



Geographical Relationship between Ungulates, Human Pressure and Territory

Riccioli Francesco¹  · Boncinelli Fabio¹ · Fratini Roberto¹ · El Asmar Jean Pierre² · Casini Leonardo¹

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Abstract

Despite the fact that at the global level, half the planet's wildlife population has declined since 1970, this trend is not homogeneous across species and areas. Indeed, focusing on the ungulates, their increasing population and density has become worrisome in several rural areas. Favoured by economic and social changes often related to human activities, ungulates have conquered areas where coexistence with humans is difficult to maintain as a result of the damage that ungulates cause to agricultural activities and forests. This work aims to analyse the relationship between the number of ungulates and the characteristics of a specific area they inhabit. Applying a Geographically Weighted Regression analysis (GWR), we analysed and tested the spatial non-stationarity of the relationship between ungulates and human activities. Mugello, an area in central Italy, was selected for this study. This area was chosen due to the presence of a high number of ungulates that interact in different territorial scenarios, including urban agglomerations located in the flat zone, agricultural areas in the central-northern part and forested areas in the northern part of Mugello. This article looks at the way the number of ungulates is directly related to human activities in a specific territory. This contributes to the literature by providing useful information to stakeholders for future planning and wildlife management in agricultural areas within the limits of sustainability. Moreover, the social and economic implications are significant, especially considering such agricultural areas are at risk of being damaged by the presence of ungulates. The result of the analysis has validated the use of GWR, highlighting the relationship of selected variables and the number of ungulates.

Keywords GIS · Ungulates damage · Geographically weighted regression · Spatial non-stationary

✉ Riccioli Francesco
francesco.riccioli@unifi.it

¹ Department of Management of Agricultural, Food and Forestry Systems, University of Florence, Florence, Italy

² Faculty of Architecture Art and Design, Notre Dame University, Louaize, Lebanon

Introduction

Wildlife management is an important issue that can be analysed from different points of view. Various strategies are generally adopted to manage fauna. Some methods tend to safeguard wildlife by creating protected areas, while others aim to control the growing number of wild animals due to a tendency of some animal to alter the landscape and interact negatively with the economic activities (Jensen et al. 2014; Gill 1992; Clasen and Knoke 2013).

As reported by the World Wildlife Fund's report of 2016, at global level, half the planet's wildlife population has declined since 1970. Due to human activity, including exploitation and habitat degradation or loss, about 58% of the world's mammals, birds, reptiles, amphibians and fish have disappeared over the last four decades.

However, this trend is not homogeneous across species and areas. In fact, in the United States and in several western European countries, agricultural area abandonment, modern techniques of animal rearing and the decline of hunting activities have fostered the increasing population and concentration of a small part of wild animals represented by ungulates, such as wild boar and deer. The current article focuses on these wild animals because their increasing numbers (in opposition to global wildlife trends) have several damaging effects on agricultural and forestry activities.

Ungulate damages are often related to browsing on forest regeneration or the removal of bark (Fratini et al. 2016). As consequence, the density of ungulates in a territory where primary activities play an important role in local economies represents a crucial issue that deserves attention. Several authors have reviewed and estimated the economic impacts of ungulates (see, among others, Gill 1992; Gill and Beardall 2001; Horsley et al. 2003; Apollonio et al. 2011). In a south region of Italy (Basilicata) Cozzi et al. (2015) observed that between 2007 and 2012, the surface areas damaged by ungulates increased from 2800 to 5850 ha and as consequence the estimated compensations increased significantly from €550,000 up to €1,134,000. In North America, the US Department of Agriculture Wildlife Service (USDA 2012) reported in 2009 that the damage to agriculture, mainly due to the presence of wild boar and deer, was estimated at about \$71,000,000, mostly from lost revenue. Furthermore, during the same year, damages from road accidents due to animal crossings involved around 29,000 people, with a loss of about \$1,000,000,000.

Côté et al. (2004) have argued that the sustainable coexistence, without notable conflicts, on the same area of agricultural activities and wild animals is determined mainly by the numerical dimension of game populations that should not exceed the territory's carrying capacity. A sustainable coexistence between human activities (particularly those that shape the landscape) and the existing animal species is an important issue to be addressed. This requires analysing and redesigning new combinations that account for both wildlife territory and human activities through environmental planning.

The aim of this study is to analyse how human activities and environmental variables can influence the number of ungulates in a region. The usual regression techniques are not fit to analyse this issue because they assume that these relationships are constant across space. Therefore, we need an econometric model that implies the spatial non-stationarity (Brunsdon et al. 1998). Spatial non-stationarity is a condition in which we can observe a variability in space of the force of influence that the same

determinant has on a certain element or economic phenomenon. The model we applied to consider spatial non-stationarity is Geographically Weighted Regression (GWR). This model is able to depict the non-stationary process regarding the correlation between ungulates and human activities and tries to capture spatial variation by calibrating multiple regression models that allow different relationships to exist at different points in space. Therefore, GWR represents a tool that is able to analyse how the problem of this delicate relationship (ungulate population versus human activities) varies spatially. Moreover, investigating this topic is useful to formulate specific policies and, accordingly, more efficient planning choices. The analysis of non-stationary data may lead to a better understanding of these relationships and their variations across space.

We applied the GWR model to data related to the Mugello, a region in northern Tuscany, in Italy. The evolution of the population of the ungulates is one of the most remarkable changes in the Italian fauna in recent decades. The deep socio-economic, cultural and regulatory changes that have taken place since the middle of the last century have led to favourable conditions for a progressive “reconquest” of old areas by ungulates. During the decade 2000–2010 in Italy, the number of ungulates (deer, roe deer, ibex, mouflon) has increased over 32% (ISPRA 2013) making their coexistence with humans difficult to manage. Mugello is a good case study for the peculiar features of this area that suit the issue under investigation, i.e., the presence of a high number of ungulates that interact in different territorial scenarios, including urban agglomerations located in the flat zone, agricultural areas in the central-northern part and forested areas in the northern part of Mugello.

The paper is organized as follows. A definition of the GWR model is provided in section 2. Section 3 introduces the area of study. An application of the proposed model is illustrated in section 4, while section 5 discusses ensuing results. Finally, section 6 is dedicated to conclusions.

The Definition of GWR

The basic statistical tool used to investigate relationships between landscape patterns and human activity is an Ordinary Least Squares (OLS) regression (Su et al. 2012). Practically, OLS assumes that the analysed variables are constant in space. However, this assumption represents an important limitation for a territorial analysis; as Tobler’s first law of geography postulated, ‘everything is related to everything else, but near things are more related than distant things’ (Tobler 1970). Therefore, an estimation strategy should consider the spatial non-stationarity.

However, spatial non-stationarity is difficult to model. One way to deal with it is to allow the estimated parameters to vary according to the location of the dependent variable. Cassetti (1972) first proposed a way to estimate parameters that vary in space. Nevertheless, his proposed method requires the knowledge (and therefore the specification) of an explicit function to describe the variation of parameters in space. Brunsdon et al. (1998), trying to overcome this limit, proposed GWR, i.e., a non-parametric estimation of the spatially varied β parameters. The idea behind GWR is to fix a point p in space and then regress a dependent variable using all the observations around ‘a circle of inclusion’ to the point p , kernel-weighted using a certain exogenous

metric with respect to the distance. GWR is a well-established model for the analysis of spatial data in different fields (Helbich and Leitner 2009; Lu et al. 2011; Jivraj et al. 2013; Megler et al. 2014; Fotheringham and Park 2017).

The OLS standard equation is:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \quad (1)$$

where

y_i = estimated value of the dependent variable at i -th location.

β_0 = intercept.

β_k = slope coefficient for independent variable x_k ,

x_{ik} = value of the variable x_k at i -th location.

ε_i = random error term for i -th location.

