The role of policy priorities and targeting in the spatial location of participation in Agri-Environmental Schemes in Emilia-Romagna (Italy)

The role of policy priorities and targeting in the spatial location of participation in Agri-Environmental Schemes in Emilia-Romagna (Italy)

The objective of the paper is to understand the determinants of the spatial location of participation in Agri-Environmental Schemes and, in particular, to understand the interplay between structural determinants, priority criteria and spillover effects in guiding participation. As a first step, the paper seeks to conceptualise the issue based on the existing literature. Thereafter, an econometric model is used to provide an empirical application on data regarding participation in measure 214 of the Rural Development Programme 2007-2013 in an Italian region (Emilia-Romagna). The results show that both priority scores and the spatial dimension are significant in affecting participation.

Keywords: Agri-Environmental Schemes, participation, targeting, priority implementation, spatial lag fractional logit model

JEL: Q18; Q28

1. Background and objectives

Determinants of participation in Agri-Environmental Schemes (AES) have been analysed from several angles, mainly by applying econometric models, using cross sectional data or panel data, usually collected at the farm level. The results of early papers on this issue highlight that profitability, risk reductions, and attitudes toward sustainable methods of production, are determinants of adoption. The literature has also pointed out the positive effects of motivations and incentives in promoting AES (Morris and Potter, 1995). Several papers have provided further evidence in recent decades and various papers also provide extensive reviews of the determinants of participation (e.g. Defrancesco et al., 2008; Uthes and Matzdorf, 2013). The determinants have been organised in different ways depending on the scientific approach of the researchers. It can be recognised, however, that the macro areas of interest can be ascribed to the socio-economic characteristics of the farmer and his/her household (e.g. age, composition, presence or lack of a successor), the attitudes and beliefs of the farmers (e.g. opinions about the environment), farming conditions (e.g. site conditions, yield expectation due to geophysical and climatic settings, designation status), structural characteristics of the farm (e.g. size, specialisation, stocking density, financial constraints) and context variables (e.g. information received, neighbours' participation, market opportunities) (Vanslembrouck et al., 2002; Knowler and Bradshaw, 2007; Defrancesco et al., 2008; Jongeneel et al., 2008; Peerlings and Polman, 2009; Barreiro-Hurlé et al., 2010; Wauters et al., 2010; Aumgart-Getz et al., 2012; Uthes and Matzdorf, 2013). Studies based on secondary information tend to put less emphasis on individual variables and more on the structural or environmental characteristics of each farm/area, which is largely driven by information availability (Borsotto et al., 2008; Hynes and Garvey, 2009; Capitanio et al., 2011; Lapple and Kelley, 2013). For example, the Farm Accountancy Data Network (FADN) information tends to record only if the farm is funded and the relevant Rural Development Program (RDP) axis, without providing specific information about the measure or sub-measure (Pascucci et al., 2013). In addition, FADN offers a meaningful aggregation only at the NUTS 2 level and is biased towards professional farms, available for bookkeeping, at least compared to Integrated Administration and Control System (IACS) data.

The literature also highlights the limitations and inconsistencies of the variables used to explain participation, emphasising how different data collection approaches affect the results and, in particular, the inconsistent use of environmental awareness and farmers' attitudes across studies (Aumgart-Getz et al., 2012). Knowler and Bradshaw (2007) even conclude that there are very few, if any, variables that consistently explain adoption of conservation practices.

In spite of this, over time, determinants have been increasingly investigated, including by enlarging the scope of attention. The recent literature recognises that participation in AES is affected by agglomeration effects due to the spatial dependence of explanatory variables, as in Schimidtner et al. (2012). The authors pointed out that, for the case of organic farming in Germany, vectors of prices and costs are heterogeneously spatially distributed due to spatial differences in distance to markets or the positive values of transportation costs. Furthermore, the authors argue that production functions and transaction costs required to participate in AES are heterogeneously distributed across the space due to different natural conditions, which implies changes in input-output relations, and heterogeneity in the quality of institutions and social capital elements. In addition, a growing body of literature on spatial phenomena points to the relevance of proper spill over effects due to, for example, imitation or economic signals outside the involved farms (e.g. through effects on prices) (Anselin 2010; Bell and Dalton, 2007; Brady and Irwin, 2011).

The above-mentioned literature, largely based on *ex-post* studies on participation, only marginally addresses policy design variables, targeting and participant selection processes. This may be justified by the fact that the case studies from which the participation data were obtained involved little targeting or poor selection priorities. Furthermore, when selection criteria are in place, the existing budget may or not be sufficient to allow for participation from all of the applicants. Regardless, farmers' decisions may be influenced by their expectations of the priority mechanisms. When the analysis is performed with secondary data (e.g. FADN), taking into account the participant selection process may be even more difficult, due to the fact that information about the full process (i.e. if the farmer applied and was not accepted or did not apply) is rarely available for researchers.

Policy design is more directly dealt with in the literature addressing farmer preferences for different contract alternatives based on hypothetical questions (e.g. Ruto and Garrod, 2009; Christensen et al., 2011; Broch et al., 2013). However, given the particular focus of this type of study on individual behaviour, the authors deal more with "hard" variables of direct interest to the farmer (such as payment levels, contract length, transaction costs etc.), rather than variables that matter mainly on the aggregate, such as those related to how the policy includes targeting and selection mechanisms for farmers.

On the other hand, the literature on AES design points out the relevance of targeting as a key issue (and a major gap) for the improvement of AES effectiveness and efficiency (Coisnon et al., 2014). In particular, the literature contrasts spatial targeting, aimed at promoting the concentration of AES in selected areas, and group targeting, more related to other farmer characteristics (Uthes et al., 2010). The former may be based on the combination of different policy components (e.g. zoning, eligibility criteria, scoring systems, differentiated payments) and is a cornerstone of environment-related measures as it allows, in principle, to concentrate measures in areas where the added value of environmental improvement is higher; at the same time, a more focused targeting approach could lead to higher administration/transaction costs and result in the perception of an unequal distribution of funding (Vatn, 2010).

Targeting, eligibility and selection criteria can interact: Bartolini et al. (2013) found that selection criteria and priority mechanisms increase the spatial targeting of agri-environmental measures. However, the authors found that sub-measures react heterogeneously to economic incentives due to the relevance of motivation and social capital in explaining spatial concentration (e.g. organic farming). Moreover, given their relationship with space, these mechanisms can interact with the occurrence of the spillover effects highlighted above. For example, on the one hand one could expect that targeting may stimulate concentration above that justified by spontaneous decisions. Yet eligibility constraints may hamper spillovers by hindering willingness to participate. However, these issues are not generally addressed in the empirical literature.

The objective of this paper is to understand the determinants of the spatial location of participation in AES and, in particular, to understand the interplay between structural determinants, priority criteria and spillover effects in guiding the spatial distribution of participation in AES.

The objective is addressed through the application of spatial econometrics on participation in measure 214 (Agri-Environmental measure) in Emilia-Romagna, Northern Italy, including priority variables to reflect the selection process mechanisms . Emilia-Romagna offers a very interesting case with respect to the objectives of the measure. This region is very heterogeneous in terms of territorial and agricultural conditions and the local administration has put in place a complex system of scoring, based on several criteria, which is aimed at guiding the selection of applications in each area, taking into account the specific environmental context.

Spatial econometrics is the chosen methodology due to its ability to account specifically for spatial dependency due to spillover effects that can be traced through the spatial association of participation. Spatial econometrics is largely applied in the regional studies literature and has recently been applied to better understand participation in AES (Schmidtner et al 2012, Yang et al 2014). The main originality of this paper, compared with the recent literature, is the use of (*ex-post*) priority setting in the context of spatial econometrics models, allowing for discussions of the interplay between spatial effects, priority targeting and other explanatory variables of participation. It also provides insights into how this interplay concerns different sub-measures (interpretable as different types of measures). In addition, in order to fit these purposes, and in particular to account for the share of participating land as the dependent variable, a fractional logit model is used. Due to the novelty of the approach and the data limitations (see discussion), this is to be considered mainly as an explorative exercise.

Section 2 provides a formalization of the problem addressed and the description of the methodology. Section 3 describes the case study area. The results are illustrated in Section 4, followed by a discussion and concluding remarks in Section 5.

