Price-induced changes in French greenhouse gas emissions from agriculture, forestry, and other land use: A spatial econometric analysis☆

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Abstract

This paper provides a quantitative assessment of the effects of input and output prices on French GHG emissions from Agriculture, Forestry and other Land Use (AFOLU) at the *Departement* level (NUTS2 regions). Four emission categories are considered: (i) N_2O emissions from the use of synthetic fertilizers, (ii) CH_4 emissions from enteric fermentation, (iii) N_2O and CH_4 emissions from manure management and spreading (iv) CO_2 emissions from Land Use, Land Use Changes, and Forestry. To account for both time-invariant unobserved heterogenity across *Departement* and spatial correlation, we estimate a random-effect spatial error model in order to assess the impact of crop, livestock, wood, and land prices on each emission category, as well as on aggregated emissions. Our findings are threefold. First, prices are found to have a significant impact on GHG emissions, although sign and magnitude vary from one emission category to the other. Second, the estimated price effects are clearer when emission categories are analyzed separately rather than aggregated. Third, our results underline the importance of spatial dimension in the study of GHG emissions from AFOLU. Our results suggest that price effects should be taken into account in the design of public policies aimed at reducing emissions or enhancing carbon sinks in these sectors.

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1. Introduction

Sources of greenhouse gases (GHG) emissions are not restricted to fossil fuel combustion for energy use. Agriculture, Forestry and other Land Use (AFOLU) also play a major role in the accumulation of GHG in the atmosphere through emissions of non-CO_2 GHG due to farming activities, release of carbon into the atmosphere due for instance to deforestation, or carbon sequestration in soils and above-ground biomass. In the recent years, these sources/sinks have been under increasing scrutiny because of both their weight in global emissions (about a third according to IPCC, 2007) and the role they could play in a cost-effective mitigation policy (Vermont and De Cara, 2010). In France, agricultural emissions of non-CO_2 GHG account for about a fifth of total French GHG emissions, while land use, land use change and forestry' (LULUCF) activities represent a net sink that offsets 14% of French total emissions (CITEPA, 2010).

AFOLU sources and sinks result from economic decisions in terms of input use (nitrogen fertilizer, feed), output level (wood harvest, milk production), and land use allocation (conversions from/to crop, grass, and forestland). Changes in input and output prices therefore impact the level of net emissions with possibly contrasted effects on the various emission categories. AFOLU emissions have played a major role in the decline of total French GHG emissions from 1990 to 2005, with the decrease of agricultural GHG sources and the strengthening of the LULUCF net sink outpacing the changes in emissions in the rest of the economy (CITEPA, 2010). In the recent period, characterized by higher agricultural prices, the contribution of these sectors to the decrease in total emissions is less clear. Given the large variability in agricultural prices observed in the recent years and the ambitious GHG abatement targets currently contemplated in the EU, the quantitative assessment of these price effects is of great policy importance in determining the mitigation effort that can be expected from AFOLU. The objective of this paper is to shed some quantitative light on this issue.

A first strand of literature focuses on mitigation costs and potential in agriculture and/or LULUCF (McCarl and Schneider, 2001; Pérez Domínguez et al., 2009; De Cara and Jayet, 2011). These papers usually rely on sector economic models of agriculture and/or forestry calibrated for given technological and market conditions. In these papers, the relationship between prices and emissions is implicit and the focus is on how a policy instrument–typically an emission tax–affects revenues, output levels, land use, and net emissions. A second strand of literature uses econometric techniques to estimate the economic determinants of land-use decisions, from which GHG sources and sinks can then be calculated. Examples of this approach can be found in Lubowski et al. (2006) for plot-level data estimations and in Plantinga et al. (1999) for an aggregated land-use share model. The scope is usually restricted to LULUCF emissions. Spatial effects are usually overlooked in these models.[1] Recent developments in spatial econometrics provide methods for accounting for such spatial effects in land-use models, in particular through the use of random effect spatial error models (Chakir and Le Gallo, 2011). See Lee and Yu (2010) for a recent overview on the estimation of spatial panel models.

In this paper, we estimate reduced form models of the four main French GHG sources/sinks from AFOLU at the *Departement*[2] level. An earlier exploratory spatial data analysis (Chakir et al., 2011) shows strong evidence of global and local spatial autocorrelation in French AFOLU sources/sinks. To the best of our knowledge, spatial autocorrelation and unobserved heterogeneity have not been taken into account in the previous literature on GHG emissions. Ignoring spatial correlation and heterogeneity due to the random *Departement* effects may result in inefficient estimates and misleading inference, as shown in Chakir and Le Gallo (2011). This paper is an attempt to fill this gap by using a random effect spatial error model (RE-SEM) that captures both time-invariant heterogeneity across *Departements* and spatial effects that may arise from omitted variables that have a spatial structure.

The remainder of the paper is structured as follows. In section 2, we present the econometric model. The data are presented in section 3. Estimation results, predictions, and simulations are presented and discussed in section 4. Section 5 concludes.

2. Econometric model

The model used in this paper is a reduced-form model of French GHG sources/sinks from AFOLU at the *Departement* level. It allows to control for both individual heterogeneity and spatial correlation across *Departements*. The GHG emissions in category m, *Departement* i, and time t is denoted by y_{mit}. We assume that y_{mit} is generated according to the following model:

$$y_{mit} = x_{mit}\beta_m + u_{mit}, \tag{1}$$

$$u_{mit} = \mu_{mi} + \varepsilon_{mit}, \tag{2}$$

$$\varepsilon_{mit} = \lambda_m \sum_{j=1}^{N} w_{ij}\varepsilon_{mjt} + v_{mit}, \tag{3}$$

where x_{mit} is a $k\times1$ vector of observed individual specific regressors on the ith cross-section unit at time t ($i = 1, ..., N$ and $t = 1, ..., T$), w_{ij} is the generic element of a nonnegative, $N\times N$ spatial-weight matrix W, μ_{mi} is the random *Departement* effect assumed to be $IID(0, \sigma^2_{\mu_m})$, ε_{mit} is the spatially autocorrelated

[1]Lubowski et al. (2006) have used spatial sampling, which is an ad hoc correction of spatial effects.

[2]The *Departement* is an administrative geographic division in France, which is equivalent to the European NUTS2 classification (Nomenclature of Territorial Units for Statistics, 96 *Departements* in mainland France).

error term, λ_m is the spatial autocorrelation coefficient, and v_{mit} is an IID error term with zero mean and variance σ^2.

The random effect specification assumes that $E(\mu_{mi} x_{mit}) = 0$, and $E(\mu_{mi} v_{mit}) = 0$ for all i, t and m. If the hypothesis that the individual-specific component is orthogonal to the explanatory variables does not hold, estimates from the random effects model suffer from possible bias due to the correlation between the error term and the regressors. In the empirical section we will test this hypothesis using Hausman test statistics.

