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Regional uptake of environmentally focused rural development measures in Bulgaria

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Abstract

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The public rural development measures that have a direct focus on the environment are Agri-environment and climate, Organic Farming and Natura 2000 compensatory payments measures. Their success and environmental effectiveness depend on the voluntary uptake by farmers. There are numerous studies assessing the factors influencing participation uptake in environmental measures but very few of them are done in the new member states of the European Union. The objective of this paper is to explore the factors that influence the spatial uptake of environmentally focused area-based measures under the Bulgarian Rural Development Programme (RDP) in the period 2014-2020 and whether there is spatial dependence of the uptake at the level of administrative districts (NUTS III level). Spatial statistics methods are applied. The results indicate lack of spatial dependence in the uptake at this administrative level. The most significant factors determining environmental measures uptake are the total sum of RDP environmental support they receive, the area of permanent pastures in the region and the rent price of agricultural land. Availability of labour and human capital is also important factors for the uptake in Bulgaria. The study identifies also between-measures differences of uptake, which deserve further exploration.

Keywords: spatial regression; agri-environment; Natura 2000; organic farming; CAP support; area-based measures

Introduction

The initiative to improve the impacts between agriculture and environment within the Common Agricultural Policy (CAP) dates back to mid-1980s, when the term “greening” of the CAP was used for the first time (Buller et al., 2000; Retter 2000). The public policy and its instruments that support environmentally friendly forms of farming have evolved since then and as of 1992 are referred to as agri-environment. Evans and Morris (1997) identify two aspects that define the territorial impact of agri-environmental measures – the geographical focus and the level of participation by farmers. The first aspect relates to measures’ design – if the geographical scope is limited to designate areas, only farmers from these areas can apply. On the other hand, if the geographical scope is national, farmers from any territory can apply. Juvancic et al. (2012) indicate that the national scope of agri-environmental measures may increase farmers’ participation but may also dilute the environmental impact due to lack of spatial targeting.

On the other hand, farmers’ participation in the measures is voluntary and even the best territorial focus may be undermined by the lack of interest and uptake by farmers. There are various factors that influence the uptake of environmental measures and an underlying assumption that farmers operate principally under economic motivations (Herzon & Mikk, 2007; Krom, 2017; Siebert et al., 2006; Stoeva, 2016). The financial incentive is only one of the factors that influence farmers' participation (Krom, 2017; Lastra-Bravo et al., 2015; Siebert et al., 2006) but "among the most important in the complex set of factors" (Georgieva, 2017).

Other factors influencing uptake often relate to the measure's design (Defrancesco et al., 2018). For example, farmers consider the five or seven-year commitment of agri-environmental measures as a limitation to their freedom of choice of farm production practices (Burton et al., 2008). It becomes a particular challenge for the farmers in the new member states where the restitution of land ownership creates a dynamic land market and longer-term commitments are not preferred. The voluntary participation itself is a challenge for the environmental effectiveness of measures especially when the uptake is low or geographically dispersed (Evans and Morris, 1997).

Social factors such as influence by peers, cultural norms and social capital (Krom, 2017; Lastra-Bravo et al., 2015; Siebert et al., 2006), farmer's positive attitude towards the environment (Defrancesco et al., 2018; Raggi et al., 2015) as well as previous experience in agri-environmental schemes (Lastra-Bravo et al., 2015;Defrancesco et al., 2018) play a role in the uptake. Population density (Marconi et al., 2015; Boncinelli et al., 2016), higher labour density and availability of full time staff (Yang et al., 2013) are other socio-economic factors that are identified as important.

Farm characteristics such as farm size, location of farms, age and education level of farmers, farm successors, influence uptake in different member-states (Lastra-Bravo et al., 2015; Marconi et al., 2015; Defrancesco et al., 2018; Boncinelli et al., 2016). At the same time, other studies cannot identify "straight forward linkages between participation in agri-environmental schemes and farm size" (Juvancic et al., 2012).

Policy support factors are identified as positive determinants for participation in agri-environmental schemes – the number of farmers who already participate in other rural development measures (Boncinelli et al., 2016) or the received amounts of CAP Pillar I or Pillar II payments (Juvancic et al., 2012). Bachev & Terziev (2018) report that farmers assess their participation in environmental rural development measures as a positive contributor to their farm's sustainability.