2. Problem setting and methodology

A framework for analysing funding priority effects

The connection between participant (self-)selection, targeting and policy design is addressed from different perspectives in the literature. Babcock et al. (1997) analyse the problem of targeting conservation payments and the role of different targeting instruments, comparing situations in which targeting is based either on cost or benefits, with a situation in which targeting is based on an ideal cost-benefit ratio. They consider three practical targeting options: acreage maximisation; enrolling land based only on environmental benefits; and maximising the environmental benefits of the programme. They find that the magnitude of losses depends on the joint distribution of costs and benefits.

Compared with this basic analysis, the potential economic benefit of targeting is made more complicated when taking into account: a) different rationales for payment settings, and b) different ways of representing the decision making process followed by farmers. With regard to point a), while in an ideal auction system payments may be more directly related to opportunity costs of alternative land uses (Babcock et al., 1997), in most of the EU the rationale is rather a fixed payment based on average costs. As a result, assuming profit maximisation decisions by farmers, farmers tend to self-select (in presenting the application) based on the difference between compliance costs and the payment offered. In addition, environmental benefits at the individual farm level are usually not explicitly taken into account in designing the measures and setting the payment. Rough approximations of these benefits may be used for farm selection, whereby the regulator can set out a selection mechanism to concentrate payments in those areas where expected environmental benefits are high using eligibility rules or scoring systems. An additional issue is that farmer participation may not necessarily follow a purely economic rationale (point b above). Morris and Potter (1995) have identified four behaviour typologies for participation in AES: active adopters, passive adopters, conditional non-adopters and reluctant adopters. While the third and fourth group are driven by economic incentives, famers in the first and fourth groups follow mainly motivational reasons (e.g. farmers participated because of their belief).

The problem of interpreting participation and priority setting in *ex-post* econometric models can then be illustrated as in Figure 1.

(Figure 1 about here)

Figure 1 depicts the distribution of a set of farms by compliance costs and decreasing priority scores. The position on the y-axis, represents the decision of the farm to participate or not based on the positioning with respect to the payment level. We assume that the different factors affecting willingness to participate contribute to decisions through (and are well represented by) the Willingness to Accept (WTA) a payment for participation in AES, equal to the perceived compliance cost. Farms with WTA below the payment level are willing to participate, while those above are not.

The public regulator selects farms based on a priority score (x-axis), based on farmer or farm characteristics (e.g. age of applicant, location, farm specialisation). This may be related to the presumed higher relevance with respect to a measure's objectives (e.g. higher likely ability to produce environmental externalities). Priority will then be given to the farms with the highest score among those applying for the payment. Assuming that there are budget limitations, the subset of funded farms will be those farms in area A. Area B includes those applying, but not funded because the budget was used up entirely by farms with higher priority. Area D includes those farms that would not apply, but would compete for the budget based on the priority score if they did. Finally, Area E includes all farms that would not apply, and that would not be funded even if they did, due to the priority mechanism.

In addition, the regulator, by setting eligibility rules based on location or farm/farmer characteristics (i.e. altitude or specific zoning based on environmental sensitivity; legal status or farm size), can exclude farms (areas C and F). Of the two sets, Area C represents the one that would have incentives to participate, as their costs would be lower than the payment.

The simple framework above involves several considerations.

From the point of view of policy design, it is important to understand the interrelationships between the different policy variables in the figure. The payment level clearly affects the individual's interest in participating, whilst the number of selected participants will depend on budget availability. However, the budget constraint will be more or less selective depending on the number of farms willing to participate. Hence, in order to be selective with respect to the priority criterion, and to be effective in selecting farms with high priority, a scheme needs to set the payment high enough to encourage excessive participation. However, in presence of a fixed budget, increasing unit payments also means strengthening the budget constraint (i.e. allowing participation from fewer farms), hence making the selection process more arduous. On the other hand, if the payment is so low that the farms willing to participate are less than that which is allowed by the budget, the priority will not be selective at all. This problem may also be altered by population distribution. For example, for the star type distribution there is no trade off and moving the payment higher or lower will end up selecting the "right" farms. On the contrary, the search for the right combination of payment and priority matters in the case of a "cloud" type distribution.

A second group of considerations concerns the connection between the distribution of farms in an area and its connection with potential analytical issues. For example, square dots in Figure 1 are distributed without any particular relationship between WTA and the priority score. On the contrary, stars represent hypothetical farms of a region in which the priority is higher for farms that also have lower WTA. It may be expected that, in this case, priorities will push participation in the same direction as was the case with WTA and that the policy variable "priority" would be highly correlated to other factors affecting participation. The opposite happens if hypothetical farms in a region are represented by circles. In this case it may be expected that the policy variable "priority" acts as a more relevant independent variable in affecting participation.

From the point of view of spatial econometrics applications, it is worth noting, first and foremost, that econometric studies may in fact use different samples with respect to this framework. Studies based on WTA usually consider the full set of farmers. Studies using information by applicants, on the other hand, observe only components A+B of the population (except when motivations other than profit affect participation). When only actual participants (approved applications, i.e. beneficiaries) are used, we consider only section A of the quadrant (with the same caveat as above). This means that, in the latter case, investigating the effect of priority setting is impossible, as in order to do so, it would be necessary to have information about the whole population characteristics and the ultimately funded farms.

Methodology

In this paper, spatial econometric methods are used to explain participation at the municipality level (1 municipality = 1 observation), which is a way of approximating the full set of potential participants (i.e. all components in Figure 1). By comparing with existing models, the aggregation of data at the municipality level and the spatial econometric methods make it possible to investigate extents and reasons for the agglomeration effects of participation in AEM. As mentioned above, agglomeration effects could be explained by design and implementation of selection mechanisms or spillover effects. Thus, ignoring the prioritisation mechanisms set out by public administrations can result in an overestimation of spatial spillovers caused, for example, by (unobserved) imitation processes, differences in the quality of extension services among observations or economic connections among neighbouring areas.

The methodology is composed of two steps. In the first step, the Exploratory Spatial Data Analysis (ESDA) is performed in order to investigate the spatial regime of the distribution of uptake of measure 214. It consistsfirst of mapping the spatial distribution of measures, followed by the compilation of a LISA cluster map, a Moran's scatter plot and the computation of a Moran's I index to identify spatial associations, using GEODA software (Anselin et al., 2006).

In the second step, spatial econometric models are applied with the aim of investigating determinants of spatial distribution of uptake, focusing on both individual municipality characteristics and the priority mechanisms implemented.

Spatial econometric models can be thought of as an extension of standard linear regression models (Lesage and Page, 2009). In this paper spatial lag models are performed. This is motivated by the fact that a preliminary analysis already showed relevant spatial correlation and because the candidate explanations for spatial correlation (after controlling for other similarities in the municipalities, such as altitude) were likely due to well identified factors, such as communication, imitation and interactions (though we do not have explicit variables accounting for them). Following Anselin (1988) the reduced form of the spatial lag model could be written as :

$$y = \rho W y + x\beta + \varepsilon$$

where W is the spatial weights matrix that specifies for each municipality the first order of contiguity with neighbours, then Wy represents the spatial lag for the dependent variable, i.e. the weighted average of the neighbours (or a spatial smoother). β and ρ are the parameters to be estimated; the first is the vector of coefficients for explanatory variables and the second reflects the spatial dependence in the sample data, measuring the average influence of neighbouring municipalities on observations in vector y.

The econometric models have been applied both to the participation in the whole measure 214 and to selected individual sub-measures (organic farming, integrated production and meadows and grazing payments). The dependent variable is the rate of participating areas in each municipality (hectares under the measure divided by the total UAA hectares of each municipality, which is also the eligible area for the measure/sub-measure in question).

The choice of the model applied needs to consider the fact that the dependent variable is calculated as a proportion (Kieschnick and Mccullough, 2003; Long, 1997; Papke and Wooldridge, 1996;

Ferrari and Cribari-Neto, 2004). The use of a linear model and an Ordinary Least Square method (OLS) presents some methodological problems as it violates the assumptions of the regression model (even if in some applications the sample sizes were large enough to invoke asymptotic arguments to reason out less stringent characterisations of the regression models). First, proportions are not normally distributed because they are not defined over the full set of real numbers, since this variable is only observed over a closed interval. This implies that the conditional expectation function must be nonlinear and that the conditional variance is a function of the mean. Moreover, the linear model is not appropriate since it does not guarantee that the predicted values of the dependent variable are restricted to the unit interval. The linear approach could be justified when all of the proportioned data fall in the middle (roughly between 0.2 and 0.8) because the effect of explanatory variables tends to be non-linear, yet the sigmoidal relationship looks like a flattened S, that is "almost" linear in the middle. Our data do not allow for this approach since they do not show any linearity and due to a high concentration of zero values.

