Geographical Relationship between Ungulates, Human Pressure and Territory

1. Introduction

The wildlife management is an important issue that can be analyzed through different points of view. Various approaches are generally adopted to manage wildlife due to a tendency of the latter to alter the landscape (Jensen et al., 2014; Gill, 1992; Clasen and Knote, 2013). Some methods tend to safeguard wildlife by creating protected areas, while others aim at controlling the growing number of wild animals. The increasing number of wild animals is in fact considered to have damaging effects on agricultural activities. As suggested by Gill (1992); Horsley et al., (2003); and Apollonio et al., (2011), those are accompanied by significant economic impacts. Cozzi et al. (2015), observed that between 2007 and 2012 the surface areas damaged by wild animals has increased from 2,800 to 5,850 hectares and consequently the estimated compensations increased significantly from € 550,000 reaching € 1,134 million.

In North America, the US Department of Agriculture Wild Life Service (USDA, 2012) reported in 2009, the damage to agriculture, mainly due to the presence of wild boar and deer estimated at about $ 71 million, mostly for lost revenue. In comparison, during the same year damages from road accidents, due to animals' crossing, that involved around 29,000 people with a loss of about $ 1 billion was also reported.

The density of wild animals on a territory where agriculture plays an important role in local economies represents an important issue to be studied. "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" (Côté et al., 2004). A sustainable coexistence between human activities in shaping the landscape, taking into consideration the existing animal species, is accordingly important to be addressed. Modelling the landscape means redesigning new combinations between the territory and human activities through a correct environmental planning. Investigating the relationship between human activities, animal pressure, and other territorial characteristics is relevant to identify policies that can reconcile a sustainable coexistence.

The aim of this study is to analyze the number of wild animals (essentially consisting of ungulates) and subsequently looking for a correlation between human activities and environmental variables. Classic techniques of regression are not useful because they assume that these relationships are constant across the space. "Spatial non-stationarity is a condition in which a simple global model cannot explain the relationships between some sets of variables. The nature of the model must alter over space to reflect the structure within the data" (Brunsdon *et al.* 1998). This limitation can be overcome by using a Geographically Weighted Regression (GWR) able to depict the non-stationary process regarding the correlation between wild animals and human activities, in a study area of Mugello in the region of Tuscany. "Geographically weighted regression attempts to capture spatial variation by calibrating a multiple regression model which allows different relationships to exist at different points in space" (Brunsdon *et al.* 1998). GWR represents a tool able to analyze how the

problem of this delicate relationship (wildlife/human activities) varies spatially. It is also 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.
Following a definition of the GWR model (section 2) mentioned above, 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.

2. Definition of the model

As stressed by Su et. al, (2012) the basic statistical tool to investigate relationships between landscape patterns and human activity is Ordinary Least Squares (OLS) regression. Practically, the OLS assumes that the analyzed variables are constant in space; this assumption represents an important limitation in territorial analysis. By relying on Tobler's first law of geography which states that "everything is related to everything else, but near things are more related than distant things." (Tobler, 1970, p 236), Geographically Weighted Regression (GWR) manages to calibrate the weights in a limited geographical area (kernel). The weights are applied to each independent variable (explanatory variable) and related coefficient, and can produce for each observation, a local regression. This is ideal for analyzing the non-stationary data (data which distribution probability, and simultaneously their statistical indices such as means and variances, change in time and space). The GWR is widely used for the analysis of spatial data in different fields (Gao and Li, 2011; Su et al., 2012; Lin and Wen, 2011; Lu et al. 2011; Nkeki and Osirike, 2013; Megler et al., 2014).
The OLS standard equation is shown in equation 1.

$$y_i = b_0 + \sum_k b_k x_{ik} + \varepsilon_i \qquad \text{Equation 1}$$

where
y_i = the estimated value of the dependent variable at i-th location
b_0 = intercept
b_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.

