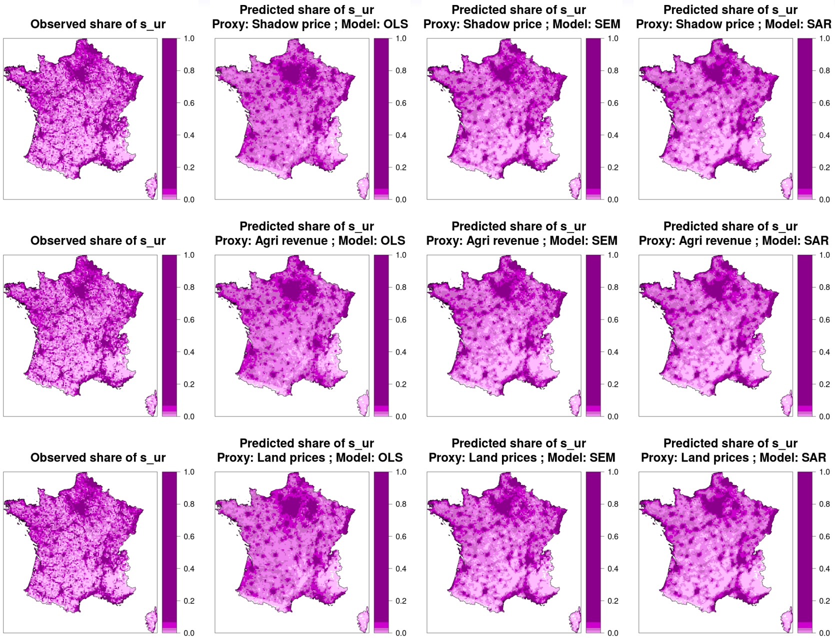
Observed share of s_ur
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Predicted share of s_ur
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Observed share of s_ur
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Proxy: Agri revenue ; Model: OLS
Predicted share of s_ur
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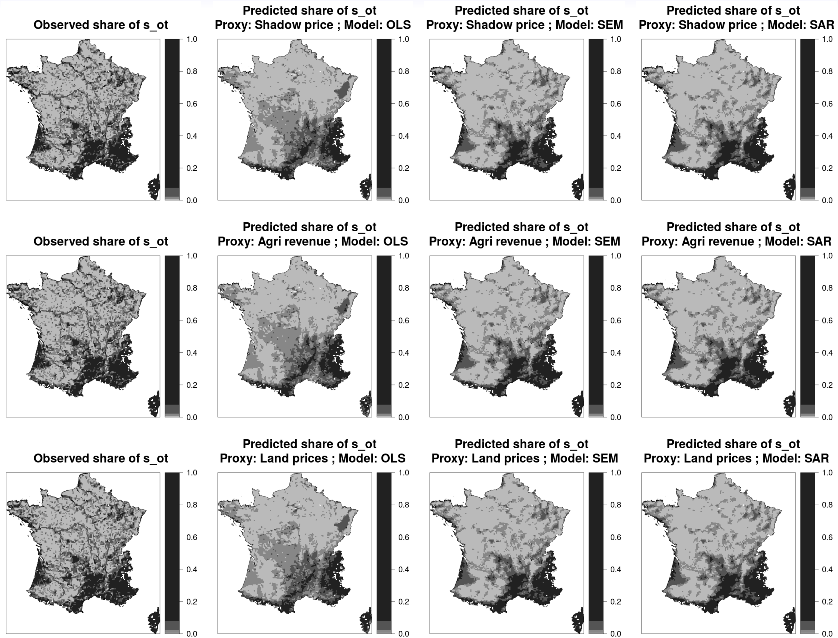
Observed share of s_ot
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Observed share of s_ot
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Proxy: Land prices ; Model: OLS
Predicted share of s_ot
Proxy: Land prices ; Model: SEM
Predicted share of s_ot
Proxy: Land prices ; Model: SAR
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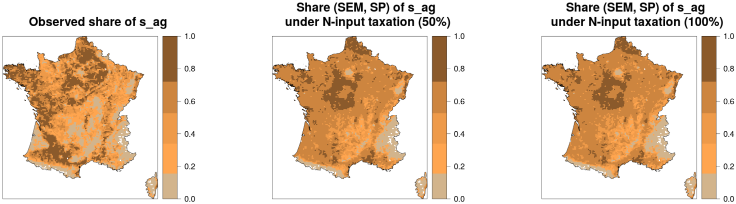
Public policy simulations: tax on fertilizers

Policy scenario	Nitrates per ha (%)	Nitrous oxide per ha (%)	Agr. area (%)		
			OLS	*SEM*	*SAR*
BAU	100.00%	100.00%	100.00%	100.00%	100.00%
Tax 50%	86.39%	75.06%	97.42%	98.07%	93.92%
Tax 100%	77.22%	59.23%	95.39%	96.53%	89.25%

Table: Emission abatement and change in agricultural area.

Public policy simulations: tax on fertilizers

- Land use change induced by the introduction of an input-based tax on fertilizers:



Simulations of CC and nitrogen tax (LUC in 1000 ha)

Scenario	s_ag	s_pa	s_fo	s_ur	s_ot
OLS					
CC=A2	5979	-3477	-3431	187	742
CC=B1	5936	-3448	-2969	-104	585
t=50%	-771	426	336	31	-25
t=100%	-1380	773	593	54	-44
CC=A2, t=50%	5038	-3115	-2908	269	716
CC=A2, t=100%	4268	-2797	-2492	331	690
CC=B1, t=50%	5040	-3088	-2471	-37	556
CC=B1, t=100%	4302	-2770	-2073	14	528
SEM					
CC=A2	4216	-2855	-1829	207	261
CC=B1	4228	-2794	-1514	-110	189
t=50%	-589	481	53	33	11
t=100%	-1056	876	85	62	27
CC=A2, t=50%	3465	-2406	-1660	290	311
CC=A2, t=100%	2849	-2003	-1549	354	349
CC=B1, t=50%	3531	-2368	-1352	-41	231
CC=B1, t=100%	2956	-1986	-1244	11	263

Conclusion 1/2

- The objective of this paper was to compare land use models based on three different proxies for agricultural land rent: farmers' revenues, land prices, and shadow land prices - derived from a mathematical programming model.
- We estimated a land use shares model for France at the scale of a homogeneous (8 km x 8 km) grid and considered five land use classes: (1) agriculture, (2) pasture, (3) forest, (4) urban and (5) other uses.
- We investigated what determines the shares of land in alternative uses using economic, pedoclimatic, and demographic explanatory variables.
- We modeled spatial autocorrelation between grid cells, and compared prediction accuracy and estimated elasticities for the different model specifications.

Conclusion 2/2

- Econometric Results
  - The three rents give similar results in terms of prediction quality of different models
  - Importance of the spatial autocorrelation (NRMSE indicators).
- Simulation Results
  - Tax simulation: results show very heterogeneous regional disparities with a decrease in the national agricultural area of 0.77 Mha and 1.4 Mha, and an increase in pasture land area of 0.42 Mha and 0.77 Mha for the 50% tax and 100% respectively.
  - CC simulation: CC mostly affects cropland area which increased by 4 Mha to 6 Mha in both scenarios. The area to pasture fell by 3.4 million ha in both scenarios while forest decreased by 2.9 million ha in scenario B1 and by 3.4 million ha in scenario A2.

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Thank you for your attention!
Questions and comments are more than welcome!!

Raja.Chakir@grignon.inra.fr
Anna.Lungarska@grignon.inra.fr