An alternative to the linear approach, used in the literature, is to first calculate the logit transformation of y and then use the linear regression on the transformed dependent variable. Obviously, this is possible only if the proportions are strictly in the open interval (0,1). On the contrary, our data include several observations for which the participation proportion is equal to 0.

A third approach is to treat the proportion as a censored continuous variable in the closed interval [0,1] and use a censored normal regression model (i.e. the Tobit model) (Cook et al., 2008). Some authors (see Maddala, 1991; Papke and Wooldridge, 1996) observe that it is not appropriate to use a censored model since the data are not censored as a natural result of choices, but are rather proportions, which are not possible outside the [0,1] interval.

The modelling approach for handling proportion data, in which zeros and ones may appear, was proposed by Papke and Wooldridge (1996), who refer to it as a fractional logit model. It consists of a Generalized Linear Method (GLM) with a binomial distribution and a logit link function. They propose the Quasi-Maximum Likelihood Estimation (QMLE) which is fully robust, relatively efficient and requires no special data adjustments for the extreme values of zero and one. Formally, to obtain consistent parameter estimates with QMLE, Papke and Wooldridge (1996) assume a logistic distribution:

$$E(y_i|x_i) = \frac{exp(x_i\boldsymbol{\beta})}{1 + exp(x_i\boldsymbol{\beta})}$$

and propose the following Bernoulli log-likelihood function:

$$l_i(\boldsymbol{\beta}) = y_i ln\big(G(x_i\boldsymbol{\beta})\big) + (1 - y_i) ln\big(1 - G(x_i\boldsymbol{\beta})\big)$$

where G is the logistic cumulative distribution function.

In this paper, we use a modified version of this approach that combines the spatial lag model and the fractional logit model. In practice, we include not only the explanatory variables X in the equation of the conditional expected value of y, but also the spatial lag WY. Estimates are obtained using a Quasi-Maximum Likelihood Estimation criteria in a Generalized Linear Method with a binomial distribution and a logit link function. The procedure was written in STATA software modifying Papke and Wooldridge (1996) to include a spatial lag component.

The explanatory variables were selected based on a preliminary analysis of expected determinants and spillover mechanisms (see Bartolini et al., 2011), in the previous literature and in local policy design. In particular, based on the discussion above, the determinants are organised into three groups:

1. the level of priority of the area where the municipality is located;
2. the characteristics of the area, the farms or farmers in the municipality, affecting WTA;
3. residual spatial effects, related to the neighbourhood and hence potentially attached to spillover effects.

The second category concerns variables related to the location of the municipalities (altitude, density of inhabitants), farm structure (amount of household and external labour used on the farm, farm specialisation income from the farming activity, farm specialisation) and farmer characteristics (age).

Municipalities are neighbours (adjacent) if they share a common border and/or vertex (Queen 1 contiguity).

The details and descriptive statistics of the dependent and explanatory variables are available in Appendix A of this paper, while further details regarding participation in the case study area and policy priority design are provided in the following section.

3. The case study: regional features, AES implementation and uptake distribution

The Emilia-Romagna region is located in north-eastern Italy, and includes the southern part of the Po plain. The region is environmentally heterogeneous. The southern portion is made up mostly of the hilly and mountainous areas of the Apennines, whilst plains dominate the northern part The plains are characterised by intensive agriculture and arable crops, the hilly area by specialised vineyards and orchards, and the mountainous area by extensive agriculture (mainly grasslands and arable crops) and woods.

The plain area is highly urbanised while, on the contrary, the mountainous area is marginalised and experiencing land abandonment in part due to the lack of services in the immediate area. The plain area has very low biodiversity and faces various risks related to water quality (mainly pollution by nitrates), while the mountainous area experiences problems related to water erosion and landslide risks for cultivated soils.

Given the complexity of the regional context, AES were designed to address different agri-environmental issues. Measure 214 (Agri-Environmental payments) is aimed at promoting the sustainable management of the territory, with a specific focus on increasing water and soil quality and biodiversity conservation. The measure is divided into 10 sub-measures, differentiated by environmental objectives, priority mechanisms and target areas.

The entire region is eligible for inclusion in measure 214. Within such an area, however, priorities are established that form a score used to rank applicants in decreasing order and then select those to be funded starting with the highest score and moving down until the budget is exhausted.

The prioritisation process is based on three groups of criteria in decreasing order of importance: a) territorial, b) sub-measures and c) farm structure characteristics. The territorial criteria (a) present a relatively high level of complexity; the RDP refers to 15 different themes. The themes are grouped into four separate typologies of protection as depicted in Table 1, in which the sub-measures affected by the various preference criteria are also presented.

(table 1 about here)

The most important territories in the selection, according to the EU strategic approach, are Natura 2000 and Nitrate Vulnerable Zones (NVZ), treated together as “absolute” priority. These are followed by lower levels of priority based on regional territorial planning and linked to nature conservation (parks, ecological networks etc.), water protection areas (related to the risk of pollution for water bodies), soil protection areas (related to the risk of erosion) and protected landscape areas. In this design, each level of environmental sensitivity is translated into a different ranking of territorial priority (e.g. Natura 2000 is ranked higher than parks). The scores given for each kind of area are added in case of overlapping, which is common at the local level.

The second level of priority, related to the sub-measures (b), enables the regional administration to link the selection to the RDP objectives by following crosscutting priorities designed across the whole programme. For example, a high ranking in this case is provided for organic farming. Other priorities are applied to a selection of measures, based on specific environmental objectives addressed by given sub-measures. In some cases the sub-measure priority is linked to the territorial criteria (the highest rankings for sub-measures related to water quality, i.e. integrated production, are provided when the farm is located in a water protection area).

The third level of priority, linked to the structural characteristics of the farm and farmer (c), always has a lower weight than the previous ones, as these characteristics are not directly linked to the environmental objectives of the programme.

Scores allocated to each relevant characteristic (territorial, sub-measure and farm characteristics) are widely differentiated across the region, making it impossible to recall them in detail here. However, given that the main rationale of this priority system is to have a concentration of applications in the most sensitive areas, the scores used for the three categories have been strongly differentiated. The territorial category always has much higher scores and the effect of the other two categories are mainly to differentiate farms with similar territorial priority scores. Similarly, the sub-measure is always prevalent on farm characteristics, in order to select farms involving higher environmental effort (e.g. organic farms).

In this paper we focus on territorial priorities. In order to feed priorities into the econometric model, specific variables have been created to account for each of the preferential dimensions illustrated in Table 1. The municipal level data were processed by calculating the overall preferential area (plots included in at least one of the areas) for each group of protection type. The resulting preferential area of the plots included in the RDP applications was compared to their total surface area. The municipality is thereby classified as “preferential” (value 1 of the related binary variable) or “not preferential” (value 0) for a certain group of protection type (water protection, nature protection etc.), if the preferential area of the participating plots is above 50% of the total participating surface for each group of priorities.

In this paper we use data from areas enrolled in the first call for measure 214 applications (RDP 2007-2013). This call, related only to year 2008, resulted in a total of 81,600 hectares being enrolled across the entire region, mostly with 5-year contracts. The most important sub-measures were: 2-organic farming (51% for over 42,000 ha), 1 - integrated farming (26% for 21,000) and 8-meadows and grazing payments (17% for 13,800 ha). In this paper we focus on the aggregate of measure 214 and on these three most important individual sub-measures.

As mentioned, in this study the dependent variable for all models and measures is the participation expressed as the ratio between the participating area for each sub-measure and the utilised agricultural area of the municipality. The number of observations is hence equal to the number of municipalities in Emilia-Romagna (341) at the time of the first call (2008).

The distribution in the region , in terms of the percentage of participating area per municipality, is rather differentiated and is different between the aggregate and specific sub-measures (Figure 2).

Moreover, the concentration of participation is very different across municipalities and hints at the fact that participation follows the zoning rules applied.