By applying a GWR the estimates of the model parameters are assumed to be spatially non-stationary and the equation 1 can be rewritten as follow (equation 2).

$$y_i = b_0(\mu_i, v_i) + \sum_k b_k(\mu_i, v_i) x_{ik} + \varepsilon_i \qquad \text{Equation 2}$$

where
μ_i, v_i = coordinate location of the i-th point
$b_0(\mu_i, v_i)$ = intercept for i-th location
$b_k(\mu_i, v_i)$ = local parameter estimate for independent variable x_k at i-th location.

The problem is mainly to estimate the *b* parameters for each variable *x* located in a specific point in the space *i*. The concept underpinning the GWR is both to analyze an area (*k*) around one variable and calibrate a regression based on the elements $b_k(\mu_i, v_i)$ within the mentioned area.
The results depend mainly on the size and the shape of area *k*. In general the size is inversely proportional to the density of the data to be analyzed.
The *b* vary with the variation of the distance from the central point of observation, by assuming different values with the introduction of a local weight w_{ij} (equation 3).

$$b(\mu, v) = (X^T W(\mu, v) X)^{-1} X^T W(\mu, v) y \qquad \text{Equation 3}$$

where
$b(\mu, v)$ = unbiased estimate of *b*,
$W(\mu, v)$ = weighting matrix which acts to ensure that observations near to the specific point have bigger weight value.

The weighting function, called the kernel function, can be stated using the exponential distance decay form (equation 4):

$$w_{ij} = \exp\left(\frac{d_{ij}^2}{b^2}\right) \qquad \text{Equation 4}$$

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

If the observation j coincides with the location i, the weight value is one. If the distance is greater than the kernel bandwidth, then the weight will be set to zero. Generally speaking the shape and extent of the bandwidth is dependent on the user input for the kernel type, bandwidth method, distance, and number of features parameters with one restriction; when the number of neighbouring features exceeds 1000, only the closest 1000 are incorporated into each local equation[1].

3. The Study Area

The area of Mugello (figure 1) is located in the north part of the province of Florence in the region of Tuscany. Due to its morphological characteristics the wild fauna has a direct contact with the territorial mosaic brought forward by the anthropogenic activities. The study area includes 9 municipalities (LAU 2) stretching approximately 1100 Km^2. It has an estimated population of 65000 with a density of 105 inhabitants per sq. km. It is mostly hilly (66.5%); it includes some plains (about 8.4% of the territory) and major mountain ranges (25.1% of area). The climate is characterized by an average annual temperatures of around 16°C, with a rainfall pattern of around 600-700 mm annually.

[1] http://resources.esri.com/help/9.3/arcgisengine/java/gp_toolref/spatial_statistics_tools/geographically_weighted_regression_spatial_statistics_.htm [last access June 1, 2017]

By observing a Digital Elevation Model of the area, it is possible to note a flat area in the central part of Mugello that includes the principal towns of San Piero a Sieve, Borgo, and Vicchio. While the municipalities of Firenzuola, Palazzuolo sul Senio e Marradi are characterized by a mountainous landscape.

Figure 1a	Figure 1b

Figure 1 Map of study area

This area of study has been chosen due to the presence of different territorial scenarios: they are characterized by urban agglomerations located in the flat zone, and by agricultural areas (mainly arable and livestock farms) mainly distributed in the central-north part of Mugello. Finally, the most distant areas are characterized by the prevalence of forests. Accordingly, the territorial variables require specific models that are able to analyze the spatial variations in the data.
With regards to fauna statistics the only reliable data are provided by the Regione Toscana (the local authority LAU 3) in particular from the database of the Agricultural Wood Plan (Piano Agricolo Forestale ; P.R.A.F) 2012-2015. According to the P.R.A.F. data it is possible to notice how the number of ungulates are continuously increasing in the area: the increase of the deer and roe populations is constant in time, while the trend of estimated consistencies relative to other species appears to be discontinuous, and the estimations of the boar population are not reliable.