Hence, the β_k parameters express the global and spatially independent relationship between each independent variable and the dependent variable. GWR estimates the model parameters, including those that are spatially non-stationary. Equation 1 can be rewritten as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (2)$$

where

u_i, v_i = location coordinates of the i -th point in space.

$\beta_0(u_i, v_i)$ = intercept for i -th location.

$\beta_k(u_i, v_i)$ = local parameters estimate for independent variables x_k at i -th location.

x_{ik} = value of the variable x_k at i -th location.

ε_i = random error term for i -th location.

To estimate the β_0 and β_k , GWR assumed that near independent variables have a greater weight in the estimation than farther realizations. Therefore, the parameters are estimated through a spatially-weighted least squares estimation.

$$\beta(\mu, \nu) = (X^T W(\mu, \nu) X)^{-1} X^T W(\mu, \nu) y \quad (3)$$

where

$\beta(\mu, \nu)$ = unbiased estimate of b .

$W(\mu, \nu)$ = n by n weighting matrix with its off-diagonal elements are zero which acts to ensure that observations near to the specific point have bigger weight value.

In order to identify the weighting matrix (W), three key elements must be considered. These are the type of distance (e.g., Euclidean, Manhattan, etc.), the kernel function and the bandwidth. As reported by Fotheringham et al. (2003) and Gollini et al. (2015), different kernel functions (continuous or discontinuous) can be used for a weighting scheme definition (e.g., Gaussian, exponential, box-car, Bi-square, and Tri-cube models). Instead, there are two general processes for bandwidth construction that are called fixed and adaptive kernel functions. As argued by Fotheringham et al. (2003) and Wheeler and Páez (2010), contrary to the fixed function, an adaptive function adjusts the window catchments for the density of data locations. In other words, we

have a bandwidth that can be specified either as a fixed distance or as a fixed number of local data (i.e., an adaptive distance). As Gollini et al. (2015) stated, in practice, a fixed bandwidth suits fairly regular sample configurations, while an adaptive bandwidth suits highly irregular sample configurations.

The Study Area

The area of Mugello (Fig. 1) is located in the northern part of the province of Florence in Tuscany, Italy. Due to its morphological characteristics, the wild fauna has direct contact with the territorial mosaic brought forward by anthropogenic activities. The study area includes nine contiguous municipalities (LAU 2) stretching approximately 1100 km². The population is almost 65,000 habitants with a density of 105 inhabitants per km². Mugello is mostly hilly (66.5%); including some plains (about 8.4% of the territory) and major mountain ranges (25.1% of the area). The climate is characterized by an average annual temperature of around 16 °C, with a rainfall pattern of around 600–700 mm annually.

By observing a digital elevation model of the area, we can note a flat zone in the central part of Mugello that includes the principal towns of San Piero a Sieve, Borgo, and Vicchio. The municipalities of Firenzuola, Palazzuolo sul Senio and Marradi are characterized by a mountainous landscape.

The presence of different territorial scenarios makes this area suitable for our analysis. Indeed, in Mugello there are several urban agglomerations located in the flat zone and agricultural areas (mostly arable and livestock farms) distributed in the central-northern part of Mugello. Finally, the areas near the mountains are predominantly covered by forests.

Regarding to the statistics on fauna, the only available and reliable data is provided by the Regione Toscana (the local authority LAU 3). According to Piano Agricolo Forestale (P.R.A.F) 2012–2015 (Regione Toscana 2012); the number of ungulates is continuously increasing in the area. The increase of the deer and roe deer populations is constant over time. The trend of estimated consistencies relative to other species appears to be discontinuous (mouflon and fallow deer). Unfortunately, the estimations of the wild boar population—which, due to their density, are considered one of the most damaging species—are not available (Table 1).

Applied Methodology

Using the framework of the National Ecological Network (REN), this study analyses ungulate distributions in the territory, looking for a correlation between the potential number of wild species examined and four variables (listed below) that take into consideration both the territorial characteristics and the anthropogenic activities taking place in the territory (Fig. 2).

The habitat and the movement of ungulates are related to fundamental requirements, including food production of the areas (trophic function), the availability of sufficient space (home range and habitat) and protection. The literature related to biodiversity analysis reflects these various aspects (Pélissier and Couteron 2007; Kry et al. 2008;



Fig. 1 Map of study area **a)** Italy **b)** Mugello

Fitterer et al. 2012; Spangenberg et al. 2012; Riccioli et al. 2016). As stressed by Chen and Koprowski (2015), the main threats to biodiversity are habitat fragmentation,