The objective of this paper is to explore the factors that influence the spatial uptake of environmentally focused area-based measures under the Bulgarian Rural Development Programme (RDP) in the period 2014-2020 and to assess if there is spatial dependence of the uptake at the level of administrative districts (NUTS III level of the EUROSTAT statistical classification of territorial units). The motivations for the common assessment of the three environmentally-focused measures comprise: (1) all of them are area-based, meaning that the interest is on the agricultural land and payments are made per hectare of land; (2) all of them require certain environmental actions to be taken on the land, so that payment is received; (3) the regions in which they are most likely to be implemented are with low intensity and low-yields production systems, grasslands tend to be more important than arable land, with likely presence of nature conservation areas and likely socio-economic constraints to intensification (Schmidtner et al., 2012; Oppermann & Parachini, 2012; Jones & Poux, 2012; Lastra-Bravo et al., 2015; Gabriel et al., 2009).

Materials and Methods

Exploratory spatial data analysis is used to investigate the spatial pattern of the uptake of environmentally focused rural development measures and spatial regression methods are applied to identify the factors that explain the uptake (Anselin, 2010; Getis, 1999; Fotheringham et al., 1998).

The methodology comprises two steps. In the first step, the district level uptake of the measures is mapped to visualise its spatial distribution. Global Moran's I indicator for spatial autocorrelation is used to assess whether the global spatial distribution of the environmental measures' uptake is clustered, dispersed or random. Local Moran's I indicator is used to assess the uptake in a given district in comparison to the uptake in its neighbouring districts (Anselin, 1995). It can identify clusters of objects (districts) with high or low values of the independent variable; outliers with low values surrounded by objects (districts) with high value; or outliers with high values surrounded by objects with low values.

Spatial weights matrix (SWM) is generated, which represents the spatial relations between the objects (districts). It is used for the computation of Global Moran's I indicator and in the geographically weighted regression. The criteria used for generating the SWM are Contiguity-Edge-Corners whereby the polygon objects are neighbours when they share common edges and/or corners. Row standardisation of weights is also applied in order to create proportional weights in the cases where the objects (districts) have different number of neighbouring districts.

In the second step, spatial regression model (Anselin, 2010; Getis, 1999; Fotheringham et al., 1998) is used to identify the factors that explain the uptake of the environmental rural development measures. It starts with Exploratory Spatial Regression that uses the Ordinary Least Squares (OLS) method to assess the range of reliable models (ESRI, 2017; Wang, 2015) that explain the uptake of environmentally focused measures. The criteria used for the selection of reliable models are summarised in Table 1.

Table 1. Criteria used for the identification of reliable models in *Exploratory Regression* tool, *ArcMap*10.5

Search criteria	Threshold values
Maximum number of explanatory variables	10
Minimum number of explanatory variables	1
Minimum acceptable *Adjusted* R^2 value	0.5
Maximum Coefficient *p-value* cut-off	0.05
Maximum *VIF* value cut-off	7.5
Minimum acceptable *Jarque Bera p-value*	0.1
Minimum acceptable *Spatial Autocorrelation p-value*	0.1

The spatial variations at district level are assessed using the Geographically Weighted Regression (GWR), which is one of the best approaches for spatial analysis of socio-economic data (Anselin, 2010). The regression equation [1] in the GWR method allows the coefficients to vary in the different locations (districts) by calculating it separately for each location (object) (Brunsdon et al., 1996; Fotheringham et al., 1998). It is presented (Lu et al., 2014) as:

$$y_i = \beta_{i0} + \sum_{(k=1)}^{m} \beta_{ik} x_{ik} + \varepsilon_i, \quad (1)$$

where y_i is the dependent variable at location (object) i; x_{ik} is the independent variable k at location (object) i; m is the number of independent variables; β_{i0} is the intercept parameter at location (object) i; β_{ik} is the local regression coefficient of the independent variable k at location (object) i; and ε_i is the random error at location (object) i.

The analysis is performed in the Spatial Statistics Toolbox of ArcMap 10.5 (ESRI, 2017). The goodness of fit measure for OLS method is *Adjusted* R^2 – the higher the value, the better the set of explanatory variables explain the independent variable. The goodness of fit measure for the GWR method is the *corrected Akaike Information Criterion (AICc)* (Charlton & Fotheringham, 2009; Hurvich & Tsai, 1989), where smaller values indicate smaller information distance between the true model and the fitted model.