4. Applied methodology

Using the framework of the National Ecological Network (REN), this study is based on the analysis of wild animals distribution on the territory: it looks for a correlation between the potential number of wild species and some variables (listed below) that take into consideration both the territorial characteristics and the anthropogenic activities taking place in the territory.
The habitat and the movement[2] of wild animals are related and follow fundamental requirements: food production areas (trophic function), availability of sufficient space (home range and habitat) and representing protection features. The literature on the study of biodiversity reflects these various aspects (Pellissier and Couteron, 2007; Kry et al., 2008; Fitterer et al., 2012; Spangenberg et al., 2012; Riccioli et al. 2016). "Habitat fragmentation, destruction, and disturbance are major threats to biodiversity. Global road networks represent one of the most significant human impacts on ecosystems, and a spatially extensive source of anthropogenic disturbance and noise" (Chen and Koprowski, 2015).
The following independent variables have been chosen taking into consideration the available resources and relying on the existing literature on the 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:

1. distance from artificial areas;
2. distance from agricultural activities;
3. ecological corridors;

[2] The word "passage" is also used during text for indicate the movement (the transit) of fauna through the space.

4. index of ecosystem richness.

The relationship between the number of wild animals and the observed variables is directly connected to their movement and could be summarized as follows: the distance from the anthropogenic areas represents a threat constraining therefore the free passage of fauna; the distance from agricultural activities offers otherwise the opportunities for food, while, the ecological corridors offer opportunities for safe passage. Finally, the richness is an index widely adopted in ecology (in our case it was applied to land use): a major diversity of the territorial ecological mosaic (diversity of land use) favour better satisfaction of the fundamental needs of animals. This is positively correlated to the number of wild species (Riccioli et al., 2016).
The cadastral parcel was chosen as the minimal unit of analysis. For this purpose a map of cadastral boundaries (scale 1:7000) developed by the Tuscany Region has been used[3]. See table 1 for the data sources used in the analysis.

Table 1 Data sources

Dependent variable

The National Ecological Network was used as the dependent variable. It is characterised by the distribution of species richness (potential number) in a specific area (polygons) of amphibians, mammals, birds, fishes and reptiles. This distribution is represented by the overlay of the networks of each animal species and is categorised by a dense fragmentation of the territory (Boitani et al., 2002). Only mammals (REN include 102 species of mammals) are used in the analysis (Figure 2); this is because the other species included in the REN[4] are not correlated with the explanatory variables used in the analysis.
It is important to highlight the fact that the examined mammals constitute an extremely diverse class that is characterized by a wide variation in body size with respect to other species. These are also characterized by a very diverse ecology: re-population activities, reintroduction, and suffering from illegal hunting (Boitani et al., 2002).

Figure 2 Map of REN (only mammals are included in the analysis)

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 mean of potential number of the wild species has been attributed to each cadastral parcel. The darkest colors[5] represent the parcels with the highest potential number of wild species.

Explanatory variables

[3] http://dati.toscana.it/dataset/dati-cartografici-del-catasto-wms-agenzia-del-territorio-citta-metropolitana-di-firenze/resource/b141635e-17da-46fd-8907-3c7709c3a591?inner_span=True
http://mappe.provincia.fi.it/tolomeo/html/servizi/mappagen/mappaGenerica.html

[4] REN also includes 244 species of nesting birds, 34 species of amphibians, 43 species of reptiles and 82 species of fish

[5] Darkest colors are always associated with highest values in the maps

Distance from artificial areas

The concept of distance from some features is widely adopted in the literature (Malczewski, 1999; Boncinelli et al. 2015, Feng and Liu, 2016). More particularly the highest distance from the artificial areas represent a positive factor with respect to the passage of wild animals (Chen and Koprowski, 2015). The calculation of the distance from the artificial areas was based on the 2012 Corine Land Cover (CLC) map developed within the CLC project as per the European Standards on Geographic Information (ENV 12657). According to the CLC legend, artificial areas include the urban fabric, the industrial, commercial and transport units, mine, dump 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). “The fuzzy distance decay membership function is used to indicate proximity to a given feature" (Al-Ahmadi et al. 2009). Rather than 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 wild animals that increase away from artificial areas.