In our model, spatial autocorrelation can arise from two possible sources (see LeSage and Pace, 2009, for further motivation of spatial econometric models). First, it may arise from unobservable latent variables that are spatially correlated. Omitted variables that are spatially correlated can result in an estimation bias as soon as they are also correlated with one or more of the observed spatial variables. In our case, this may be due to underlying pedo-climatic characteristics (e.g. dairy production tends to take place in rainy areas, cereal production is located in plains, etc.) that are correlated over space. Moreover, the geographic distribution of agricultural systems are partly the consequences of historical and institutional determinants (e.g. the location of intensive livestock production is partly linked to infrastructure such as harbor facilities for importing soybeans, the production of vegetables tends to be close to consumption centers, etc.). Second, it may arise because of the measurement error spillovers across neighboring boundaries or because of the scale mismatch and the inherent need to integrate data from different scales. For example, the data about fertilizers delivery at the *Departement* level do not always reflect the location where these fertilizers are used. This is particularly true when deliveries are made to harbors or distribution organizations, which then distribute fertilizers to other *Departements*.

The spatial weight matrix used in this paper is the Gabriel Neighbors matrix (Matula and Sokal, 1980). Any two points are considered to be Gabriel neighbors if the enclosing circle formed with the distance between these two points as diameter contains no other point.[3] The matrix W is constant over time.

Two main approaches have been developed in the literature to estimate panel data models that include spatially correlated error terms: one based on maximum likelihood (Anselin, 1988; Baltagi et al., 2003; Elhorst, 2003), and another relying on method of moments techniques (Kapoor et al., 2007). In the present paper, the maximum likelihood approach is used.

[3] An alternative (Delauney) weight matrix has also been tested. The estimation results were found to be robust to the choice of the weight matrix.

Consider equation (4) in matrix form (index m is omitted):

$$y = X\beta + u \tag{4}$$

y and u are of dimension $NT \times 1$, X is $NT \times K$, β is $K \times 1$. The observations are sorted first by time t and then by spatial units i, i.e., $y' = (y_{11}, ..., y_{1N}, ..., y_{T1}, ...y_{TN})$

Equation (2) can be rewritten in vector form as:

$$u = (i_T \otimes I_N) + [I_T \otimes B^{-1}]v \tag{5}$$

with $B = I_N - \lambda W$, i_T is a vector of ones of dimension T, I_T is an identity matrix of dimension T and $\otimes$ denotes the Kronecker product. Using results in Anselin (1988), the log-likelihood function of the spatial random effects model is

$$L = -\frac{NT}{2} ln 2\pi\sigma_v^2 - \frac{1}{2} ln[|T\phi I_N + (B'B)^{-1}|] + \frac{T-1}{2} ln|B'B| - \frac{1}{2\sigma_v^2} e'\Sigma_u^{-1} u \tag{6}$$

with $u = y - X\beta$, $\phi = \frac{\sigma_\mu^2}{\sigma_v^2}$ and

$$\Sigma_u^{-1} = \overline{J}_T \otimes \left(T\phi I_N + (B'B)^{-1}\right)^{-1} + E_T \otimes (B'B) \tag{7}$$

with $\overline{J}_T = J_T/T$, $E_T = I_T - \overline{J}_T$, J_T is a matrix of ones of dimension T.

Following Elhorst (2003), the parameters β and σ_v^2 can be computed from their first-order maximizing conditions. The parameters ϕ and λ given β and σ_v^2 are obtained by numerical methods as the equations cannot be solved analytically. Elhorst (2003) proposes a two-stage iterative procedure whereby $\widehat{\beta}$ and $\widehat{\sigma_v^2}$ are computed by setting initial values for ϕ and λ in a first stage. In the second stage, ϕ and λ are estimated by maximizing the concentrated log-likelihood.

3. Data

3.1. GHG Emissions from AFOLU

3.1.1. Agricultural emissions

Three agricultural emission categories are distinguished: *(i)* N_2O emissions from the use of synthetic fertilizers (EMNITR), *(i)* CH_4 emissions from enteric fermentation (EMFERM), (iii) N_2O and CH_4 emissions from manure management and spreading (EMMANU)[4].

[4] CH_4 emissions from rice are neglected as they are very small in France.

Note that this classification slightly differs from that prescribed by the IPCC for establishing emission inventories in which the category 4D (emissions from agricultural soils) pools together emissions resulting from both synthetic and organic nitrogen applications. Our classification explicitly distinguishes these two nitrogen sources. Emissions from the use of synthetic fertilizers are thus unambiguously related to crop production, whereas emissions from manure management and spreading are related to both livestock and crop production. Emissions from enteric fermentation are directly linked to livestock production. Otherwise, the computation of emissions follows closely the methodology used by the CITEPA (2010) to establish the French GHG inventories at the national scale. Emissions are calculated by multiplying activity variables (nitrogen applied, animal numbers, etc.) by emission factors specific to each emission category. Emissions are calculated at the *Departement* level[5], which is the finest resolution available.

Despite the complexity of the biological processes involved in emissions from the use of synthetic fertilizers (EMNITR), the methodology used by the IPCC remains relatively simple. Nitrogen quantities at the *Departement* level (1990-2007) are taken from UNIFA (2009) and multiplied by the emission factors used in CITEPA (2010). These factors account for the shares of applied nitrogen that are leached and volatilised. Emissions factors are constant over time and space.

CH_4 emissions from enteric fermentation (EMFERM) are calculated by using animal numbers (taken from AGRESTE, 2011b) and animal-specific emission factors (for dairy cattle, non-dairy cattle, sheep, goats, horses and swines). The emission factor associated to dairy cattle depends on milk yield (each additional liter of milk yield leads to 0.01 $kgCH_4.hd^{-1}.yr^{-1}$ with a minimum of 55.7 $kgCH_4.hd^{-1}.yr^{-1}$). This emission factor thus varies over time and space according to the average milk yield at the *Departement* level (taken from AGRESTE, 2011b). The emission factor associated to non-dairy cattle varies according to the herd composition at the *Departement* level. The emission factors associated to the remaining animal categories are constant over time and space.

Emissions from manure (EMMANU) include emissions occurring during manure storage (N_2O and CH_4) and N_2O (direct and indirect) emissions due to manure spreading on agricultural soils. N_2O emissions related to manure storage and management depends on the amount of nitrogen produced by animals and the manure management system (solid or liquid). Nitrogen quantities produced are calculated by multiplying livestock numbers and per-head nitrogen quantity produced by each animal category (CITEPA, 2010). The share of nitrogen managed under each management system is based on the average national distribution of solid and liquid management systems as no information was

[5]Departement 2A and 2B are aggregated into one, six *Departements* (78, 91, 95, 92, 93, 94) are aggregated into one single region.

available at a finer resolution level. Nitrogen quantities managed under each management system are then multiplied by the respective emission factors from CITEPA. The emission factors related to CH_4 emissions from manure management and storage is specific to each animal category (emission factors in kgCH_4.head^{-1}). N_2O emissions (direct and indirect) that result from the nitrogen directly excreted by animals on pastures or spread on agricultural soils after storage, are calculated using the same methodology as N_2O emissions from the use of synthetic fertilizers. Total agricultural emissions (EMAGRI) are computed as the sum of the three agricultural emission sources (EMNITR, EMMANU, EMFERM).

Emissions are converted into tCO_2eq using Global Warming Potential (GWP, Solomon et al., 2007). Each ton of CH_4 corresponds to 25 tCO_2eq, each ton of N_2O to 298 tCO_2eq. Emissions are normalized by the total area of the respective *Departement*.