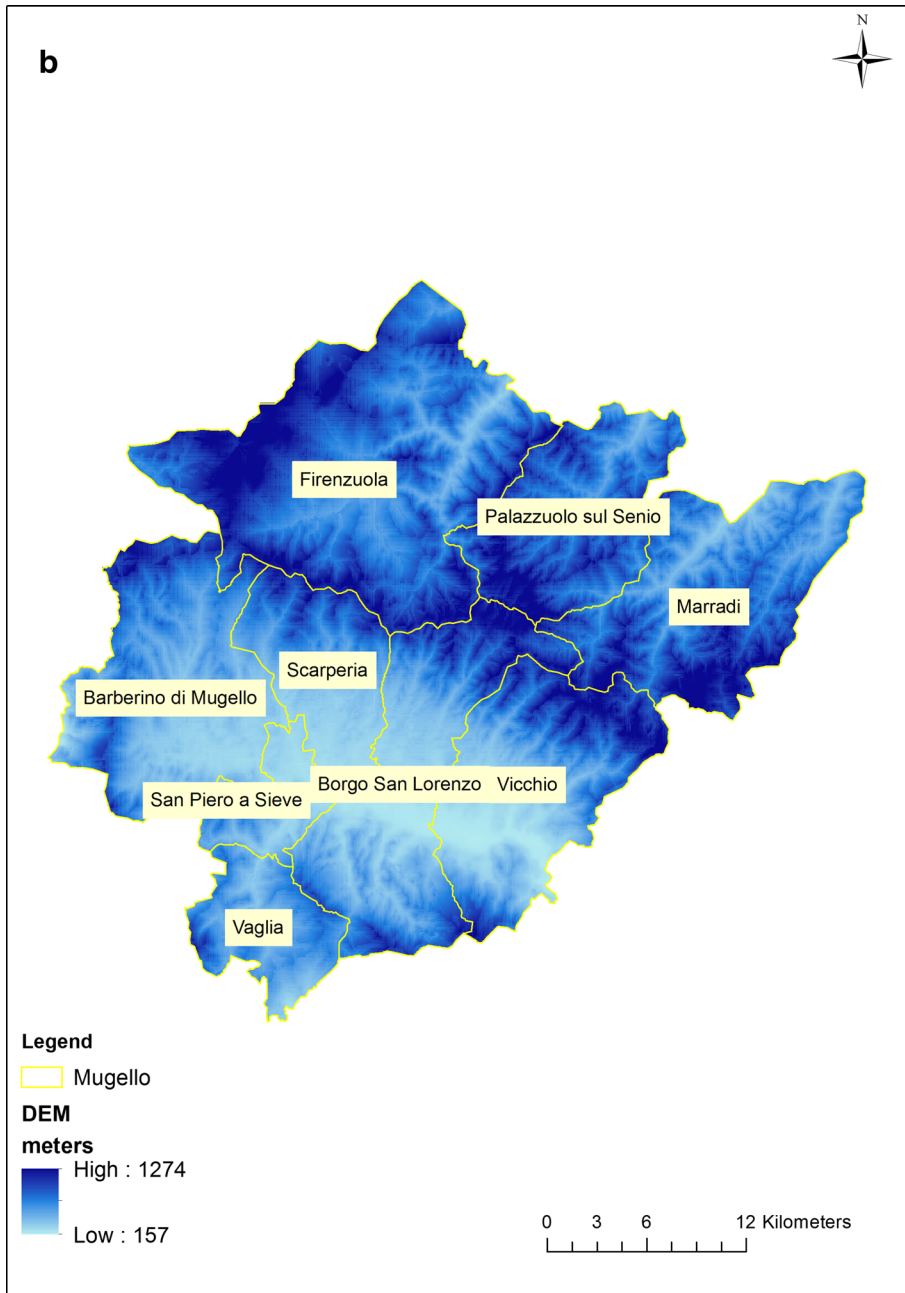


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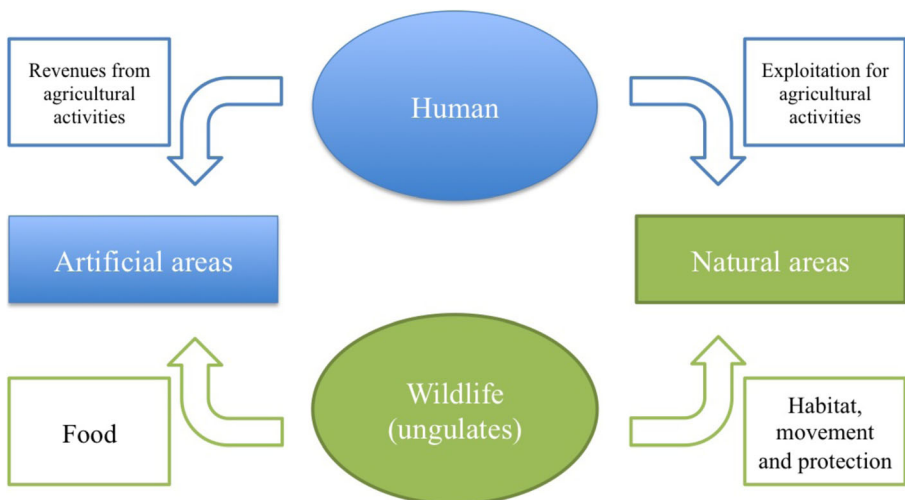
destruction, and noise, whereas the global road networks represent one of the most significant human influences on ecosystems and a spatially extensive source of the anthropogenic disturbance.

Table 1 Ungulates population trend in Tuscany (source PRAF 2012–2015)

Year	Roe deer	Fallow deer	Deer	Mouflon
2000	91,872	8464	2600	2934
2001	98,151	11,138	2613	2424
2002	110,162	10,701	2735	1906
2003	108,011	8124	2977	1954
2004	112,893	8824	2785	1841
2005	117,223	9588	3000	2936
2006	138,366	10,097	3086	1161
2007	140,639	7593	3651	1760
2008	144,586	7814	3996	2543
2009	159,858	8268	4277	2433
2010	153,134	8841	3621	2562

The following independent variables have been chosen to take into consideration the available resources and relying on the existing literature on territorial analysis through GWR (Su et al. 2012; Gao and Li 2011; Nilsson 2014; See et al. 2015; Huang et al. 2015). The independent variables chosen are: (i) distance from artificial areas; (ii); distance from agricultural activities; (iii) ecological corridors; (iv) index of ecosystem richness.

The relationship between the number of ungulates and the observed variables is directly connected to ungulate movement and could be summarized as follows: the distance from the anthropogenic areas represents a threat, therefore constraining the free passage of fauna. The distance from agricultural activities offers other opportunities for food, while the ecological corridors offer opportunities for safe passage. Finally, ecosystem richness is an index widely adopted in ecology (in our case, we applied it to

**Fig. 2** Interaction between humans, ungulates and territory

land use). A major diversity of the territorial ecological mosaic (diversity of land use) favours better satisfaction of the fundamental needs of animals. This is positively correlated to the number of wild species (Riccioli et al. 2016).

The minimal unit of analysis is the cadastral parcel. For this purpose, we used a map of cadastral boundaries (scale 1:7000) developed by the Tuscany Region. Table 2 shows the data sources. The spatial reference used in the analysis is EPSG projection 32,632-WGS 84/UTM zone 32 N.

We produced a thematic map for the dependent and each explanatory variable. Moreover, we normalized data to compare values with different units of measurement. The normalization is based on fuzzy logic (or the infinite values method) where the logical variable can take on any continuous interval value of truth ranging from zero to one (Zadeh 1965; Chen and Hwang 1992). Table 3 includes the normalization parameters used for variables, where each variable has a minimum and a maximum value (control points).

Dependent Variable

The National Ecological Network was used as the dependent variable. It contains the distribution of species richness (a potential number) in a specific area (polygons) of amphibians, mammals, birds, fish and reptiles. This distribution is represented by the overlay of the networks of each animal species and is categorized by a dense fragmentation of the territory (Boitani et al. 2002). The analysis focused only on ungulates that are mainly represented by deer, fallow deer and mouflon (Fig. 3). Other species (e.g., birds or amphibians) included in the REN are not correlated with the explanatory variables used in the analysis.¹

The REN database provides the potential number of species outside the protected areas. In order to associate this value to the minimal unit of the analysis, the average of the potential number of ungulates has been attributed to each cadastral parcel. The darker colours represent the parcels with the higher potential numbers (expressed as normalized values) of ungulates (Fig. 3).

Distance from Artificial Areas

The concept of distance from some features is widely adopted as covariate in the literature (Malczewski 1999; Boncinelli et al. 2015; Feng and Liu 2016). In particular, the greater distances from the artificial areas represent a positive factor with respect to the passage of wild animals (Chen and Koprowski 2015). The calculation of this variable was based on the 2012 Corine Land Cover (CLC) map developed within the CLC project. According to the CLC legend, artificial areas include the urban fabric, industrial, commercial and transport units, mines, dumps and construction sites, artificial, non-agricultural vegetated areas.

The distance module is based on the calculation of the fuzzy distance from a target feature (agricultural areas, in our analysis) to each cadastral unit. Following Al-Ahmadi et al. (2009), the fuzzy distance decay membership function is used to weigh the

¹ REN also includes 244 species of nesting birds, 34 species of amphibians, 43 species of reptiles and 82 species of fish.

Table 2 Data sources

Source	Years	Type of elaboration
Corine Land Cover	2012	Richness of land use, distance from specific land use
REN - National Ecological Network	2005	Distribution of species richness (potential number) in a specific area of wild animals
ISTAT, 6th Agriculture General Census	2010	Distance from georeferenced farms
Landsat 7 ETM +	2012	Normalized Difference Vegetation Indicator (NDVI)
Map of cadastral parcels	2012	Cadastral boundaries

strength of the proximity to a given feature. Instead of having a single crisp threshold that denotes a distance from a feature, the fuzzy distance decay function is capable of describing the potential number and the ability of movement of ungulates that increases with distance from artificial areas.

A raster map with a pixel resolution of 75 m was created. An average distance from the artificial areas was attributed to each cadastral parcel. The higher values in Fig. 4 represent the polygons of the parcels with greater distances (metres are expressed as normalized values) from artificial areas.