Figure 3 Distance from artificial areas

A raster map with a pixel resolution of 75 meters has been created. Similarly to the dependent variables, an average distance from the artificial areas was attributed to each cadastral parcel. The highest values in figure 3 represents the polygons of the parcels with highest distances 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 areas could influence the number of wild species. Thanks to agricultural productions this variable represents an opportunity for animals to feed themselves (van Wenum et al., 2004; Argenti el 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. The 6th Agriculture General Census provided by the National Institute of Statistics (Statistic National Institute - ISTAT, 2010) and the CLC 2012, were used as database: starting from a map including the geo-referenced farms and the agricultural areas, a fuzzy distance was calculated. A raster map with a pixel resolution of 75 meter represents the result. These areas should offer an opportunity of food for wild animals, in an inversely proportional measure with respect to the distance from them, (the small distances from agricultural activities should favour a higher number of wild animals). Even in this case, for each cadastral parcel an average distance from agricultural activities has been considered: the darkest colors represent the parcels’ polygons with lower distance from agricultural activities (figure 4).

Figure 4 Distance from agricultural activities

Analysis of ecological corridors

The forest environment has a fundamental role in the animals' populations to find protection and food. The fragmentation of natural and semi-natural areas is one of the principle threats for wild animals to find protection and displacement opportunity through ecological networks (Jongman, 2004; Jongman et al., 2004). The ecological network map was developed starting from the measurement of the Normalized Difference Vegetation Indicator (NDVI). This indicator was calculated by relying on satellite images Landsat 7 ETM + (Enhanced Thematic Mapper) of 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 the values above 0.20 were selected. As stated by Agone and Bhamare, 2012 these areas, represented by scrub, grasslands, and dense forest, permit wild animals passage. An average value of adjacent pixels was assigned using a moving window filter for each pixel (cell 7x7, corresponding to a geographic neighbourhood of 48 pixels): the maximum values correspond to the areas in which animals move freely. It was the assigned to each cadastral parcel an average value of pixels located in it, where the highest values represent the polygons of the parcels with highest presence of ecological corridors (figure 5).

Figure 5 Ecological corridors

Relative richness of land use

A relatively simplified agricultural landscape where, the territorial matrix is represented by monoculture does not represent an opportunity for wild animals to find food during all the seasons of the year. Notwithstanding the existence of numerous indicators able to describe the heterogeneity of land use (Shannon index, Fragmentation index, Edge density analysis, see Eastman, 2009) this indicator was calculated using a Relative Richness index. Analyzing the landscape pattern of the study area, the CLC map was modified by eliminating all land cover that do not represent opportunities for food provision (artificial areas) for wild animals. The 'relative richness' is one of some measures of diversity of cover classes used in landscape ecology (equation 5).

$$R = n/n_{max}*100 \quad \text{Equation 5}$$

where
R = Relative Richness index
n = number of different classes present in the geographic neighbourhood
n_{max} = maximum number of classes in entire image

The geographic neighbourhood was defined by a 7x7 square grid (48 pixels adjacent to the reference pixel were examined). As per the previous case the raster map shows high values of pixels (high values of relative richness) proportional to the number of land use present in the considered geographic neighbourhood. Through this index it was possible to highlight the richest areas in terms of land use (highest values), that should represent areas most suitable for wild animals. Like previous variables, an average value of relative richness of land use was assigned to each cadastral parcel: the darkest colors represent the area of the parcels with the highest relative richness values.

Figure 6 Relative richness of landuse

5. Results and discussions

By basing the analysis on cadastral maps (scale 1:7000), a total of 1356 cadastral parcels have been estimated. The first analysis of the variables was performed by a standard regression (Ordinary Least Squares method) that revealed a negative skewed distribution. By examining more in depth the data, 4 parcels were excluded from the analysis because they represented unusual values and have been considered outliers. The sample was accordingly reduced to 1352 cadastral parcels. The OLS analysis without outliers has shown a normal distribution of the residues with a coefficient of determination (R^2) equal to 0.50. The results are shown in tables 2 and 3.

