Agricultural land rents in land use models: a spatial econometric analysis

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Agricultural land rents in land use models: a spatial econometric analysis

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Abstract

The objective of this paper is to compare land use models based on three different proxies for agricultural land rent: farmers' revenues; land price and shadow price of land derived from a mathematical programming model. We estimate a land use shares model of France at the scale of a homogeneous grid (8 km x 8 km). We consider five land use classes: (1) agriculture, (2) pasture, (3) forest, (4) urban and (5) other uses. We investigate the determinants of the shares of land in alternative uses using economic, physical and demographic explanatory variables. Data on land use is derived from the remote sensing database Corine Land Cover. We model spatial autocorrelation between grid cells and compare the prediction accuracy as well as the estimated elasticities between different model specifications. Our results show that the three rent proxies give similar results in terms of prediction quality of different models. Our results also show that including spatial autocorrelation in land use models improve the quality of prediction (RMSE indicators). One of our econometric land use models is used to simulate the effects of a nitrogen tax as well as to project land use changes in France under two IPCC climate scenarios.

Keywords: Land use share model, spatial autocorrelation, land rent, prediction.

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1 Introduction

Land use and land use change are the main human pressures on the environment (Foley and al., 2005). Some land use changes such as deforestation or overturning of permanent pastures may have adverse effects on the environment such as: the decline of biodiversity (Sala and al., 2000), the release of carbon into the atmosphere (Rhemtulla et al., 2009), alteration of water cycles (Stevenson and Sabater, 2010) and loss of ecosystem services (Schroter and al., 2005). Other land use changes such as the establishment of permanent grassland or afforestation can store carbon in the soil and thus contribute the reduction of greenhouse gas (GHG) emissions and to the preservation of the environment.

The empirical economic literature on land use has had an important growth in recent years. Although each study has its own purpose, its data set and estimation methods, all studies are based on a common economic theory of land use which assumes profit maximization of landowners. The differences in rents associated with each use determine the optimal one that the landowner will choose for his land. According to this theory, these rents vary depending on land characteristics, including fertility (Ricardo, 1817) and its location (Von Thünen, 1966). However, other factors could affect the land use decision for a given plot. These include socio-economic factors, such as prices of production, and policy variables, such as taxes or subsidies. Econometric studies on land use generally examine the relationship between land use choices and a set of explanatory variables, namely the rents of different land uses or proxies such as input and output prices, subsidies, soil and climatic variables (slope, altitude, soil quality, temperature, precipitation, etc.) The land rent is a rather complex notion and several concepts of economic rents had been advanced in the literature [1].

As usually land use rents are not directly observed, most studies in the literature use proxies of these rents. These approximations of land use rents can vary greatly from one study to another. In general, the most frequently used proxies for the agriculture and forestry include producers' revenues, agricultural land prices, outputs or input prices, yields, land quality and government payments (*e.g.* Wu and Segerson, 1995, Plantinga, 1996, Stavins and Jaffe, 1990, Plantinga and Ahn, 2002). The objective of this paper is to compare land use models based on three different proxies for land rent from agriculture. These are: (i) farmers' revenues; (ii) land price; and (iii) shadow price of land derived from a mathematical programming model (AROPAj). The first one, "Farmers' revenues", is the most common in the literature. Often, the data on this proxy is directly observed or derived from agricultural census or surveys (Stavins and Jaffe, 1990; Plantinga and Ahn, 2002; Lubowski et al., 2008; Chakir and Le Gallo, 2013). Our second proxy, "Land price" is generally assumed to be the net present value (NPV) of future land rents (Ricardo, 1817). Evidences from the literature show that this is not always verified (Clark et al.,

[1] See Randall and Castle (1985) for a detailed presentation on the concept of land rent

1993; Gutierrez et al., 2007; Karlsson and Nilsson, 2013). The standard NPV formula ignores the possibility of converting agricultural land to other uses. Ay et al. (2014a) use this property[2] to approximate land rents in the econometric model of their study on the impacts of climate change on land use and common birds in France. Concerning our third proxy, "Land shadow price", to the best of our knowledge, it has never been used in econometric land use shares models thus far. These shadow prices correspond to the marginal productivity of land estimated by a mathematical programming model of the European Union agriculture. The economic supply-side model AROPAj (for detailed description see Jayet et al., 2015) is based on the Farm Accountancy Data Network (FADN).

In order to compare the impacts of different agricultural rent proxies, we estimate land use share models at the resolution of a homogeneous grid with 8km x 8km cells covering the territory of metropolitan France. The land use classes considered are five: agriculture, pastures, forestry, urban and other. Data on land uses is derived from the remote sensing database Corine Land Cover (CLC [3]). We model the spatial correlations between land uses in neighbour grid cells. Most studies in the literature assume spatial independence of land use choices. Some recent exceptions include: Ay et al. (2014b); Chakir and Le Gallo (2013); Li et al. (2013); Sidharthan and Bhat (2012); Ferdous and Bhat (2012); Chakir and Parent (2009). Incorporating spatial autocorrelation into land use models improve prediction accuracy but could raise several issues related to econometric estimation, hypothesis testing and prediction (Anselin, 2007; Brady and Irwin, 2011).

2 The Model

2.1 Land use share model

Following the lead given in the literature on land use change, we estimate in this paper a land use share model. Such 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 of the modelling procedure assumes that the landowner derive the optimal land allocation from his profit-maximization problem. We focus this paper on the landowner's decision to allocate land to five possible uses: agriculture, pastures, forest, urban and other uses. As in Plantinga (1996) and Stavins and Jaffe (1990) landowners allocate land to the use providing the greatest present discounted value of 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}.

There exists a large literature on econometric land use models estimated on aggregate

[2] Also known as Ricardian approach, following (Mendelsohn et al., 1994).

[3] For more information: `http://land.copernicus.eu/pan-european/corine-land-cover` .

data: Lichtenberg (1989), Stavins and Jaffe (1990), Wu and Segerson (1995), Plantinga (1996), and Miller and Plantinga (1999) are the most significant papers. The underlying micro-economic theory is identical but individual choices are aggregated in order to estimate land use shares models instead of individual discrete choice models. In this paper we use grid-level data, where shares are defined as the percent of total grid area devoted to given uses. The observed share of land use k $(k = 1, ..., K)$ in grid cell i $(i = 1, ..., I)$ is expressed as:

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

where p_{ki} is the expected share of land allocated to use k in grid cell i. The observed land allocation y_{ki} may differ from the optimal allocation due to random factors such as bad weather or unanticipated price changes. These random events are assumed to have a zero mean.

As in Wu and Segerson (1995) and Plantinga et al. (1999), we assume a logistic[4] specification for the share functions as follows:

$$p_{ki} = \frac{e^{\beta'_k X_i}}{\sum_{j=1}^{K} e^{\beta'_j X_i}} \tag{2}$$

where X_i are explanatory variables and β'_k measure the effect of explanatory variables on the expected shares.

Following Zellner and Lee (1965), the natural logarithm of each observed share normalized on a common share (here y_{Ki}) is approximately equal to:

$$\widetilde{y}_{ki} = ln(y_{ki}/y_{Ki}) = \beta'_k X_i + u_{ki} \text{ for } \forall i = 1, \ldots, I, \quad \forall, k = 1, \ldots, K, \tag{3}$$

where u_{ki} is the transformed error term.

2.2 Spatial autocorrelation

In the context of aggregated land use share models, spatial autocorrelation could result from a structural spatial relationship among values of the dependent variable or a spatial autocorrelation among error terms. The former is viewed as a fundamental characteristic of spatial processes, which are characterized by potentially complex interactions, and dependent structures among neighbouring values. On the other hand, spatial autocorrelation due to a spatially correlated error structure is essentially a data measurement problem. For example, it may arise from data measurement errors, in which the bound-

[4]The logistic share models are mainly used for three reasons: (i) they ensure that the predicted share functions (strictly) lie in the interior of the zero-one interval, (ii) they are parsimonious in parameters and (iii) they are empirically tractable thanks to the so-called log-linear transformation.

ary of the spatial phenomena differs from the boundaries used for measurement, or from omitted variables that are spatially correlated[5].

An econometric model that fails to include spatial autocorrelation when the DGP[6] is spatial could be adversely affected by its omission (bias in the regression coefficients, inconsistency, inefficiency, masking effects of spillovers, prediction bias). Several procedures exist to statistically test for the presence of spatial dependence against the null hypothesis of spatial independence Anselin (1988). The most commonly used measure for spatial autocorrelation is Moran's I statistic Moran (1948) which indicates the degree of spatial association reflected in the data. Considering spatial autocorrelation in an econometric model could be done in different ways by including spatially lagged variables, namely weighted averages of observations for the "neighbours" of a given observation (Anselin, 1988). These spatially lagged variables could be: the dependent variable (spatial autoregressive model), explanatory variables (spatial cross regressive model) and the error terms (spatial error model) or the combination of any of these options which gives a wide range of spatial models (Elhorst, 2010).

We consider in this paper two specifications for the spatial autocorrelation: as an additional regressor in the form of a spatially lagged dependent variable (*spatial autoregressive model, SAR*) and in the error structure (*spatial error model, SEM*). The spatial autoregressive model is appropriate when the focus of interest is the assessment of the existence and strength of spatial interaction. This is interpreted as substantive spatial dependence in the sense of being directly related to a spatial model (e.g., a model that incorporates spatial interaction, yardstick competition, etc.)

The SAR model can be described as follows Anselin (1988):

$$\widetilde{y_i} = f(\widetilde{y_1}, ..., \widetilde{y_{i-1}}, \widetilde{y_{i+1}} ..., \widetilde{y_n}) \tag{4}$$

This provides the following equation:

$$\widetilde{y} = \rho W \widetilde{y} + X\beta + \varepsilon \tag{5}$$

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

The SEM takes into account the interactions between non-observed factors that affect the agricultural land use conversion decision. The interactions in error terms can be expressed as follows:

$$\varepsilon_i = f(\varepsilon_1, ..., \varepsilon_{i-1}, \varepsilon_{i+1} ..., \varepsilon_n) \tag{6}$$

[5]See LeSage and Pace (2009) who provide motivations for regression models that include spatial autoregressive processes.

[6]Data generating process.

where ε_i is the spatial residual in the grid i and $\varepsilon_1, ..., \varepsilon_{i-1}, \varepsilon_{i+1}..., \varepsilon_n$ are spatial residuals in the other grids.

$$\begin{aligned} \widetilde{y} &= X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + u \end{aligned} \tag{7}$$

The parameter λ expresses the interaction between residuals and u is an iid[7] error term such that $u \sim iid(0, \sigma^2 I)$.

We estimate the spatial error model (SEM) and spatial autoregressive model (SAR) using the `R` package `spdep` (Bivand et al., 2013; Bivand and Piras, 2015). The spatial neighbourhood matrix is obtained by triangulation of the centroids of the grid cells and its values are consequentially row-weighted.

3 Data presentation

3.1 Land use data

The land use data is derived from the Corine Land Cover (CLC) database on the European Union at the scale of 100 m x 100 m (1 ha) grid and for 2000. Land cover classes are aggregated in five categories: agriculture, pastures, forest, urban and other. Table 11) in Appendix A summarizes the rules applied for the aggregation of the land use classes. The resulting map is given in Figure 1. Then, we calculate the share of each land use class for each grid cell (8 km x 8 km), knowing that in each cell there are at most 6400 ha. Land use shares are expressed as the sum of hectares of the same land use class divided by the surface of the grid cell. Although these cells are generated as homogeneous, they are altered due to the intersection with the actual French borders. For instance, grid cells on coastlines are restrained only to their part on dry land.

3.2 Agricultural and forestry rent proxies

General information and descriptive statistics of the variables used in the study are summarized in Table 1.

Farmers' revenues Data on farmers' revenues is provided by the European Union Farm Accountancy Data Network (FADN) at the European NUTS 2 scale level. We focus on the revenues from crop production (cereals, oleaginous and other field crops) and animal breeding. Revenues from viticulture, horticulture and other perennial crops are excluded because of the high profits per hectare and their limited area (Table 12 in Appendix A).

[7]Independent and identically distributed random variable.

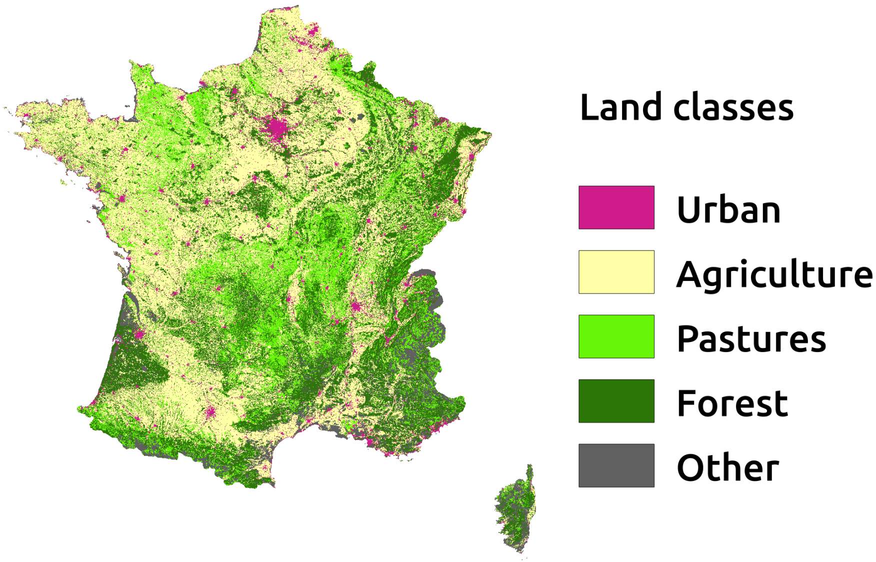

Figure 1: Corine Land Cover (CLC) data aggregated in five land use classes for the year 2000.

For instance, viticulture in France is covering only 1.5% of the metropolitan territory but provides about 15% of the value in the agricultural sector[8].

Land price Land prices are generally assumed to be the net present value (NPV) of future land rents (Ricardo, 1817). Evidences from the literature show that this could be a strong assumption as the standard NPV formula ignores the possibility of land conversion to other than the agricultural use (Clark et al., 1993; Gutierrez et al., 2007; Karlsson and Nilsson, 2013). In order to address this issue, Guiling et al. (2009) extend the NPV formula. The most profitable conversion is land development (switch to urban use). In the case of France, Cavailhes and Wavresky (2003) find that the immediate proximity to cities is resulting in high development premiums which fall sharply when distance increases. In land use models land prices are often used in the context of the hedonic approach to climate change impacts assessment otherwise known as the Ricardian method proposed initially by Mendelsohn et al. (1994) and focused solely on the agricultural use. Ay et al. (2014a) use the Ricardian approach in order to assess the effects of climate change on land use in France and consequently on common birds. Annual data on land prices is provided by the statistical department of the French Ministry of Agriculture (Agreste) at the scale of the French small agricultural region.