The spatial level of the analysis is administrative district, NUTS III level. The reasons are the following: first, this is the regional level at which policy traditionally is implemented in the country and which is recognised by society. Second, most of the relevant territorial, socio-economic and policy support data is published at this regional level.

The uptake of the environmentally-friendly rural development measures at district level represents the dependent variable in the model. It is based on the district-level uptake of the agri-environment and climate measure, organic farming measure and the measure for the compensatory payments for agricultural land in Natura 2000 areas, thus covering the entire population of beneficiaries. It is calculated using the following formula [2]:

$$\mathrm{Yd} = \sum_{d=1}^{z} \left(\sum_{j=1}^{a} YAE_{dj} + \sum_{k=1}^{b} YOF_{dk} + \sum_{i=1}^{c} YN2K_{di} \right), \quad (2)$$

where Y_d is the value of the dependent variable in district d; z is the number of districts in Bulgaria; YAE_{dj} is the uptake of agri-environmental scheme j in district d; a is the number of schemes under the Agri-environment and climate measure; YOF_{dk} is the uptake of organic farming scheme k in district d; b is the number of schemes under measure Organic Farming; $YN2K_{di}$ is the uptake of action i under the Natura 2000 compensatory measure in district d; and c is the number of actions under the Natura 2000 compensatory measure.

The uptake data for the three measures is for year 2017. The motivation for using 2017 data comprise: (1) this is the last year of which data is publicly available at the time of the analysis; (2) two of the measures – Agri-environment and Organic farming are implemented in five-year commitments and 2017 is in the middle of the 2014-2020 programming period. Thus, the 2017 uptake covers commitments both from the previous programming period (starting in 2013, lasting until 2018) and from the current programming period. The uptake data is retrieved from the online database for the beneficiaries of CAP support maintained by State Fund Agriculture/Paying Agency[1].

The list of candidate explanatory (independent) variables is organised in three groups – socio-economic characteristics of the districts; natural and territorial characteristics, and policy support data.

All data for the model is secondary, and is collected from several official sources. The National Statistics Institute (NSI, 2017) data at regional level is about the socio-economic and demographic characteristics of the districts – population in working and in above-working age, unemployed people, population density, gross value added from agriculture sector, as well as the selling and rent price of the agriculture land. The Land Parcel Identification System (LPIS) maintained by the Ministry of Agriculture[2]is used for three categories of agricultural land, eligible for CAP support in 2017 – arable land, permanent pastures and mixed land use. The Agriculture Census data (2012) is used for farms in size groups 1-10 ha and 10-50 ha, farms with access to water sources, age of farm workers. The public register of the CAP support beneficiaries maintained by the State Fund Agriculture is used for the calculation of the number of beneficiaries of the main CAP support scheme – Single area-based payment (SAPS), average size of the farms supported under SAPS, the total amount and the

[1] http://www.dfz.bg/

[2] http://www.mzh.government.bg/

average size of the support for the environmentally focused measures under the RDP. Google Maps[3] was used for the calculation of the distance in kilometres between the district administrative centres and the capital city.

Results and Discussion

Uptake of environmentally focused rural development measures in 2017

The uptake of environmentally focused rural development measures at national level reveals that Natura 2000 compensatory measure has the highest number of beneficiaries (Table 2). Its uptake is higher than the sum of uptakes of the Agri-environment and Organic farming measures. The focus of the current study is the total uptake of all three environmentally focused measures; however, the results suggest that a detailed assessment of between-measures differences is necessary. From a territorial perspective, Natura 2000 compensatory measure can only be implemented in designated Natura 2000 zones – 119 Special Protected Areas for wild birds (22.7% of the national territory), while most of the Agri-environmental schemes and the Organic farming measure can be applied in any part of the country. The explanations of this difference comprise: (1) the annual commitment of the Natura 2000 compensatory measure are preferred in comparison to the multi-annual commitment of the other two measure; (2) the image of Natura 2000 measure as an "easier" measure among farmers and local agriculture administration; (3) the restriction for applicants with permanent pastures in Natura 2000 zones to apply only for the Natura 2000 compensatory measure and not for the High Nature Value grasslands scheme under the Agri-environment and climate measure; (4) the full commitment of the budgets of Agri-environment and Organic farming measures which prevented more farmers to apply for them, etc.

