Climate induced land use change in France: impacts of agricultural adaptation and climate change mitigation

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Abstract

We assess in this study the impacts of climate change adaptation of agriculture and forestry, the mitigation of greenhouse gases from agriculture, and the resulting land use change for France. We estimate a spatial econometric land use model where agricultural and forestry rents are approximated by the results from sector-specific models. The model represents four major land use categories: (i) agriculture, (ii) forestry, (iii) urban, and (iv) other; at the scale of a homogeneous grid with resolution of 8 km x 8 km covering metropolitan France. We simulate the impacts of two IPCC climate change scenarios (A2 and B1, 2100 horizon), and different tax levels for greenhouse gas emissions (from 0 to 200 €/t CO_2 equivalent) aiming at the reduction of greenhouse gases from agriculture. Our results show that both climate change scenarios lead to an increase in agricultural area at the expense of forests. The greenhouse gas mitigation policy allows to curtail agricultural expansion and so could counteract the effects of climate change on land use. Accounting for land use change results in reducing the abatement costs of the mitigation policy in the agricultural sector.

Keywords: Spatial land use share model, greenhouse gas tax, climate change, mitigation, adaptation, land rent.

JEL Classification: Q15, Q54, Q52, C31

1 Introduction

In March 2015, the European Union (EU) announced its intended contribution to the climate change mitigation effort by promising a 40% cuts in its greenhouse gas (GHG) emissions by 2030 in comparison to 1990 levels. Few months later, during the 2015 United Nations Climate Change Conference (COP 21) held in Paris, France pledged a 75% emissions reduction by 2050. These ambitious commitments have greatly contributed to the adoption of the first universal, legally-binding global climate agreement. French government also adopted a national low-carbon strategy (Ministère de l'écologie, du développement durable et de l'énergie, 2015) which establishes carbon budgets for the 2015-2018, 2019-2023, and 2024-2028 periods. In order to attain the national reduction goals, the strategy is announcing carbon taxation for the energy sector, namely 22 €/tCO2 in 2016, 56 €/tCO2 in 2020, and 100 €/tCO2 in 2030.

The energy use in France (production, transport, residence, etc.) represents about 70% of the GHG emissions of the country. The other major source of GHG is agriculture representing some

16 - 18 %[1] of national emissions. The mitigation goal for this sector is a reduction of some 12% for the third carbon budget (2024-2028) comparing to 2013 and cutting the GHG emissions in 2050 by half comparing to 1990. Nevertheless, no economic incentive policy is planned for agricultural pollution. Grosjean et al. (2016) discuss the barriers to GHG pricing (through cap and trade schemes or taxation) in agriculture, and sum them up into three classes of concerns: i) transaction costs; ii) leakages; and iii) distributional effects. Their article proposes a framework for analyzing potential solutions for these issues through policy design. Nevertheless, current policies still propose to reduce sector's emissions by implementing agroecological measures such as the maintenance of meadows, the development of agro-forestry and the optimization of input use. One of the emblematic measures proposed during the COP 22 held in Marrakech in autumn 2016 is the "4 per 1000" increase in carbon stock in soils. This measure is associated with gains in terms of soils fertility and of the supply of other ecosystem services. In this paper, we argue that GHG taxation in agriculture can have indirect effects that are in the direction of the proposed agroecological measures. Moreover, such policies should incite farmers to explore and adopt new techniques for GHG mitigation.

In this study, we investigate the effects of climate change on land use in France at the 2100 horizon in the context of a climate change mitigation policy based on a tax for agricultural GHG emissions. We use the results of previous studies concerning the impact of climate change on the profitability of agriculture and forestry, and introduce a spatial econometric land use share model that captures the change in land rents for different land use classes. Furthermore, we study the impact of a mitigation policy (tax on GHG emissions) on land use and on overall agricultural emissions. We build on three branches of the literature devoted to agriculture and climate change adaptation and mitigation: i) impact of climate change on agricultural sector; ii) impact of climate change on land use; and iii) abatement costs for greenhouse gases from agriculture.

First, numerous studies aim at assessing the direct effects of climate change on agriculture (Adams et al., 1990; Rosenzweig and Parry, 1994). Scholars initially based their analysis on agronomic models and neglected possible land use changes within the agricultural sector. Mendelsohn et al. (1994) address this issue and propose a method that relies on the Ricardian theory of differential land rent. The Ricardian method supposes that land price is the net present value of future land rents. However, future land rents may be stemming from other than the agricultural use (Capozza and Helsley, 1990; Plantinga et al., 2002). Schlenker et al. (2005) account for urban pressure on agricultural land price in their assessment of climate change impact on U.S. agriculture. In response to the critics made by Mendelsohn et al. (1994), the possibilities for adaptation by switching crops were introduced in the analysis via economic modules combined with crop models (Easterling et al., 1993; Adams et al., 1995; Leclère et al., 2013). Leclère et al. (2013) use a supply-side model of European agriculture and a crop model to show that adaptation can have significant impact on farmers' profits. Their results integrate different adaptation options in terms of changes in sowing dates or crop varieties.