(Figure 2 about here)

In particular, sub-measure 1 (integrated production) is mainly located in the plain and is particularly focused on areas characterised by a concentration of fruit production (eastern part of the region). This is largely connected to a deliberate strategy of valorisation and targeting of the fruit sector. On the contrary, organic production (sub-measure 2) is much more widespread in hill and mountain areas, characterised by more extensive systems and requiring fewer chemicals for plant protection. This is true with the exception of Ferrara Province, which is a completely flat area, and where the main farming systems are cereal and alfalfa crops located in the municipalities with the highest participation rate. Measure 8, which is related to meadow and grazing conservation, is mainly distributed in the hill and mountain area, and in the Parma and Reggio Emilia Provinces, which are characterised by a high concentration of dairy farming.

4. Results

4.1 LISA cluster map and Moran scatter plots

The LISA cluster map and Moran scatter plots, depicting the spatial associations of participation in measure 214 and in the three selected individual sub-measures, are presented in Figures 3 to 6, respectively. In all of the figures the participation is measured as the ratio between uptake and the total utilised agricultural area in each municipality.

The figures show a different level of spatial agglomeration and occurrence of hotspots, which in fact largely reflects the concentration already noted in the participation maps. The Moran Index (Moran's I) is positive and varies slightly between sub measures, with values changing from 0.403 to 0.455, hence representing rather strong evidence of spatial correlation.

Measure 214, as a whole, indicates a large hot spot (i.e. high participation municipalities close to high participation municipalities), represented by red cells in the centre-west mountain area of the region, in contrast with a large cold spot (i.e. low participation municipalities close to low participation municipalities) in the lowland area. The Moran's I is 0.447.

(Figure 3 about here)

Two sub-measures (1-integrated production and 2-organic farming) have a higher Moran's I index compared to the measure 214 as a whole i.e. higher spatial correlation. In the LISA maps, sub-measure 1 shows a major hot spot in the eastern part of the region (orchard and vineyard specialisation), while cold spots are small (basically each derived from the combination of a couple of municipalities) and located in the Apennine area.

(Figure 4 about here)

Sub-measure 2 - Organic farming (Figure 5) has one major hot spot and one major cold spot. In particular, the main hotspot area is located in the western Apennines, while the main cold spot is found in the centre-east part of the low plain area, though agglomeration also occurs in most of the lowest part of the entire plain area.

(Figure 5 about here)

Sub-measure 8 – Meadows and grazing payments (Figure 6) is the least spatially correlated sub-measure according to the Moran's I (0.449). In this case, a large cold spot covers the plain area where the participation is very low or null (particularly in the east side), while small hot spot areas can be identified in the Apennines and in the plain area close to Reggio Emilia (the main dairy cattle area in the region).

(Figure 6 about here)

4.2 Spatial econometric models

Tables 2 and 3 present the results of the a-spatial fractional logit model and the spatial lag fractional logit model, respectively. Estimates are obtained using the Quasi-Maximum Likelihood Estimation criteria explained in the methodology section. The a-spatial fractional logit model allows for the identification of benchmark results, ignoring the spatial dependency component and identifying the determinants. In comparison, the spatial lag fractional logit model is capable of identifying changes in the overall performance of the model and in the role of different explanatory variables due to the introduction of a spatial lag component, which takes into account spatial spillovers.

For each table, the model is applied to data regarding participation in measure 214 as an aggregation of all sub-measures and to the data involving individual sub-measures 1, 2 and 8. The presentation of the data in this way allows for a smooth comparison of the results of the same set of explanatory variables across the different sub-measures, hence highlighting the (different) role of priority mechanisms in affecting different measures. The results are presented as marginal effects.

The a-spatial fractional logit model (Table 2) AICs show that each sub-measure model is better than the ones that consider the aggregate of measure 214. No variable is significant for all sub-measures and the aggregate. Only the percentage of farms with livestock (LIVESTOCK) and priority related to nature conservation areas (PREFNAT) are significant for all measures individually, without being significant for the aggregate. While several variables are significant for more than one measure, they often change their sign, i.e. the direction of the marginal effect.

(Table 2 about here)

As for variables related to location in preferential areas, the absolute preference variable (PREFASS) is positively and highly significantly related to the participation in the aggregate measure for integrated production and grazing, but not for organic production. Being located in a preferential area for water protection (PREFIDRO), landscape protection (PREFPAE) and soil protection (PRESUOLO) is never significant on the aggregate or for the single sub-measures considered. Being in a preferential area for nature conservation (PREFNAT) has a negative marginal effect on sub-measure 1 (integrated production) and on sub-measure 2 (organic farming), while it has a positive marginal effect on sub-measure 8 (grazing). Altogether the results demonstrate the relevance of the priority mechanism implemented by the regional administration. The weak effects of the priority mechanism for organic farming might be due to the higher relevance of motivation and attitude variables in explaining participation compared with other measures.

With regard to altitude, only location in hills and mountains (codes HILL and MOUNTAIN respectively) has been retained, while location in plains (PLAIN) has been omitted due to collinearity with HILL and MOUNTAIN. With respect to PLAIN, municipalities located in HILL and MOUNTAIN have a positive and significant effect on participation in organic farming (sub-measure 2), while MOUNTAIN has a negative effect on sub-measure 1 (integrated production). This is generally consistent with integrated production being applied more often on relatively intensive arable and perennial crops in the plain area.

Density of inhabitants (DENS_AB) is negative for measure 214 as a whole and for sub-measures 1 and 2, hence showing that participation tends to be higher in the more remote/rural areas. Most likely, the effect on overall participation is largely due to the combined effect of sub-measures 1 and 2. The share of different crops has markedly different behaviour across sub-measures. In particular, the share of arable farming (ARABLE) in the municipality negatively affects the aggregate measure 214 as well as sub-measures 1 and 8, while fruit (FRUIT) positively affects sub-measure 2, which is also negatively affected by grazing land (GRAZING). GRAZING, as expected, has a positive marginal effect on measure 8. The share of forest (FOREST) is also positively associated with the aggregate measure 214 and sub-measure 2. The livestock variable (LIVESTOCK) also has complex behaviour, as it is positively associated with participation in sub-measure 8 (grazing) and 2 (organic farming), while being negatively related to integrated production (sub-measure 1). A large share of older farmers (AGE_MORE65) is positively related to sub-measure 8. Part time farming (PARTIME) is negatively related to integrated production (sub-measure 1), hinting at the fact that this measure best suits professional productive farms.

Table 3 illustrates the results of the spatial lag models. The ρ parameter (coefficient of spatial dependence) has a positive value and is highly significant in all models, hence corroborating the notion that relevant spatial concentration phenomena can indeed occur. However, its value is rather low, as it is higher for the aggregate 214 and lower for sub-measure 1. Spatial dependency coefficients show *inter alia* high spillover effects for the organic measure. AIC increases in all cases (indicating worse fitness of the models), but the size of change is negligible. The same is the case for BIC: a slight increase, yet almost negligible.

(Table 3 about here)

The results in terms of significant variables are largely consistent with an a-spatial fractional logit model, but with several noteworthy differences. Notably, absolute preferences (PREFASS) keep the same sign but take a lower value for measure 214 as a whole and for sub-measure 8, and become non-significant for sub-measure 1 (integrated production). PRFENAT roughly maintains the sign and size of the marginal effect for measures 1, 2 and 8. The results of the spatial model makes it possible to present a more accurate estimation of the priority mechanism effects, disentangled from other agglomeration effects that are derived from imitation among farmers, other processes or differences in the quality of extension services. The outcome confirms that even when the model removes those spatial components, the priorities mechanism remains as a significant variables to explain participation and hence as a tool to target AEM.

Of the altitude variables, the main change occurs for MOUNTAIN, which becomes non-significant for sub-measure 1. This could be expected as mountain areas are mostly contiguous and the effect of this feature may hence be absorbed by the spatial component. The inhabitant density (DENS_AB) does not show relevant changes. The fact of having only household labour (ONLY_HHLAB) becomes significant with a positive sign for measure 214 as a whole only.

Arable crops (ARABLE) remain stable (with an increase in absolute values for sub-measure 8), while FRUIT and GRAZING lose significance. FOREST remains significant for 214-All and sub-measure 2, but also becomes significant with negative signs for sub-measure 1. LIVESTOCK maintains its role for sub-measures 1 and 8, but loses significance for measure 2.

AGE_MORE65 becomes non-significant, while part-time maintains its role in sub-measure 1 (integrated production).

The effect of the shift to the spatial model in terms of reduction of significance of MOUNTAIN, FRUIT and GRAZING variables may be attributed to the fact that these explanatory variables are very prominent in groups of geographically contiguous municipalities. This concentration effect is absorbed by the spatial variable when it is introduced.