Over the 1990-2007 period, emissions from manure management and spreading represent 42% of total agricultural emissions, emissions from enteric fermentation about one third, emissions from the use of synthetic fertilizers around 23%. Over the eighteen-year period, the cumulative emissions from these three sources amount to 1.8 GtCO_2eq. Figure 2 (in Appendix) shows the evolution of the three agricultural emission categories over the period Between 1990 and 2007, emissions from enteric fermentation and manure management and spreading have decreased by 9.8% and 11.8%, respectively. Emissions from the use of synthetic fertilizers show a greater variability over the period. Figure 3 (in Appendix) shows the spatial distribution of 1990-2007 cumulative emissions by category. The distribution of each emission category shows a clear polarization between high- (north-west and center for EMMANU and EMFERM, north and west for EMNITR) and low-emission regions.

3.1.2. LULUCF sources and sinks

Similarly to what is done for agricultural emissions, net emissions from LULUCF (EMLUCF) are calculated by multiplying activity variables by emission factors. In this case, activity variables correspond to areas changing from one land use to another between year $t-1$ and t. Each pair of land uses (i, k) is associated with a region-specific emission factor (in tCO_2eq.ha^{-1}.an^{-1}) that corresponds either to the source (+) or sink (-) of CO_2 due to the conversion of one hectare from i in year $t-1$ to k in year t.

Land-use data are taken from TERUTI (AGRESTE, 2004), in which 550,903 points throughout mainland France are surveyed on a yearly basis (in June). Each point is associated to one land-use category (among 81 categories). These data were used to calculate yearly land use changes for each observed point and each pair (i, k) among the nine following categories: coniferous forest, decidious forest, poplar, mixed forest, cropland, pastures, urban, wetlands, other uses. These categories are derived from physical and functional criteria used in the TERUTI land use classification. Land-use change for each pair (i, k) was then aggregated at the *Departement* level. Region-specific emission factors have been obtained from CITEPA. These factors take into account carbon stock changes both in biomass and soils and vary both over time and space.

Total net emissions from land-use change and forestry at the *Departement* level are calculated over the 1993-2003 period[6] and normalized by the total area of the respective *Departement*. EMNET denotes the total net emissions from all AFOLU emission categories (EMAGRI+EMLUCF).

Figure 2 shows the evolution of the average per-ha sequestration rate (the opposite of EMLUCF, in $tCO_2eq.ha^{-1}.yr^{-1}$). Over this period, emissions from LULUCF show a greater variability than the three agricultural emission categories. The steady increase of the sequestration rate is mainly due to the biomass growth in existing forests and, more marginally, to the increase of forest areas over the period. The peak for the year 2000 corresponds to Lothar and Martin storms (December 1999), which resulted in the destruction of large forest areas in France. Again, Figure 3 (appendix) shows a net polarization between high- (in the east and the south-east) and low-sequestration regions.

3.2. Explanatory variables

3.2.1. Commodities and input prices

Crop, livestock, wood and grassland prices were gathered from three main sources (cf table 1). Crop, cattle, milk, hog and fertilizer prices at the country level over the 1990-2007 period are taken from Eurostat (2011). Wood prices were obtained from the *Laboratoire d'Economie Forestière (LEF)*. Grassland prices were taken from AGRESTE (2011a). All prices are deflated using a Harmonized Index of Consumer Prices from OECD (2011) when needed.

In order to limit multicollinearity issues among crop price variables, the prices of five crops (wheat, barley, rapeseed, maize, sunflower) were grouped into one price index using agricultural areas at the *Departement* level from AGRESTE (2011b) as weights. The crop price index variable $pcrop_{it}$ for *Departement* i at year t is :

$$pcrop_{it} = \frac{\sum_{c=1}^{5} p_{ct} S_{cit}}{\sum_{c=1}^{5} S_{cit}} \tag{8}$$

where c is the index for crop, p_{ct} is the price of crop c in year t and S_{cit} is the area of crop c in *Departement* i in year t. A similar approach was used to compute the cattle price index ($pcatt_{it}$) from cattle and milk prices using dairy and non-dairy animal numbers as weights :

[6]TERUTI data are not available to us before 1993 and for the years between 2004 and 2006. Despite the availability of data for the 2007-2009 period, we chose not to include them in our sample because of consistency issues between the two sets of data.

$$pcatt_{it} = \frac{p_t^{non-dairy} N_{it}^{non-dairy} + p_t^{milk} N_{it}^{dairy}}{N_{it}^{non-dairy} + N_{it}^{dairy}} \tag{9}$$

where $N_{it}^{non-dairy}$ and N_{it}^{dairy} are non-dairy and dairy cattle numbers, in *Departement* i in year t. $p^{non-dairy}$ and p^{milk} are non-dairy cattle and milk price in year t, respectively. As a consequence, $pcrop_{it}$ and $pcatt_{it}$ vary over both space and time. All prices are converted into indexes (year 2000 = 100). Summary statistics on prices variables are reported in table 1.

Table 1: Explanatory variables sources and description

	variable	Source	Mean	Std.dev.	Spatial resolution
crop prices	p_{ct}	Eurostat			country
crop areas	S_{cit}	Agreste			Departement
crop price index	$pcrop_{it}$	(1)	116.23	24.20	Departement
cattle prices	$p_t^{non-dairy}$	Eurostat	109.46	21.90	country
milk prices	p_t^{milk}	Eurostat	98.01	7.95	country
dairy cattle numbers	N_{it}^{dairy}	Agreste	48.97	56.48	Departement
non-dairy cattle numbers	$N_{it}^{non-dairy}$	Agreste	178.07	153.01	Departement
cattle price index	$pcatt_{it}$	(1)	106.86	18.05	Departement
hogs prices	$phogs_t$	Eurostat	102.63	17.77	country
wood prices	$pwood_{it}$	LEF	101.85	19.24	Departement
N fertilizer prices	$pfert_t$	Eurostat	104.54	11.11	country
grassland prices	$pgras_{it}$	Agreste	103.29	25.15	Departement
Spatial clusters			no/HH/HL/LH/LL (2)		
EMNITR	cl_{1i}	(1)	900/252/18/36/396		Departement
EMMANU	cl_{2i}	(1)	1170/162/0/0/270		Departement
EMFERM	cl_{3i}	(1)	1134/198/0/0/270		Departement
EMUTCF	cl_{4i}	(1)	954/324/0/18/306		Departement
EMAGRI	cl_{5i}	(1)	1170/180/0/0/252		Departement
ENET	cl_{6i}	(1)	1062/252/0/0/288		Departement

(1): own calculations (See text).
(2): numbers of observations for each modality of the spatial clusters.

Price changes may not affect in the same way the various activity variables and the corresponding emission categories. Estimating one model for each emission category allows us to separate the effects of price changes on each emission category. We also estimate models for total agricultural emissions (EMAGRI) and total net emissions (EMNET) in order to compare the combined effects of price changes on aggregated emissions to the case where each source is isolated.