Distance from Agricultural Activities

The distance from the agricultural areas was measured with the intention to verify how the distance from such cadastral unit could influence the number of ungulates. Thanks to agricultural production, this variable represents an opportunity for animals to feed themselves (van Wenum et al. 2004; Argenti et al. 2012; Apollonio et al. 2011; Clasen and Knoke 2013; Jensen et al. 2014; Fratini et al. 2016). Farms and agricultural areas were selected for the analysis. Data comes from the 6th Agricultural General Census provided by the National Institute of Statistics (ISTAT 2010) and the CLC 2012. Starting from a map that included the georeferenced farms and the agricultural areas, a fuzzy distance was calculated. A raster map with a pixel resolution of 75 m represents the result. These areas should offer an opportunity of food for ungulates, in an inversely proportional measure with respect to the distance from them (i.e., shorter distances from agricultural activities should favour a higher number of ungulates). Even in this

Table 3 Normalization of the parameters

Indicators	Type of normalization	Control points	
		<i>a</i>	<i>b</i>
REN	Linear increasing	0	152
Distance from artificial areas	Linear increasing	0	6954
Distance from agricultural activities	Linear decreasing	0	7061
Ecological corridors	Linear increasing	0	405
Relative richness index	Linear increasing	0	0.022

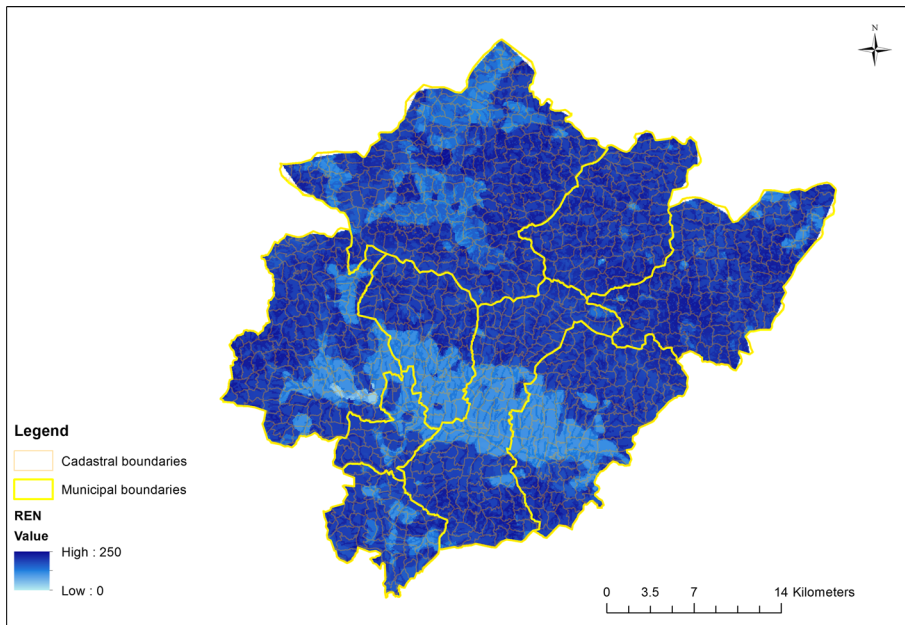


Fig. 3 Map of REN (only ungulates are included in the analysis)

case, for each cadastral, parcel an average distance from agricultural activities has been considered. The darker colours represent the parcels' polygons with shorter distances (meters are expressed as normalized values) from agricultural activities (Fig. 5).

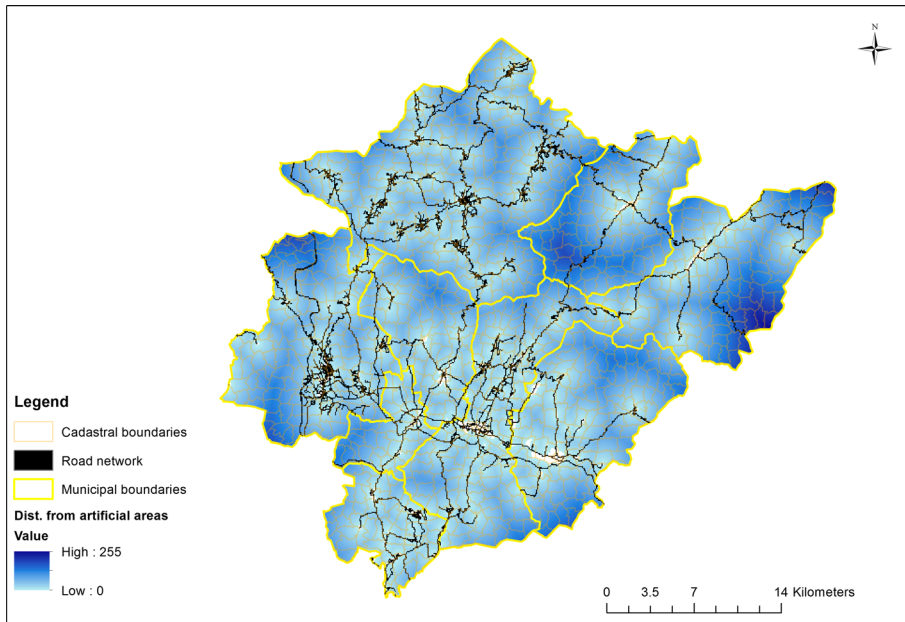


Fig. 4 Distance from artificial areas

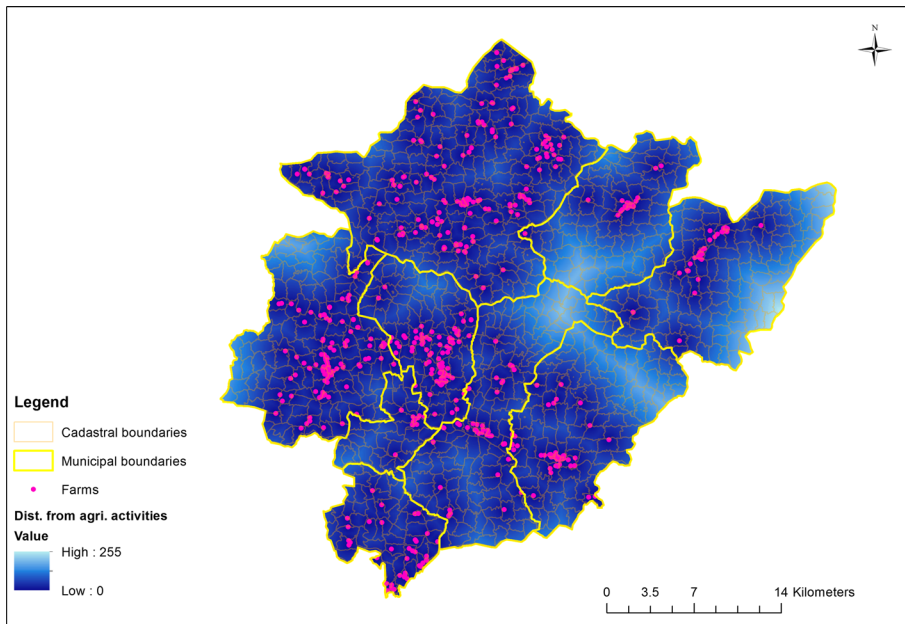


Fig. 5 Distance from agricultural activities

Analysis of Ecological Corridors

The forest environment has a fundamental role in the ability of animal populations to find protection and food. The fragmentation of natural and semi-natural areas is one of the principal threats to the ability of ungulates to find protection and displacement opportunities through ecological networks (Jongman et al. 2004).

Some GIS tools can be used for the creation of aeological corridors, including Least-cost paths, CorriDorDesign or Linkage Mapper tool implemented in ArcGIS (Hepcan et al. 2009; Gurrutxaga et al. 2010; Liang et al. 2018; Majka et al. 2007; McRae et al. 2008; McRae et al. 2016) or spatial pattern indices (e.g., the patch corridor model) developed for Fragstat (Kong et al. 2010; Vergnes et al. 2012). Generally speaking, there are some important elements that must be considered for the creation of ecological corridors, including land use, road density or physical barriers. In the current article, the ecological network map was developed starting from the measurements of the Normalized Difference Vegetation Indicator (NDVI) that it considers the above-mentioned factors. This indicator operates on a specific colour spectrum (range) that excludes with specified precision both anthropogenic components (e.g., roads, human activities, etc.) and other non-forested areas (e.g., natural barriers such as rivers, lakes and rocks).