Table 4 shows the change in marginal effects of preference variables between the values of 0 and 1 of the preference variables, assuming an average value for all other explanatory variables, computed based on the spatial lag fractional logit model.

(Table 4 about here)

Moving from 0 to 1 causes a decrease in the marginal value of the effect of PREFASS on the aggregate of measure 214, and of PREFNAT on sub-measures 1 and 2; on the contrary, both PREFASS and PREFNAT show an increase in the marginal effect on sub-measure 8.

6. Discussion and conclusions

The main objective of this paper is to understand the determinants of the spatial location of participation in AES and, in particular, to understand the interplay between structural determinants, priority criteria and spillover effects in guiding participation.

This work is affected by several weaknesses, the main one of which results from limitations in the scale of analysis, the only feasible scale being the municipality level. This has implications for consistency with potential spillover effects and also with respect to the priority criteria used by the regional administration, which are mainly related to the farm level. This also affects the availability of explanatory variables, which in most cases are limited to a small amount of information related to secondary data about crops, age and population in a given municipality. As is the case with other studies using aggregated data, this study was not able to take into account personal and attitudinal variables that are considered important in explaining participation in AES. This, on the one hand, leaves open the possibility that relevant spillover is not taken into account by the model, while, on the other hand, the spatial variable could also incorporate spatial differentiation that is explained by variables not accounted for in the model due to a lack of data.

Another relevant limitation concerns the time frame covered by the data on participation, as data were available only for the initial part of the programme. As a result, participation is largely focused on "first comers" and this may yield a somewhat biased picture of participation, particularly in light of the fact that different calls may change the weighting of the priorities and have irregular budget endowments. In addition, due to the limitation of the time frame considered, participation could not be treated in the form of a time series, but was rather presented as a "one-off" participation.

In spite of the limitations, the spatial econometric exercise showed altogether a satisfactory ability to explain participation in measure 214. In the estimated models, the regional priorities are significant in affecting the results. This occurs in a differentiated way across sub-measures and the effects are more evident for individual sub-measures than on the aggregate.

It is relevant to note that the priorities affected the participation level and localisation, even though in the 2008 call, and in the subsequent calls (2011 and 2012, not studied in this paper), the resources allocated were sufficient to fund all of the admissible applications. This contradicts the expectation that an excessive budget would nullify the use of articulated priorities to select farms and may point to the importance of expectations about the selection process with regard to farmers' decisions whether or not to apply. However, this also means that the role of priority variables in the model is likely lower than what it could have been in case for a higher number of applications compared to the available budget.

The concentration of the commitments followed the territorial priorities, especially for the absolute preference which is consistently relevant in most of the models. This is not the case for the other preference variables (cfr. Table 1), with extreme cases for hydrological, landscape and soil preferences, which are never significant, even though they should be relevant for all of the measures considered, according to the intended design of such preferences. Moreover, the nature protection variable is not always significant and, when it is, it has contradictory results (signs).

Hence, altogether, the weight of the priority variables for participation seems to be low compared to the sophisticated zoning system underlying such priorities. In fact, only absolute priority and priority related to natural areas seem to work. One likely explanation is that some elements of the other priority variables are actually incorporated into these two priority indicators. Another explanation is that the measures considered (in particular integrated production) are rather a-specific and target several priorities at the same time. Accordingly, they end up being rather uniformly distributed.

The other explanatory variables were sharply differentiated by sub-measures. Most of them are consistent and confirm previous results. For example, higher participation in most remote areas confirms previous literature findings on the positive effect of increasing distances from urban areas on participation in AEM (Coisnon et al., 2014). Altogether, socio-economic variables appear to be less often significant and less stable across models, compared to "harder" structural, location and specialisation-related variables. This may suggest that the participation decision process is more affected by such structural variables (or related profitability considerations) than by socio-economic factors or softer preferences and attitudinal factors, though this judgement may be biased by data limitations related to personal and attitudinal information, due to the scale of analysis and the sources of information.

The additional spatial component was highly significant demonstrating the relevance of spatial effects beyond the characteristics discussed above; this confirms previous findings, highlighting in particular that this effect is stronger for organic farming (Schmidtner, 2012). However, the spatial variant adds little to the overall explanatory ability of the model.

In spite of these qualifications, this exploratory paper demonstrates the potential relevance of accounting for policy design variables and, in particular, for policy priorities, in the analysis of participation in AES, and hints at several directions for further research in this field. The most relevant ones include the extension of the range of policy variables in the model (including, for example, payment levels) and the investigation of the connection between econometric models and normative policy design models able to exploit information about policy design in *ex-ante* policy evaluation exercises. In order to be effective, however, this needs to be backed by appropriate data collection systems, in particular those designed to be usable at the farm level, making it possible to cover both participants and non-participants and to connect information about participation in AES and other structural farm and household information.

Acknowledgments

This research was carried out as part of a project entitled "SPARD; Spatial Analysis of Rural Development Measures", funded by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement no.244944. This work does not necessarily reflect the view of the European Union and in no way anticipates the Commission's future policy in this area. The authors would like to thank the two anonymous referees. The usual disclaimers apply.

References

Anselin L. (1988) Spatial Econometrics: Methods and Models (Studies in Operational Regional Science), Kluwer Academic Publishers.

Anselin L. (2010). Thirty years of spatial econometrics, *Papers in Regional Science* 89, 3-25.

Anselin, L., Syabri I., Kho Y. (2006). GeoDa: An Introduction to Spatial Data Analysis. Geographical Analysis 38 (1), 5-22.Babcock B.A., Lakshminarayan P.G., Wu J.J., Zilberman, D. (1997). Targeting tools for the purchase of environmental amenities, *Land Economics* 73(3),325-339.

Barreiro-Hurlé J., Espinosa-Goded M., Dupraz P. (2010). Does intensity of change matter? factors affecting adoption of agri-environmental schemes in Spain, *Journal of Environmental Planning and Management* 53(7), 891-905.

Bartolini F., Viaggi D., Bryson J., Silburn A. L., Desjeux Y., Latruffe L., Kuhlman T., Juvancic L., Travnikar T., Berges R., Piorr A., Uthes S., Zasada I. (2011). *Report on data screening and qualitative identification of causal relationships,* SPARD Deliverable 5.1.

Bartolini F., Brunori G., Fastelli L., Rovai M. (2013). Understanding the participation in agri-environmental schemes: evidences from Tuscany Region, 53rd ERSA conference: "Regional integration: Europe, the Mediterranean and the World economy", Palermo, Italy.

Bell K.P., Dalton T.J. (2007). Spatial Economic Analysis in Data-Rich Environments, *Journal of Agricultural Economics* 58, 487-501.

Borsotto P., Henke R., Macrì M.C., Salvioni C. (2008). Participation in rural landscape conservation schemes in Italy, *Landscape Research* 33(3), 347-363.

Brady M., Irwin E. (2011). Accounting for Spatial Effects in Economic Models of Land Use: Recent Developments and Challenges Ahead, *Environmental and Resource Economics* 48, 487-509.

Broch S.W., Strange N., Jacobsen J.B., Wilson K.A. (2013). Farmers' willingness to provide ecosystem services and effects of their spatial distribution, *Ecological Economics* 92, 78-86

Baumgart-Getz A., Prokopy L., Floress K.. (2012). Why Farmers Adopt Best Management Practice in the United States: A Meta-analysis of the Adoption Literature, *Journal of Environmental Management* 96,17-25.

Capitanio F., Adinolfi F., Malorgio G. (2011). What explains farmers' participation in rural development policy in italian southern region? an empirical analysis, *New Medit* 10(4), 19-24.

Christensen T., Pedersen A.B., Nielsen H.O., Morkbak M.R., Hasler B., Denver S. (2011). Determinants of farmers' willingness to participate in subsidy schemes for pesticide-free buffer zones-A choice experiment study, *Ecological Economics* 70(8), 1558-1564.

Coisnon T., Oueslati W. Salanié J. (2014). Spatial Targeting of agri-environmental policy and urban development. Ecological Economics,101: 33-42.

Cook D.O., Kieschnick, R., McCullough B.D. (2008) Regression analysis of proportions in finance with self selection. *Journal of Empirical Finance* **15**, 860-867.