[8]FranceAgriMer, `www.franceagrimer.fr` .

Land shadow price In this study we test as a proxy the land shadow price which, to our knowledge, has not been used in statistical land use shares models thus far. Shadow prices can capture the non-market value that farmers attribute to their production. We use the values estimated by a mathematical programming model of European Union agriculture applied to France. The economic supply-side model AROPAj (for a detailed description see Jayet et al., 2015) is based on the FADN data and accounts for the Common Agricultural Policy.

The economic agents of the model are representative farms grouped in farm types maximizing their gross margin (revenues minus variable costs). For each farmer the only publicly available information concerning its location is the FADN region in which she operates. In order to maximize their profits, farmers in the model allocate their land to different crops while respecting a total area constraint. It is the Lagrange multiplier associated with this constraint that we use in the comparative study of agricultural returns proxies. From microeconomic theory, we know that at the optimum this shadow price (or dual value) should be equal to the agricultural rent[9].

Shadow prices are used when no proper market values are available or when the existing ones are not taking into account some particularity of the goods as in the case of traditional maize varieties in Mexico (Arslan, 2011). In the case of France, land rental prices are administered by public authorities[10] and thus the shadow price and the observed rental prices do not coincide (Dupraz and Temesgen, 2012). Furthermore, agriculture is a complex system where some of the products are consumed on-farm[11] and, thus, not valued on the market.

The data on the agricultural rent proxies are available at different scales and for different years. Some aggregations were necessary in order to have the data at the same scale. Thus, the farmers' revenues and the land prices are averaged over a five and a six years periods, respectively[12]. When information on land prices lacks for a given small agricultural region, the mean value for the French *département* is used. The data on land shadow prices from the AROPAj model is considered at its original scale, namely the FADN region (corresponding to the NUTS 2 level).

[9] Agricultural rent is the remuneration of land as a factor of production. The equality between the Lagrange multiplier associated with the total land constraint and agricultural rent results from the application of the duality theorem to the profit maximization problem. Following this approach the profit maximization problem is equivalent to the cost minimization problem. For a general description see McFadden (1978).

[10] French Rural Code, Article L411-11. In some regions this regulation is circumvented and new tenants are often obliged to pay under-the-counter former ones in order to obtain rights on land.

[11] For instance, manure could be used as a fertilizer on crops while some of the biomass produced could be destined for animal feeding.

[12] Inflation estimates for the period are provided by the World Bank, `http://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG` .

Forestry rent is approximated by the expected returns estimated by the partial-equilibrium model FFSM++ (Caurla and Delacote, 2012; Caurla et al., 2013; Lobianco et al., 2014) developed by the Forestry Economics Laboratory at the French Agricultural Research Institute (INRA) in Nancy. The expected returns are calculated for 2006 at the scale of the French administrative region (NUTS2) and for coniferous and broadleaved forests. We use an average of these two values.

Both the AROPAj and the FFSM++ models dispose of biological modules. AROPAj is partly coupled with the generic crop model STICS (Brisson et al., 2003, 2009) while FFSM++ uses parameters (mortality and growth of trees) derived from statistical data. Through their biological modules the two models can take into account the effects of climate change (Leclère et al., 2013). Furthermore, the economic components of the models allow also to simulate different price and policy scenarios[13]. In this paper we assess the land use changes induced by the introduction of a tax on the mineral nitrogen fertilizers used by farmers (Section 4.3). We also evaluate the effects of the policy in the context of climate change based on the estimates provided by the biological and economical components of AROPAj and FFSM++ (Section 4.4).

3.3 Demography

The approximation of the urban rent is done through the population density (in terms of number of households per ha) and households revenues. Both indicators are provided by the French statistical institute (INSEE), revenues are available at the scale of the *commune* while the number of households is given for a regular 200 m x 200 m grid[14].

3.4 Physical data

In the study we use also data on relief and soils.

Soils are represented by the data provided by the Joint Research Centre (JRC Panagos et al., 2012) at the scale of 1:1000000 and further aggregated at the grid cell level. The indicator for soil quality that we retained is soils' texture classified in 4 levels. The worst quality, level 1, is used as referent.

Relief is derived (altitude and slope) from the digital elevation model (DEM) GTOPO available at the scale of 30 arc seconds (approximately 1 km). Only slope is introduced in the model because of the high correlation between the slope and altitude.

[13]For instance, an obligatory set-aside clause increases the demand for low quality land and consequently its rent.

[14]INSEE, `http://www.insee.fr/fr/themes/detail.asp?reg_id=0&ref_id=donnees-carroyees&page=donnees-detaillees/donnees-carroyees/donnees_carroyees_diffusion.htm` .

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 *Source*: CLC 2000 *Scale*: aggregated at 8 km x 8 km	0.065	0.133	0	1
Shadow price	Land shadow price (k€/ha) *Source*: AROPAj v.2 (2002) *Scale*: NUTS 2	0.576	0.197	0	1.029
Agri revenue	Farmers' revenues (k€/ha) *Source*: FADN, mean 1995-1999 *Scale*: NUTS 2 scale	0.651	0.153	0.19	0.975
Land price	Price for arable land (k€/ha) *Source*: Agreste, mean 1995-2000 *Scale*: French small agricultural region or *département*	3.035	1.485	0	20.256
For revenue	Forestry revenues (€/ha) *Source*: FFSM++, 2006 *Scale*: NUTS 2 scale	65.295	34.279	0	133.915
Pop revenues	Households' revenues (k€/ year/ household) *Source*: INSEE, 2000 *Scale*: French *commune*	12.424	3.213	0	44.642
Pop density	Households density (households/ ha) *Source*: INSEE, 2010 *Scale*: 200 m x 200 m grid	5.541	2.973	2.75	140.131
Slope	Slope (%) *Source*: GTOPO 30 *Scale*: 30 arc sec $\sim$ 1 km	4.363	6.211	0	44.2
TEXT	Soils' texture classes	*1*	*2*	*3*	*4*
	Number of cells *Source*: JRC, Panagos et al. (2012) *Scale*: 1:1000000	1180	4258	2859	525

Table 1: Summary statistics of land use shares and the explanatory variables.

4 Estimation results

In order to compare the estimations and to evaluate the gains associated with different spatial autocorrelation specifications, three estimators are considered for each land use shares model:

1. The pooled OLS which ignores spatial autocorrelation.
2. The SEM (Spatial Error Model) estimator which takes into account the autoregressive spatial error autocorrelation
3. The SAR (Spatial Auto-Regressive model) which takes into account the autoregressive spatial autocorrelation

We begin by estimating an Ordinary Least Squares (OLS) model. We, then, estimate a Spatial Error Model (SEM) and Spatial Autoregressive Model (SAR). Each specification (OLS, SEM, SAR) is estimated for the three proxies of agricultural land rents considered (i) shadow price, (ii) farmers' revenues, and (iii) prices of arable land and pastures. The results are presented in Tables 13, 14 and 15. For each of the OLS models the Moran's I score is significant meaning that we reject the null hypothesis of no spatial autocorrelation. The estimated spatial autocorrelation, λ for the SEM models and ρ for the SAR models, are also significant.

The log-likelihood function value of the OLS models increases when the SEM or SAR models are estimated. This is true for all land use equations and for all agricultural rent considered. In order to decide whether it is the SAR or the SEM model that better describes the data we use the classic LM-tests proposed by Anselin (1988) as well as the robust LM-tests proposed by Anselin et al. (1996). Results of these tests are provided in Table 16. Using the classic tests, both the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially autocorrelated error term are rejected at five per cent significance for all models. The robust LM test results show that both SAR and SEM specifications are relevant for $ln(pst/oth)$ and $ln(agr/oth)$. Concerning the forest land share, on the basis of robust LM tests the SAR model is more appropriate. For urban use the SEM is more appropriate for the specifications with Land Prices and Agri Revenue.

As for the OLS specification, the Agricultural *vs* Other use and the Urban *vs* Other use models perform better in terms of explained variance with R^2 close or superior to 40%. The other two models, Forest *vs* Other use and Pastures *vs* Other use, score not as good, the R^2 coefficients is lower than 20%. Population density and revenues are significant and have the expected signs (positive) for the Urban *vs* Other model regardless of the agricultural rent proxy employed and the model specification. Furthermore, the coefficients for these two explanatory variables remain stable. These two findings are valid for the forestry revenues in the Forest *vs* Other use models. The SEM and SAR specifications are notably improving the coefficients of determination and their results are close. Thus, for the Agriculture *vs* Other use model, the R^2 increases with about 25%, for the Forest *vs* Other use and Pastures *vs* Other use models the increase is of more than 40% and for the Urban *vs* Other use the score is up with some 20%. In addition, the results for these models seem to be independent of the agricultural proxy employed.

As regards the Agriculture *vs* Other use models, the parameters associated with land shadow price is significant for all specifications.The parameter associated with agricultural revenue is positive but only significant for the OLS model.Arable land prices' impact on the agricultural share is reported significant at the 10% confidence level for the OLS and SEM models and at the 1% confidence level for the SAR model. The three proxies are reported to have negative impact on the pastures' share which is also significant for all model specifications.

4.1 Elasticities

We calculate the elasticities for agricultural land share with respect to the agricultural rent following the Equation 8. More details on the calculus of the elasticities' Equation 8 are provided in Appendix B.

$$\frac{\partial s_{ag}}{\partial Agr\ rent} * \frac{Agr\ rent}{s_{ag}} = \beta_{agr\_rent} * Agr\ rent \tag{8}$$

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

Table 2: Elasticities of agricultural land with respect to different agricultural rent proxies.

4.2 Predictions

The fitted values used in the models SEM and SAR are obtained thanks to the `R` package `spdep` package. These estimates are made using the response variables which are available

(Equations 5 and 7). As these variables are unknown when predictions are established, we use Equations 10, 11 and 12. From a technical point of view, the point of departure is Equation 3:

$$\widetilde{y}_k = \beta_k^{'} X_k + u_k \quad \forall k = 1, \ldots, K \tag{9}$$

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

$$\hat{\widetilde{y}}_{ik}^{OLS} = X_{ik}\hat{\beta}_{k,OLS} \tag{10}$$

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:

$$\hat{\widetilde{y}}_{ik}^{SEM} = X_{ik}\hat{\beta}_{k,SEM} \tag{11}$$

where $\hat{\beta}_{k,SEM}$ is the SEM estimator obtained for equation k.

In case of the SAR model the predictor is as follows:

$$\hat{\widetilde{y}}_{ik}^{SAR} = (I - \hat{\rho}_k W)^{-1} X_{ik}\hat{\beta}_{k,SAR} \tag{12}$$

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

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

Table 3: Normalized root-mean-square error for the different proxies and the three model specifications.

4.3 Environmental policy simulations: nitrogen pollution from agriculture

Since the Second World War, agricultural intensification has led to a significant increase in food production in developed countries. Nevertheless, the high quantities of fertilizers and pesticides employed are also sources of environmental issues namely soil erosion, water and air pollution, loss of biodiversity, etc. For instance, the use of fertilizers results in three types of nitrogen pollution: (i) nitrate pollution of soils and water; (ii) nitrous oxide; and (iii) ammonia atmospheric emissions (Bourgeois et al., 2014). Given the high nitrate concentrations observed in French water bodies, a tax on nitrogen fertilizers can be used as an instrument of environmental policies aiming at reducing the anthropogenic pressure on the water resources. Furthermore, fertilizers are also associated with greenhouse gas emissions (nitrous oxide) and, thus, can be targeted for the mitigation of climate change.

One of the major interests of mathematical programming models of agriculture is the possibility to introduce different public policy scenarios as a set of parameters or constrains. The model AROPAj, for instance, is taking into account the major animal and crop activities observed in the European Union. These activities are parametrized in details. For eight of the major crops[15] dose-response functions are estimated (Leclère et al., 2013) thanks to the crop model STICS (Brisson et al., 2003, 2009). These functions define the response to nitrogen of the crops and serve as production functions. STICS is also evaluating the nitrogen pollutants emissions so that pollution functions are fitted and introduced in AROPAj (Bourgeois et al., 2014). This methodology allows us to test the reaction of farmers in terms of quantity of nitrogen fertilizer used and the resulting pollutant emissions when there is a price shock. If a tax per unit of nitrogen is set up this could be regarded as a price shock.

Assuming a price of about 1 Euro per kg of nitrogen content in fertilizers, we test two nitrogen tax policies. In the first case we increase the price by 50% and in the second one by 100%[16]. Such a policy is reducing the profitability of agriculture (ceteris paribus, no price feedback is considered) and consequently the land's shadow price (Figure 2). Using the econometric land use models presented above, we can evaluate the effects of the tax in terms of land use change (LUC). The results are summarized in Tables 5, 6, 7 and maps are provided in the Appendix E. In Table 4 we present the emission abatement per ha and the change in agricultural area following the introduction of the taxation policies (OLS estimates). As the results show, the impact of the policy is reinforced because not only the pollutants emissions per ha are reduced (intensive margin) but also the total number of ha in agricultural use (extensive margin). The coefficient associated with the shadow price of land for the urban use under the SAR specification is negative and significant. For this model, the estimated land use share for urban is greatly increased at the expense of the other uses.

[15]Durum and common wheat, maize, barley, soybean, rapeseed, potatoes and sugar beet.

[16]Jayet and Petsakos (2013) simulate numerous tax levels and Common Agricultural Policy scenarios using the AROPAj model

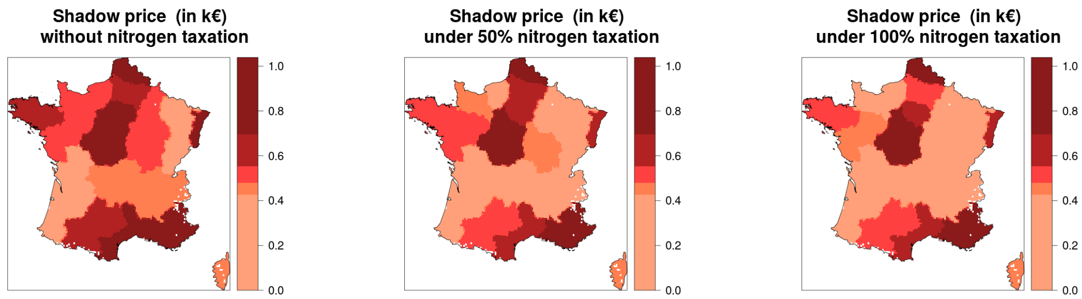

Figure 2: Land shadow price in the BAU case and under nitrogen taxation policy schemes.