Second, some recent studies (Ay et al., 2014 and Haim et al., 2011, for instance) investigate the effects of climate change on land use. The study by Ay et al. (2014) uses the same principle as in Mendelsohn et al. (1994) in estimating future land rents for their land use model. While the study by Mendelsohn et al. (1994) focuses solely on the adaptation of agriculture in terms of crops and practices, the study by Ay et al. (2014) evaluates the impact of climate change in terms of LUCs. Haim et al. (2011) approximate the future agricultural and forestry productivity by the net primary productivity of ecosystems. In the present study, we use the results of the study by Leclère et al. (2013) in order to evaluate the effects of climate change on agricultural profitability and the resulting impact on land use. In the same manner, the future climate profits for the forestry sector

[1] Cited figures are from UNFCC data for France up to 2013. Emissions include LULUCF and indirect CO_2.

are employed in our econometric model. The estimates for the forestry sector are derived from the FFSM++ model (Caurla et al., 2013; Lobianco et al., 2016). Thanks to our modeling strategy, we can account for the crop or tree species switch within these two sectors as an adaptation measure reducing the losses related to climate change.

Third, the marginal abatement costs of GHG for agriculture have been studied through different modeling techniques. In their meta-analysis on the subject, Vermont and De Cara (2010) classify the different approaches in three groups: i) supply-side models specialized in agriculture; ii) general equilibrium models; and iii) engineering studies. The authors argue that the results from the first type of models are generally closer to the microeconomic definition of marginal costs, while general equilibrium models integrate the commodity price responses to pollution abatement. Nevertheless, supply-side models represent better the heterogeneity in farming systems. The detail in the description of the production function is even higher in the engineering studies but at the expense of the geographical extent to which these studies apply.[2] Except general equilibrium models, the response of farmers to GHG taxation in terms of land use has been ignored.

As in previous greenhouse mitigation studies (De Cara and Jayet, 2000; De Cara et al., 2005; De Cara and Jayet, 2011) we use the supply-side agricultural model AROPAj (Jayet et al., 2015) to evaluate the GHG abatement for different levels of GHG taxation. Thanks to the inclusion of crop-yield functions of the nitrogen input (Godard et al., 2008) in AROPAj, we account for a larger portfolio of abatement strategies of the economic agents. Furthermore, as mentioned before, the work by Leclère et al. (2013) introduces two climate change scenarios in the supply-side model. This way, we can simulate the abatement rates under different climates. Since, carbon budgets span over multiple decade horizons, accounting for climate change when evaluating GHG mitigation is necessary especially for climate sensitive sectors such as agriculture.

In the present study, we allow also for a reallocation of land among four land uses, namely: i) agriculture (crops and pastures); ii) forest; iii) urban; and iv) other. In order to model land use, we employ a spatial econometric land use share model where we explicitly model spatial autocorrelation between land uses in neighboring grid cells. Most studies in the literature assume spatial independence of land use choices between neighboring areas. Some recent exceptions include Ay et al. (2017); Chakir and Le Gallo (2013); Li et al. (2013); Sidharthan and Bhat (2012); Ferdous and Bhat (2013); Chakir and Parent (2009). Incorporating spatial autocorrelation into land use models allows to have more precise estimations and improves the prediction accuracy (**?**). We can thus account for the policy and climate change impact in terms of land use. Our results show that when farmers adapt their land use the GHG abatement rates are higher because of the decrease in agricultural land use share.

This article is organized as follows. In section 2, we first present the models that we use in our assessment on GHG from agriculture. We then present the data employed in the study in section 3. Finally, the results of our simulations are provided and discussed in section 4.

2 Methodology

The methodology used in this study is based on two mathematical programming models (AROPAj for agriculture and FFSM++ for forestry), coupled to bio-ecological models, and a spatial econometric land use model that allows us to combine the results of the sector-specific models. The bio-ecological components of the sector specific models account for the direct impact of climate

[2] For more details on the methodologies and the results of these studies, please refer to Vermont and De Cara (2010)

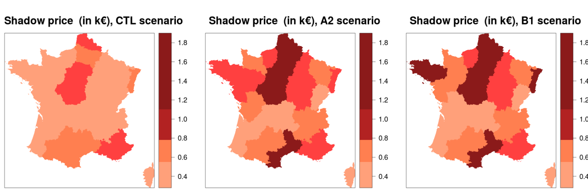
change on agriculture and forestry in terms of crops' and forestry yields. These results are integrated in the economic models where economic agents maximize their returns by modifying their input (fertilizers for farmers) and/or land use (crops, tree species). The evaluated profits are then used in the econometric land use model which provides us with estimates of the land shares dedicated to each of the four major land use classes.

Climate change scenarios (A2 and B1) are first simulated via bio-ecological models. For agriculture, this model is the crop model STICS developed by the French National Institute for Agricultural Research, INRA, in Avignon (Brisson et al., 2003, 2009). The model allows to capture the effects of different weather conditions and of CO_2 fertilization. The model can also simulate change in sowing and harvesting dates, new varieties and different levels of nitrogen input.

The response of forests to climate change is captured through two indicators: tree growth and tree probability of presence. These indicators are derived from data provided by the French National Geographic Institute (IGN). The effects of current climate and soil conditions on the indicators is estimated via generalized additive models (GAM) and future values under climate change are projected. This work has been conducted by Pierre Mérian and Jean-Daniel Bontemps from INRA, Nancy.