Defrancesco E., Gatto P., Runge F., Trestini S. (2008). Factors Affecting Farmers' Participation in Agri-environmental Measures: A Northern Italian Perspective, *Journal of Agricultural Economics* 59, 114-31.

Ferrrari S., Cribari-Neto F.(2004) Beta regression for modeling rates and proportions. *Journal of Applied Statistics*. **31**, 799-815.

Kieschnick R., McCullough B.D. (2003) Regression analysis of variates observed on (0, 1): percentages, proportions and fractions, *Statistical Modelling*, **3**, 193-213.

Hynes S., Garvey E. (2009). Modelling farmers' participation in an agri-environmental scheme using panel data: An application to the rural environment protection scheme in Ireland, *Journal of Agricultural Economics* 60(3), 546-562.

Jongeneel R.A., Polman N.B.P., Slangen L.H.G. (2008). Why are Dutch farmers going multifunctional? *Land Use Policy* 25(1), 81-94.

Knowler D., Bradshaw B.. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research, *Food Policy* 32, 25-48.

Lapple D., Kelley H. (2013). Understanding the uptake of organic farming: Accounting for heterogeneities among Irish farmers, *Ecological Economics* 88, 11-9.

Lesage J.P., Pace R.K. (2009). *Introduction to Spatial Econometrics*. Chapman and Hall/CRC.

Morris C., Potter C. (1995) Recruiting the New Conservationists: Farmers' Adoption of Agri-environmental Schemes in the U.K, *Journal of Rural Studies* 11, 51-63.

Long J.S. (1997). Regression Models for Categorical and Limited Dependent Variables. Sage Publishing.

Madddala G.S. (1991) A perspective on the use of limited-dependent and qualitative variables models in accounting research. *Accounting Review*, **66 (4),** 788-807.

Papke L.E., Wooldridge J.M. (1996) Econometric Methods for Fractional Response Variables with an Application to 401(k) Plan Participation Rates. *Journal of Applied Econometrics*, **11(6),** 619-632.

Pascucci, S., T. de-Magistris, L. Dries, F. Adinolfi, and F. Capitanio. 2013. "Participation of Italian Farmers in Rural Development Policy." *European Review of Agricultural Economics* 40 (4). Oxford University Press: 605–31. doi:10.1093/erae/jbt005.

Peerlings J., Polman N. (2009) Farm choice between agri-environmental contracts in the European Union, *Journal of Environmental Planning and Management* 52(5), 593-612.

Ruto E., Garrod G. (2009). Investigating farmers' preferences for the design of agri-environment schemes: a choice experiment approach, *Journal of Environmental Planning and Management* 52

Schmidtner E., Lippert C., Engler B., Haring A.M., Aurbacher J., Dabbert S. (2012) Spatial distribution of organic farming in Germany: does neighbourhood matter?, *European Review of Agricultural Economics* 39, 661-83.

Uthes, Sandra, Bettina Matzdorf, Klaus Müller, and Harald Kaechele. 2010. "Spatial Targeting of Agri-Environmental Measures: Cost-Effectiveness and Distributional Consequences." *Environmental Management* 46 (3): 494–509. doi:10.1007/s00267-010-9518-y.

Uthes S., Matzdorf B. (2013). Studies on Agri-environmental Measures: A Survey of the Literature, *Environmental Management* 51, 251-66.

Vanslembrouck I., Van Huylenbroeck G., Verbeke W. (2002) Determinants of the Willingness of Belgian Farmers to Participate in Agri-environmental Measures, *Journal of Agricultural Economics* 53 (3), 489-511.

Vatn A. (2010). An insitutional analysis of payments for environmental services. Ecological Economics, 6: 1245-1252.

Yang, Anastasia L, Mark D A Rounsevell, Ronald M Wilson, and Claire Haggett. 2014. "Spatial Analysis of Agri-Environmental Policy Uptake and Expenditure in Scotland." *Journal of Environmental Management* 133 (January): 104–15. doi:10.1016/j.jenvman.2013.11.038.

Wauters E., Bielders C., Poesen J., Govers G., Mathijs E. (2010) Adoption of soil conservation practices in Belgium: An examination of the theory of planned behaviour in the agri-environmental domain, *Land Use Policy* 27 (1), 86-94.

Appendix A - Descriptive statistics for dependent and independent variables

Table A.1 Descriptive statistics of independent variables (n=341)

Code	Description	Mean	Sd	min	max
PREFASS	1 for location in area with absolute preference 0 else	0.31	0.46	0	1
PREFIDRO	1 for location in prefered area for water protection 0 else	0.31	0.46	0	1
PREFNAT	1 for location in prefered area for nature protection 0 else	0.25	0.43	0	1
PREFPAE	1 for location in prefered area for landscape protection 0 else	0.18	0.38	0	1
PREFSUOLO	1 for location in prefered area for sol protection 0 else	0.36	0.48	0	1
PLAIN	1 for location in plain 0 else	0.50	0.50	0	1
HILL	1 for location in hill 0 else	0.22	0.41	0	1
MOUNTAINT	1 for location in mountain 0 else	0.28	0.45	0	1
DENS_AB	Density of in-habitants (n. per square Km)	219.3	318.2	3.9	2793.8
COND_DIR	Percentage of farms directly conducted by farmers	91.0	8.5	8.8	100
ONLY_HHLAB	Percentage of farms that used only household labour on-farm	82.0	12.1	47.7	100
ARABLE	Percentage of farms with arable crops	73.6	20.6	0	100
FRUIT	Percentage of farms with fruit crops	22.5	22.3	0	94.1
GRAZING	Percentage of farms with grazing	26.5	30.1	0	100
FOREST	Percentage of farm with forest	38.9	39.2	0	100
LIVESTOCK	Percentage of farm with livestock	14.5	11.7	0	67.1
YOUNG	Percentage of farms youger than 40 years old	8.8	3.4	0.8	21.2
AGE_MORE65	Percentage of farms older than 65 years old	38.2	8.0	18.0	63.4
PARTIME	Percentage of part-time farming	58.6	13.9	24.6	95.1

Table A.2: Descriptive statistics for dependent variables (percent of funded farms over the total number of farms in each municipality) (n=341)

	Mean	**sd**	**min**	**max**
All 214	8.4675	10.2610	0	100
Sub-measure 1 (integrated production)	1.0234	2.5388	0	23.2560
Sub-measure 2 (organic farming)	4.8410	7.0432	0	46.6256
Sub-measure 8 (Meadows and grazing payments)	2.3380	6.4744	0	100

Table 1 – Regional Cartography used for the management of axis 2 in RDP 2007-2013

Type of protection	**Sub-measures involved**	**Description**	**Variable in the model**
Absolute	All	Natura 2000 network Area vulnerable to nitrates	PREFASS
Water protection	1 – 2 – 3 – 8 – 9 – 10	Protected area for environmental characteristics of lakes, basins and streams. Protected area for superficial and subterranean water bodies. Area of protected water for human consumption. Protected area for subterranean water in foothills and plains. Protected area for subterranean water in hills and mountains. Hydrologic pertinence of drainage canals.	PREFIDRO
Nature protection	1 – 2– 8 – 9 – 10	Parks and reserves Nature protection area Faunal areas (Fauna hunting farms – Faunal Protection Oasis– Faunal production centres) Ecological network.	PREFNAT
Landscape protection	8 – 9 – 10	Area of particular landscape-environmental interest	PREFPAE
Soil protection	3 - 8	Risk of erosion	PREFSUOLO

Table 2: Marginal effects (dy/dx) on the participation rates considering a fractional logit at 0 for all priority (PREF) variables

Variable	**All 214**	**214-sub-measure 1**	**214-sub-measure 2**	**214-sub-measure 8**
PREFASS[1]	**0.050499*** **	**0.005319** **	0.008572	**0.008212*** **
PREFIDRO[1]	-0.007162	0.000657	-0.00578	0.000943
PREFNAT[1]	-0.007211	**-0.001149* **	**-0.013222*** **	**0.006435*** **
PREFPAE[1]	0.008466	-0.000215	0.008930	-0.000035
PREFSUOLO[1]	0.000799	0.000792	-0.004939	0.001883
PLAIN[2]	**-**	-	**-**	-
HILL[1]	0.018806	0.000863	**0.045055*** **	-0.001324
MOUNTAIN[1]	0.026961	**-0.003223* **	**0.040369** **	-0.000382
DENS_AB	**-0.000038** **	**-7.53e-06** **	**-0.000019* **	1.45e-06
COND_DIR	-0.000311	-0.000033	-0.000422	-0.000022
ONLY_HHLAB	0.000769	0.000073*	0.000327	0.000056
ARABLE	**-0.000432** **	**-0.000068** **	-0.000043	**-0.000079*** **
FRUIT	0.000179	-0.000024	**0.000207** **	5.88e-06
GRAZING	-0.00009	0.000021	**-0.000181* **	**0.000035* **
FOREST	**0.000509*** **	-0.000045*	**0.000520*** **	0.000048
LIVESTOCK	0.000427	**-0.000205*** **	**0.000495** **	**0.000189*** **
YOUNG	0.001292	0.000073	-0.000212	0.000076
AGE_MORE65	0.000441	0.000016	-0.000024	**0.000114* **
PARTIME	-0.000325	**-0.000109*** **	0.000062	0.000065
AIC	0.499864	0.1909676	0.367849	0.250077
BIC	-1860.505	-1871.98	-1865.047	-1871.18
Log pseudolikelihood	-66.226837	-13.559979	-43.718228	-23.638161

Note: Single, double, and triple asterisks indicate significance at the 10, 5, and 1 percent level of significance.