Table 2 Estimated parameters of OLS model (*statistically significant at 0.05 level)

The highest positive determinant is related to the ecological corridors, while the highest negative determinant is represented by a relative richness of land use. All the variables are statistically significant at 0.05 level (prob <0.05) without redundancy phenomena. This is also confirmed by the variance inflation factors (VIF) that resulted slightly above 1 (showing therefore low degree of multicollinearity). The Moran's index resulted equal to 0.34 indicating a positive auto-correlation on the residuals (distance threshold equal to 3 Km). The statistic tests of Moran have revealed a variance equal to 0.000114, z-score 31.769[6], p-value equal to 0.000 (statistically significant at the 0.05 level).

Figure 7 OLS residuals

Moreover, by analyzing the outcomes of the OLS, it is assumed that the results are not stationary through the Koenker test - K(BP). The test and the significance of the explanatory variables (Robust_P) resulted significant. This explains how the relationships vary across the study area and are therefore non-stationary. The explanatory variables observed have a consistent correlation to the REN both in geographic space and in data space (Table 3).

Table 3 Diagnostic statistics of OLS model (*statistically significant at 0.05 level)

[6] Given the z-score of 31.769, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Assuming that the coefficients vary across space, the next step is focused on the analysis of the variables through a GWR (table 4 and figure 8), in order to verify how the determinant used are able to influence the potential number of wild animals in the study area.

Table 4 GWR statistics

Based on R^2 analysis, the kernel type of bandwidth chosen was the fixed one because the non-adaptive ones gave worse results: the R^2 of the fixed bandwidth (0.74) is higher than the R^2 of adaptive one (0.67). This is probably due to the fact that, by using the cadastral map, the parcels are uniformly distributed on the territory and their distribution is constant and presenting a low dispersion. In addition to a higher R^2, the GWR results reveal an additional better parameter than the OLS: the Akaike Information Criterion (AIC) shows a sensible reduction (Hipel and McLeod, 1994; Erickson, 2015), by passing from 12232 to 11754. An analysis of Multicollinearity (ML) was applied to the GWR in a similar way as applied to the OLS method. The results have shown that in all observations (1352) the condition number was found to be lower than 30. It is important to note that in the presence of strong local collinearities results become unstable, and results related to condition numbers over 30 may be unreliable. The non-stationarity of the data was also confirmed through the analysis of the spatial correlations. Moran's index has revealed a lower spatial dependence (0.19 using same distance threshold) than the correlation measured in the global regression. The statistic tests of Moran have revealed a variance equal to 0.000114, z-score 17.968[7], p-value equal to 0.000 (statistically significant at the 0.05 level).

Figure 8 GWR residuals

To better understand how the explanatory variables affect the dependent variable, it is useful to analyze the maps of the coefficients. Similarly to Megler et al., 2014, table 5 "summarizes the characteristics of the coefficients for GWR, and compares them to the coefficients for OLS. The medians from GWR can be seen to be relatively similar to those for OLS but the minimums and maximums vary substantially, lending support to the spatial non-stationarity of the variables".

Table 5 Coefficients of OLS and GWR of regression model

Through a graphical analysis of the coefficients (figure 9) it is possible to note that each variable coefficient shows a non-stationarity distribution and it is more homogenous than the patterns exhibited in the data: as stressed by Megler et al., 2014 this implies that "a geographic process is present rather a direct relationship at each location. In addition, each variable shows a different spatial pattern of effects. These variations support the use of GWR in modeling our dependent variable".