2.1 Sector specific models for agriculture and forestry

Agriculture supply-side model We study the agricultural sector via the economic supply-side model AROPAj (for a detailed description see Jayet et al., 2015). It is a linear programming model based on FADN data and accounting for the Common Agricultural Policy. The economic agents in the model are representative farms grouped by farm types maximizing their gross margins (revenues minus variable costs). For each farmer the only publicly available information concerning location is the FADN region in which he/she operates. In order to maximize their profits, farmers in the model allocate their land to different crops while respecting a total area constraint. We use the shadow price (dual value) associated with this constraint to measure the land rent.[3]



Scenario	Agricultural land shadow price (quantiles in k€ per ha) 0%	25%	50%	75%	100%
Present climate (CTL)	0.29	0.42	0.49	0.68	1.03
A2	0.36	0.58	0.79	1.01	1.84
B1	0.36	0.54	0.78	1.16	1.62

Figure 1: Simulated values for the agricultural rent under present climate (CTL) and for climate change scenarios A2 and B1

The AROPAj model is combined with the crop model STICS via dose-response functions representing crop yields as a function of the quantity of nitrogen applied on field (Godard et al., 2008). Thanks to the crop model, AROPAj can also account for variations in crop yields under future climate scenarios (Leclère et al., 2013). Another important advantage of the dose-response functions is that it allows the economic agents of the model to adjust the quantity of nitrogen used in the production depending on the economic conjuncture (input and output prices, policies, etc.). Previous studies allow for a crop switch but consider a constant level of input per crop (De Cara and Jayet, 2000; De Cara et al., 2005). In the present study, we asses the effects of climate change on agriculture and on land use in France for two IPCC scenarios, A2 and B1. The simulated agricultural land shadow prices for the present climate scenario and the two climate change scenarios (A2 and B1) are given in figure 1. Although, land shadow price is increasing under future climate

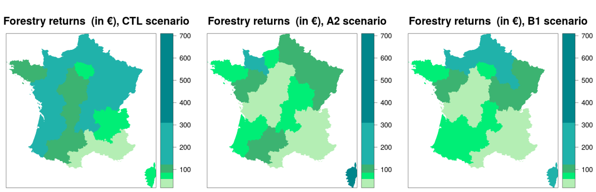
[3]Fallowing the duality theorem, the shadow price provides us with an estimate of the marginal profitability of land or, in other words, its rent (under the economic equilibrium hypothesis).

scenarios, there are some regional disparities visible in the figure.

AROPAj models farmers' choice between land uses in terms of crops and/or pastures. Farmers can also choose between different feeds for their animals[4] which has an impact on their GHG emissions. We simulate GHG tax levels from 0 to 200 €/tCO_2 eq. Such policies reduce the profitability of agriculture (*ceteris paribus*, no price feedback is considered). In this case, the land shadow price estimated by the model decreases as well meaning that agricultural rent is lowered. We use these values in the land use share model. The model captures the heterogeneity among farmers in terms of production and response to the tested mitigation policies. This feature of the model is extremely relevant since agriculture is one of the GHG emitting sectors characterized by important heterogeneity among polluters. We also use the estimated shares of pastures and crops chosen by the economic agents.

Forest sector model The forestry land rents are approximated by the expected returns estimated by the partial-equilibrium model FFSM++ (French Forest Sector Model, Caurla and Delacote, 2012; Caurla et al., 2013; Lobianco et al., 2016). The recursive structure of the model is based on two modules – the first one is dedicated to the wood resource dynamics; and the second one focuses on the sector's market dynamics. The output prices are endogenous for the national market and exogenous when the international market is in consideration. Recent developments of the model include a spatialization of wood resources (Lobianco et al., 2015) and the introduction of forestry management module allowing for the introduction of new tree species depending on expected future profits (Lobianco et al., 2016). The expected returns are calculated for 2006 and 2100 at the scale of the French administrative region (NUTS2) and for coniferous and broadleaved forests. We use an average of these two values. FFSM++ is based on parameters (mortality and growth of trees) derived from statistical data. These parameters are estimated through a generalized additive model (GAM, Wood, 2006) under present climate conditions. The GAM model then allows the simulation of the parameters under climate change. The results of these simulations in terms of expected returns for forestry are summarized in figure 2. As in the case of agriculture, the response of forestry returns to climate change is not uniform through space.

2.2 Land use share model



	Forestry returns (quantiles in € per ha)				
Scenario	0%	25%	50%	75%	100%
Present climate (CTL)	29	91	133	192	308
A2	18	45	74	96	709
B1	19	58	85	121	277

Figure 2: Simulated values for the forestry rent under present climate (CTL) and for climate change scenarios A2 and B1

In line with the literature on LUCs, we estimate 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 in the modeling procedure assumes that the landowner derives the optimal land allocation from his/her profit-maximization problem. In this paper we focus on the landowner's decision to allocate land among four possible uses: agriculture (crops and pastures), forest, urban, and other. As in Plantinga (1996) and Stavins and Jaffe (1990) landowners allocate land to the use providing the greatest net present value of future profits. In the second step, and following the literature, we aggre-

[4]For simplicity, we consider that the number of animals is invariant in our simulations. We have tested different levels of animal variation (±15 and ±30%) and the results are similar especially for GHG taxation between 50 and 100 €/t CO_2 eq.

gate the optimal allocations by individual landowners to derive the observed share of land in the grid cell i in use k, denoted y_{ki}.