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 4: Emission abatement and change in agricultural area.

4.4 Adaptation and mitigation of climate change

Land use change is one of major sources of greenhouse gases with 12.2% of the total emissions in 2005 (Herzog, 2009) and as such it is one of the causes for climate change. Nevertheless, land use change can also result from climate change as means of economic adaptation. The methodology proposed for the study of the climate induced land use change is summarized in Figure 3. The biological modules of the two mathematical models, AROPAj and FFSM++, allow the simulation of climate change scenarios where the switch to other crops and tree species is taken into account. We evaluate here two IPCC emissions scenarios A2 (pessimistic) and B1 (optimistic). For the land shadow price we use the results from Leclère et al. (2013) based on the ECHAM5 model[17]. Concerning forest rents they are based on the simulations from the ARPEGE Model of Meteo-France[18]. The projections of the population and revenues are from INSEE (2010) and Center for International Earth Science Information Network (CIESIN, 2002). We also evaluate the effects of two climate change mitigation policies, namely the two nitrogen input tax levels presented in Section 4.3, in the context of the IPCC SRES scenarios.

The predicted impacts of climate change on land use using the OLS model are reported in Table 8. We present the impacts of climate change on the land use changes in ha as well as in percent. Results show that the impacts of CC on agriculture, pasture and forest are almost similar for A2 and B1 scenarios. Under the two scenarios agricultural land use share increases by 20%, pastures decrease by 50% and forests decrease by 22% to 25%. Results for urban land are contrasted as there is an increase in urban area by 7.6% under A2 scenario and a decrease by 4% under B1 scenario. Results also show that a tax on

[17]`http://www.mpimet.mpg.de/en/wissenschaft/modelle/echam/echam5.html`
[18]`http://www.cnrm-game.fr/spip.php?article124&lang=en`

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
			Tax=+50%			
Land share changes						
ag	-0.04	-0.018	-0.014	-0.014	-0.01	0.126
pa	-0.046	0.004	0.007	0.008	0.011	0.031
fo	-0.073	0.004	0.006	0.006	0.008	0.029
ur	-0.003	0	0	0.001	0.001	0.015
ot	-0.02	0	0	0	0	0.007
Land use change in ha						
ag	-255.3	-115.1	-89.53	-87.41	-57.61	25.33
pa	-10.14	25.57	44.74	48.33	69.76	197.9
fo	-51.01	25.57	38.29	38.11	51.17	185.1
ur	-19.2	0	0	3.499	6.372	95.96
ot	-127.7	0	0	-2.796	0	19.15
			Tax=+100%			
Land share changes						
ag	-0.077	-0.033	-0.026	-0.025	-0.018	0.12
pa	-0.044	0.007	0.013	0.014	0.019	0.055
fo	-0.069	0.007	0.01	0.011	0.014	0.054
ur	-0.006	0	0	0.001	0.001	0.026
ot	-0.037	0	0	-0.001	0	0.006
Land use change in ha						
ag	-491.4	-204.9	-160	-156.4	-108.8	24.12
pa	-8.844	44.75	76.82	87.62	121.6	351.5
fo	-95.86	44.78	63.96	67.23	89.42	344.6
ur	-31.98	0	0	6.139	6.398	166.3
ot	-236.3	0	0	-4.975	0	38.3

Table 5: Nitrogen tax simulations (OLS estimates).

nitrogen allows to mitigate the impacts of CC on land use change. A tax that implies a 100% increase in the price of fertilizers leads to a lesser reduction in forest area (15% to 18% instead of 22% and 25%).

The estimates of the SEM and SAR model (Tables 9 and 10) are both predicting and increase in cropland are by some 34% while pastures and forests are reduced by 62% and 24-28% respectively.

The spatial dimension of our land use model allows us to present more precisely the geographical impacts of CC. See Figures 10, 13 and 16.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
			Tax=+50%			
Land share changes						
ag	-0.026	-0.014	-0.011	-0.011	-0.008	0.115
pa	-0.088	0.006	0.009	0.009	0.011	0.027
fo	-0.02	0.001	0.002	0.001	0.003	0.048
ur	-0.003	0	0	0.001	0.001	0.013
ot	-0.006	0	0	0	0	0.006
Land use change in ha						
ag	-165.9	-89.43	-70.33	-66.77	-44.83	23.12
pa	-18.98	38.38	51.22	54.49	70.36	172.6
fo	-127.7	5.607	12.77	6.013	19.15	57.5
ur	-12.8	0	0	3.774	6.386	83.11
ot	-6.398	0	0	1.283	0	31.92
			Tax=+100%			
Land share changes						
ag	-0.051	-0.025	-0.021	-0.019	-0.015	0.11
pa	-0.084	0.011	0.016	0.016	0.02	0.053
fo	-0.04	0.001	0.003	0.002	0.005	0.043
ur	-0.004	0	0	0.001	0.001	0.022
ot	-0.005	0	0	0	0.001	0.012
Land use change in ha						
ag	-325.5	-153.6	-127.9	-119.7	-89.6	22.11
pa	-16.9	70.24	96.22	99.28	128	338.7
fo	-255.4	6.396	19.19	9.626	25.62	102.2
ur	-25.6	0	0	7.029	6.401	140.7
ot	-12.78	0	0	3.043	6.388	57.45

Table 6: Nitrogen tax simulations (SEM estimates).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
			Tax=+50%			
Land share changes						
ag	-0.113	-0.028	-0.013	-0.017	-0.001	0.116
pa	-0.001	0	0	0.003	0.001	0.111
fo	-0.049	0	0	0	0	0.021
ur	-0.115	0.002	0.012	0.015	0.024	0.079
ot	-0.065	0	0	-0.001	0	0.001
Land use change in ha						
ag	-721.3	-179	-76.79	-109	-6.398	31.8
pa	-0.26	0	0	16.43	6.392	710.2
fo	-312.4	0	0	1.264	0	134.2
ur	-274.2	6.402	70.37	95.9	153.5	504.3
ot	-415.5	0	0	-4.879	0	6.397
			Tax=+100%			
Land share changes						
ag	-0.201	-0.051	-0.022	-0.031	-0.002	0.094
pa	0	0	0	0.005	0.001	0.202
fo	-0.091	0	0	0	0	0.037
ur	-0.094	0.003	0.02	0.027	0.044	0.149
ot	-0.122	0	0	-0.001	0	0.002
Land use change in ha						
ag	-1283	-320.1	-134.4	-192.8	-12.78	18.89
pa	0	0	0	31.55	6.404	1289
fo	-580.2	0	0	2.283	0	236.5
ur	-510.2	12.8	121.6	167.5	275.2	951.2
ot	-779.8	0	0	-8.805	0	12.79

Table 7: Nitrogen tax simulations (SAR estimates).

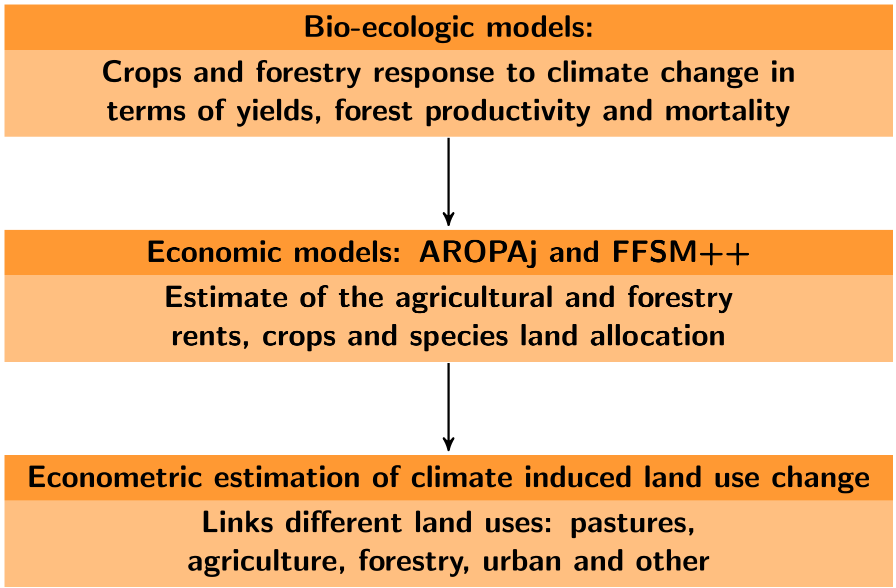

Figure 3: Methodology for the assessment of the climate induced land use change.

Scenario	s_ag	s_pa	s_fo	s_ur	s_ot
Land use change in %					
CC=A2	20 %	-50.7 %	-25.2 %	7.6 %	46 %
CC=A2, t=50%	16.8 %	-45.4 %	-21.4 %	10.9 %	44.5 %
CC=A2, t=100%	14.3 %	-40.8 %	-18.3 %	13.4 %	42.8 %
CC=B1	19.8 %	-50.2 %	-21.8 %	-4.2 %	36.3 %
CC=B1, t=50%	16.8 %	-45 %	-18.2 %	-1.5 %	34.5 %
CC=B1, t=100%	14.4 %	-40.4 %	-15.2 %	0.6 %	32.8 %
Land use change in 1000 ha					
CC=A2	5979	-3477	-3431	187	742
CC=A2, t=50%	5038	-3115	-2908	269	716
CC=A2, t=100%	4268	-2797	-2492	331	690
CC=B1	5936	-3448	-2969	-104	585
CC=B1, t=50%	5040	-3088	-2471	-37	556
CC=B1, t=100%	4302	-2770	-2073	14	528

Table 8: Simulations of climate change and nitrogen tax (OLS estimates).

Scenario	s_ag	s_pa	s_fo	s_ur	s_ot
Land use change in %					
CC=A2	33.9 %	-62 %	-28.3 %	11.2 %	7.2 %
CC=A2, t=50%	30.4 %	-57.9 %	-24.6 %	14.7 %	6 %
CC=A2, t=100%	27.6 %	-54.3 %	-21.7 %	17.3 %	4.8 %
CC=B1	33.8 %	-61.6 %	-25 %	-1 %	0 %
CC=B1, t=50%	30.4 %	-57.6 %	-21.5 %	1.8 %	-1.3 %
CC=B1, t=100%	27.7 %	-54 %	-18.7 %	4 %	-2.6 %
Land use change in 1000 ha					
CC=A2	9104	-5513	-4015	268	157
CC=A2, t=50%	8162	-5151	-3493	350	132
CC=A2, t=100%	7393	-4833	-3076	412	105
CC=B1	9061	-5484	-3553	-23	0
CC=B1, t=50%	8164	-5124	-3055	44	-29
CC=B1, t=100%	7426	-4806	-2658	95	-57

Table 9: Simulations of climate change and nitrogen tax (SEM estimates).

Scenario	s_ag	s_pa	s_fo	s_ur	s_ot
Land use change in %					
CC=A2	34.3 %	-62.2 %	-27.4 %	9.1 %	1.2 %
CC=A2, t=50%	30.8 %	-58.2 %	-23.7 %	12.5 %	0.1 %
CC=A2, t=100%	27.9 %	-54.6 %	-20.7 %	15.1 %	-1 %
CC=B1	34.1 %	-61.9 %	-24.1 %	-2.8 %	-5.6 %
CC=B1, t=50%	30.8 %	-57.9 %	-20.6 %	-0.1 %	-6.8 %
CC=B1, t=100%	28 %	-54.3 %	-17.7 %	2 %	-8 %
Land use change in 1000 ha					
CC=A2	9172	-5580	-3842	222	28
CC=A2, t=50%	8231	-5218	-3320	304	2
CC=A2, t=100%	7461	-4900	-2903	366	-24
CC=B1	9129	-5551	-3380	-69	-129
CC=B1, t=50%	8233	-5190	-2882	-2	-158
CC=B1, t=100%	7494	-4873	-2485	49	-186

Table 10: Simulations of climate change and nitrogen tax (SAR estimates).

5 Conclusion and perspectives

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

Our results show that the three rent proxies give similar results in terms of prediction quality of different models. Our results also show that including spatial autocorrelation in land use models improve the quality of prediction (RMSE indicators). We use the estimated models to simulate the impact of an input-based tax on fertilizers in terms of land use change. We simulate two tax levels: increase in nitrogen price by 50% and by 100%. Results show very heterogeneous regional disparities with a national decrease of agricultural area by 0.77 millions hectare and 1.4 million hectares and an increase of 0.42 million hectares and 0.77 million ha in pasture for the 50% tax and 100% respectively[19].

We also used our econometric land use models to project land use in France under two IPCC climate change scenarios (A2, B1). Results show that under climate change cropland area is mostly influenced, increasing by 6 million hectares under both A2 and B1 scenarios. Pasture areas fall by 3.4 million under both scenarios while forest areas decrease by 2.9 million under B1 and by 3.4 million hectare under A2. Our methodology allows us to take into account the autonomous adaptation capacity of farmers and forest managers in terms of possible switch in crops, tree species and management practices.

[19]OLS estimates.

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Appendix A Data

Land Cover class	CLC value	LU class
1 Artificial Surfaces	1, ..., 11	Urban
2 Agricultural Areas	12, ..., 17 and 19, ..., 22	Agriculture
2.3 Pastures	18	Pastures
3 Forest and Semi Natural Areas	23, 24 and 25	Forest
3.2.1 Natural grasslands	26	Pastures
3.2.2 Moors and heathland	27	Other
3.2.3 Sclerophyllous vegetation	28	Other
3.2.4 Transitional woodland-shrub	29	Other
3.3 Open spaces with little or no vegetation	30, ..., 34	Other
4 Wetlands	35, ..., 39	Other
5 Water bodies	40, ..., 44	Other

Table 11: Extract from the CLC classification and the corresponding LU aggregation.

Appendix B Elasticities

Calculus for the elasticities.