[1] dy/dx is for discrete change of dummy variable from 0 to 1

[2] Omitted because of collinearity

Table 3: Marginal effects (dy/dx) on the participation rates considering spatial lag fractional logit model at 0 for all priority (PREF) variables

Variable	**All 214**	**214-sub-measure 1**	**214-sub-measure 2**	**214-sub-measure 8**
PREFASS[1]	**0.041543*** **	0.003342	0.007154	**0.006159** **
PREFIDRO[1]	-0.005907	0.001345	-0.004603	0.001409
PREFNAT[1]	-0.003598	**-0.001517** **	**-0.010758** **	**0.005426*** **
PREFPAE[1]	0.008704	-0.000514	0.008873	0.000125
PREFSUOLO[1]	0.000781	0.000265	-0.00470	0.001658
PLAIN[2]	-	-	-	-
HILL[1]	0.013202	0.002079	**0.035639** **	-0.001151
MOUNTAIN[1]	0.015301	-0.003113	**0.027314***	-0.000449
DENS_AB	**-0.000035** **	**-7.23e-06*** **	**-0.000021***	1.68e-06
COND_DIR	-0.000169	-0.000033	-0.000426	0.000050
ONLY_HHLAB	**0.000669** **	0.000040	0.000313	0.000041
ARABLE	**-0.000489*** **	**-0.000068*** **	-0.000083	**-0.000101*** **
FRUIT	0.000141	-0.000034	0.000157	0.000011
GRAZING	-0.000085	0.000023	-0.000154	0.000019
FOREST	**0.000413** **	**-0.000048***	**0.000449*** **	0.000042
LIVESTOCK	0.000346	**-0.000209*** **	0.000348	**0.000193*** **
YOUNG	0.001488	0.000088	0.000124	0.000017
AGE_MORE65	0.000189	0.000038	-0.000096	0.000018
PARTIME	-0.000217	**-0.000088***	0.000098	0.000069
SPATIAL LAG (rho)	**0.030635*** **	**0.009629** **	**0.022605** **	**0.011308*** **
AIC	0.503499	0.201893	0.372468	0.254488
BIC	-1855.434	-1860.591	-1859.64	-1865.844
Log pseudolikelihood	-65.846529	-13.422793	-43.505862	-23.390219

Note: Single, double, and triple asterisks indicate significance at the 10, 5, and 1 percent level of significance.

[1] dy/dx is for discrete change of dummy variable from 0 to 1

[2] Omitted because of collinearity

Table 4: Variation of marginal effects of priority variables on the participation rates in the spatial lag fractional logit model (marginal value for values=0 minus marginal value for values=1; all other explanatory variables have value equal to the average)

Priority variable	**All 214**	**214-sub-measure 1**	**214-sub-measure 2**	**214-sub-measure 8**
PREFASS	**0.000777*** **	0.001076	0.002856	**-0.013919** **
PREFIDRO	0.005145	0.000032	-0.000583	-0.006277
PREFNAT	0.002849	**0.002487** **	**0.001564** **	**-0.013434*** **
PREFPAE	-0.004027	0.000336	0.003774	-0.000707
PREFSUOLO	-0.000515	-0.000075	-0.000579	-0.007078

Figure 1: Exemplary illustration of selection process (stars, square dots and circles refer to different hypothetical populations with different distributions)