In this paper we use grid-level data, where shares are defined as the percentage 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[5] 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 $\beta_k^{'}$ measure the effect of the 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:

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

where u_{ki} is the transformed error term. The model in equation 3 is identified if we constrain $\beta_K = 0$ which is a standard assumption for this type of land use models (Ahn et al., 2000).

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, or a spatial autocorrelation among the error terms. 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 (Anselin, 1988).

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), the dependent and the explanatory variables (spatial Durbin model, SDM), or the error terms (spatial error model, SEM), or any combination of these options, which results in a wide range of spatial models (Elhorst, 2010).

We estimate a modified spatial Durbin error model (SDEM) using the `R` package `spdep` (Bivand et al., 2013; Bivand and Piras, 2015). We use two spatial neighborhood matrices, W_1 and W_2. The former represents grid cell neighbors based on a Queen contiguity rule while the latter is build at the administrative region level. The explanatory variables are lagged with one of these two matrices depending on the variable's geographical scale. We have decided to use this model specification following the results found in **?**.

[5]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.

The SDEM takes account of the interactions between non-observed factors that affect the agricultural land use conversion decision (equation 4).

$$\begin{aligned} \widetilde{y} &= X\beta + W_1 X' \beta' + W_2 X'' \beta'' + \varepsilon \\ \varepsilon &= \lambda W_1 \varepsilon + u \end{aligned} \tag{4}$$

W_1 is an $n \times n$ spatial weight matrix for grid cell neighbors, W_2 is a $m \times m$ spatial weight matrix for regional neighbors, X' are the fine scale explanatory variables, X'' are regional variables, β' and β'' are the associated parameters, and the parameter λ expresses the interaction between residuals and u is an iid[6] error term such that $u \sim iid(0, \sigma^2 I)$.

3 Data presentation

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

3.1 Land use data

Variable	Description	Mean	St. dev.	Min	Max
Land use					
s_{ag}	Share of crops and pastures	0.601	0.289	0	1
s_{fo}	Share of forest	0.264	0.225	0	1
s_{ur}	Share of urban	0.049	0.093	0	1
s_{fo}	Share of forest	0.264	0.225	0	1
s_{ur}	Share of urban	0.049	0.093	0	0.992
s_{ot}	Share of other uses *Source*: CLC 2000 *Scale*: aggregated at 8 km x 8 km	0.086	0.173	0	1
Shadow price	Land shadow price (k€/ha) *Source*: AROPAj v.2 (2002) *Scale*: NUTS 2 and lower	0.554	0.218	0	1.11
For revenue	Forestry revenues (€/ha) *Source*: FFSM++, 2006 *Scale*: NUTS 2 scale	138	67	29	308
Pop revenues	Households' revenues (k€/ year/ household) *Source*: INSEE, 2000 *Scale*: French *commune*	12.31	3.239	0	41.80
Pop density	Households density (households/ ha) *Source*: INSEE, 2000 *Scale*: 200 m x 200 m grid	5.432	2.274	2.75	59
Slope	Slope (%) *Source*: GTOPO 30 *Scale*: 30 arc sec ~ 1 km	4.325	6.155	0	47.72
Texture	Soils' texture classes	*1*	*2*	*3*	*4*
	Number of cells *Source*: JRC, Panagos et al. (2012) *Scale*: 1:1000000	1242	4820	3120	579

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

The land use data are from the CLC database for France at the scale of 100 m x 100 m (1 ha) grids and for the year 2000. The land cover classes are agriculture, forest, urban, and other. Then, we calculate the share of each land use class for each (8 km x 8 km) grid cell; we know that each cell includes a maximum of 6,400 ha. Land use shares are expressed as the sum of the same land use classes in hectares divided by the surface of the grid cell. Although these cells are generated as homogeneous, they are changed by their intersection with French borders. For instance, grid cells on the coast are restricted to their parts on dry land.

3.2 Demography

Approximation of the urban rent is based on population density (in terms of number of households per ha) and household revenues. Both indicators are provided by the French statistical institute (INSEE), revenues are available at the scale of the *commune*, and the number of households is available for a regular 200 m x 200 m grid[7]. We use projections on de-

[6] Independent and identically distributed random variable.

[7] 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`.

mographic evolution from the INSEE (at the *département* level, 2040 horizon) and estimates from Center for International Earth Science Information Network (2002) for the simulation of climate induced land use change (section 4).

3.3 Physical data

We also use data on topography of land:

Soils are represented by the data provided by the Joint Research Centre (JRC, Panagos et al., 2012) at the scale of 1:1,000,000 and further aggregated at grid cell level. The indicator we use for soil quality is soil texture according to four levels. The lowest quality, level 1, is used as the reference. Land quality is an important variable in land use models (Chakir and Le Gallo, 2013; Ahn et al., 2000; Lubowski et al., 2008).

Topography (altitude and slope) is derived from the digital elevation model (DEM) GTOPO, available at the scale of 30 arc seconds (approximately 1 km). In the model only slope is introduced because of the high correlation between slope and altitude. Slope is also leading to better results in terms of fit of the models.