Table 2. Uptake of the nature-friendly RDP measures at national level in 2017

RDP code	Measure	Number of beneficiaries*
10	Agri-environment and climate	6169
11	Organic Farming	4031
12	Natura 2000 compensatory payments	10710
	Total	20910

Source: Own calculation based on data from the CAP beneficiaries register (http://www.dfz.bg/). Accessed on 3 July 2018

* Some beneficiaries may implement more than one scheme or more than one measure, therefore the number of farms implementing nature-friendly measures is lower

[3] https://www.google.com/maps/

Global and local spatial patterns of the environmentally focused measure's uptake

The spatial distribution of the uptake of the environmentally focused rural development measures in 2017 is presented in Figure 1. The values represent the number of beneficiaries per schemes under each measure and not the number of farms, thus some farms may implement more than one scheme and more than one measure. The districts with the highest uptake are Sofia-district (2172), Sliven (1507), Silistra (1467), Haskovo (1414), and Burgas (1277). The lowest uptake is registered in Gabrovo (145), proceeded by Pernik (199), Vidin (203), Montana (227) and Kyustendil (243).

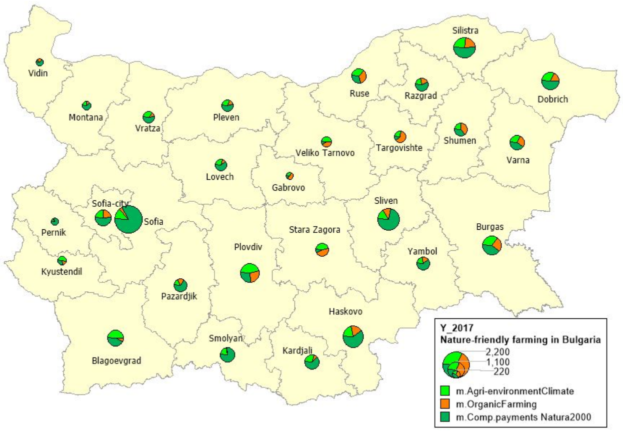

Fig. 1. District-level uptake of the environmentally focused rural development measures in Bulgaria, 2017

Source: Own calculation based on data from the CAP beneficiaries register (http://www.dfz.bg/). Accessed on 3 July 2018

The Global Moran's I index -0.04 (p-value = 0.96; z-score = -0.04) indicates a random global spatial pattern of the uptake of environmentally focused measures in Bulgaria, meaning that the uptake of the measures in one district is not influenced by their uptake in other districts. The Local Moran's I index indicates two districts (Pazardjik and Yambol, not neighbours) as outliers with low values of the uptake surrounded by districts with high values of the uptake. The results differ from the literature about the spatial dependency of participation in agri-environmental or organic farming schemes, where spatial clustering was observed (Yang et al., 2014; Boncinelli et al., 2015; Juvancic et al., 2012; Schmidtner et al., 2012). This difference could be due to the administrative level at which the analysis is carried out. Most of the studies that detect spatial clustering are carried out at the level of local administrative units (LAU) (Boncinelli et al., 2016; Yang et al., 2014; Juvancic et al., 2012). In Germany the analysis is performed at NUTS III level (Schmidtner et

Table 3. Reliable models with their explanatory variables and goodness-of-fit criteria

Models	Passing models according to the number of explanatory variables									
	1var.	2 var.	3 var.	4 var.	5 var.	6 var.	7 var.	8 var.	9 var.	10var.
Number of models passing the criteria	0	5	9	10	19	29	19	15	10	2
Model with max *Adjusted* R^2		0.65	0.65	0.71	0.75	0.80	0.82	0.86	0.82	0.72
AICc		402.4	403.8	400.8	399.3	395.9	395.9	391.5	403.5	420.6
Territorial variables (TER)										
Permanent pastures				+**	+***	+**	+**	+***		
Arable land					–**	–***	–***			
Mixed land use										+***
Access to water sources										
Distance to capital								+***		+***
Socio-economic variables (S-EC)										
Population density								+***	+***	+***
Unemployed							+**	+***	+***	+**
People > work age										
Farm workers > 65 yrs								+***	+**	+***
Farm workers 25-34 yrs										
Farms 1 to 10 ha										
Farms 10 to 50 ha									–**	
Sell price of agri land										–**
Rent price of agri land				+**	+***	+***	+***	+***	+**	+***
GVA from agriculture								–***	–**	–***
Policy support variables (POL)										
Sum of support for environmental measures		+***	+***	+***	+***	+***	+***		+***	
Average support for environmental measures						–**	–***	–***	–***	–**
Number of SAPS beneficiaries			+***			+**	+**		+**	
Sum of SAPS support			–**							+**
Average size (ha) of SAPS support		–***		–***	–**					