The ecological network map was calculated by relying on satellite images from Landsat 7 ETM+ (Enhanced Thematic Mapper) from the year 2012. As suggested by Bocchi et al. (1997), the NDVI relates the chlorophyll absorption spectrum in the red with the typical reflection in the near infrared where it is strongly influenced by the type of leaf structure. In order to measure the ecological corridors, values above 0.20 were selected. As stated by Agone and Bhamare (2012), these areas, represented by scrub, grasslands and dense forest, permit ungulate passage. An average value of adjacent pixels was

assigned using a moving window filter for each pixel (cell 7×7 , corresponding to a geographic neighbourhood of 48 pixels). The maximum values correspond to the areas in which animals move freely. An average value of this indicator was assigned to each cadastral parcel. The higher values represent the polygons of the parcels with the higher presence (expressed as normalized values) of ecological corridors (Fig. 6).

Relative Richness of Land Use

Land use heterogeneity is positively correlated with the ungulate presence in a given area, as a relatively simplified agricultural landscape in which the territorial matrix is represented by monoculture does not represent an opportunity for ungulates to find food during all the seasons of the year. Notwithstanding the existence of numerous indicators able to describe the heterogeneity of land use (including the Shannon index, the fragmentation index and edge density analysis; see Eastman 2009), in the current study, the richness of land use is measured by the relative richness index.

Analysing the landscape pattern of the study area, the CLC map was modified to eliminate all land cover that does not represent opportunities for food provision (artificial areas) for ungulates. The relative richness index can be written as:

$$R = n/n_{\max} \cdot 100 \quad (4)$$

where:

R = relative richness index.

n = number of different classes present in the geographic neighbourhood.

n_{\max} = maximum number of classes possible.

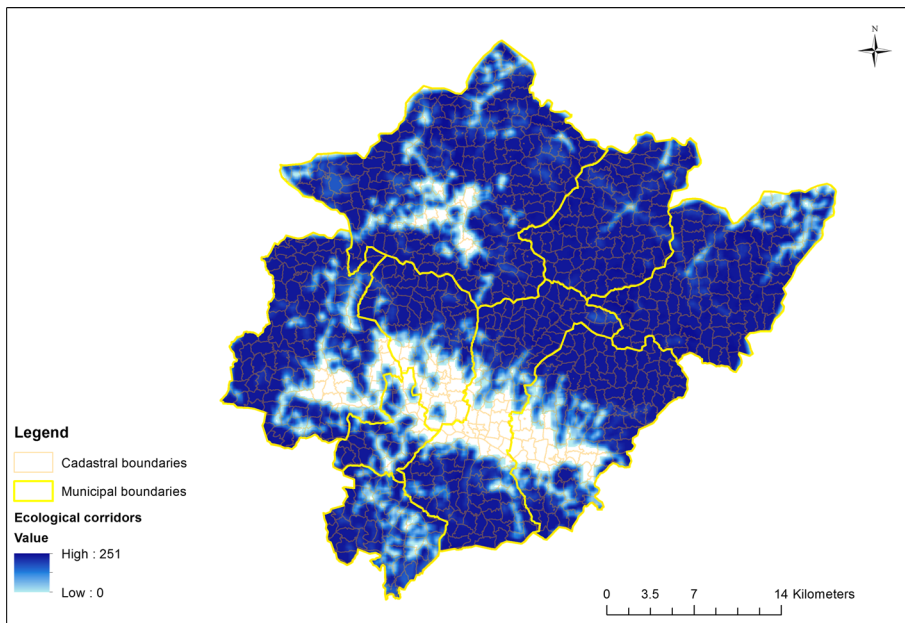


Fig. 6 Ecological corridors

The geographic neighbourhood was defined by a 7×7 square grid (48 pixels adjacent to the reference pixel were examined). Generally speaking, there is not any definitive theory as to what is the ultimate size a kernel should be. In landscape ecology software (e.g., Idrisi) there is some defined mask, usually 3×3 , 5×5 or 7×7 (Eastman 2009), and it is an art to find the right kernel size related to the kind of data under analysis. With a pixel resolution equal to 75 m, a 7×7 square grid allowed us to analyse about 27 ha (one-third of the average area of the cadastral parcels), which could be a good compromise for calculating the diversity of land use. In order to perform a proper analysis to all case study areas (including the edges), the variable was also calculated on the areas surrounding Mugello.

Using the relative richness index, we can identify the richer areas in terms of land use (higher values) that represent areas most suitable for ungulates. As for previous explanatory variables, an average value of relative richness of land use was assigned to each cadastral parcel. In Fig. 7, the darker colours represent the area of the parcels with higher relative richness values (expressed as normalized values).

Results and Discussion

Out of a total of 1356 cadastral parcels, four were excluded from the final analysis because they represented unusual values and were considered outliers. Therefore, the sample was accordingly reduced to 1352 cadastral parcels. First, a standard regression was performed, i.e., the Ordinary Least Squares (OLS). The OLS analysis produced a coefficient of determination (R^2) equal to 0.50. The overall model significance is statistically significant at the 99% level according to a Wald test. Table 4 reports the OLS results.

The distance from artificial areas is statistically significant at the 95% level while the distance from agricultural activities, ecological corridors and relative richness areas are statistically significant at the 99% level. The highest positive determinant is related to the ecological corridors, while the highest negative determinant is represented by the relative richness of land use. The negative coefficient of the variable distance from artificial areas indicates that increasing the distance from artificial areas decreases the number of ungulates. The variance inflation factors (VIF) slightly above values of one confirm a low redundancy of each variable, and thus a low degree of multicollinearity.

Figure 8 includes the map of the standardized residual (StdResid) values. A Moran's I was calculated on the residuals to test their spatial autocorrelation.² In other words, the intention was to verify whether the model residuals are spatially random. The resulting Moran's I equals 0.34, indicating a positive autocorrelation of the residuals. The statistical test of Moran's I reveals a z -score of 31.769 and a p -value equal to 0.000. Therefore, the likelihood that this clustered pattern could be the result of a random chance is less than 1%.

In addition, a Koenker test (K(BP)) was performed to determine whether the independent variables in the model have a consistent relationship to the dependent variable, both in geographic space and in data space. Considering that K(BP) is statistically significant, it can be deduced that the observed explanatory variables have

² A distance threshold equal to 3 km is considered in order to calculate the spatial weights matrix.

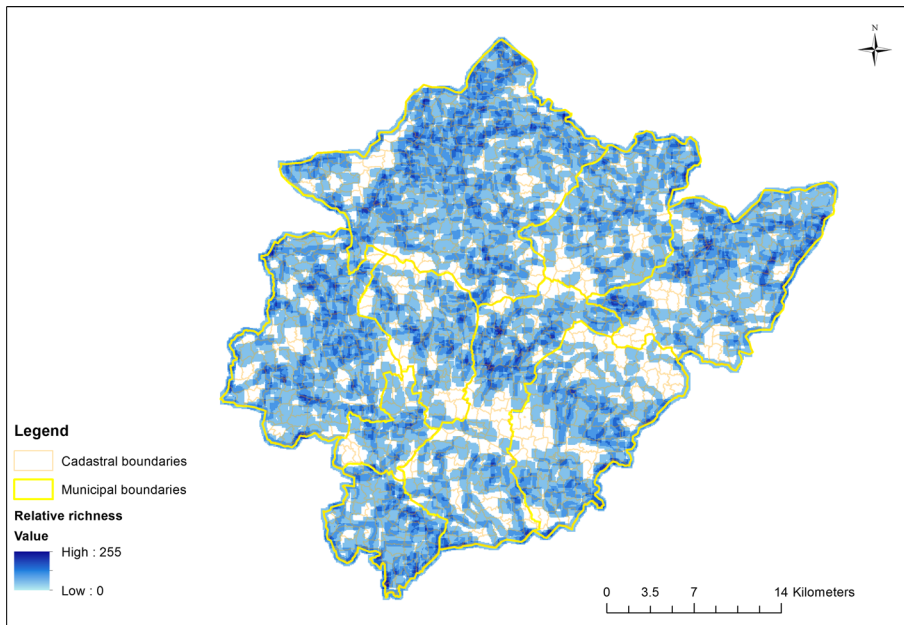


Fig. 7 Relative richness of land use

a spatially consistent correlation to the REN. Therefore, the relationships vary across the study area and are spatially non-stationary.

