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RESEARCH ARTICLE

Estimating land market values from real estate offers: A replicable method in support of biodiversity conservation strategies

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Abstract While cost estimation is a very positive tool for spatial conservation prioritisation, there are few examples where costs (in monetary terms) are applied. We present a repeatable method to estimate and map field values in monetary terms using common correlative models. We modelled, with a resolution of 1 km^2, the information obtained by several real estate's agencies with a set of eleven environmental, climatic, and anthropogenic variables. Land cover was the main influencing factor, but further variables were affecting bids on field sales according to the socio-economic specificity of each administrative province. The estimated values were related to endemic plant species richness, their conservation status and altitudinal ranges. Richest areas in endemics have lower values given current market conditions and, within these endemic rich areas, values near the coast were generally higher than the rest of endemic-rich territories. Despite their limits, our method offers an alternative perspective on the challenges of simplifying the extrapolation of useful information for planning and disseminating the conservation of many ecosystem services providers.

Keywords Conservation planning · Decision making · Endemic vascular plants · Generalised Linear Models · Land prices modelling · Mediterranean islands

INTRODUCTION

Determining the direct costs of conservation, which are influenced by financial and politically based decisions (Newburn et al. 2005), may be critical to the successful creation of protected areas and to inform decision making (e.g. Brooks et al. 2006; Haase et al. 2014). However, quantifying the economic costs of conservation, not only in monetary terms but also according to other metrics, such as the ecosystems services, is often very difficult (e.g. Naidoo and Ricketts 2006; Underwood et al. 2009). Land economic value is an important parameter and a positive and constructive contribution to the cost–benefit tradeoffs that occur during conservation planning (Naidoo and Ricketts 2006). For instance, most used softwares for spatial prioritisation, such as Marxan (Ball et al. 2009) or Zonation (Moilanen and Kujala 2008), are rightly conceived to include such costs as limiting targets. The information about land economic values could also be used to effectively buy lands of conservation interest since, especially in developed countries and in Latin America and Sub-Saharan Africa, land trusts and government agencies rely on land purchases or easements to protect habitats or species (Armsworth and Sanchirico 2008). Especially within the boundaries of European Natura 2000 network, land purchase for conservation purposes has traditionally been an eligible action in several EU funding programmes, of which LIFE+ and the rural development programmes (RPD) figure most prominently (Disselhoff 2015).

Nonetheless, a literature survey on Protected-Area Planning found that only the 9% of them explicitly incorporate costs of land acquisition, conservation easements, or management agreements into prioritisation schemes (Newburn et al. 2005). In some cases, such as in California (Underwood et al. 2009), the acquisition cost was directly derived by the large investments made by the government in acquiring land and conservation easements; otherwise, there is a great deal of examples where no spatially explicit economic information, that would be appropriate for use in conservation planning, is readily available (Naidoo and Ricketts 2006).

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The usefulness of this information, especially if spatialised, has encouraged many researchers to deal with modelling the land values. On one hand, economists often compute this information for land valuation; hedonic price model approach is the most common technique in this sense (e.g. Rosen 1974; Tyrväinen 1997). It is a common approach among economists for the study of land and housing prices and it is based on the premise that the price of a marketed good is related to its characteristics, or the services it provides (Rosen 1974). In other words, the hedonic approach is a valuation that permits to estimate how factors are correlated to the consumers' preference of one's property and to model and map its spatial pattern (Bastian et al. 2002). Examples of empirical applications of property value models include works relating housing pricing to, for instance, school quality (Gravel et al. 2006), bicycle trail access (Mogush et al. 2016) or distances to recreation areas (Tyrväinen 1997), and land pricing to access to roads (Kostov 2009) or other recreational and aesthetic values (Ma and Swinton 2011).