Legend: +/– is the sign of the relationship between the explanatory variable and the independent variable.Levels of statistical significance: * p-value < 0.05; ** p-value < 0.01;*** p-value < 0.001.GVA – gross value added

al., 2012) and authors stress that the aggregation of data at the administrative level usually leads to loss of the diversity within the administrative unit.

The factors that determine the uptake of environmentally focused measures and the total number of reliable models respecting our criteria (118) are presented in Table 3. The explanatory variables included in the models differ depending on the number of variables as well as the values of the goodness-of-fit criteria (*Adjusted* R^2 and *AICc*). A summary of the variables' significance in all reliable models is presented in Table 4.

Explanatory power of the models depending on the number of variables in them

The analysis of the reliable models based on the number of explanatory variables in them reveals the factors that influence the uptake of environmentally focused measures in Bulgaria.

There are no passing models with one explanatory variable due to the set minimum level of *Adjusted* R^2 at 0.5. If we reduce it to 0.4, then there is one passing model with permanent pastures as the variable, which is able to explain 40% of the uptake of all environmentally focused measures in the country. It confirms the importance of permanent pastures and semi-natural vegetation for the uptake of agri-environmental schemes, organic farming practices and designated areas under protection (Schmidtner et al., 2012; Oppermann & Parachini, 2012; Jones & Poux, 2012; Lastra-Bravo et al., 2015; Gabriel et al., 2009).

However, the requirement for models with *Adjusted* $R^2 >= 0.5$ provides 118 passing reliable models (Table 3). The models with two or three variables are explained only by policy support variables – the total sum of support provided to environmentally focused measures (positive relationship in almost all models) and different combinations of the variables related to SAPS scheme support. This confirms findings from studies

Table 4. Explanatory variables' significance in the reliable models (share in all models)

Type	Variable	% Significant	% Negative	% Positive
POL	Sum of support for env. measures	88.44	0.36	99.64
TER	Permanent pastures	66.95	1.31	98.69
S-EC	Rent price of agri land	54.24	0.28	99.72
POL	Number of SAPS beneficiaries	37.56	0.57	99.43
POL	Average support for env. measures	35.10	75.20	24.80
TER	Mixed land use	27.80	22.73	77.27
TER	Distance to capital	23.51	21.93	78.07
S-EC	Population density	22.54	12.50	87.50
POL	Average size (ha) of SAPS support	18.11	89.33	10.67
TER	Arable land	15.50	76.78	23.22
POL	Sum of SAPS support	15.34	35.63	64.37
S-EC	People > work age	11.97	46.05	53.95
S-EC	Sell price of agri land	10.70	83.51	16.49
S-EC	Unemployed	10.11	3.51	96.49
TER	Access to water sources	8.37	30.10	69.90
S-EC	GVA from agriculture	7.78	84.08	15.92
S-EC	Farm workers >65 yrs	7.59	37.21	62.79
S-EC	Farms 1 to 10 ha	4.95	36.33	63.67
S-EC	Farm workers 25-34 yrs	4.80	53.63	46.37
S-EC	Farms 10 to 50 ha	3.02	54.53	45.47

Legend: Type POL – policy support variable; TER – territorial variables; S-EC – socio-economic variables.
GVA – gross value added

in both other member-states (Herzon & Mikk, 2007; Juvancic et al., 2012; Krom, 2017; Siebert et al., 2006) and Bulgaria (Bachev & Terziev, 2018; Georgieva, 2016) that financial aspects are primary motivator for farmers.

The models with four to seven variables, where the explanatory power of the models is increasing, are comprised again of policy support variables complemented by land use variables (permanent pastures – positive relationship and arable land-negative relationship) and price of land rent variable (positive relationship). It suggests that the farms' land assets (permanent pastures or arable land), the costs (land rent prices) and benefits (CAP support) explain a very large share (82%) of the uptake of environmental measures.