4 Results

	Dependent variable:		
	ln((agr+pst)/oth)	ln(for/oth)	ln(urb/oth)
	(1)	(2)	(3)
Constant	2.827^{***}	3.104^{***}	-6.269^{***}
	(0.577)	(0.559)	(0.515)
Shadow price (spat)	0.757^{**}	-0.457	0.407
	(0.297)	(0.296)	(0.297)
For. revenues	0.003^{***}	0.003^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)
Pop. density	-0.131^{***}	-0.145^{***}	0.168^{***}
	(0.013)	(0.014)	(0.015)
Pop. Revenues	0.047^{***}	0.062^{***}	0.236^{***}
	(0.014)	(0.014)	(0.016)
Slope	-0.155^{***}	0.027^{**}	-0.153^{***}
	(0.012)	(0.013)	(0.014)
Texture (cl.2)	0.669^{***}	0.315^{***}	0.509^{***}
	(0.098)	(0.100)	(0.111)
Texture (cl.3)	1.186^{***}	0.675^{***}	0.898^{***}
	(0.115)	(0.118)	(0.129)
Texture (cl.4)	1.780^{***}	0.982^{***}	0.921^{***}
	(0.159)	(0.163)	(0.180)
Shadow price (W2)	1.531^{**}	-0.594	0.932
	(0.780)	(0.762)	(0.716)
For. revenues (W2)	0.011^{***}	0.008^{***}	0.011^{***}
	(0.002)	(0.002)	(0.002)
Pop. density (W1)	-0.240^{***}	-0.214^{***}	-0.166^{***}
	(0.035)	(0.036)	(0.037)
Pop. Revenues (W1)	-0.011	-0.028	0.096^{***}
	(0.029)	(0.029)	(0.029)
Slope (W1)	-0.140^{***}	-0.118^{***}	-0.099^{***}
	(0.019)	(0.019)	(0.019)
Texture (cl.2, W1)	0.114	0.209^{**}	0.344^{***}
	(0.096)	(0.098)	(0.106)
Texture (cl.3, W1)	0.130	0.248^{***}	0.202^{**}
	(0.094)	(0.095)	(0.103)
Texture (cl.4, W1)	0.244^{**}	0.083	0.193^{*}
	(0.105)	(0.107)	(0.115)
N	9761		
R2	0.634	0.443	0.558
Moran's I	0.438^{***}	0.402^{***}	0.343^{***}
λ	0.759^{***}	0.738^{***}	0.658^{***}
Log Lik.	-22129.8	-22391.02	-23449.93
AIC	44297.6	44820.04	46937.86
(AIC for LM)	48529.63	48486.51	49561.97
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Spatialized dual value, 4 LU

Table 2 represents the estimated coefficients of the land use share models. The estimated Moran's I statistics and the λ parameters are proving the presence of a significant spatial autocorrelation in all three models. The Akaike information criterion (AIC) under the SDEM specification are lower than those for non-spatial models. Land shadow price has a positive and significant effect on agricultural land use. Forestry revenues are influencing positively agriculture, forestry and urban land uses. Urban rent proxies (population density and revenues) influence positively the urban *vs.* other uses. Slope and its lagged value have a negative impact on all alternatives to the other uses (except forestry for the non-lagged slope) while soil's quality has a positive impact. As for the lagged values of land shadow price, neighboring regions' shadow price influences positively agriculture.

The results of the performed simulations can be analyzed in terms of: i) the impact of the GHG taxation; ii) the impact of climate change; and iii) the combined impact on land use. Figure 3 summarizes the results of the simulations.

As expected, taxing GHG emissions from

agriculture is reducing agricultural land use share as a consequence of the lower profitability of the sector. Crops area is much more affected than pastures. The loss in agricultural area is profiting mainly forests. Thus, the tax has an effect on the intensive margin of agriculture (lowering the input use per hectare) but also on the extensive margin by reducing the share of agricultural land use. Furthermore, the increase in forests can lead to further GHG mitigation through carbon stocking.

As figure 3 shows, our land use model predicts an increase in the crops area under the two climate change scenarios comparing to present climate (CTL scenario). The figure also shows that under the B1 scenario, the increase in crops area is more important than the increase under the A2 scenario. This increase is at the expenses of forests and pastures. As for urban, the hypothesis behind the SRES (IPCC Special rapport on emissions scenarios) climate change scenarios posit an increase in French demography for the A2 scenario and a stabilization or even a decrease for the B1 scenario. The reflection of this hypothesis is visible in the results, as urban area is increasing more in the A2 case. We can also see that the greater increase in crops area for B1 is associated with the lower increase in urban and other uses areas for this scenario.

The taxation of GHG emissions is restraining the decrease in forests and pastures under the two climate change scenarios. Since the conversion of pastures and forests into crops is a source of GHG, the emissions associated with this land use change are avoided thanks to the tax. Although total agricultural area (crops and pastures) in the A2 scenario for a tax of 100 €/tCO_2 eq. is lower than in the CTL scenario (table 3), land devoted to crops is increasing.