3.2.2. Spatial clusters

The exploratory spatial data analysis of French GHG sources and sinks from AFOLU conducted in a previous study Chakir et al. (2011) showed strong evidence of global and local spatial autocorrelation for each emission category and for total net emissions throughout the period. Results from this study are used to capture information about local spatial autocorrelation among *Departements*. For each emission category m, spatial clusters of *Departements* cl_{mi} are constructed:

- $cl_{mi} = HH$ if emissions m in i are high and i is surrounded by high-emission *Departements*;
- $cl_{mi} = LL$ if emissions m in i are low and i is surrounded by low-emission *Departements*;
- $cl_{mi} = LH$ if emissions m in i are low and i is surrounded by high-emission *Departements*;
- $cl_{mi} = HL$ if emissions m in i are high and i is surrounded by low-emission *Departements*;
- $cl_{mi} = no$ if there is no significant spatial autocorrelation.

These clusters were computed using the cumulative emissions over the period. They are therefore constant over time. Table 1 reports, for each emission category, the number of observations for each modality of the spatial cluster variable.

4. Results

In order to compare the estimations and to evaluate the gains associated to allowing for spatial correlation and individual heterogeneity, four estimators are considered for each equation y_{mit}:

1. The pooled OLS which ignores individual heterogeneity and spatial correlation.
2. The RE (Random effect) estimator which takes into account random individual heterogeneity but ignores spatial correlation.
3. The SEM (Spatial Error Model) estimator which takes into account the autoregressive spatial error autocorrelation but ignores individual heterogeneity.
4. The RE-SEM estimator which takes into account spatial error autocorrelation as well as random individual heterogeneity.

Equations for emissions EMNITR, EMMANU, EMFERM, EMAGRI are estimated over the 1990-2007 period using a logarithm transformation of the dependent variables and of the price variables. The coefficients associated to each price variable have thus a straightforward interpretation as the price elasticity of the corresponding emission category. Given the unavailability of data for EMLUCF and EMNET after 2003, equations for these two emissions are estimated over the 1993-2003 period. In addition, as these two emission categories have both positive and negative values, they were estimated without any log transformation of the variables.

4.1. *Tests of specification*

Hausman (1978) test statistic based on the difference between the fixed effects and the random effects estimators is used to analyze the consistency of the RE estimator. We use in this paper the joint and the conditional LM tests developed by Baltagi et al. (2003) for error correlation as well as random individual effects. The test hypotheses and results are reported in table 2.

The χ^2_k statistics (k is the number of regressors that are not constant over time) for the Hausman test are not statistically significant at 1% for each emission category. The null hypothesis is not rejected which confirms that the RE estimator is consistent for each emission category. The joint test for spatial error correlation and random effects (T1) as well as the conditional tests for spatial error correlation (T2) and random individual effects (T3) are significant at 1% for each emission category (except (T3) for EMLUCF). This justifies the choice of a model taking into account both spatial error autocorrelation and random individual heterogeneity (RE-SEM).

Table 2: Specification tests

Tests	Hypothesis	EMNITR	EMMANU	EMFERM	EMAGRI	EMLUCF	EMNET
HT	H_0: RE is more efficient	$\chi^2_4 = 0.50$	$\chi^2_3 = 0.02$	$\chi^2_3 = 0.00$	$\chi^2_4 = 0.00$	$\chi^2_5 = 0.22$	$\chi^2_7 = 0.57$
	H_1: RE is inconsistent	(0.97)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
T1	H_0: $\sigma^2_\mu = \lambda = 0$	11551.83	13414.47	13475.52	13135.13	2974.10	3943.52
	H_1: $\sigma^2_\mu \neq 0$ or $\lambda \neq 0$	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
T2	H_0: $\lambda = 0$ (ass $\sigma^2_\mu \geq 0$)	15.64	16.62	16.02	15.37	2.15	7.23
	H_1: $\lambda \neq 0$ (ass $\sigma^2_\mu \geq 0$)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
T3	H_0: $\sigma^2_\mu = 0$ (allowing $\lambda \neq 0$)	4.81	2.70	4.67	4.11	0.82	4.94
	H_1: $\sigma^2_\mu > 0$ (allowing $\lambda \neq 0$)	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)	(0.00)

For tests T1 to T3, the values reported are the lagrange multiplier statistics of the tests, p-values are between brackets.

4.2. *Estimations results*

Estimation results are reported in tables 3 to 5. For all emission category, results from both the RE and the RE-SEM models confirm the existence of random individual heterogeneity as the parameter $\phi = \frac{\sigma^2_\mu}{\sigma^2_v}$ is significant at the 1% level. Moreover, the spatial autocorrelation parameter λ is also significant (at the 1% level) for both the SEM and the RE-SEM models. This confirms the results of the specifications tests and suggests that the RE-SEM[7] estimator suits the best our data.

We now turn to the economic interpretation of the results based on the RE-SEM estimator. For each individual emission category, crop prices have a positive and significant effect on the corresponding emissions (significance level of at least 5%). Higher crop prices tend to increase the per-hectare

[7]To measure the goodness-of-fit of the RE-SEM model, we calculate the counterpart of the R^2 of an OLS regression model to the spatial panel model (Elhorst, 2009). We have also calculated an alternative goodness-of-fit measure to the R^2 which is the squared correlation coefficient between actual and fitted values.

Table 3: Estimations results for emissions from enteric fermention (EMFERM) and manure management and spreading (EMAMNU).

	Dependant variable: ln($EMFERM$) (N = 89, T = 18)				Dependant variable: ln($EMMANU$) (N = 89, T = 18)			
	OLS	RE	SEM	RE-SEM	OLS	RE	SEM	RE-SEM
Intercept	-1.36**	-1.32***	-1.49	-1.25***	-1.74***	-1.51***	-1.80***	-1.5***
	(0.565)	(0.095)	(1.080)	(0.097)	(0.533)	(0.092)	(0.445)	(0.099)
ln($pcrop_{i,t-1}$)	0.037	0.069***	-0.015	0.068***	-0.068	0.064***	-0.098	0.047**
	(0.223)	(0.016)	(0.269)	(0.024)	(0.210)	(0.018)	(0.220)	(0.023)
ln($pcatt_{i,t-1}$)	0.047	0.024*	0.094	0.003	0.185	0.059***	0.216	0.061***
	(0.188)	(0.014)	(0.231)	(0.020)	(0.178)	(0.015)	(0.193)	(0.019)
ln($phogs_{i,t-1}$)	0.050	0.032**	0.072	0.039*	0.129	0.073***	0.140	0.086***
	(0.183)	(0.013)	(0.239)	(0.020)	(0.173)	(0.015)	(0.185)	(0.019)
$cl_{mi} = LL$	-1.60***	-1.60***	-1.27***	-1.60***	-1.42***	-1.42***	-1.31***	-1.42***
	(0.047)	(0.196)	(0.059)	(0.165)	(0.044)	(0.185)	(0.041)	(0.185)
$cl_{mi} = HH$	1.12***	1.12***	1.15***	1.12***	1.37***	1.37***	1.33***	1.37***
	(0.053)	(0.223)	(0.062)	(0.188)	(0.054)	(0.229)	(0.059)	(0.229)
λ			0.226***	0.438***			0.113***	0.272***
			(0.021)	(0.028)			(0.018)	(0.031)
ϕ		191***		160***		139***		149***
		(29.4)		(18.3)		(21.5)		(23)
R^2	0.55	0.22	0.58	0.55	0.56	0.31	0.56	0.56
$corr^2$				0.55				0.56
$logLik$			-1070.10	2287.79			-1011.50	2072.42

Significance levels: ***: 0.01, **: 0.01, *: 0.1. Standard deviations in parentheses.