Agricultural activity	Profit before tax (1000 euros)	Average farm surface (ha)
Cereals and protein crops	24.1	68
Horticulture	30.7	7
Wine under geographical label	52,9	12*
Other wine	13.1	12*
Fruits and others	10.5	13
Bovine (milk)	28.8	58
Bovine (meat)	24.2	46
Bovine (mixed)	33.1	75
Sheep and other	17.6	25
Pig, poultry and other	36.6	34
Mixed farming	27.0	48

* Average for viticulture in general

Table 12: Average farmers' profits for 2005 per agricultural activity. The data on farms' size in hectares is for 2000. Source: Agreste, French Ministry of agriculture.

$$
\begin{aligned}
\frac{\partial ln\left(\frac{s_{ag}}{s_{ot}}\right)}{\partial Agr\ rent} &= \beta_{agr\_rent} \\
\frac{\partial\left(\frac{s_{ag}}{s_{ot}}\right)}{\partial Agr\ rent} * \frac{s_{ot}}{s_{ag}} &= \beta_{agr\_rent} \\
\frac{\partial s_{ag}}{\partial Agr\ rent} * \frac{1}{s_{ot}} * \frac{s_{ot}}{s_{ag}} &= \beta_{agr\_rent} \\
\frac{\partial s_{ag}}{\partial Agr\ rent} &= s_{ag} * \beta_{agr\_rent} \\
\frac{\partial s_{ag}}{\partial Agr\ rent} * \frac{Agr\ rent}{s_{ag}} &= s_{ag} * \beta_{agr\_rent} * \frac{Agr\ rent}{s_{ag}} \\
\frac{\partial s_{ag}}{\partial Agr\ rent} * \frac{Agr\ rent}{s_{ag}} &= \beta_{agr\_rent} * Agr\ rent
\end{aligned} \tag{13}
$$

Appendix C Models estimates

Tables 13, 14 and 15 present the estimated parameters for the three agricultural rent proxies under the different model specifications.

Table 13: Regional dual

	Dependent variable:											
	ln(pst/oth)			ln(agr/oth)			ln(for/oth)			ln(urb/oth)		
	OLS	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	1.928***	2.207***	0.508***	1.504***	2.339***	0.477***	2.536***	1.896***	0.739***	−4.919***	−4.180***	−2.342***
	(0.254)	(0.493)	(0.178)	(0.215)	(0.408)	(0.166)	(0.204)	(0.377)	(0.161)	(0.215)	(0.375)	(0.185)
rdual02_me	−1.138***	−1.029**	−1.147***	0.727***	0.864**	0.497***	−0.434**	0.307	−0.297**	0.086	0.299	−0.404***
	(0.214)	(0.514)	(0.150)	(0.181)	(0.416)	(0.144)	(0.172)	(0.382)	(0.133)	(0.181)	(0.369)	(0.147)
revfor_mean	0.027***	0.018***	0.023***	0.014***	0.014***	0.007***	0.016***	0.016***	0.014***	0.018***	0.017***	0.015***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
men_ha	−0.134***	−0.094***	−0.307***	−0.139***	−0.099***	−0.274***	−0.173***	−0.117***	−0.324***	0.081***	0.122***	0.150***
	(0.014)	(0.012)	(0.009)	(0.011)	(0.012)	(0.009)	(0.011)	(0.011)	(0.008)	(0.011)	(0.012)	(0.010)
rev00_mean	−0.122***	−0.021	−0.098***	0.091***	0.075***	0.161***	0.058***	0.051***	0.122***	0.315***	0.279***	0.403***
	(0.013)	(0.016)	(0.009)	(0.011)	(0.014)	(0.008)	(0.010)	(0.014)	(0.008)	(0.011)	(0.015)	(0.009)
slope	−0.056***	−0.062***	−0.066***	−0.292***	−0.258***	−0.341***	−0.058***	−0.033***	−0.053***	−0.218***	−0.217***	−0.244***
	(0.007)	(0.013)	(0.005)	(0.006)	(0.011)	(0.005)	(0.006)	(0.010)	(0.004)	(0.006)	(0.010)	(0.005)
TEXT2	1.563***	0.428***	2.035***	1.696***	0.635***	2.232***	0.021	0.053	0.030	1.011***	0.462***	1.323***
	(0.118)	(0.111)	(0.081)	(0.100)	(0.104)	(0.077)	(0.095)	(0.099)	(0.028)	(0.100)	(0.110)	(0.084)
TEXT3	2.479***	0.817***	3.393***	2.647***	1.168***	3.470***	0.721***	0.290**	0.911***	1.683***	0.827***	2.036***
	(0.125)	(0.129)	(0.086)	(0.106)	(0.120)	(0.083)	(0.100)	(0.114)	(0.058)	(0.106)	(0.126)	(0.089)
TEXT4	2.934***	1.044***	4.317***	2.883***	1.403***	4.063***	0.669***	0.197	0.649***	1.516***	0.570***	1.583***
	(0.188)	(0.177)	(0.128)	(0.159)	(0.166)	(0.122)	(0.151)	(0.158)	(0.108)	(0.159)	(0.175)	(0.133)
Moran's I	0.567***			0.456***			0.458***					
λ		0.792***			0.731***			0.714***			0.644***	
ρ			0.779***			0.704***			0.705***			0.612***
N	8822											
R^2	0.182	0.629	0.63	0.403	0.657	0.657	0.133	0.491	0.493	0.38	0.578	0.57
Log Lik.	-23704.86	-20892.41	-20848.63	-22230.67	-20325.95	-20285.2	-21752.48	-19910.07	-19878.68	-22223.33	-20923.09	-20956.42

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: Land prices

	Dependent variable:											
	ln(pst/oth)			ln(agr/oth)			ln(for/oth)			ln(urb/oth)		
	OLS	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	1.605***	2.082***	0.449***	1.909***	2.753***	0.524***	2.495***	2.392***	0.764***	−4.995***	−4.344***	−2.508***
	(0.217)	(0.356)	(0.144)	(0.185)	(0.305)	(0.143)	(0.174)	(0.282)	(0.117)	(0.184)	(0.290)	(0.159)
tl00	−0.390***	−0.270***	−0.428***	0.053*	0.090*	0.153***	−0.231***	−0.138***	−0.247***	0.129***	0.195***	0.156***
	(0.032)	(0.056)	(0.022)	(0.027)	(0.049)	(0.021)	(0.026)	(0.046)	(0.020)	(0.027)	(0.047)	(0.023)
revfor_mean	0.030***	0.020***	0.026***	0.012***	0.012***	0.006***	0.017***	0.015***	0.015***	0.018***	0.017***	0.016***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
men_ha	−0.128***	−0.092***	−0.297***	−0.138***	−0.099***	−0.276***	−0.169***	−0.115***	−0.317***	0.078***	0.119***	0.145***
	(0.013)	(0.012)	(0.009)	(0.011)	(0.012)	(0.009)	(0.011)	(0.011)	(0.008)	(0.011)	(0.012)	(0.010)
rev00_mean	−0.092***	−0.016	−0.065***	0.092***	0.074***	0.150***	0.078***	0.058***	0.144***	0.302***	0.270***	0.383***
	(0.013)	(0.016)	(0.009)	(0.011)	(0.015)	(0.008)	(0.010)	(0.014)	(0.008)	(0.011)	(0.015)	(0.010)
slope	−0.041***	−0.061***	−0.049***	−0.297***	−0.260***	−0.347***	−0.050***	−0.034***	−0.045***	−0.222***	−0.220***	−0.247***
	(0.007)	(0.013)	(0.005)	(0.006)	(0.011)	(0.005)	(0.006)	(0.010)	(0.004)	(0.006)	(0.010)	(0.005)
TEXT2	1.603***	0.445***	2.070***	1.685***	0.625***	2.216***	0.042	0.056	0.051	1.001***	0.453***	1.314***
	(0.117)	(0.111)	(0.080)	(0.100)	(0.104)	(0.077)	(0.094)	(0.099)		(0.100)	(0.110)	(0.084)
TEXT3	2.511***	0.842***	3.415***	2.661***	1.158***	3.461***	0.748***	0.302***	0.942***	1.662***	0.813***	1.993***
	(0.124)	(0.129)	(0.086)	(0.106)	(0.120)	(0.083)	(0.100)	(0.114)	(0.046)	(0.106)	(0.126)	(0.089)
TEXT4	3.015***	1.066***	4.378***	2.858***	1.392***	4.033***	0.711***	0.205	0.690***	1.496***	0.558***	1.570***
	(0.187)	(0.177)	(0.128)	(0.159)	(0.166)	(0.122)	(0.150)	(0.158)	(0.104)	(0.159)	(0.175)	(0.133)
Moran's I	0.562***			0.457***			0.453***			0.38***		
λ		0.789***			0.732***			0.71***			0.643***	
ρ			0.775***			0.704***			0.702***			0.61***
N	8822											
R^2	0.193	0.629	0.63	0.403	0.657	0.657	0.14	0.491	0.493	0.381	0.578	0.57
Log Lik.	-23645.51	-20883.08	-20840.54	-22236.85	-20326.42	-20283.39	-21715.63	-19905.85	-19872.08	-22212.19	-20914.75	-20953.39

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15: Agri revenue

	Dependent variable:											
	ln(pst/oth)			ln(agr/oth)			ln(for/oth)			ln(urb/oth)		
	OLS	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*	*OLS*	*spatial error*	*spatial autoregressive*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	1.782***	2.305***	0.501***	1.756***	2.668***	0.557***	3.397***	2.783***	1.035***	−5.476***	−4.603***	−2.581***
	(0.254)	(0.518)	(0.169)	(0.215)	(0.420)	(0.128)	(0.202)	(0.383)	(0.135)	(0.214)	(0.377)	(0.184)
gmnvh00	−1.159***	−1.450**	−1.400***	0.417*	0.497	0.083	−2.305***	−1.227**	−2.324***	1.243***	1.160**	0.697***
	(0.271)	(0.698)	(0.179)	(0.229)	(0.553)		(0.215)	(0.499)	(0.167)	(0.228)	(0.479)	(0.190)
revfor_mean	0.031***	0.022***	0.028***	0.012***	0.011***	0.005***	0.020***	0.017***	0.018***	0.016***	0.015***	0.015***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
men_ha	−0.137***	−0.094***	−0.311***	−0.137***	−0.098***	−0.272***	−0.174***	−0.116***	−0.322***	0.081***	0.122***	0.148***
	(0.014)	(0.012)	(0.009)	(0.011)	(0.012)	(0.009)	(0.011)	(0.011)	(0.008)	(0.011)	(0.012)	(0.010)
rev00_mean	−0.123***	−0.020	−0.097***	0.095***	0.076***	0.165***	0.072***	0.056***	0.136***	0.305***	0.276***	0.393***
	(0.013)	(0.016)	(0.009)	(0.011)	(0.015)	(0.008)	(0.010)	(0.014)	(0.008)	(0.011)	(0.015)	(0.009)
slope	−0.054***	−0.062***	−0.064***	−0.295***	−0.259***	−0.343***	−0.061***	−0.036***	−0.056***	−0.216***	−0.216***	−0.241***
	(0.007)	(0.013)	(0.005)	(0.006)	(0.011)	(0.005)	(0.005)	(0.010)	(0.004)	(0.006)	(0.010)	(0.005)
TEXT2	1.543***	0.423***	2.010***	1.700***	0.633***	2.230***	−0.038	0.041	−0.030	1.045***	0.474***	1.344***
	(0.118)	(0.111)	(0.080)	(0.100)	(0.104)	(0.077)	(0.094)	(0.099)		(0.100)	(0.110)	(0.084)
TEXT3	2.436***	0.813***	3.349***	2.673***	1.167***	3.488***	0.696***	0.286**	0.885***	1.692***	0.838***	2.024***
	(0.125)	(0.129)	(0.085)	(0.106)	(0.120)	(0.083)	(0.100)	(0.114)	(0.045)	(0.106)	(0.126)	(0.089)
TEXT4	2.907***	1.036***	4.280***	2.885***	1.401***	4.058***	0.571***	0.184	0.547***	1.572***	0.588***	1.624***
	(0.188)	(0.177)	(0.127)	(0.159)	(0.166)	(0.122)	(0.150)	(0.158)	(0.100)	(0.159)	(0.175)	(0.133)
Moran's I	0.567***			0.457***			0.449***			0.378***		
λ		0.792***			0.732***			0.71***			0.642***	
ρ			0.779***			0.704***			0.701***			0.61***
N	8822											
R^2	0.181	0.629	0.63	0.403	0.657	0.657	0.143	0.491	0.493	0.382	0.578	0.57
Log Lik.	-23709.75	-20892.24	-20848.73	-22237.04	-20327.71	-20285.76	-21698.72	-19907.44	-19870.24	-22208.62	-20920.5	-20955.95

Note: *p<0.1; **p<0.05; ***p<0.01

Table 16: Lagrange miltiplier tests

		Models											
		ln(pst/oth)			*ln(agr/oth)*			*ln(for/oth)*			*ln(urb/oth)*		
Proxy	LM Test	Statistic	df	p-value	Statistic	df	p-value	Statistic	df	p-value	Statistic	df	p-value
Shadow price	LMerr	8402.81	1	0	5502.83	1	0	5508.71	1	0	3824.11	1	0
	LMlag	8593.49	1	0	5513.07	1	0	5642.74	1	0	3674.2	1	0
	RLMerr	46.38	1	0	173.39	1	0	6.04	1	0.014017401	194.62	1	0
	RLMlag	237.05	1	0	183.63	1	0	140.07	1	0	44.71	1	0
	SARMA	8639.86	2	0	5686.46	2	0	5648.77	2	0	3868.82	2	0
Land prices	LMerr	8256.74	1	0	5513.64	1	0	5402.61	1	0	3817.44	1	0
	LMlag	8432.28	1	0	5529.6	1	0	5533.84	1	0	3652.69	1	0
	RLMerr	52.54	1	0	174.19	1	0	7.84	1	0.0051083418	204.61	1	0
	RLMlag	228.07	1	0	190.15	1	0	139.07	1	0	39.86	1	3e-10
	SARMA	8484.82	2	0	5703.79	2	0	5541.68	2	0	3857.3	2	0
Agri revenue	LMerr	8422.24	1	0	5510.55	1	0	5301.49	1	0	3785.84	1	0
	LMlag	8612.21	1	0	5524.85	1	0	5468.63	1	0	3629.37	1	0
	RLMerr	46.31	1	0	173.59	1	0	2.85	1	0.0912817067	196.27	1	0
	RLMlag	236.28	1	0	187.89	1	0	169.99	1	0	39.8	1	3e-10
	SARMA	8658.52	2	0	5698.44	2	0	5471.49	2	0	3825.65	2	0