Figure 9a	Figure 9b

[7] Given the z-score of 17.968, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

a- Distance from artificial areas	b- Distance from agricultural activities
Figure 9c	Figure 9d
c- Ecological corridors	d- Relative richness of landuse

Figure 9 Maps of coefficients

The artificial areas essentially consist of urban agglomerations that find their maximum expansion in the flat area of the Mugello and next to the main towns. The roads connecting the above mentioned centers are considered also an artificial element. These reach their maximum capillarity in the flat area and in the west Mugello. The analysis of the map of the coefficients (fig. 9a) shows the western area, where, the distance from the artificial areas reach the maximum impact on the dependent variable: in the proximities of the artificial areas, the number of wild animals decreases.
The agricultural activities are mainly located next to the roads network (for commercial-logistic reasons) and in the flat area. The analysis of the map of coefficients (fig 9b) shows that the flat area has the major impact on the wild animals: in this case when the distance from agricultural activities decreases, the number of wild animals should increase. However, in the flat area, the high human pressure has a negative effect on wild animals decreasing significantly their presence. The distribution of ecological corridors reveals a low presence of animals in the flat area and in the urban area of Firenzuola. The coefficient map (fig. 9c) shows a maximum impact on the wild animals in the northern area close to the flat area, and in the north east of Marradi's municipality: this area is distinguished by the maximum presence of the ecological corridors and the maximum values of wild animals. Analyzing the last variable, the flat area reveals a low value of richness of landuse. The same values were attributed to the south of the municipalities of Marradi, Palazzuolo sul Senio, and Firenzuola. The analysis of the map of the coefficients (fig. 9d) shows a maximum impact of the variable on the number of wild animals in the northern zone close to the flat area, and in the north east of the municipalities of di Palazzuolo sul Senio and Marradi. In these areas it is possible to note high values of y. The visual analysis of the local R^2 can give additional useful information. Figure 10 shows where the model's prediction and strength of relationship is improved. It's important to note that there is spatial variation in the strength of relationships in the study area.

Figure 10 Map of local R^2

The "global" R^2 value (0.74) shows a strong significant relationship between potential number of wild animals and selected independent variables. The highest values can be observed in the area close to the flat zones and in the north east of Mugello: these zones correspond to areas with highest correlation between the dependent variable and the explanatory variables. The correlation observed in the flat areas confirms the low number of animals: despite the numerous agricultural activities, flat areas are characterized by a capillary road network, high urban densities, absence of ecological corridors and low values of relative richness of land use. However, in the North West Mugello the strong correlation with the dependent variable with the other variables confirms the high number of animals. This is due to the high values of relative richness of land use, a high number of ecological corridors, few agricultural activities, and the longer distance from the artificial areas. Despite the selected variables used in GWR model represent strong predictors of dependent variable, the study of the potential number of wild animals is complex: for a more exhaustive analysis, it is necessary to introduce more variables that are related to the dependent variable. They could focus on the number of hunters, or take into account factors related to seasonality (considering different wild animals species, nutrition varies in summer compared to winter), or they could be related to the different vegetation cover or types of forestry (Cotè 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).

6. Conclusions

This work has analyzed the possible correlations existing between the number of wild animals 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 with respect to the traditional data analysis techniques. Accordingly, the results are geo-referenced and showed through thematic maps, which are easy to read and available for further analysis.

This work allowed us to find correlations between variables throughout the area and to analyze information concerning the non-stationarity in spatial data. The number of wild animals was analyzed through a model allowing the highlighting of the spatial heterogeneity of the phenomenon: "it also contends that various competing theories regarding the influence of certain variables may all be ''correct'' but their predictive capacity depends on the specific location being considered" (Todd and Rickman, 2010).

Classic regression techniques usually assume that the relations between dependent variables and explanatory variables are homogeneous throughout the area, while using the spatial data, this relationship is not stationary: considering this, the results of a traditional OLS regression have been compared with the results of the GWR. The use of the GWR has allowed the detailed analysis of the spatial interactions between the dependent variables and the explanatory variables examined. The results detect the areas where these interactions are stronger with the aim to better understand the difficult balance between wild animals and human activities on the territory.

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