At the same time, the model with highest explanatory power (Adjusted $R^2 = 0.86$) and best fit (AICc = 391.5) is dominated by socio-economic and territorial variables and only one policy support variable (average support to environmental measures – negative relationship). One interpretation is that policy support is a big motivator for the uptake; however, the practical on-farm activities require people. Therefore, this best model includes three variables (positive relationships) related to human capital – population density (more people more potential workers), number of unemployed people (usually a source of seasonal labour), and farm workers above 65 years old (usually family members or seasonal workers). This corresponds to the findings of Bachev & Terziev (2018), Boncinelli et al. (2016), Marconi et al. (2015) and Yang et al. (2014) that the availability of labour and human capital is also important factor for the uptake of environmental rural development measures.

The model includes the variable for gross value added (GVA) from agriculture sector (negative relationship), suggesting that in regions where intensive and profitable agriculture exists, the uptake of environmental measures is less likely.

The increase of explanatory variables (nine or ten) in the models leads to decrease in the models' explanatory power and in the goodness-of-fit, despite their dominance by socio-economic and policy support variables.

Overall significance of the explanatory variables tested in the models

The three factors that are significant in more than half of the models with almost always positive relationships are the sum of support for environmental measures (policy support variable), the area of permanent pastures (territorial variable), and the rent price of agricultural land (economic variable) (Table 4).

The performance of the other two land use variables – arable land and mixed land use, deserves attention too. Arable land appears in three of the models presented in Table 3. It is