Assuming that the coefficients vary across space, the next step focused on the analysis of the variables through the GWR, in order to verify how the determinants in the model are able to influence the potential number of ungulates in the study area.

Based on R^2 analysis, a fixed kernel type of bandwidth was selected. In fact, the R^2 of the fixed bandwidth (0.74) is higher than the R^2 of the adaptive one (0.67). This is probably due to the evidence that, by using the cadastral map, the parcels (and observations) are uniformly distributed across the territory; their distribution is constant and presents a low dispersion.

Table 4 Estimated parameters of OLS model

Variable	Coefficient	Robust St. Error	<i>t</i>	<i>p</i> -values	VIF
Intercept	124.469	2.574	48.352	0.000	–
Distance from artificial areas	−0.044	0.018	−2.483	0.013	1.288
Distance from agricultural activities	0.098	0.017	5.681	0.000	1.467
Ecological corridors	0.321	0.013	24.818	0.000	1.510
Relative richness	−0.046	0.023	−2.000	0.004	1.069
R^2	0.502				
Adjusted- R^2	0.501				
Wald	1254.11			0.000	
Moran's <i>I</i>	0.338			0.000	
K(BP)	105.219			0.000	

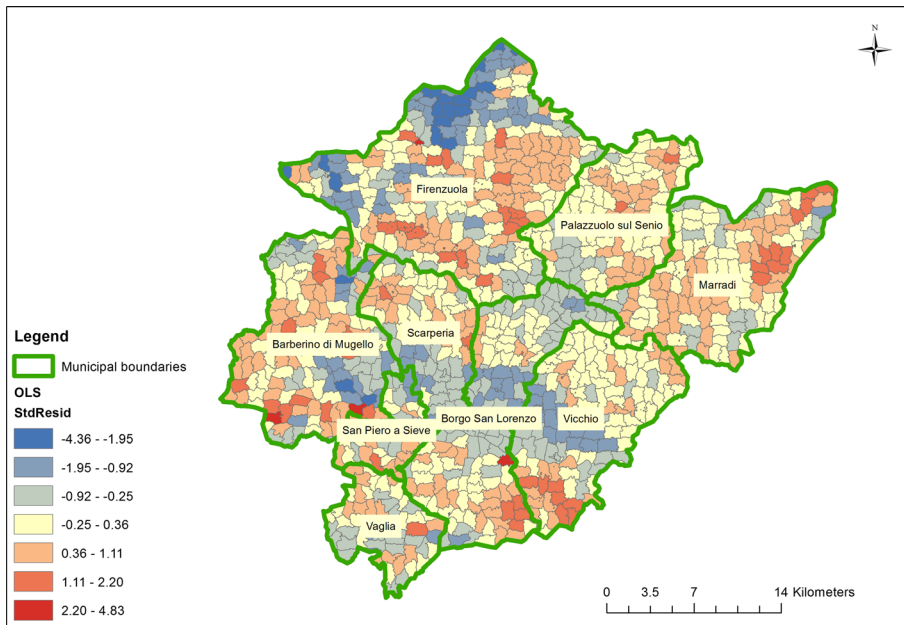


Fig. 8 OLS standardized residuals

As suggested by Harris et al. (2010), the optimal bandwidth was identified using the Akaike Information Criterion (AICc). Therefore, a bandwidth with a value of 5123.02 was identified. In addition, the Gaussian kernel weighting function is expressed by the following equation:

$$w_{ij} = \exp\left(-\frac{1}{2} \left(\frac{d_{ij}}{b}\right)^2\right) \tag{5}$$

where

- w_{ij} = weight of j -th observation for i -th location,
- d_{ij} = Euclidean distance between points i and j ,
- b = kernel bandwidth.

Hence, if observation j coincides with location i , the weight value is one. Where the distance is greater than the kernel bandwidth, the weight is set to zero.

The GWR showed a higher R^2 compared to the OLS estimation. An analysis of multicollinearity was applied to the GWR in a manner similar to how it was applied to the OLS method. This diagnostic evaluates local multicollinearity, since results become unstable in the presence of strong local collinearities. All observations show a condition number less than the threshold of around 30 suggested by both Myers (1986) and Belsey et al. (2004) for indicating regression calibration issues.

The map of the standardized residual values is provided in Fig. 9. The very large positive residuals (StdResid residual >0.85) are mainly located in the southern and central-northern parts of Mugello (the municipalities of Vaglia, Barberino and Firenzeuola). Therefore, given the variables included, the model tends to underestimate the number of ungulates in this study area, while it tends to overestimate them (StdResid residual <-1.05)

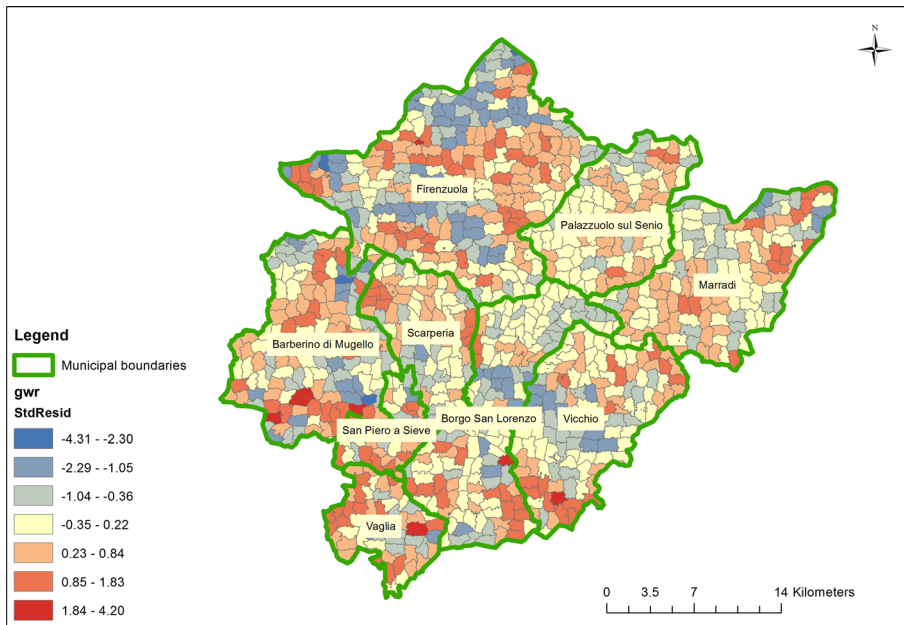


Fig. 9 GWR standardized residuals

in the northern part of the study area (municipality of Firenzuola). Again, another important question is related to the spatial autocorrelation of residuals. Moran’s *I* on residuals yields a value equal to 0.19, showing a lower spatial dependence than the correlation measured in the global regression. The statistical tests of Moran’s *I* have revealed a *z*-score of 17.968 and a *p*-value equal to 0.000. This evidence confirms that if the non-stationarity of the data is controlled for, the residuals are less spatially correlated. Compared to the OLS residuals map (Fig. 8), the GWR residuals show less autocorrelation in the flat zone of Mugello (the municipalities of Barberino, Scarperia, Borgo and Vicchio) and in the central-eastern area close to the flat zone (the municipalities of Borgo and Palazzuolo).