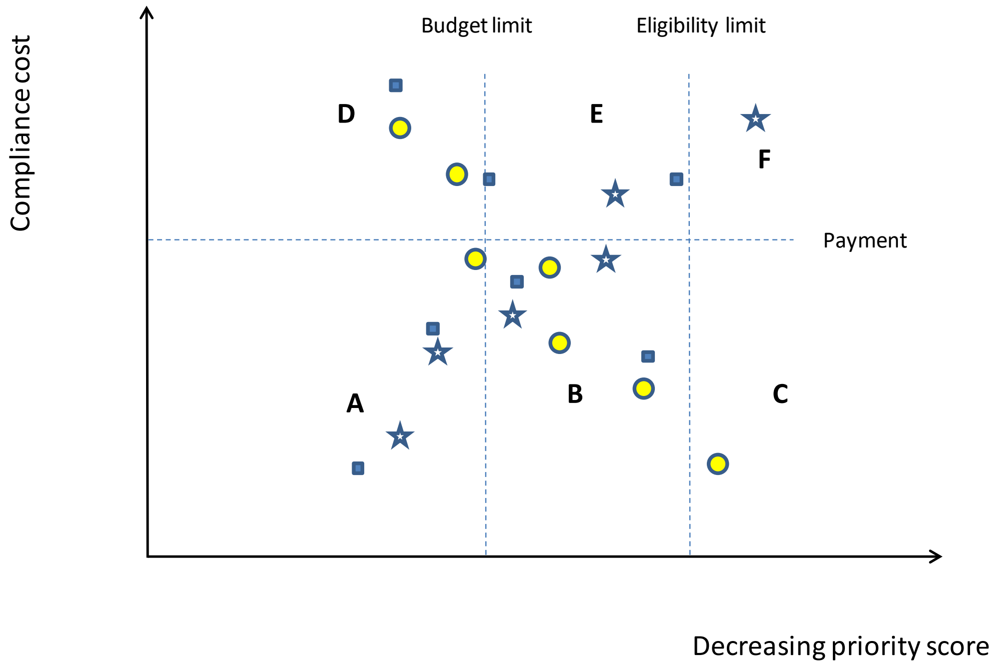

Figure 2: Spatial distribution for measure 214 and sub-measures

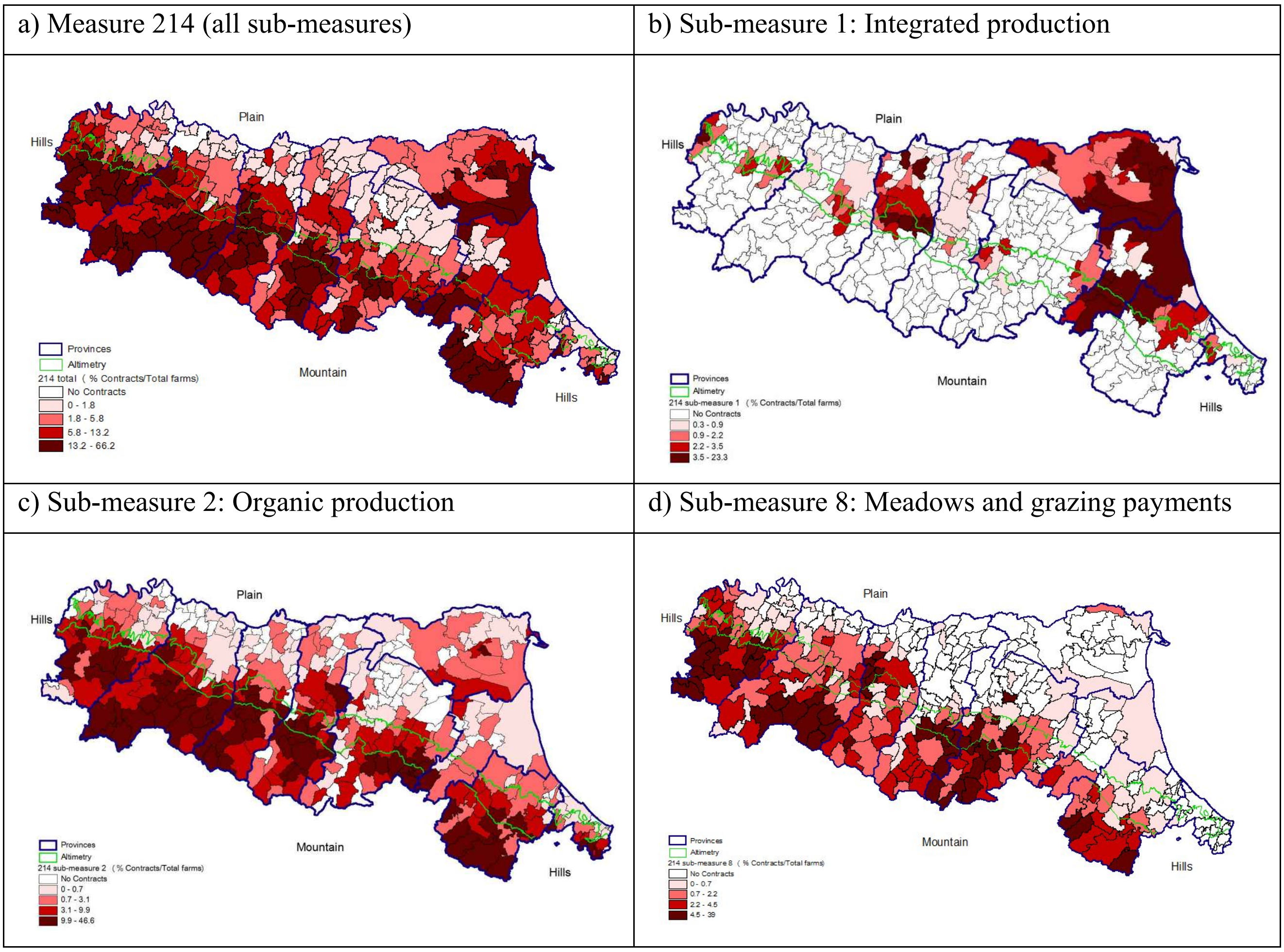

Figure 3: LISA Cluster Map and Moran's I for measure 214 (all sub-measures)

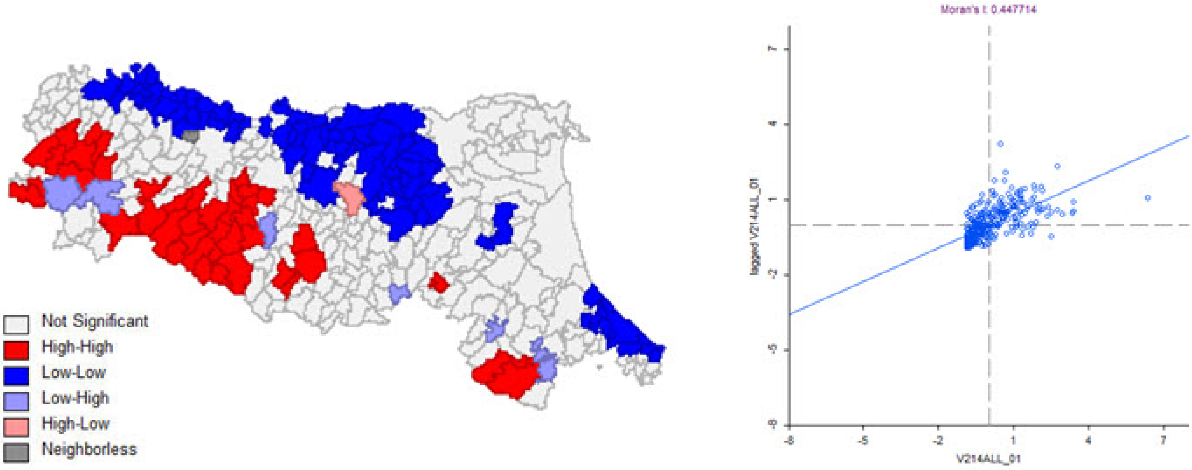

Figure 4: LISA Cluster Map and Moran's I for measure 214 (sub-measure 1)

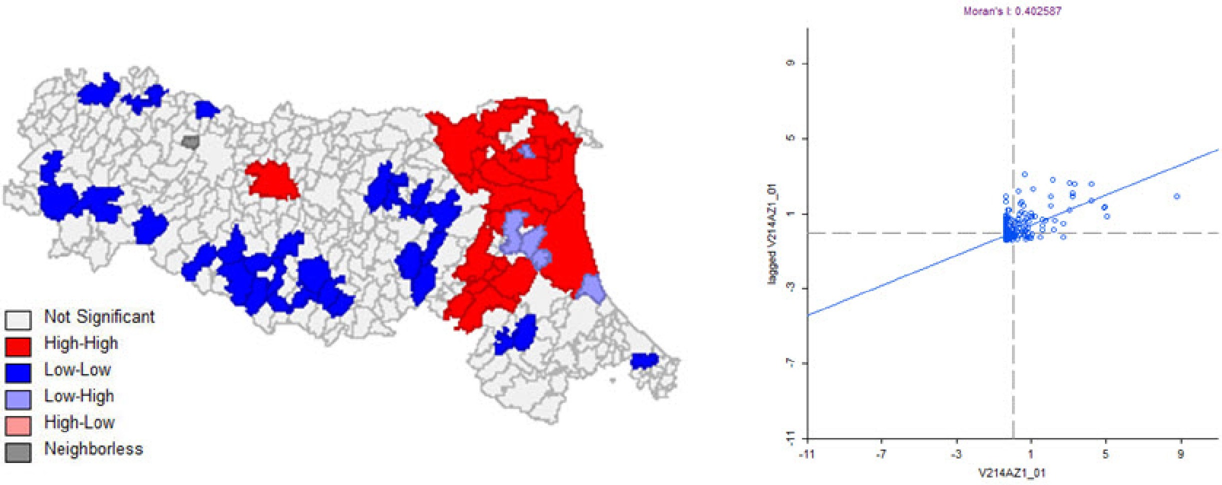

Figure 5: LISA Cluster Map and Moran's I for measure 214 (sub-measure 2)

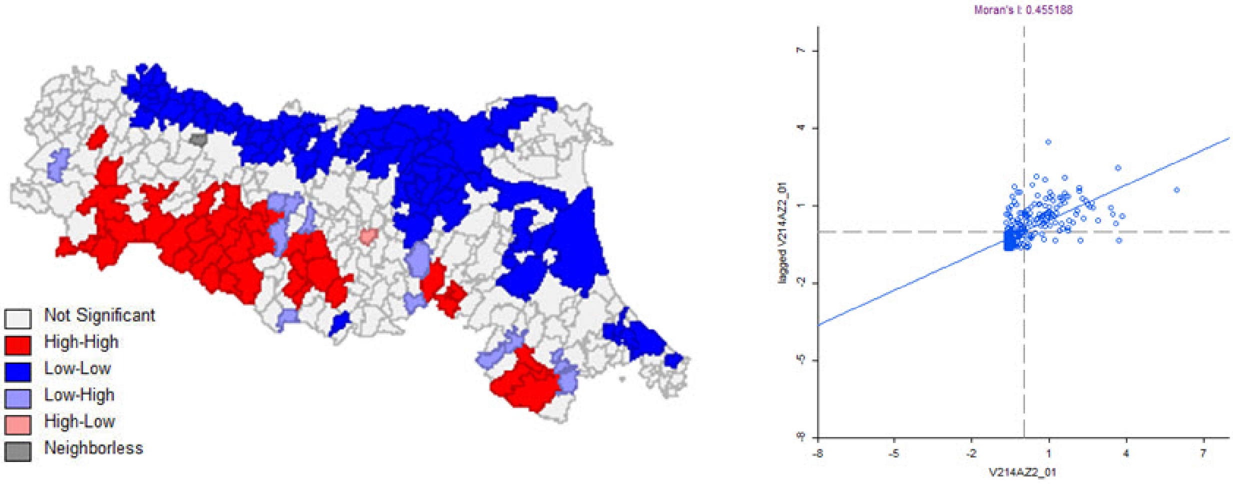

Figure 6: LISA Cluster Map and Moran's I for measure 214 (sub-measure 8)