Table 4: Estimations results for emissions from synthetic fertilizer use (EMNITR) and aggregated agricultural emissions (EMAGRI).

	Dependant variable: ln($EMNITR$) (N = 89, T = 18)				Dependant variable: ln($EMAGRI$) (N = 89, T = 18)			
	OLS	RE	SEM	RE-SEM	OLS	RE	SEM	RE-SEM
Intercept	-3.68**	-1.56***	-4.07***	-1.63***	-0.24	-0.14	-0.34	-0.12
	(1.430)	(0.407)	(0.84)	(0.565)	(0.922)	(0.143)	(1.130)	(0.173)
ln($pcrop_{i,t-1}$)	0.760***	0.437***	0.942***	0.532***	0.162	0.148***	0.169**	0.151***
	(0.198)	(0.053)	(0.229)	(0.075)	(0.127)	(0.017)	(0.083)	(0.022)
ln($pfert_{i,t}$)	-0.277	-0.180***	-0.226	-0.160*	-0.090	-0.083***	-0.065	-0.081***
	(0.234)	(0.063)	(0.144)	(0.091)	(0.151)	(0.020)	(0.185)	(0.026)
ln($pcatt_{i,t-1}$)	-0.516**	-0.146**	-0.671***	-0.224**	-0.039	-0.019	-0.020	-0.027
	(0.233)	(0.063)	(0.254)	(0.089)	(0.150)	(0.020)	(0.114)	(0.026)
ln($pgras_{i,t}$)	0.577***	-0.021	0.571***	-0.044	0.095	0.062***	0.055	0.058***
	(0.198)	(0.058)	(0.199)	(0.059)	(0.127)	(0.019)	(0.126)	(0.019)
$cl_{mi} = LL$	-1.48***	-1.48***	-1.25***	-1.48***	-1.20***	-1.20***	-0.88***	-1.20***
	(0.054)	(0.221)	(0.063)	(0.221)	(0.040)	(0.168)	(0.031)	(0.168)
$cl_{mi} = HH$	0.71***	0.71***	0.61***	0.71***	1.09***	1.09***	1.06***	1.09***
	(0.064)	(0.261)	(0.069)	(0.262)	(0.046)	(0.193)	(0.054)	(0.193)
$cl_{mi} = LH$	-0.02	-0.03	-0.10	-0.03				
	(0.152)	(0.624)	(0.148)	(0.623)				
$cl_{mi} = HL$	0.22	0.20	0.41**	0.20				
	(0.213)	(0.873)	(0.207)	(0.873)				
λ			0.19***	0.361***			0.236***	0.256***
			(0.0145)	(0.0311)			(0.0192)	(0.0319)
ϕ		13***		14.6***		55***		58.2***
		(2.02)		(2.26)		(8.5)		(8.99)
R^2	0.42	0.14	0.45	0.42	0.52	0.2	0.56	0.52
$corr^2$				0.42				0.52
$logLik$			-1506.75	-162.09			-774.03	1563.59

Significance levels: ***: 0.01, **: 0.01, *: 0.1. Standard deviations in parentheses.

Table 5: Estimations results for net emissions from land use, land use change and forestry (EMLUCF) and aggregated net AFOLU emissions (EMNET).

	Dependant variable: $EMLUCF$ ($N = 89$, $T = 11$)				Dependant variable: $EMNET$ ($N = 89$, $T = 11$)			
	OLS	RE	SEM	RE-SEM	OLS	RE	SEM	RE-SEM
Intercept	-2.6***	-2.69***	-2.3***	-2.29***	-1.51*	-1.79***	-0.965	-1.46***
	(0.264)	(0.172)	(0.322)	(0.24)	(0.774)	(0.296)	(0.944)	(0.555)
$pwood_t$	5.69e-05	0.00243*	0.00027	0.00126	-0.0046	0.0022	-0.00248	0.000743
	(0.00177)	(0.00131)	(0.00181)	(0.00109)	(0.00282)	(0.00139)	(0.00281)	(0.00112)
$pcrop_{i,t-1}$	0.00763***	0.00673***	0.00475*	0.00345*	0.0162***	0.00934***	0.0165***	0.00356
	(0.00246)	(0.00117)	(0.00286)	(0.00191)	(0.00536)	(0.00169)	(0.00632)	(0.00231)
$pfert_{i,t}$					0.00508	0.00477***	0.00605	0.00411
					(0.00529)	(0.00164)	(0.00658)	(0.00386)
$pcatt_{i,t-1}$	0.00363*	0.0033***	0.00411*	0.00439**	0.000645	0.00311**	-0.00166	0.00534**
	(0.00209)	(0.000983)	(0.00243)	(0.00187)	(0.00396)	(0.00124)	(0.00475)	(0.00211)
$phogs_{i,t-1}$					-0.00304	-0.000106	-0.00793	0.00307
					(0.00426)	(0.00133)	(0.00484)	(0.00261)
$pgras_{i,t}$	0.000264	0.00018	0.000204	4.61e-06	0.00196	0.000305	0.00176	-1.15e-05
	(0.000837)	(0.000413)	(0.000822)	(0.000298)	(0.00132)	(0.000432)	(0.00127)	(0.000305)
$yr2000$	0.275***	0.265***	-0.114	0.225**	0.314**	0.315***	-0.249	0.317***
	(0.0917)	(0.0428)	(0.115)	(0.0971)	(0.157)	(0.0486)	(0.193)	(0.115)
$cl_{mi} = LL$	-1.14***	-1.16***	-1.04***	-1.14***	-1.94***	-2.01***	-1.85***	-1.98***
	(0.0678)	(0.195)	(0.0743)	(0.199)	(0.109)	(0.332)	(0.125)	(0.336)
$cl_{mi} = HH$	1.57***	1.57***	1.46***	1.56***	3.87***	3.89***	3.47***	3.88***
	(0.0646)	(0.19)	(0.0728)	(0.195)	(0.111)	(0.35)	(0.135)	(0.354)
$cl_{mi} = LH$	-0.297	-0.319	-0.411*	-0.324				
	(0.239)	(0.705)	(0.235)	(0.704)				
λ			0.171***	0.666***			0.22***	0.681***
			(0.0168)	(0.0285)			(0.0189)	(0.0276)
ϕ		3.56***		5.97***		9.46***		16.3***
		(0.575)		(0.965)		(1.5)		(2.61)
R^2	0.56	0.24	0.57	0.56	0.67	0.3	0.69	0.67
$corr^2$				0.56				0.67
$logLik$			-798.86	-397.77			-1231.57	-469.43

Significance levels: ***: 0.01, **: 0.01, *: 0.1. Standard deviations in parentheses.

emission rate for each category. Among agricultural emission sources, crop prices have the greatest impact on emissions from the use of synthetic fertilizer EMNITR with a price elasticity of emission of 0.53. Estimated elasticities for EMMANU and EMFERM are around ten times lower. The positive effect of crop prices on EMNITR may be explained by the fact that *(i)* higher crop prices may increase the profitability of crop production inducing a substitution from other activities to crop production and thus a higher N-fertilizer use and *(ii)* higher crop prices may encourage farmers to increase N applications on existing crops. The former effect may also explain the positive effect of crop prices on emissions from land use change, as an increase in the relative profitability of crops may induce land conversion into cropland (in particular, from grassland to cropland). The resulting effect of crop prices on EMAGRI and EMNET is as expected positive but not significant for EMNET.