Appendix D Predicted land use shares

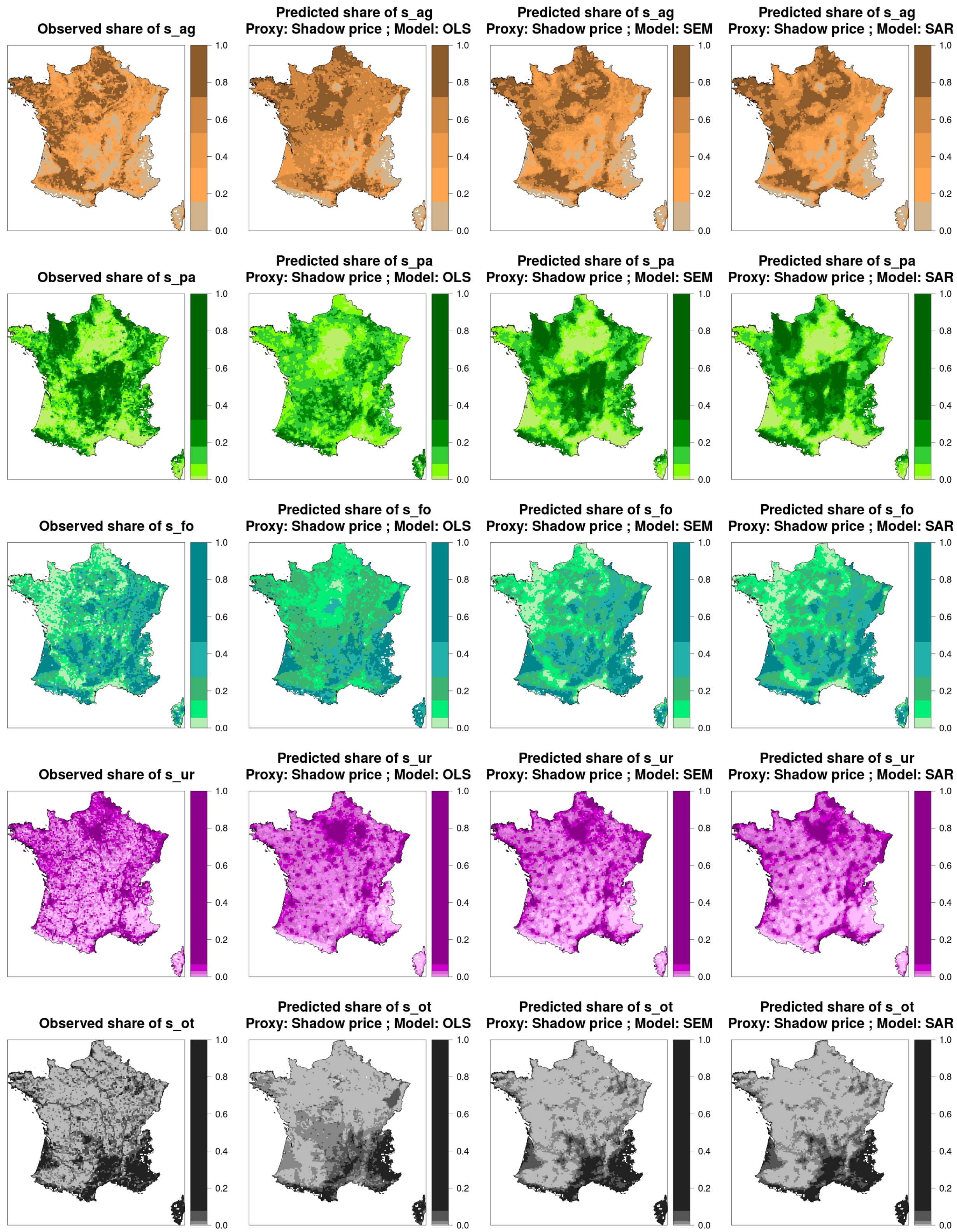

Figure 4: Observed land use shares (left pane) and predicted (OLS model in the middle and SEM on the right). Proxy for the agricultural rent: shadow price.

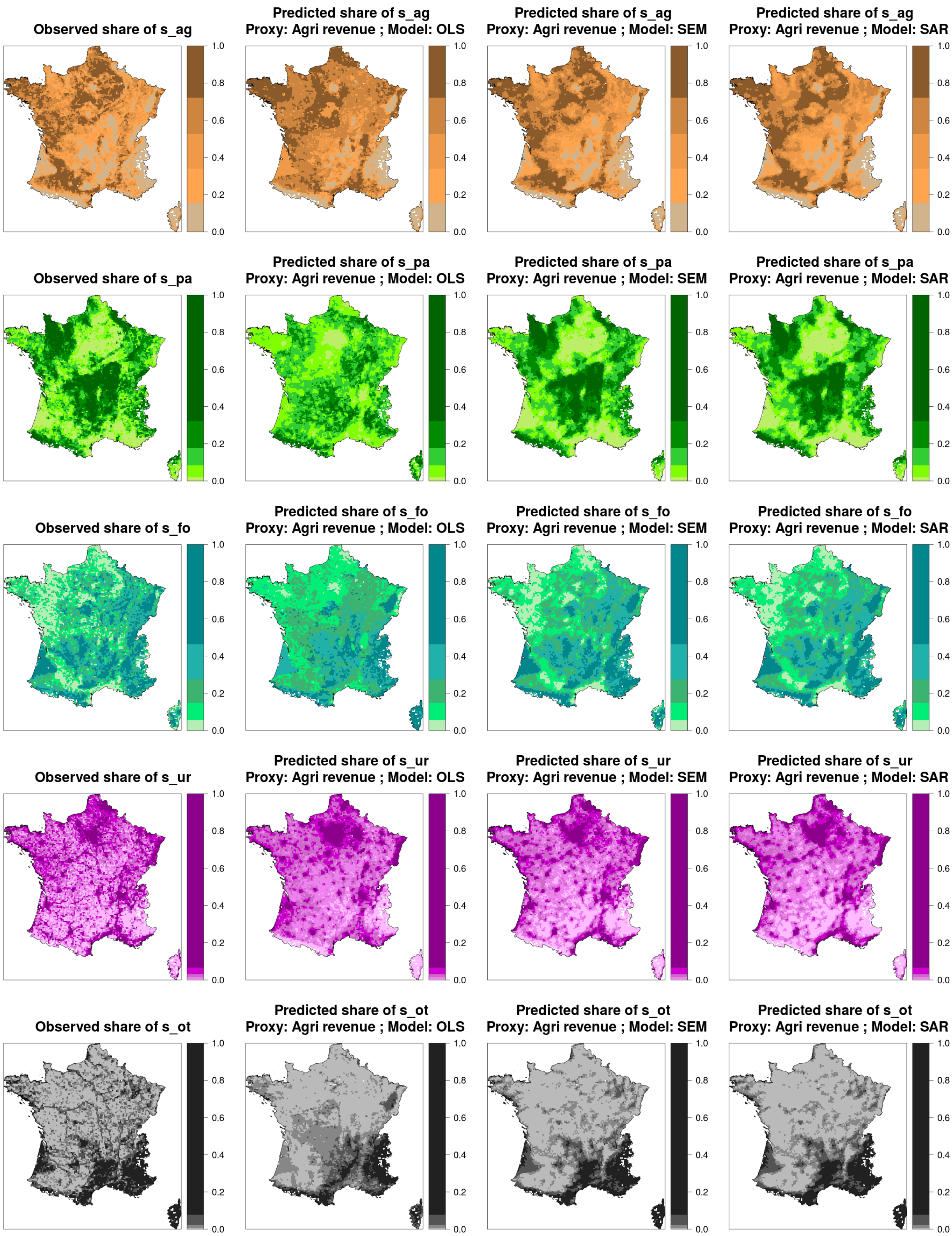

Figure 5: Observed land use shares (left pane) and predicted (OLS model in the middle and SEM on the right). Proxy for the agricultural rent: farmers' revenues.

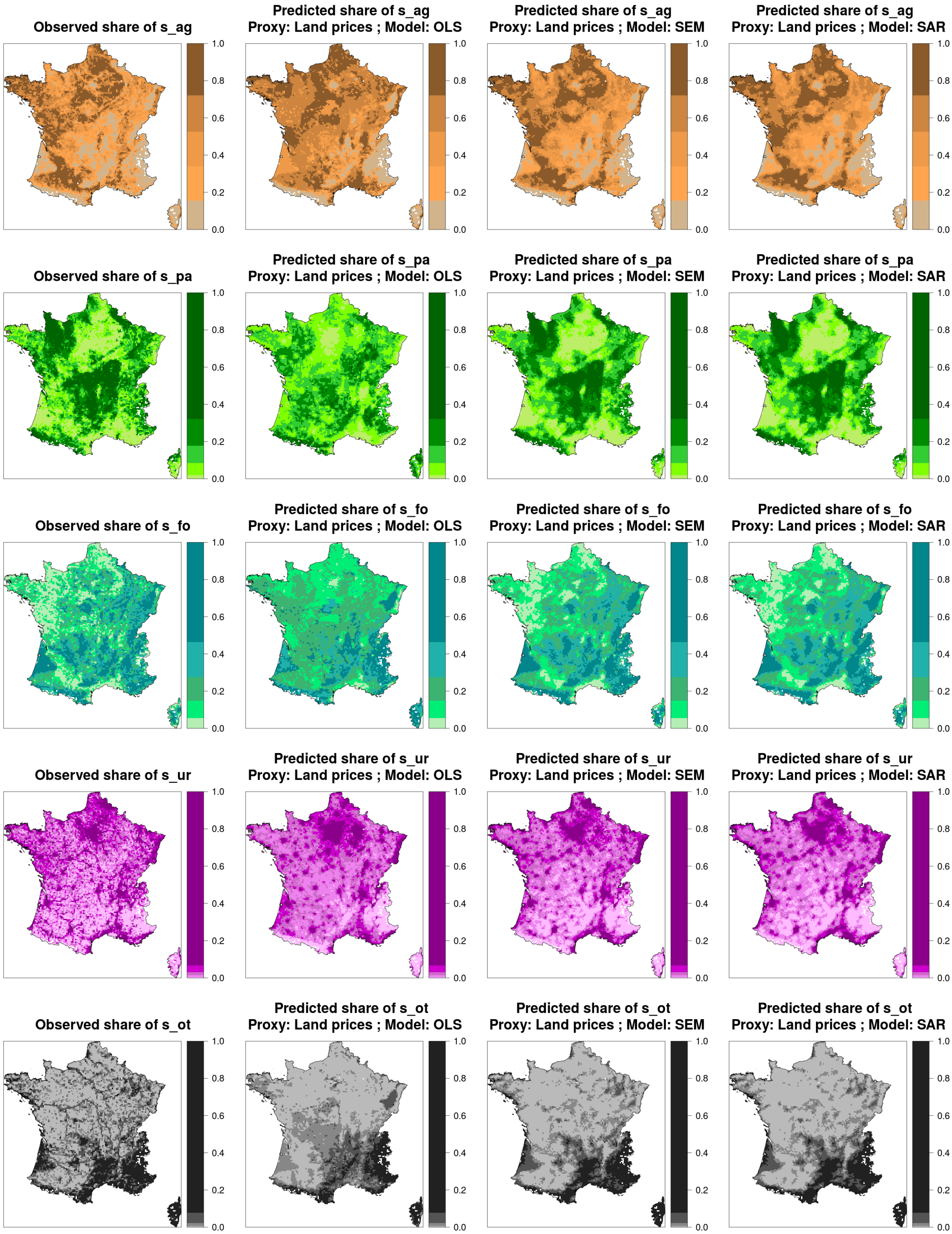

Figure 6: Observed land use shares (left pane) and predicted (OLS model in the middle and SEM on the right). Proxy for the agricultural rent: agricultural land and pastures prices.

Appendix E Land use shares and nitrogen input tax

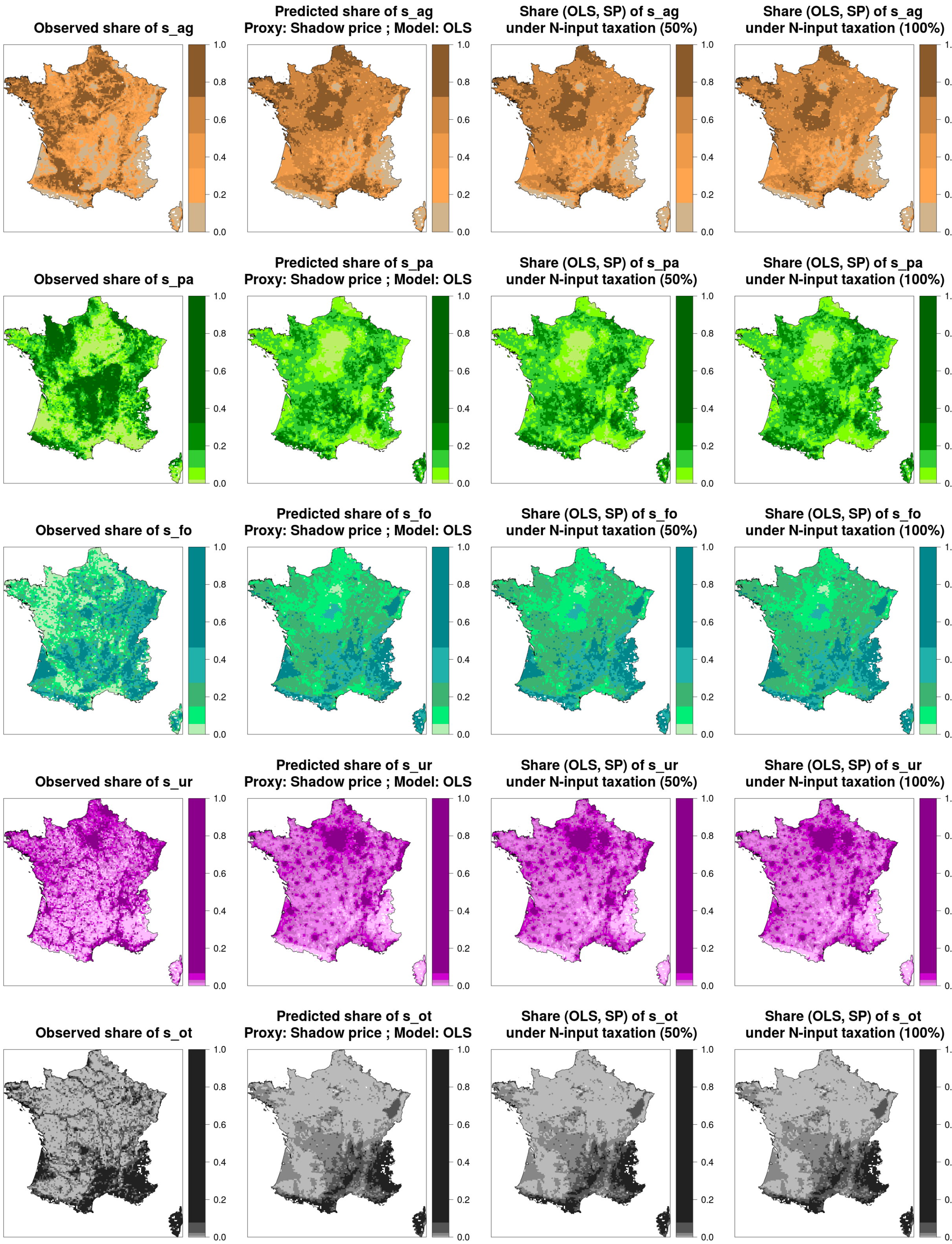

Figure 7: Predicted (via OLS) land use without tax (left), with 50% tax (middle) and with 100% tax (right) on the mineral nitrogen input. Proxy for the agricultural rent: shadow price.