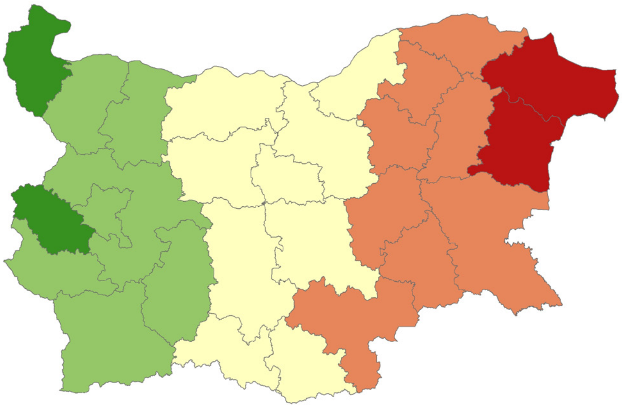

Fig. 2.1. Permanent pastures

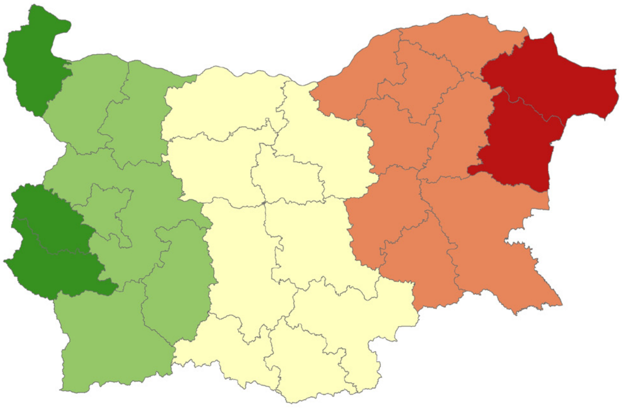

Fig. 2.2. Distance to capital city

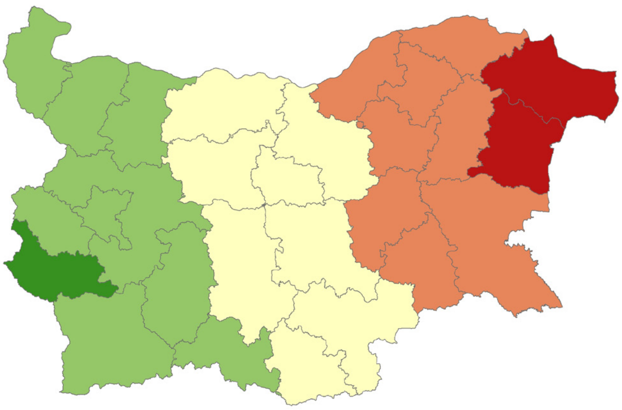

Fig. 2.3. Population density

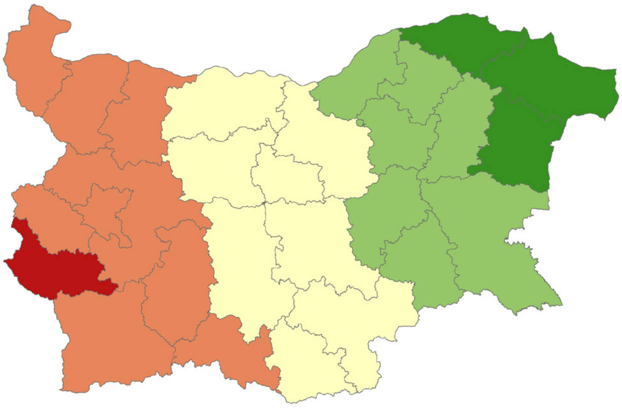

Fig. 2.4. Unemployed people

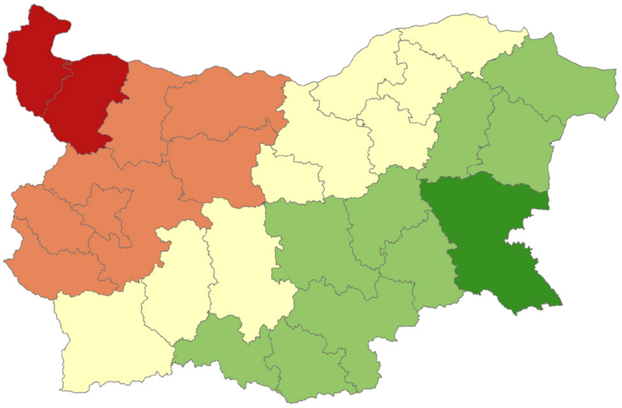

Fig. 2.5. Farm workers >65 yrs

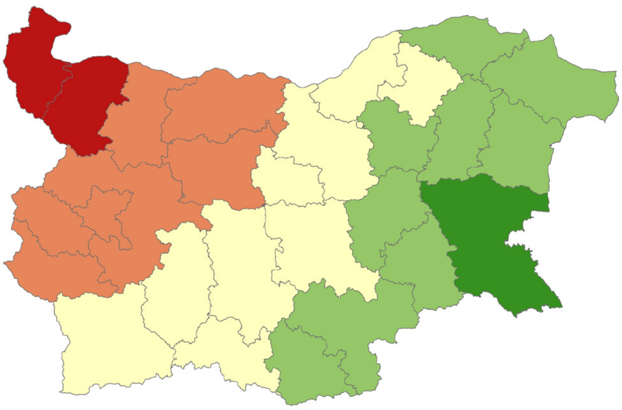

Fig. 2.6. Rent price of agri land

Fig. 2. Local (district) regression coefficients of the factors explaining the uptake of environmental measures
Legend: Local regression coefficients of the factors (presented in Standard Deviations); Dark green. 1.50 to 2.0 Std.Dev; Light green 0.50 to 1.50 Std.Dev; Yellow-0.50 to0.50 Std.Dev; Light red -1.50 to -0.50 Std.Dev; Dark red< -1.50 Std.Dev