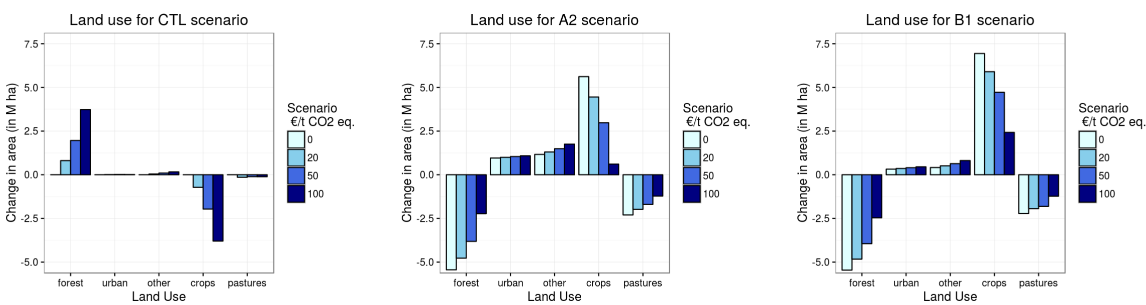


Figure 3: Land use shares evolution depending for the three climate scenarios and four of the GHG pricing levels.

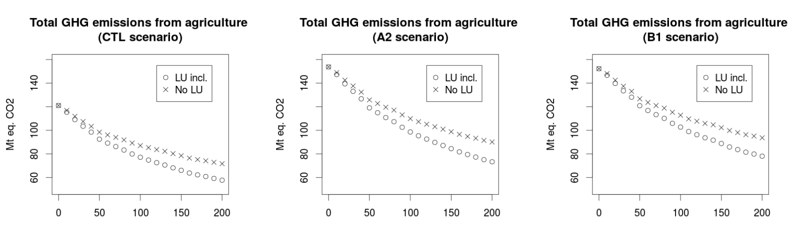


Figure 4: National GHG emissions from agriculture when accounting for LUC.

Figure 4 traces the evolution of the GHG emissions for the three climate change scenarios and the various GHG taxation levels. GHG emissions are would be increasing under both climate change scenarios, meaning that more nitrogen input is to be used by farmers and animals' gazing would be restricted. The figure shows also that when we account for the potential land use change due to GHG taxes, the reduction in GHG can be greater than if we consider the agricultural area constant. These differences are more important for GHG tax levels higher than 50 €/t CO_2 eq. Comparing to the results obtained in De Cara and Jayet (2011) and in Vermont and De Cara (2010), the abatement rates for the same GHG taxes are higher in our study. For instance, for a price of 20 and 50 €/t CO_2 eq. we obtain a reduction in emissions of about 10% and 25% while De Cara and Jayet (2011) report 6% and 16% reductions for France (approximate figures). The abatement rates in our study are higher also when we compare them with the results of the meta-analysis by Vermont and De Cara (2010).

Climate change scenario	GHG taxation (€/tCO_2 eq.)	All GHG evolution (%)	GHG emissions per ha (tCO_2 eq.)	Utilized agricultural area evolution (%)
CTL	0	100.00	3.453	100.00
	20	90.11	3.190	97.54
	50	76.41	2.805	94.08
	100	63.76	2.478	88.85
A2	0	127.04	4.008	109.47
	20	115.18	3.716	107.05
	50	98.36	3.277	103.65
	100	81.49	2.864	98.26
B1	0	125.80	3.829	113.47
	20	115.47	3.583	111.29
	50	99.85	3.184	108.30
	100	84.89	2.835	103.41

*Utilized agricultural area equals the sum of land devoted to crops and to pastures.

Table 3: Emission abatement, change in agricultural area, and abatement costs.

These results are summarized in table 3. This table represents the double effect of GHG taxation on the two dimension mentioned before: the extensive and the intensive margins of agriculture. Results show that even for high levels of GHG tax, there is an increase in agricultural area for the B1 scenario. Tax levels of 50 €/t CO_2 eq. allow a stabilization of GHG emissions to current levels. We should note that these costs are not only associated with a decrease in N_2O and CH_4 emissions, but also with a reduction in nitrate emissions due to the application of mineral fertilizers (Bourgeois et al., 2014). In general, economic theory suggests that each pollutant should be targeted individually depending on its respective environmental impact. Nevertheless, there could be possible synergies between different environmental objectives.

In both present and future climate, the internalization of the negative externalities could potentially lead to an increase in forest area, or curtail its reduction due to climate change. The reforestation or the non-deforestation is associated with new carbon sinks or preserved existing ones. Through this process, the GHG abatement costs should be further reduced. A logical extension of our current work is the integration of the GHG emissions resulting from LUCs. A preliminary assessment of the organic carbon storage variation due to LUCs indicated a relatively small level of CO_2 emissions (about 1% of current levels).

5 Conclusion and perspectives

In the present paper, we explored the potential of a combined use of sector-specific bio-economic models, AROPAj and FFSM++, and an econometric land use shares model for the study of climate change adaptation and mitigation. The effects of climate on agriculture and forestry are captured through a generic crop model and a statistical model of tree growth and mortality. The obtained results are then used in economic models for the two sector-specific models. These two models allow us to evaluate the economic profits for agriculture and forestry. We estimate a spatial econometric land use model where agricultural and forestry rents are approximated by the results from sector-specific models. We studied four LU classes: i) agriculture; ii) forest; iii) urban; and iv) other uses. Our land use shares model is accounting for spatial autocorrelation thanks to the spatial Durbin error model specification. We simulate two climate change scenarios and GHG taxation levels (from 0 to 200 €/tCO_2 eq.) that aim at reducing greenhouse gas emissions from agriculture.