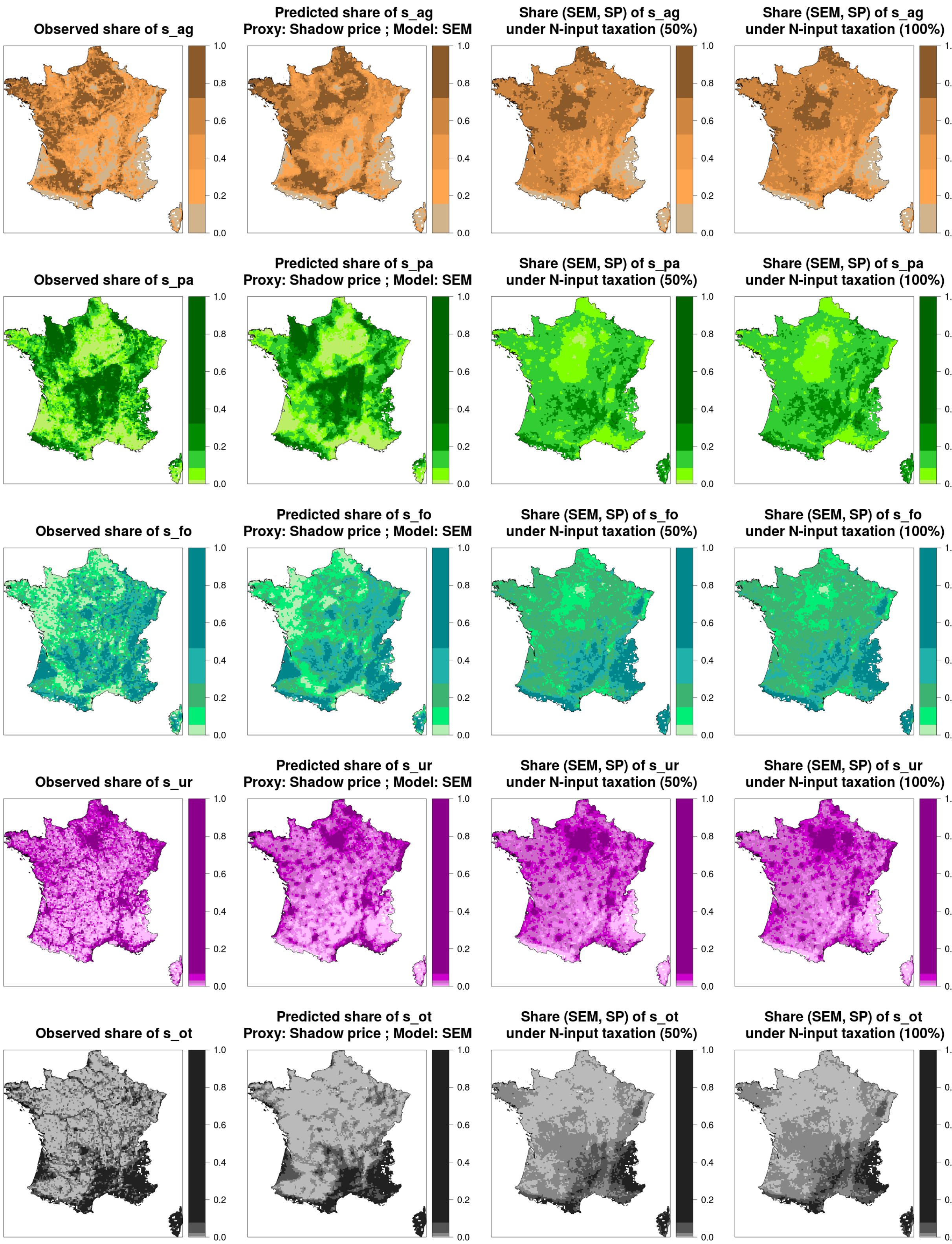

Figure 8: Predicted (via SEM) land use without tax (left), with 50% tax (middle) and with 100% tax (right) on the mineral nitrogen input. Proxy for the agricultural rent: shadow price.

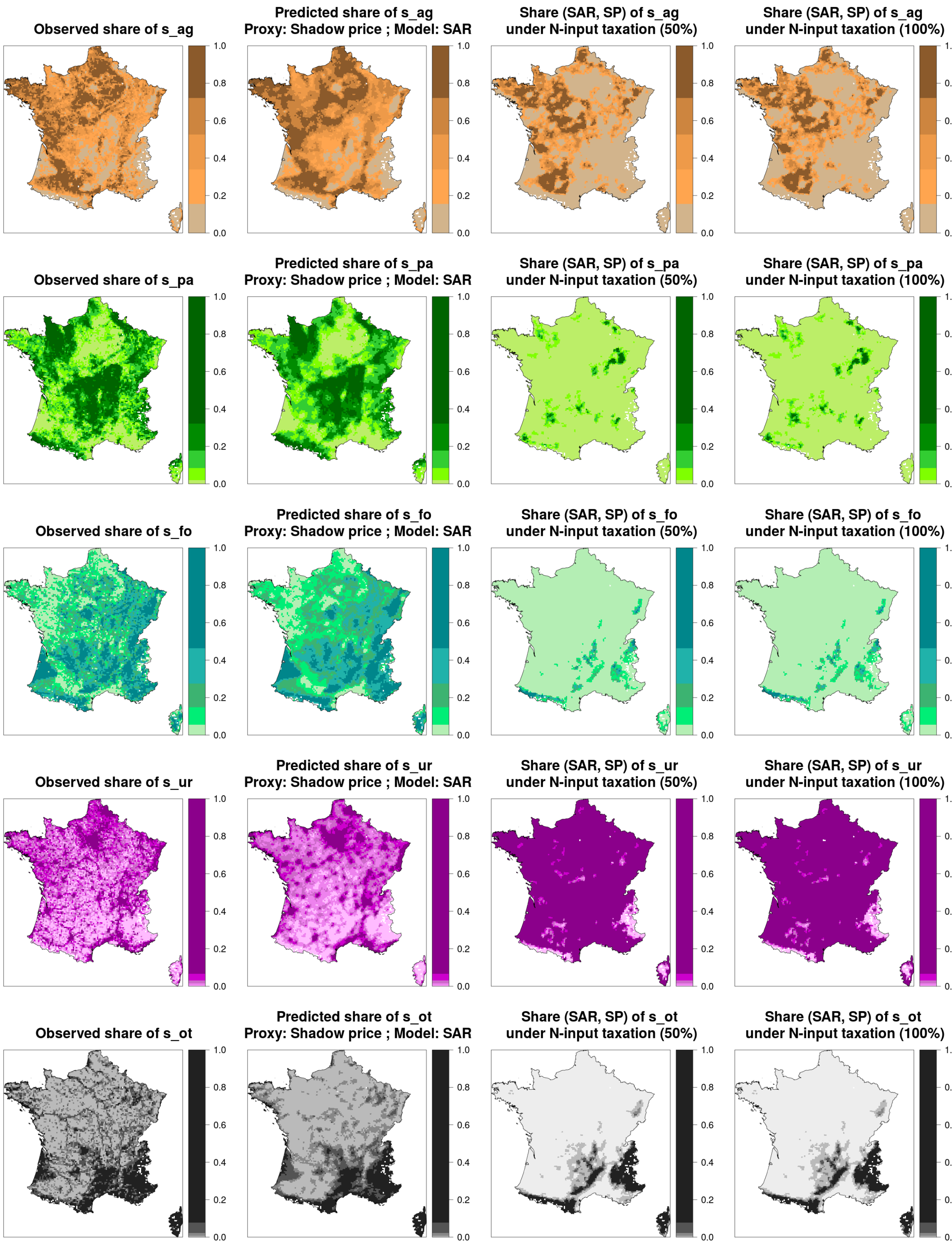

Figure 9: Predicted (via SAR) land use without tax (left), with 50% tax (middle) and with 100% tax (right) on the mineral nitrogen input. Proxy for the agricultural rent: shadow price.

Appendix F Land use shares under CC A2, B1

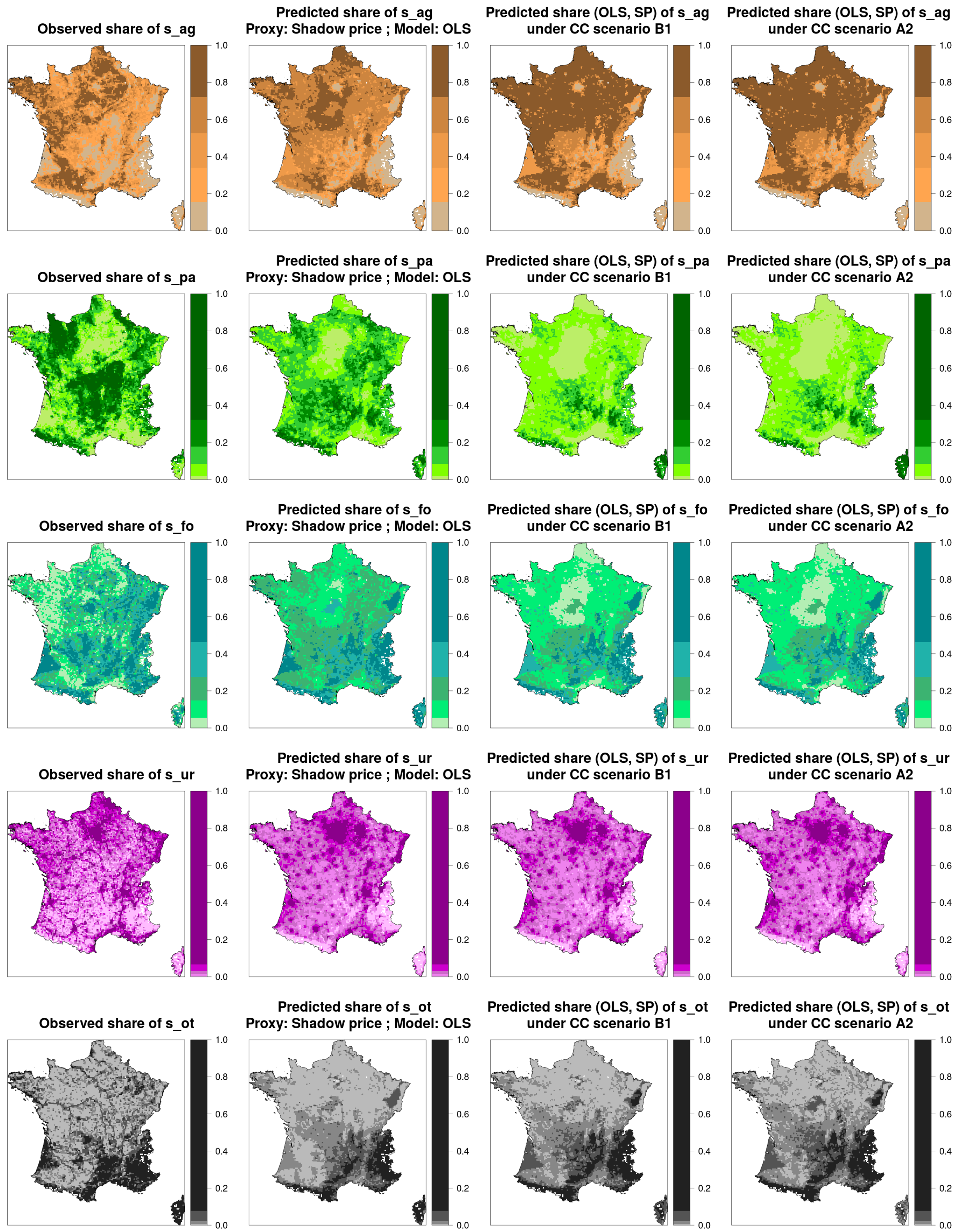

Figure 10: Predicted (via OLS) land use under CC scenarios B1 and A2. Proxy for the agricultural rent: shadow price.

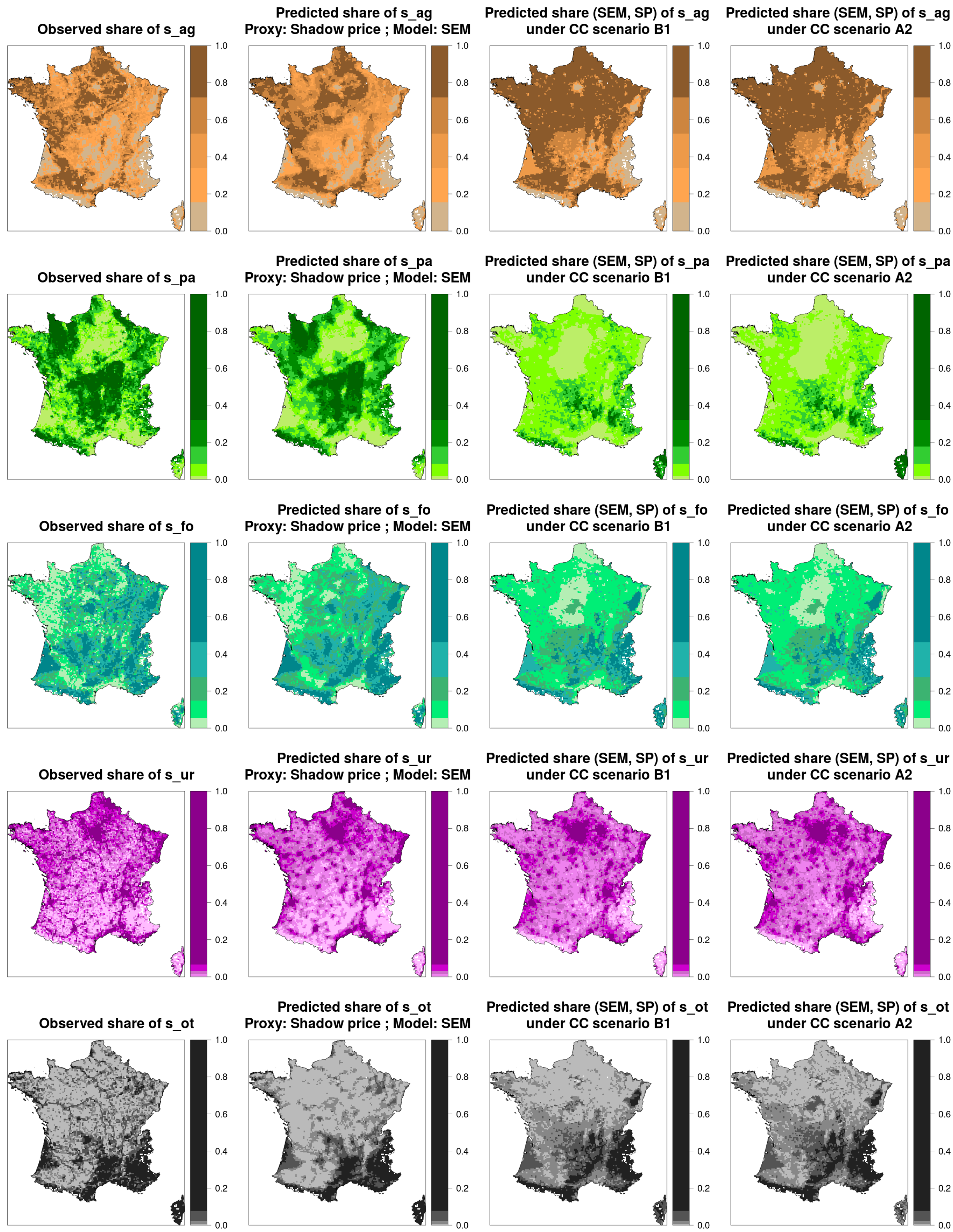

Figure 11: Predicted (via SEM) land use under CC scenarios B1 and A2. Proxy for the agricultural rent: shadow price.