Statistics of the coefficients in Table 5 provide a comparison between the OLS and the GWR models. Despite the fact that medians from the GWR appear quite similar to those of the OLS, the minimum and maximum values show a substantial variation that confirms again the hypothesis of spatial non-stationarity of the examined variables.

Table 5 Global (OLS) and local (GWR) coefficients’ statistics of the regression model

Variable	OLS	GWR				
		min	Q ₁	median	Q ₃	max
Intercept	124.47	86.758	113.935	135.703	154.060	174.449
Dist. from artificial areas	-0.044	-0.365	-0.074	-0.034	0.014	0.299
Dist. from agricultural act.	0.098	-0.369	0.023	0.089	0.234	0.800
Ecol. corridors	0.321	0.035	0.176	0.264	0.330	0.517
Relative rich.	-0.046	-0.341	-0.133	-0.028	0.033	0.121

Indeed, through a graphical analysis of the GWR coefficient maps (Fig. 10), it is noted that each variable's coefficient shows a non-stationary distribution and the patterns of the coefficients are more homogenous than the patterns exhibited in the data. This provides additional support for the use of GWR in our analysis.

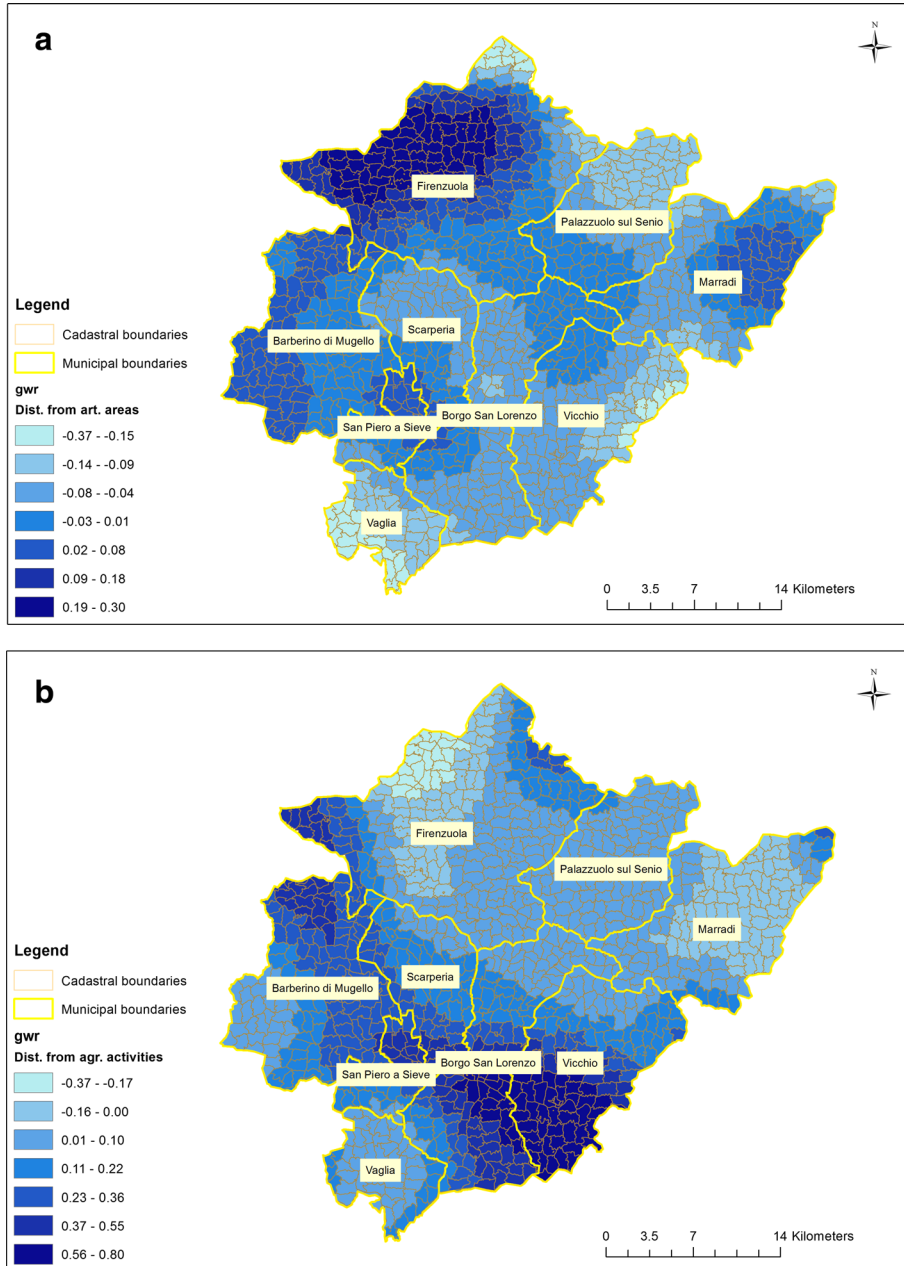


Fig. 10 Maps of coefficients **a**) distance from artificial areas; **b**) distance from agricultural activities; **c**) ecological corridors **d**) relative richness of land use

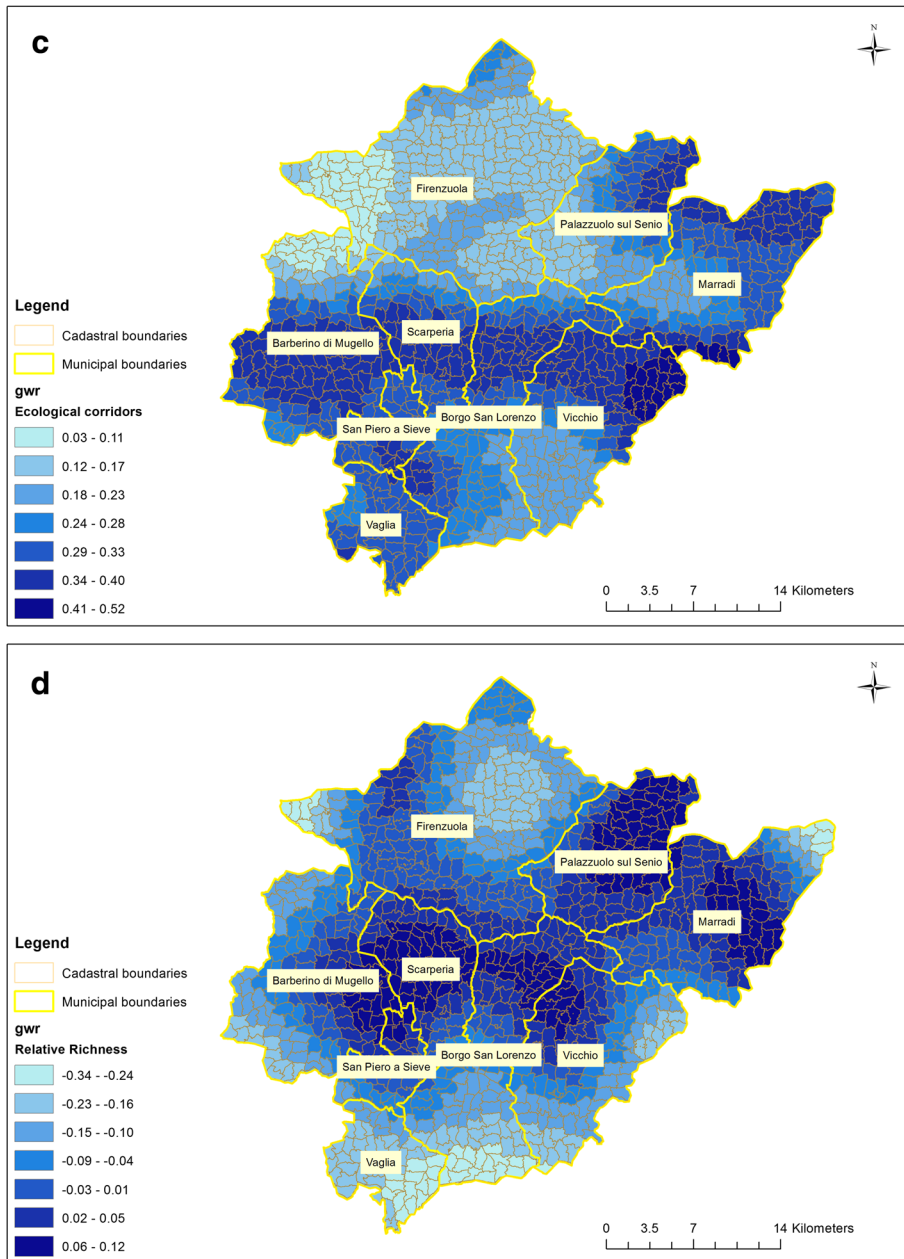


Fig. 10 (continued)