The results of our study show that both climate change scenarios (A2 and B1) lead to an increase in agricultural area at the expense of forests. The progression is lower for the A2 than it is for the B1 climate change scenario. The simulated taxation schemes addressing GHG decrease farmers' profits and thus curtail some agricultural expansion. This process can reduce the abatement costs associated with the public policy. When farmers are subject to GHG taxation, they reduce their input use (intensive margin of agriculture) and convert smaller area of forests and pastures to agriculture. This behavior is compatible with the agroecological measures supposed to cut the sector's GHG emissions. Furthermore, some potentially "win-win" measures (such as the "4 per 1000" program) could increase the abatement rates, soils quality and thus agricultural productivity.

References

Adams, R. M., Fleming, R. a., Chang, C.-C., McCarl, B. a. and Rosenzweig, C. (1995). A reassessment of the economic effects of global climate change on U.S. agriculture. *Climatic Change*, 30(2), 147–167.

Adams, R. M., Rosenzweig, C., Peart, R. M., Ritchie, J. T., McCarl, B. A., Glyer, J. D., Curry, R. B., Jones, J. W., Boote, K. J. and Allen, L. H. (1990). Global climate change and US agriculture. *Nature*, 345(6272), 219–224.

Ahn, S., Plantinga, A. J. and Alig, R. J. (2000). Predicting Future Forestland Area : Comparison of Econometric Approaches. *Forest Science*, 46(2384), 363–376.

Anselin, L. (1988). *Spatial Econometrics : Methods and Models*. Kluwer Academic Publishers, Dordrecht.

Ay, J.-S., Chakir, R., Doyen, L., Jiguet, F. and Leadley, P. (2014). Integrated models, scenarios and dynamics of climate, land use and common birds. *Climatic Change*, 126(1-2), 13–30.

Ay, J.-S., Chakir, R. and Le Gallo, J. (2017). Aggregated Versus Individual Land-Use Models: Modeling Spatial Autocorrelation to Increase Predictive Accuracy. *Environmental Modeling & Assessment*, advance online publication.

Bivand, R., Hauke, J. and Kossowski, T. (2013). Computing the jacobian in gaussian spatial autoregressive models: An illustrated comparison of available methods. *Geographical Analysis*, 45(2), 150–179.

Bivand, R. and Piras, G. (2015). Comparing implementations of estimation methods for spatial econometrics. *Journal of Statistical Software*, 63(18), 1–36.

Bourgeois, C., Fradj, N. B. and Jayet, P.-A. (2014). How Cost-Effective is a Mixed Policy Targeting the Management of Three Agricultural N-pollutants? *Environmental Modeling & Assessment*, 19(5), 389–405.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., Bussière, F., Cabidoche, Y., Cellier, P., Debaeke, P., Gaudillère, J., Hénault, C., Maraux, F., Seguin, B. and Sinoquet, H. (2003). An overview of the crop model STICS. *European Journal of Agronomy*, 18(3-4), 309–332.

Brisson, N., Launay, M., Mary, B. and Beaudoin, N. (2009). *Conceptual Basis, Formalisations and Parameterization of the STICS Crop Model*. QUAE.

Capozza, D. R. and Helsley, R. W. (1990). The stochastic city. *Journal of Urban Economics*, 28(2), 187–203.

Caurla, S. and Delacote, P. (2012). Ffsm : un modèle de la filière forêts-bois française qui prend en compte les enjeux forestiers dans la lutte contre le changement climatique. *INRA Sciences Sociales*, 4.

Caurla, S., Delacote, P., Lecocq, F., Barthès, J. and Barkaoui, A. (2013). Combining an inter-sectoral carbon tax with sectoral mitigation policies: Impacts on the french forest sector. *Journal of Forest Economics*, 19(4), 450–461.

Center for International Earth Science Information Network (2002). Country-level Population and Downscaled Projections based on the A1, B1, A2 and B2 Scenarios, 1990-2100, [digital version]. `http://www.ciesin.columbia.edu/datasets/downscaled`.

Chakir, R. and Le Gallo, J. (2013). Predicting land use allocation in France: A spatial panel data analysis. *Ecological Economics*, 92(0), 114–125.

Chakir, R. and Parent, O. (2009). Determinants of land use changes: A spatial multinomial probit approach. *Papers in Regional Science*, 88(2), 327–344.

De Cara, S., Houzé, M. and Jayet, P.-A. (2005). Methane and nitrous oxide emissions from agriculture in the EU: a spatial assessment of sources and abatement costs. *Environmental and Resource Economics*, 32(4), 551–583.

De Cara, S. and Jayet, P.-A. (2000). Emissions of greenhouse gases from agriculture: the heterogeneity of abatement costs in France. *European Review of Agriculture Economics*, 27(3), 281–303.

De Cara, S. and Jayet, P.-A. (2011). Marginal abatement costs of greenhouse gas emissions from European agriculture, cost effectiveness, and the EU non-ETS burden sharing agreement. *Ecological Economics*, 70(9), 1680–1690.

Easterling, W. E., Crosson, P. R., Rosenberg, N. J., McKenney, M. S., Katz, L. A. and Lemon, K. M. (1993). Paper 2. agricultural impacts of and responses to climate change in the Missouri-Iowa-Nebraska-

Kansas (MINK) region. *Climatic Change*, 24(1-2), 23–61.