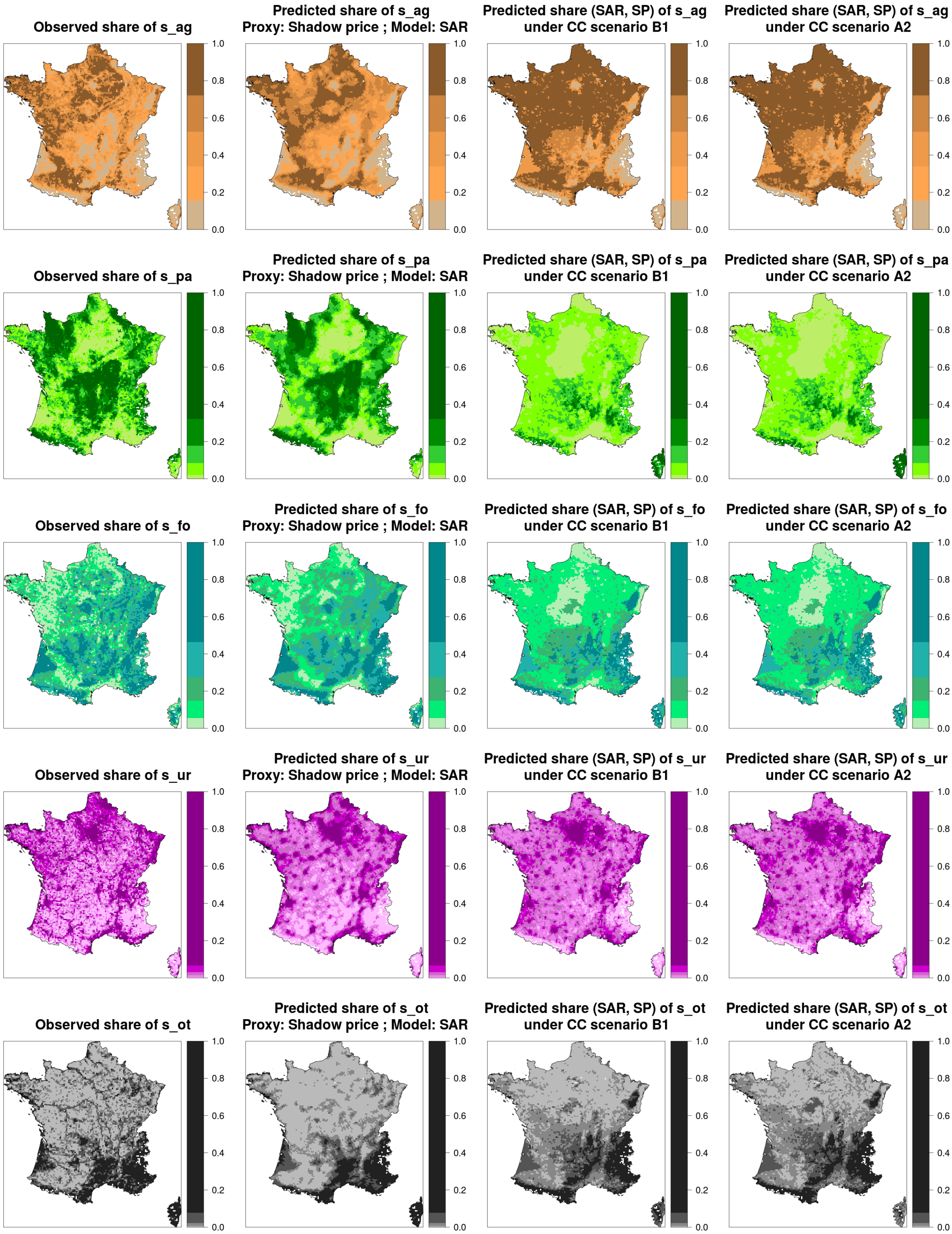

Figure 12: Predicted (via SAR) land use under CC scenarios B1 and A2. Proxy for the agricultural rent: shadow price.

Appendix G Land use shares under CC A2, B1, N tax

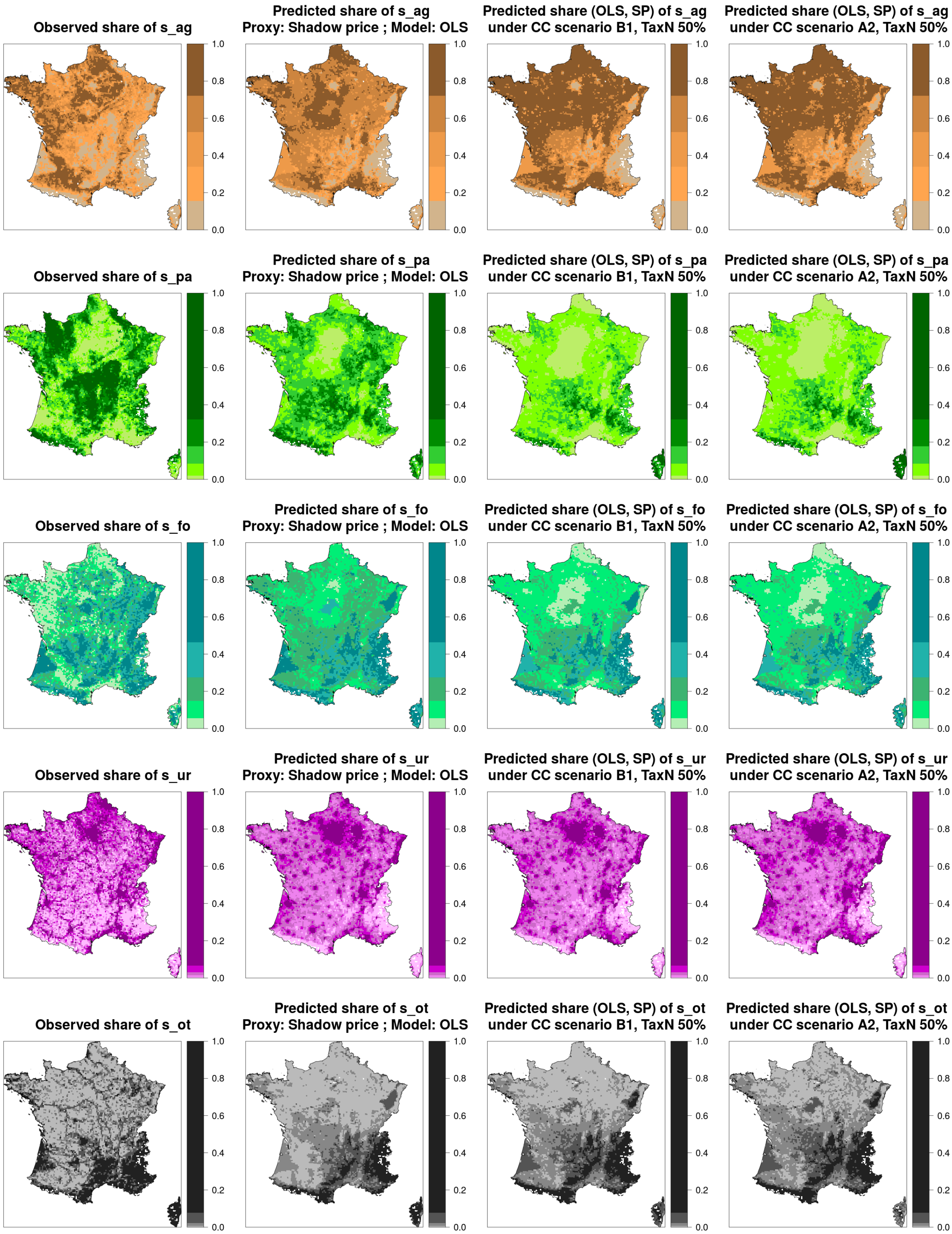

Figure 13: Predicted (via OLS) land use under CC scenarios B1 and A2 and 50% N tax. Proxy for the agricultural rent: shadow price.

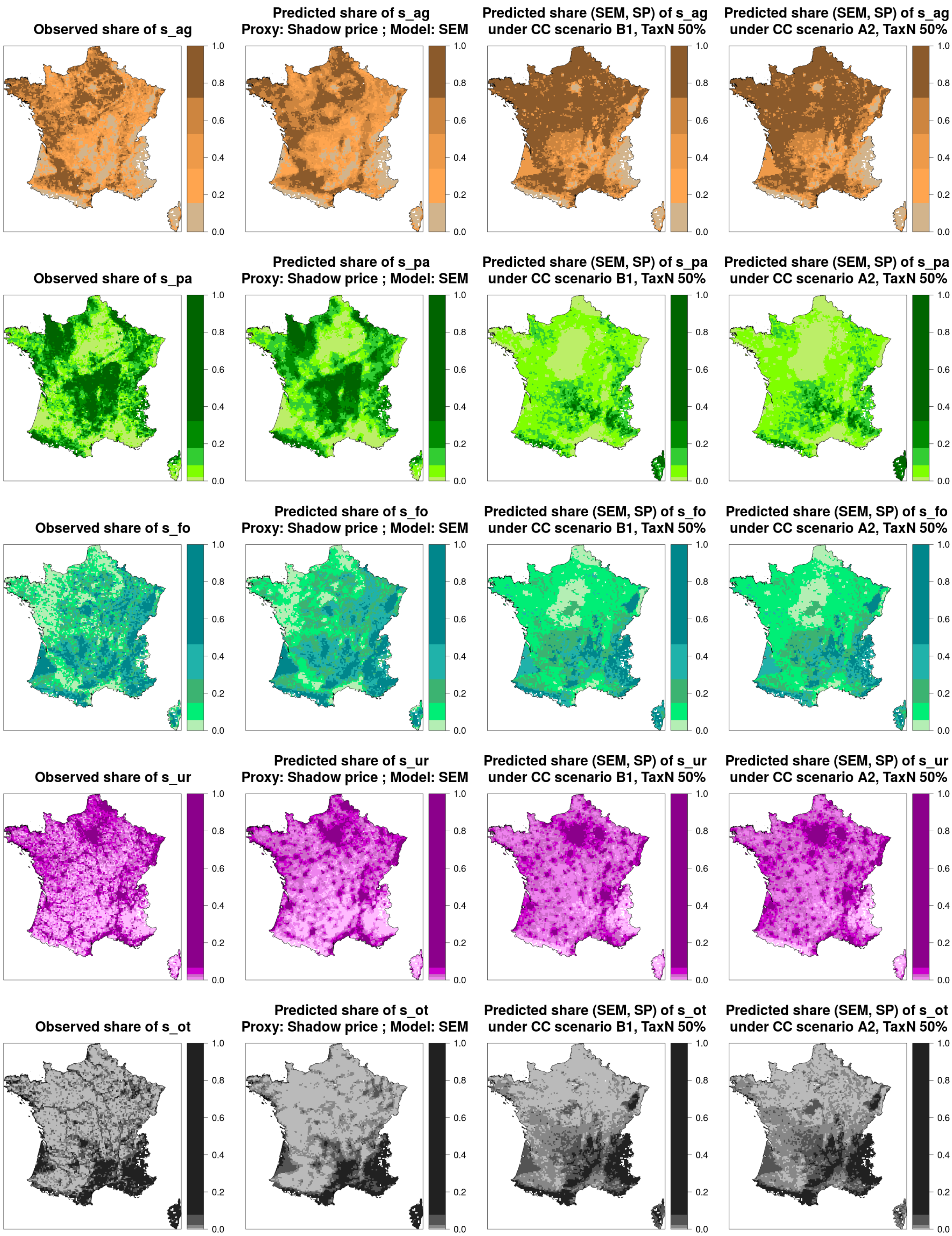

Figure 14: Predicted (via SEM) land use under CC scenarios B1 and A2 and 50% N tax. Proxy for the agricultural rent: shadow price.