Empirical hedonic pricing studies with sales data are usually preferred, but this needs a long-lasting market survey, which is in some case unfeasible or too costly (Newburn et al. 2005; Haase et al. 2014). Nowadays, a great deal of real estates are posting their selling offers on specific websites, providing also their locations by using the desktop web mapping service Google Maps and thus facilitating a land price data collection. Even if information from such web facilities could be biased (e.g. the bargaining power of either the sellers or the buyers is not always correlated with the characteristics of the good), limited (e.g. transactions which are not made via a real estate agent were not possible to be considered) and only a value given current market conditions is retrievable, this method holds the promise of simplifying procedures. On the other hand, there is a great deal of predictions based on relationships between environmental and climate factors with many different aspects, such as land use (e.g. Lindborg et al. 2013), species occurrence or abundance (e.g. Feng et al. 2017), tourism (e.g. Köberl et al. 2016), pests or human diseases (e.g. Bosso et al. 2016). Since pioneering studies, property price models have become one of the common ways of valuing environmental characteristics. Generally, environmental characteristics can be subdivided into two categories: environmental quality and environmental amenities. Environmental quality includes, for example, air pollution, water pollution, and noise, while environmental amenities can be interpreted as aesthetic views and proximity to recreational sites. Some environmental (dis)qualities or disamenities, such as air pollution, noise or unaesthetic views have clear negative effects on house/land prices (Ma and Swinton 2011; Mogush et al. 2016). Nonetheless, positive effects of environmental amenities associated with ecosystem services may be decreased when overweighed by some specific characteristic, for example when it is associated with crime (Troy and Grove 2008) or heavy recreation use (Tyrväinen 1997). In other cases, incongruences between economic and environmental values may be even less clear, such as in the cases of distances from protected areas or mountains, which could be an indirect measure of inaccessibility or agricultural infertility. Additionally, although markets provide useful information on the economic value of traded commodities, they fail to fully account for environmental values, without revealing social objectives for biodiversity conservation (Mallawaarachchi et al. 2006).

The goal of this research was to develop a practical methodology to extrapolate land values in monetary terms, which are relevant for assessing different land management options and informing policy. We used—to our knowledge for the first time—a "reduced-form" hedonic model to spatially estimate land values with a resolution of 1 km^2. Such approach can be largely applied by biologists and can be transferred to facilitate modelling of consumers' preferences using globally available environmental layers and to, therefore, approximate a projection of possible impediments to conservation goals due, for instance, to low acceptance rates.

As a case of study, we have essayed the performance of Generalised Linear Models (GLMs) to spatialise the acquisition cost of a territory of about 24 000 km^2. In particular, several real estate market prices were modelled for the entire Island of Sardinia (Western Mediterranean Basin) according to a heterogeneous set of variables reflecting anthropogenic, geographical and environmental characteristics. In this way, we aimed to set a practical and easily reproducible method in order to satisfy the decision makers' plea of implementing the economic information for the planning of the necessary and impellent efforts in spatial conservation (Shaw and Wlodarz 2013; Haase et al. 2014). Finally, the usefulness of this approach was tested by analysing if significant evidence can be found in terms of predicted land values among the territories defined by the endemic plant species exclusive to Sardinia with different altitudinal range, conservation status and levels of co-occurrence.

MATERIALS AND METHODS

Study area

Sardinia (Fig. 1) is the second largest island in the Mediterranean Basin after Sicily, with a main inland surface area of 23 833 km^2 and a total of 24 089 km^2 including the minor satellite islands. The island is mainly

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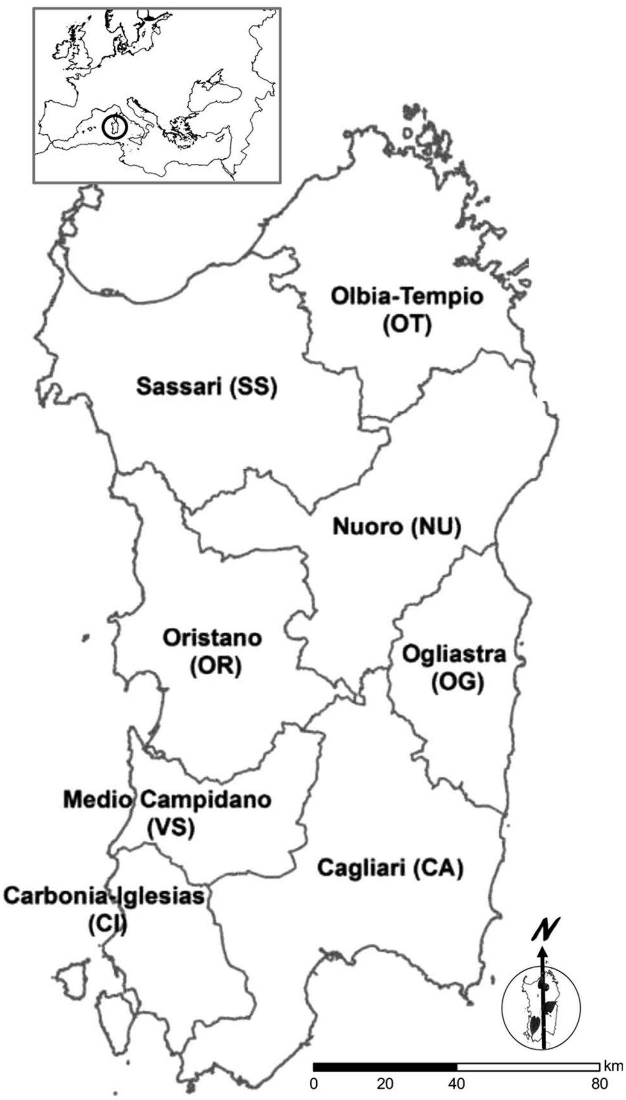