Elhorst, J. P. (2010). Applied spatial econometrics: Raising the bar. *Spatial Economic Analysis*, 5(1), 9–28.

Ferdous, N. and Bhat, C. R. (2013). A spatial panel ordered-response model with application to the analysis of urban land-use development intensity patterns. *Journal of Geographical Systems*, 15(1), 1–29.

Godard, C., Roger-Estrade, J., Jayet, P., Brisson, N. and Le Bas, C. (2008). Use of available information at a European level to construct crop nitrogen response curves for the regions of the EU. *Agricultural Systems*, 97(1-2), 68–82.

Grosjean, G., Fuss, S., Koch, N., Bodirsky, B. L., De Cara, S. and Acworth, W. (2016). Options to overcome the barriers to pricing European agricultural emissions. *Climate Policy*, 1–19.

Haim, D., Alig, R. J., Plantinga, A. J. and Sohngen, B. (2011). Climate change and future land use in the united states: an economic approach. *Climate Change Economics*, 02(01), 27–51.

Jayet, P.-A., Petsakos, A., Chakir, R., Lungarska, A., De Cara, S., Petel, E., Humblot, P., Godard, C., Leclère, D., Cantelaube, P., Bourgeois, C., Bamière, L., Ben Fradj, N., Aghajanzadeh-Darzi, P., Dumollard, G., Ancuta, I. and Adrian, J. (2015). *The European agro-economic AROPAj model*. Thiverval-Grignon: INRA, UMR Economie Publique, `https://www6.versailles-grignon.inra.fr/economie_publique_eng/Research-work`.

Leclère, D., Jayet, P.-A. and de Noblet-Ducoudré, N. (2013). Farm-level Autonomous Adaptation of European Agricultural Supply to Climate Change. *Ecological Economics*, 87(0), 1 – 14.

Li, M., Wu, J. and Deng, X. (2013). Identifying drivers of land use change in China: A spatial multinomial logit model analysis. *Land Economics*, 89(4), 632–654.

Lichtenberg, E. (1989). Land quality, irrigation development, and cropping patterns in the northern high plains. *American Journal of Agricultural Economics*, Vol. 71, No. 1, 187–194.

Lobianco, A., Delacote, P., Caurla, S. and Barkaoui, A. (2015). The importance of introducing spatial heterogeneity in bio-economic forest models: Insights gleaned from FFSM++. *Ecological Modelling*, 309-310, 82–92.

Lobianco, A., Delacote, P., Caurla, S. and Barkaoui, A. (2016). Accounting for active management and risk attitude in forest sector models. *Environmental Modeling & Assessment*, 21, 391–405.

Lubowski, R., Plantinga, A. and Stavins, R. (2008). What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions. *Land Econmics*, 84(4), 551–572.

Mendelsohn, R., Nordhaus, W. D. and Shaw, D. (1994). The impact of global warming on agriculture: A Ricardian analysis. *American Economic Review*, 84(4), 753–771.

Miller, D. J. and Plantinga, A. J. (1999). Modeling land use decisions with aggregate data. *American Journal of Agricultural Economics*, 81(1), 180–194.

Ministère de l'écologie, du développement durable et de l'énergie (2015). Stratégie nationale bas-carbone.

Panagos, P., Van Liedekerke, M., Jones, A. and Montanarella, L. (2012). European Soil Data Centre: Response to European policy support and public data requirements. *Land Use Policy*, 29(2), 329–338.

Plantinga, A., Mauldin, T. and Miller, D. (1999). An econometric analysis of the costs of sequestering carbon in forests. *American Journal of Agricultural Economics*, 81, 812–24.

Plantinga, A. J. (1996). The effect of agricultural policies on land use and environmental quality. *American Journal of Agricultural Economics*, 78(4), 1082–1091.

Plantinga, A. J., Lubowski, R. N. and Stavins, R. N. (2002). The effects of potential land development on agricultural land prices. *Journal of Urban Economics*, 52(3), 561–581.

Rosenzweig, C. and Parry, M. L. (1994). Potential impact of climate change on world food supply. *Nature*, 367(6459), 133–138.

Schlenker, W., Hanemann, W. M. and Fisher, A. C. (2005). Will us agriculture really benefit from global warming? accounting for irrigation in the hedonic approach. *American Economic Review*, 395–406.

Sidharthan, R. and Bhat, C. R. (2012). Incorporating spatial dynamics and temporal dependency in land use change models. *Geographical Analysis*, 44(4), 321–349.

Stavins, R. N. and Jaffe, A. B. (1990). Unintended impacts of public investments on private decisions: The depletion of forested wetlands. *American Economic Review*, 80(3), 337–352.

Vermont, B. and De Cara, S. (2010). How costly is mitigation of non-CO2 greenhouse gas emissions from agriculture?: A meta-analysis. *Ecological Economics*, 69(7), 1373–1386.

Wood, S. (2006). *Generalized Additive Models: An Introduction with R*. Chapman & Hall/CRC Texts in Statistical Science, Taylor & Francis.

Wu, J. and Segerson, K. (1995). The Impact of Policies and Land Characteristics on Potential Groundwater Pollution in Wisconsin. *American Journal of Agricultural Economics*, 77(4), 1033–1047.

Zellner, A. and Lee, T. (1965). Joint estimation of relationships involving discrete random variables. *Econometrica*, 33, 382–94.