Fertilizer prices have a negative and significant effect on EMNITR and EMAGRI. The elasticity of fertilizer prices on EMNITR is however more than three times lower than that of crop prices on the same emission category.

Contrary to crop prices, the sign of the coefficients associated to cattle prices differ between emission categories. As expected, higher cattle prices tend to increase emissions from manure and enteric fermentation. The effect of cattle prices on EMFERM is however not significant for the RE-SEM model. On the contrary, higher cattle prices tend to lower emissions from the use of synthetic fertilizers. This positive effect may result from (i) the conversion of croplands into pastures (increasing need for pastures as the profitability of animal production increases) and (ii) the substitution of synthetic fertilizers to organic fertilizers. The results suggest that the latter effect dominates. Lastly, the positive effect of cattle prices on total net emissions suggest that the combined effects cattle prices on each individual emission source is positive. Hogs prices have a positive and significant effect on both emission sources related to animal production (EMMANU and EMFERM).

The dummy for the year 2000 has a significant and positive effect on emissions from land use change (at 5%) and consequently on total net emissions (at 1%). This result is not surprising as the 1999 storms resulted in a large amount of carbon released in the atmosphere.

Wood prices seem to have no significant impact on land use and land use change decisions. Grassland prices have no significant effect on individual categories and on total net emissions.

For each emission category, the HH and LL modalities of the cluster variables have a significant effect on emissions. As expected, *Departement* for which $cl_{mi} = HH$ ($cl_{mi} = LL$) tend to have significantly (at 1%) higher (lower) values of emissions than the others.

4.3. Predictions

Following Baltagi and Li (1999) who derived the best linear unbiased predictor (BLUP) correction term when both error components and spatial autocorrelation are present, the prediction from our model reduces to

$$\widehat{y}_{iT+S}^{RE-SEM} = x_{iT+S}\widehat{\beta}^{RE-SEM} + T\phi \sum_{j=1}^{N} \delta_j \overline{u}_{j.}, \tag{10}$$

where $\phi = \frac{\sigma_\mu^2}{\sigma_\nu^2}$, δ_j is the jth element of the ith row of V^{-1} with $V = T\phi I_N + (B'B)^{-1}$ and $\overline{u}_{j.} = \sum_{t=1}^{T} \widehat{u}_{jt}/T$, with $\widehat{u}_{it} = y_{it} - x_{it}\widehat{\beta}$.

For the RE model[8], the spatial autocorrelation correction is null and the BLUP reduces to:

$$\widehat{y}_{iT+S}^{RE} = x_{iT+S}\widehat{\beta}^{RE} + \frac{T\sigma_\mu^2}{T\sigma_\mu^2 + \sigma_\nu^2}\overline{u}_{j.} \tag{11}$$

For the OLS and the SEM estimators the BLUP correction term is null so that the BLUP equals to a simple pooled OLS predictor computed as

$$\widehat{y}_{iT+S}^{OLS} = x_{iT+S}\widehat{\beta}^{OLS}, \tag{12}$$

and for the SEM model the BLUP reduces to:

$$\widehat{y}_{iT+S}^{SEM} = x_{iT+S}\widehat{\beta}^{SEM}. \tag{13}$$

The BLUP associated to each estimator using the same sample periods as the ones used in the estimations. Predictions are then compared with observed data available for 2008 for agricultural emission sources and 2007 for EMLUCF and EMNET. The Root Mean Square of Error (RMSE) are reported in table 6. For each emission category, the RMSE is of the same magnitude for the first three estimators (OLS, RE, SEM) but it markedly drops for the BLUP related to the RE-SEM estimator. This suggests that the RE-SEM estimator provides more accurate predictions. The performance of the RE-SEM predictor is however much greater for agricultural emission sources (RMSE between 0.03 and 0.13) than for emissions from LUCF and total net emissions (RMSE of 0.52 and 0.63).

The RE-SEM BLUP is then used to predict the effects on each emission category of a doubling of crop prices. All explanatory variables, excluding crop prices, are taken at their observed values for the last sample year, i.e 2007 for EMNITR, EMMANU, EMFERM and EMAGRI and 2003 for EMLUCF and EMNET. The predicted values of the changes in emissions are reported on Figure 1.

[8]See Baltagi and Li (2006) for more details.

Table 6: Root Mean Square Error for the four predictors

	OLS	SEM	RE	RE-SEM
EMNITR	0.23	0.23	0.23	0.10
EMMANU	0.29	0.29	0.28	0.04
EMFERM	0.24	0.25	0.24	0.03
EMAGRI	0.58	0.59	0.58	0.13
EMUTCF	0.74	0.75	0.74	0.52
EMNET	1.10	1.15	1.11	0.63

Figure 1 shows that a 100% increase of crop prices (holding all other variables constant) leads to an increase of about 33% of EMNITR and 7% of EMMANU and EMFERM at the national level. This illustrates the higher price-responsiveness of emissions from the use of synthetic fertilizer relative to animal-related emissions. Changes in emissions are not equally spatially distributed. The effects of a crop price increase seems to be higher in *Departements* for which observed 2007 emissions were higher. The total agricultural emissions increase is of about 11.4 $MtCO_2eq$ which corresponds to a 12% increase compared to 2007 emissions. Using the reduced form of the abatement supply curve found in (De Cara and Jayet, 2011, table 2), compensating this increase in emissions would require a tax of approximately 37 €.tCO_2eq^{-1}.

The results of Figure 1 show that the effect of a crop prices increase on EMLUCF (and consequently on EMNET) are much greater compared to agricultural emissions. This suggests that price variability may have an important impact on emissions from land use and land use changes and thus on the mitigation potential that can be associated to AFOLU. These results may however be interpreted with caution as the accuracy of our predictions for emissions from land use and land use changes is much lower than for agricultural emissions.