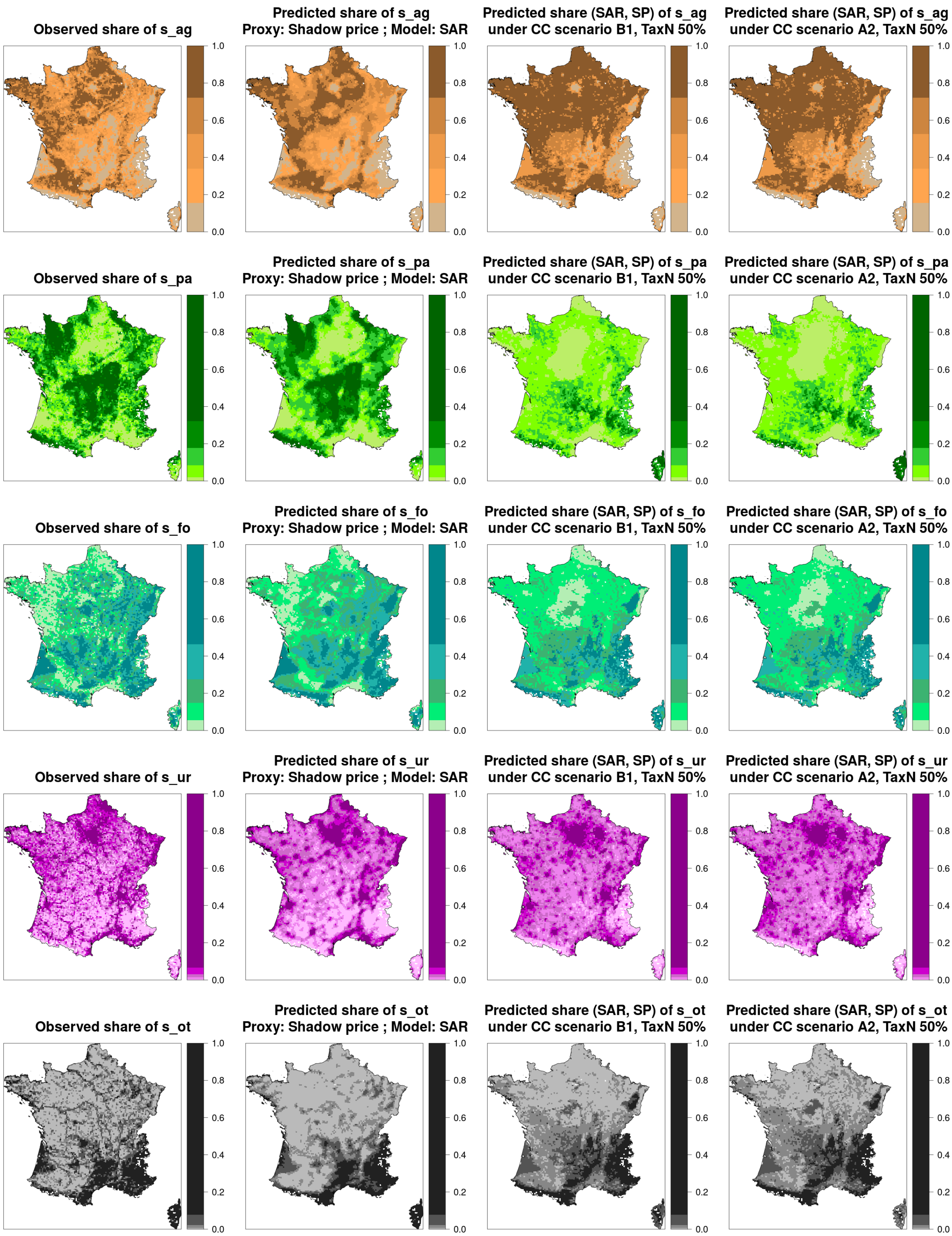

Figure 15: Predicted (via SAR) land use under CC scenarios B1 and A2 and 50% N tax. Proxy for the agricultural rent: shadow price.

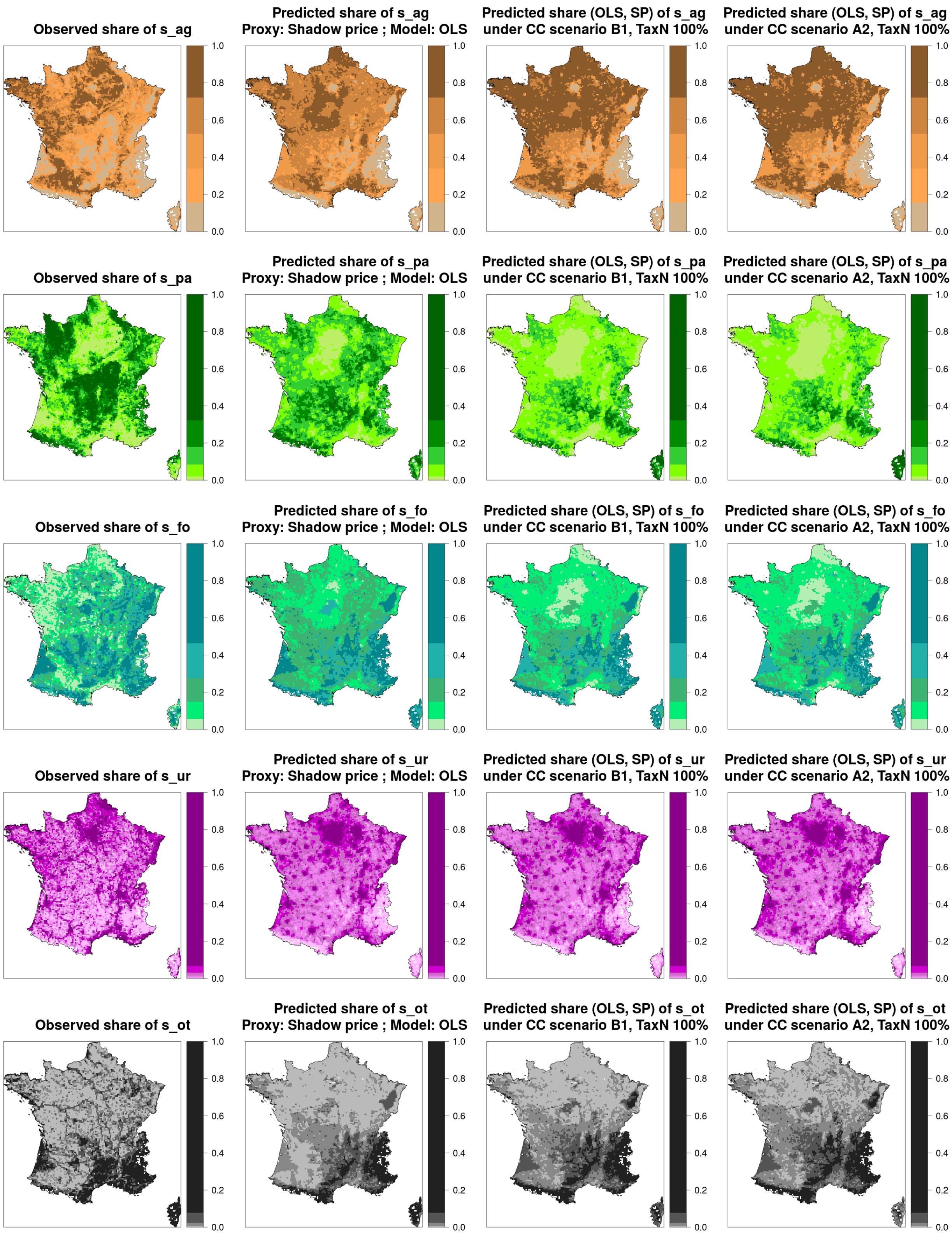

Figure 16: Predicted (via OLS) land use under CC scenarios B1 and A2 and 100% N tax. Proxy for the agricultural rent: shadow price.

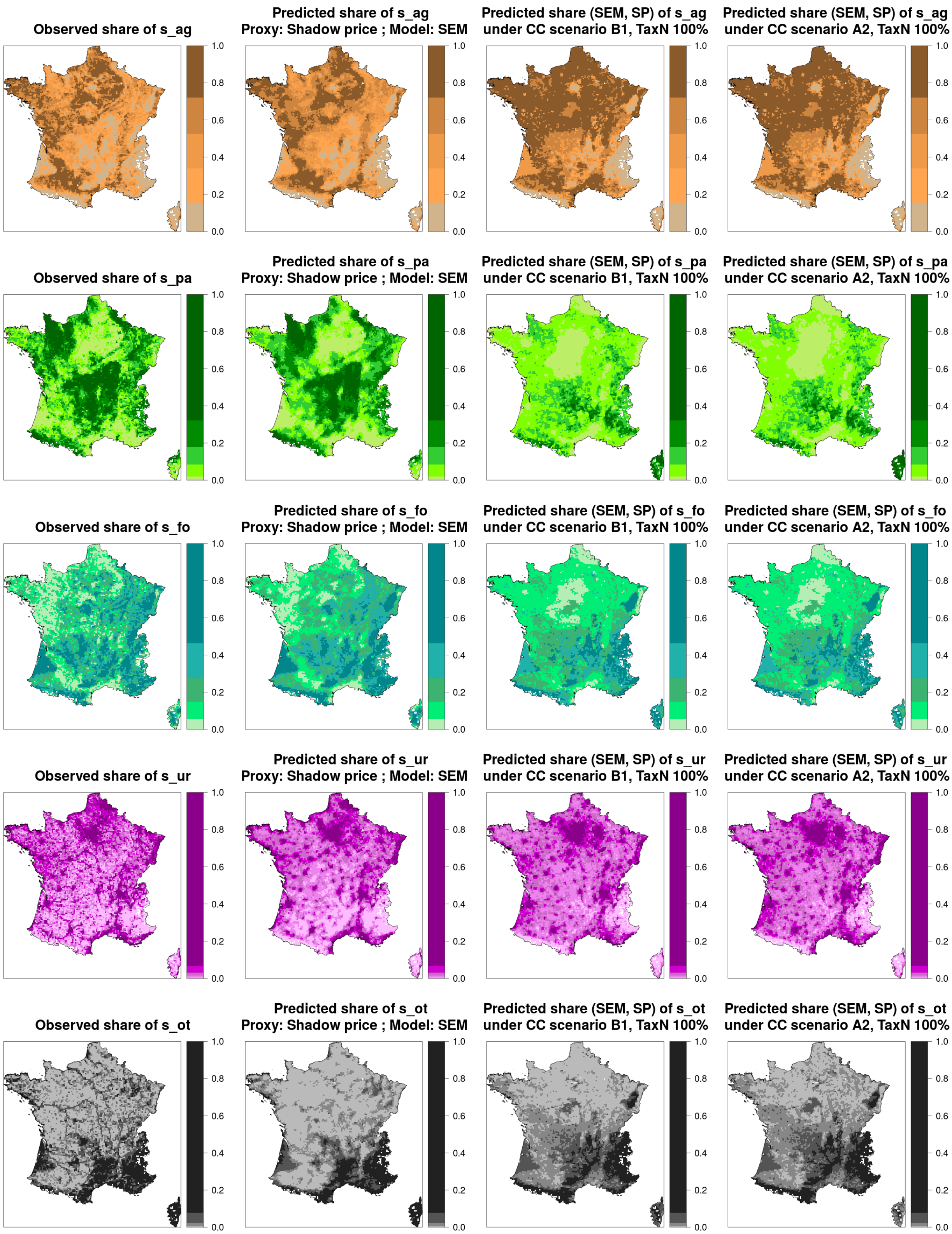

Figure 17: Predicted (via SEM) land use under CC scenarios B1 and A2 and 100% N tax. Proxy for the agricultural rent: shadow price.

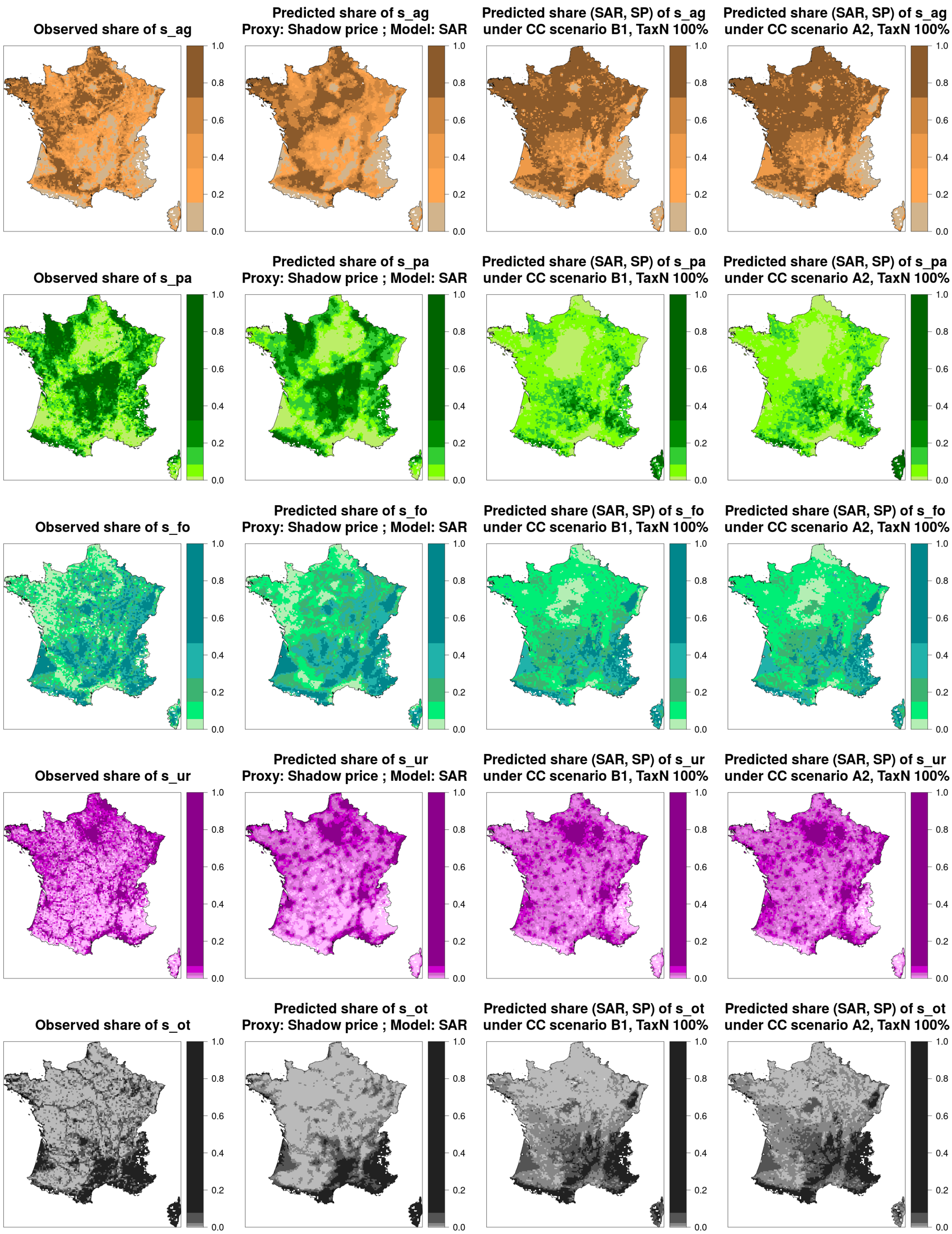

Figure 18: Predicted (via SAR) land use under CC scenarios B1 and A2 and 100% N tax. Proxy for the agricultural rent: shadow price.