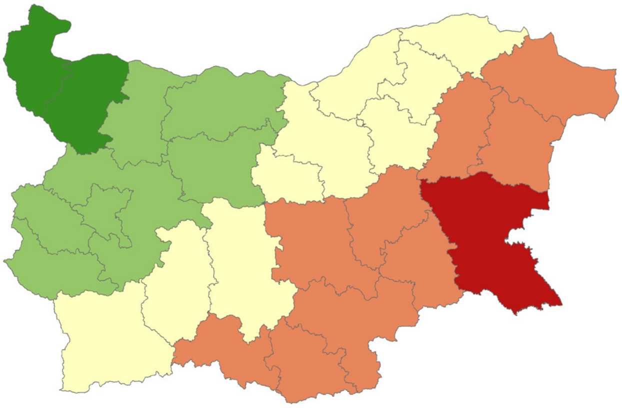

Fig. 2.7. GVA in agriculture

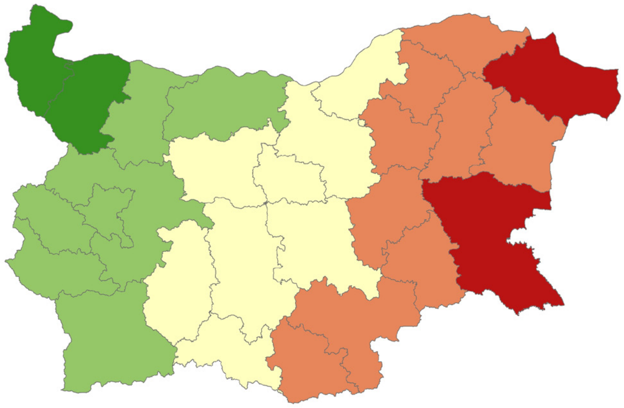

Fig. 2.8. Average support for environmental measures

Fig. 2. Continued

significant in only 15.5% of the models and the relationship with the uptake is mostly negative (in 76.78% of the models). The interpretation of the results is that the more arable land there is in the region, the fewer uptakes is expected. On the other hand, mixed land use appears in only one model in Table 3, but it is significant in 27.8% of all models. The relationship with uptake is mostly positive (in 77.27% of the models), interpreted as the more mixed land use there is in the region, the more likely the uptake increases.

Other factors with predominantly positive relationship, although with lower percentage of significance in models, are the number of SAPS beneficiaries (policy support variable), unemployed people (social variable) and population density (social variable). All three relate to the human capital in the region. The number of SAPS beneficiaries can also be interpreted as a proxy indicator for the number of market-oriented professional farmers in the region. Many of the subsistence and some of the semi-subsistence farmers in Bulgaria do not bother to deal with the administrative burden of registering their agricultural land for SAPS payments, especially if the areas they manage are less than 1 ha.

The factors that have predominantly negative relationship with the uptake of environmental measures are average size (ha) of SAPS support (policy support variable), GVA from agriculture (economic variable) and sell price of agricultural land (economic variable). The larger the average farm size and the more profitable agriculture is the less likely to participate in environmental measures. The negative relationship of the land sell price with the uptake of environmental measures is linked to some extent to GVA, but also can be interpreted as unwillingness of landowners to engage in longer term commitments.

The three factors that are least significant (in less than 5% of the models) are the farms with 1-10 ha, farms with 10-50 ha and farm workers 25-34 years of age. These socio-economic factors have varied relationships (positive-negative) in the different models. It relates to the finding by Juvancic et al. (2012) about the lack of direct link between farm size and participation in agri-environmental measures.

Spatial variation in the factors determining the uptake of environmental measures

The local (district) regression coefficients of the factors specifying the model with the highest explanatory (8 variables, *Adjusted* $R^2 = 0.86$, $AICc = 391.5$ in Table 3) are mapped for visualisation of their spatial variation (Figure 2).

The spatial variation in the regression coefficients is clearly in west-east direction (and vice versa) or in northwest-southeast direction (and vice versa). The factors that have higher importance (dark green and green colours) in the west and northwest part of the country are permanent pastures, population density and distance to capital city. The factors that have higher importance in the east and southeast are rent price of agricultural land, unemployed people and farm workers older than 65 years. The two factors with negative relationship, GVA in agriculture and average support for environmental measures, have similar spatial variation – they are stronger in the northwest districts.

Conclusions

This is the first study of regional uptake of environmental rural development measures in Bulgaria, which examines the factors explaining their spatial variation. The uptake of environmentally focused rural development measures in Bulgaria shows no spatial dependence at administrative district level (NUTS III), suggesting that the uptake in one district is not influenced by the uptake in neighbouring districts.

Overall, the most significant factors for the uptake of the three environmentally focused measures in Bulgaria are the total amount of the support under the measures, the area of permanent pastures and the rent price of agricultural land in the respective administrative districts. The use of GWR allows the identification of the spatial variation of the importance of the different factors. Thus, in the west and northwest districts in Bulgaria, permanent pastures and population density have higher importance for the uptake of environmental rural development measures, while in the east and southeast districts the factors with higher importance are the rent price of agricultural land and number of farm workers over 65 years. These findings can serve as an important tool in the design and implementation of environmentally focused rural development policy measures.

The study identifies between-measures differences of uptake (Agri-environmental, Organic farming and Natura 2000 measures), which deserve further exploration – would the factors determining uptake of the three environmental measures change in the assessment of individual measures uptake, would the spatial dependence change and in what way.

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