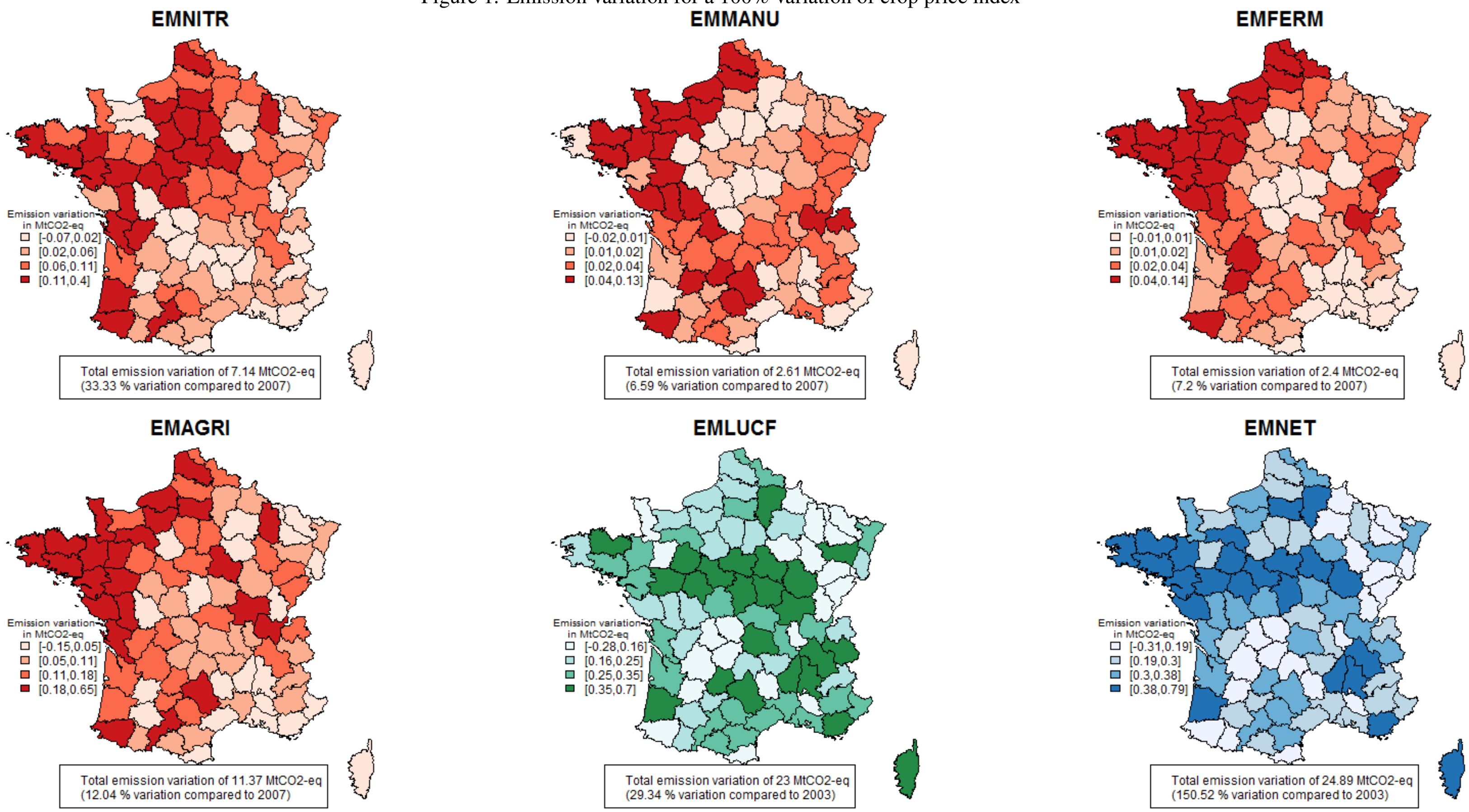
5. Conclusion

The objective of this paper was to assess the effects of input and output prices on GHG sources/sinks from AFOLU at the *Departement* level in France. To this end, various estimation methods have been applied to reduced-form models of the relationship between emissions and prices, for each AFOLU emission categories as well as for aggregated emissions. Results of the specifications tests show that the random effect spatial error models (RE-SEM) estimator suits the best our data and leads to more accurate predictions than alternative estimators (OLS, random error, spatial error models). These results confirm the importance of taking into account both spatial error autocorrelation and random regional effects.

Our main empirical findings are threefold. First, prices do have an impact on both the level and spatial distribution of emissions. Although expected, this result underlines the importance of taking into account spatial structure and decomposition by emission category. Second, the price effects are more significant for individual emission categories than for total net emissions from AFOLU. Separating emission sources and sinks thus allows us to decompose effects of that might be masked at the aggregated level. Third, the price effects are larger for N_2O emissions due to synthetic fertilizer use than for other agricultural sources. This emission category seems to be more price responsive than animal-related GHG. Our results suggest that prices may have an important impact on both the level and decomposition of the mitigation potential associated to AFOLU. This effect should be thus taken into account in the design of public policies aimed at reducing emissions or enhancing carbon sinks in these sectors.

The use of a reduced form rather has the advantage to summarize the complex interactions that may exist between the various emission categories, whilst keeping the approach relatively simply. However, it does not permit to explicitly describe the causal chain from economic land-use decisions to AFOLU emissions. Further research is needed in this direction.

Figure 1: Emission variation for a 100% variation of crop price index



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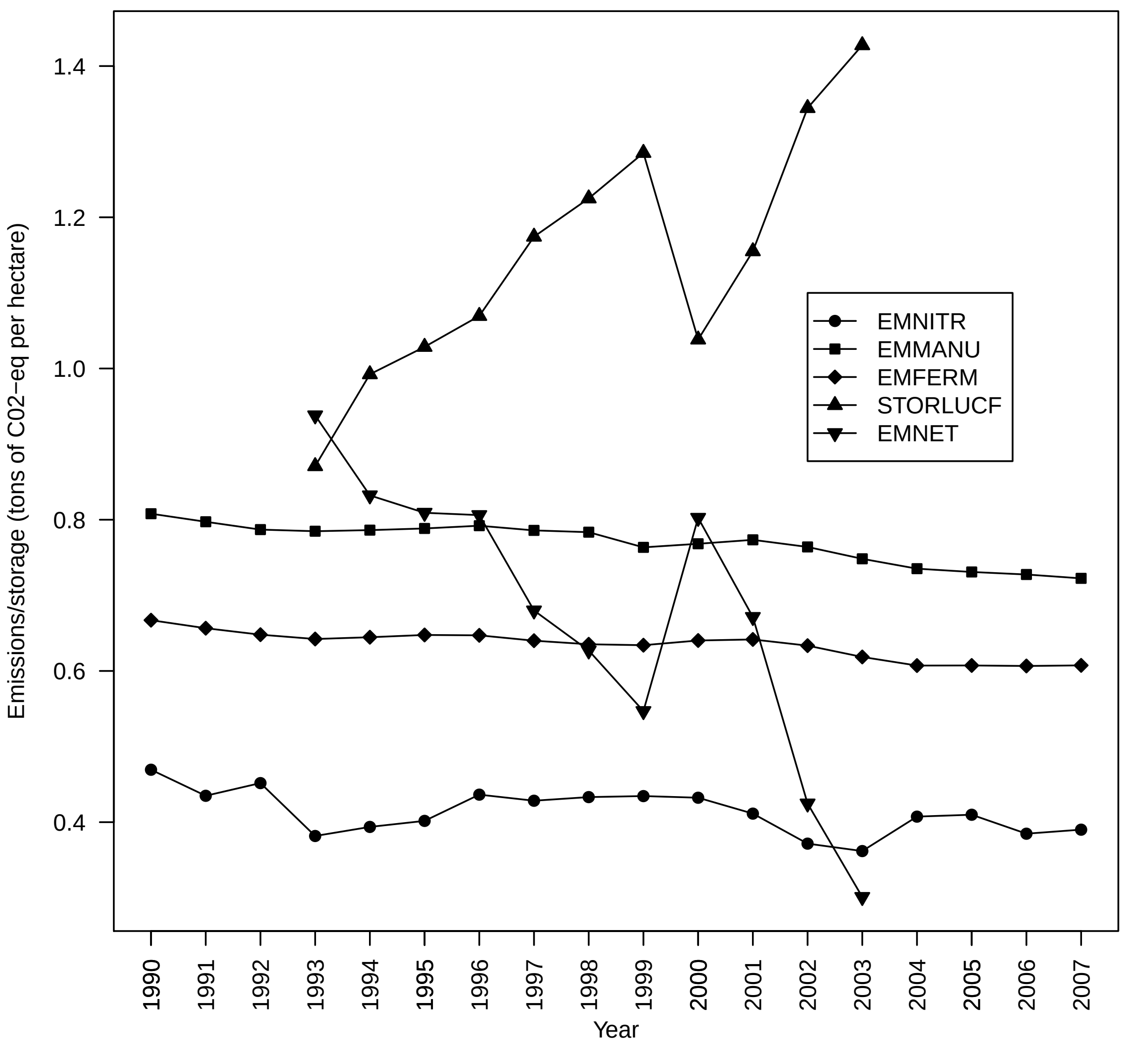
A.