The artificial areas consist mainly of urban agglomerations that find their maximum expansion close to the main towns. The roads connecting the above-mentioned centres are also considered an artificial element. These areas reach their maximum capillarity in

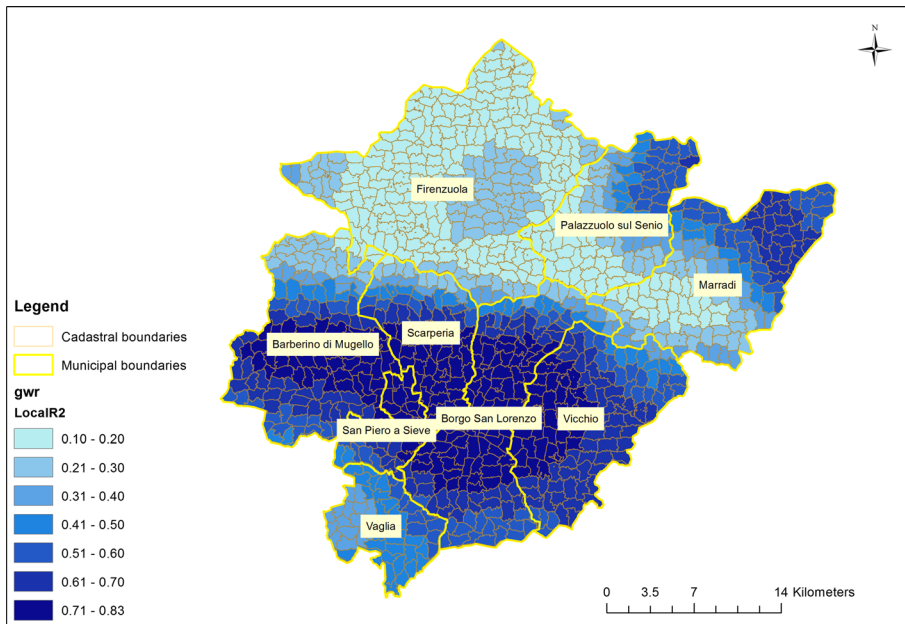


Fig. 11 Map of local R^2

the flat zone and in the western part of Mugello. The results of the GWR help provide a better interpretation of the results of the OLS. In fact, from the negative sign of this variable by the OLS, it must be concluded that the ungulate population is concentrated in proximity to artificial areas, i.e., close to urban areas. In the first analysis, this result could seem counterintuitive. In truth, it may be noted that the more positive estimates are concentrated precisely around the main urban areas that, as already mentioned, are the core of the artificial areas of Mugello. The high density of ungulates favors their presence near urban areas: it is probable that in these areas, human activities provide the animals with indirect support, such as food from waste or water from hydraulic infrastructures.

Figure 10b shows that the agricultural activities mainly located in the flat zone have a major impact on the ungulates, such that when the distance from agricultural activities increases, the number of ungulates decrease. This result confirms that, as mentioned above, agricultural activities represent a food-opportunity for ungulates: this is also (unfortunately) confirmed by the fact that agricultural activities are the most affected economically by the presence of ungulates.

The coefficient map of ecological corridors in Fig. 10c reveals a very interesting pattern. Indeed, the lowest impact of this variable is concentrated in the north of Mugello where there are the highest values of this factor. In contrast, the highest impacts are located in the south of Mugello where there is the lowest presence of ecological corridors. Therefore, the GWR results seem to indicate a decreasing marginal effect of this factor. An “extra unit” of ecological corridors has a greater effect where the presence of ecological corridors is scant.

Analysing the heterogeneity of land use with the map of the coefficients of relative richness (Fig. 10d), it is estimated that the maximum impact on the number of ungulates is located mainly in the centre of Mugello. The lowest and negative coefficients are concentrated in the borders of the region. This result does not confirm the hypothesis that ungulates concentrate in areas with higher heterogeneity of land use.

This could be related to the above-mentioned presence of ungulates near urban areas that represent areas with low heterogeneity of land use. However, this result deserves more in-depth future analysis.

The visual analysis of the local R^2 provides additional useful information. Figure 11 shows where the model's accuracy is stronger in replicating the observed values. It is observed that there are large variations in space in the model goodness-of-fit statistics. The R^2 values range from 0.10 to 0.83. The best prediction of the number of ungulates by the GWR is in a large area in southern Mugello. This area corresponds to the most populated, urban and flat area and it has a lower ungulate population. In contrast, in northern Mugello, the model replicates the ungulate population less well, with some areas showing goodness-of-fit statistics with a lower magnitude, from 0.10 to 0.22. This evidence can be used to develop future models related to ungulate populations. As mentioned above, in general the GWR R^2 value (0.74) shows a strong significant relationship between the dependent and the selected independent variables. Despite this consideration, the study of the potential number of ungulates is complex. Therefore, for a more exhaustive analysis, the impact of other variables related to the dependent variable should be tested, especially for areas with lower R^2 that indicate the need for additional covariates. For example, further studies could focus on the number of hunters, factors related to seasonality (the nutrition needs of different ungulate species vary in summer compared to in winter), different vegetation cover or types of forestry (Côté et al. 2004; Cozzi et al. 2015; Gill and Beardall 2001; Jensen et al. 2014; Horsley et al. 2003; Trdan and Vidrih 2008; Allen et al. 2016).

Conclusions

This work analysed the possible correlations existing between the number of ungulates and human activities on a specific territory. This was conducted by performing a GWR in the area of Mugello, located in the province of Florence. The use of GIS simplified the implementation of the methodology and offered advantages in terms of model goodness-of-fit and interpretation power of the results with respect to the traditional data analysis techniques. Moreover, the results are georeferenced and showed through thematic maps, which are easy to read and available for further analysis.

Our starting hypothesis was that the relationship between ungulate populations and the selected variables (i.e., distance from artificial areas, distance from agricultural activities, ecological corridors and relative richness of land use) are spatially non-stationary. In other words, the impacts of the covariates have different weights across space. However, classic regression techniques, assuming that the relationships between dependent variables and explanatory variables are homogeneous throughout the area, are not able to gather this phenomenon. Considering this, we compared the OLS regression results with those of the GWR.

Therefore, we demonstrated spatial non-stationarity and using GIS tools we mapped the results. The use of GWR has allowed for a detailed analysis of the spatial interactions between the dependent variables and the explanatory variables examined.

This is relevant because we detected the areas where these interactions are stronger with the aim to better understand the difficult balance between ungulates and human activities on the territory. Considering the huge damages that these animals cause to rural areas every year, this article can provide useful information to stakeholders in order to improve policy strategies and geographical policy targeting.

The main limit of GWR is that it requires a demanding calculation process, so we can test only a small set of variables at once or for limited areas. Moreover, this model is linked to the availability of georeferenced databases that are often difficult to acquire.

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