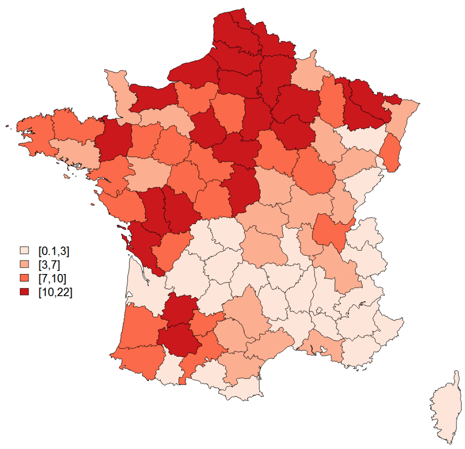
Figure 2: Evolution of agricultural and net emissions during the 1990-2007 period (in tons of CO_2eq per hectare)



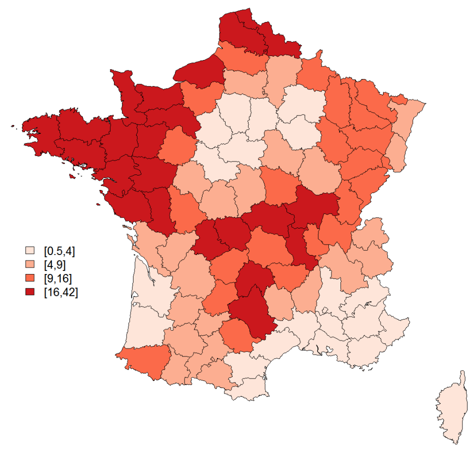
B.

Figure 3: Spatial distribution of the four emission categories in tCO_2-eq per hectare

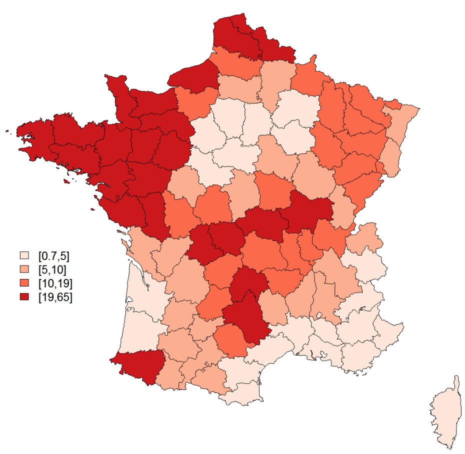
(a) Emission from the use of synthetic fertilizers



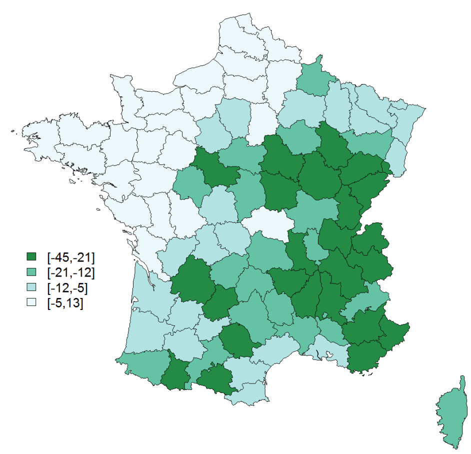
(b) Emissions from enteric fermentation



(c) Emission from manure management and spreading

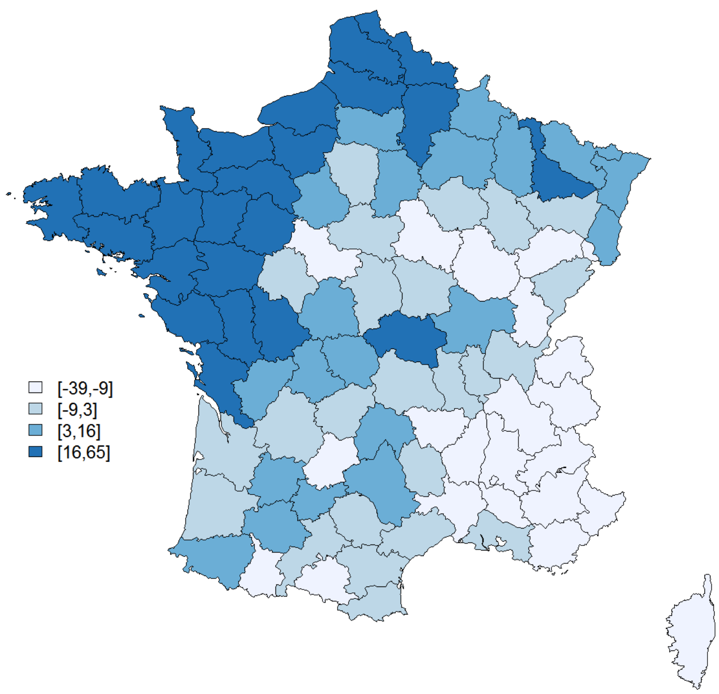


(d) Net emissions from LULUCF



Emissions are expressed in tCO_2-eq per hectare emitted over 1990-2007 for EMNITR, EMFERM and EMMANU and over 1993-2003 for EMLUCF. Negative values correspond to a sink of CO_2 whereas positive values correspond to a source of emissions.
Source : AGRESTE (2011b); CITEPA (2009); UNIFA (2009); TERUTI; own calculations.

Figure 4: Total net emissions (agriculture + LULUCF) (sum over 1993-2003 in tCO_2-eq per hectare)



Lecture : Emissions nettes totales (cumul 1993-2003 en tCO_2-eq par hectare)
Champ : Départements français entre 1993 et 2003.
Source : AGRESTE (2011b); CITEPA (2009); UNIFA (2009); enquête TERUTI; calculs des auteurs.