Fig. 1 Map of the eight administrative provinces of Sardinia, retrieved from the database of the official Sardinian geo-portal (http://www.sardegnageoportale.it)

mountainous with several groups of mountains such as Limbara, Sette Fratelli and Gennargentu (the highest of all at 1834 m), but also with hilly lands, plateaus and a few plains; coast is marked by a variety of landscapes, such as cliffs, sandy dunes, and beaches. The long presence of humans on the island has been of vital importance in shaping the landscape; accordingly, the administrative subdivisions reflect the diversified geomorphology and the consequent anthropogenic land uses that characterise the island (Pungetti et al. 2008). Sardinia could be divided into eight administrative provinces: besides the four historical provinces, i.e. Sassari (SS), Nuoro (NU), Oristano (OR) and Cagliari (CA), recently four more provinces, i.e. Medio-Campidano (VS), Ogliastra (OG), Gallura (OT) and Sulcis Iglesiente (CI), have been instituted to facilitate general planning and management (Fig. 1). Sardinia is underpopulated when compared to other Italian and European regions: it has a demographic density of 69 inhabitants per km^2, compared with the average of 201 persons per km^2 for Italy (ISTAT 2014). Although the population density in Sardinia is low, the 1 663 286 inhabitants are unevenly distributed over the island: 40% of the Sards live in urbanised zones in the north (Sassari) or in the south, near the island's capital Cagliari. The interior of Sardinia is still relatively isolated; especially NU and OG provinces, covering the mountainous heart of the island, is sparsely populated (Pungetti et al. 2008).

Despite the typical Mediterranean warm climate, the high landscape diversity permits the practice of irrigated agriculture in Sardinia only on the alluvial plains (provinces of CA, VS, OR and SS). Livestock farming takes widely place in all the territory of Sardinia: sheep are still the strength of livestock farming, goats are also significant due to the diversification into the production of goat cheese. Furthermore, tourism is one of the most important economic sectors of Sardinia, having grown considerably in the post-war period. Due to the pre-eminence of natural over cultural resources, Sardinian tourism has a seasonal (summertime) and local (coastal) character (e.g. Pungetti et al. 2008; Köberl et al. 2016). Nevertheless, Sardinia still retains a natural environment which has been relatively well preserved. Indeed, owing to its high concentration of endemic species (especially plants and invertebrates), it has therefore been identified as a biodiversity hotspot of global and regional significance (Fois et al. 2017). While about the 18% of its territory have been already designated as protected areas, several highly biodiverse places—mainly along the coast—are still unprotected or the management of the already designated areas, such as the National Park of Gennargentu (Italian Law 394/91), is still difficult due to the conflicts with local communities or the presence of other economic or strategic interests (Fois et al. 2018b).

Property sales prices collection and variable selection

Different Sardinian areas have different market values based on their environment and economy (Pungetti et al. 2008). In order to better consider such variability, the analyses were repeated for each of the eight administrative provinces. Data on bids (in euro; €) were retrieved from the online and private databases of several estate agents only when locality and price per m^2 were clearly reported; all selling offers were made from 2015 to date. Depending on the extension, data availability and representativeness, a range from 21 up to 59 locations per each administrative province were georeferenced for a total of 337 data points. This number of data points used for the modelling was

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reduced up to 333 after checking for spatial autocorrelation among model residuals using Moran's I; inverse distance matrix was employed as the weighting matrix. Significant autocorrelations ($p > 0.05$) at distances < 2 km were found in the OR and OT provinces and spatial dependency was limited by removing points at distances lower than 2 km. Although it is likely not able to fully eliminate spatial autocorrelation effects (Segurado et al. 2006), it is one of the most used techniques, due to its effectivity in substantially reducing it (e.g. Diniz-Filho et al. 2003; Yang et al. 2012). The software SAM 4.0 (Rangel et al. 2010) was used for the analysis of spatial autocorrelation. We only checked for spatial autocorrelation even if most conventional hedonic approaches should consider the presence of both spatial error and lag process, since this would have denatured the idea of this experimental study, which was to find a practical and low-costly method to estimate economic values through the most common modelling approaches used by biologists.

A suite of 11 geographic, climatic and anthropogenic variables (Table 1) were used as the basis of the explanatory factors of GLMs. In case of categorical variables [i.e. Land Cover (LC)], they were rasterised into 1 × 1 km grid cells using the area-proportional threshold value of 0.5 (Araújo 2004). For each province, data were examined and reduced to a final set in two steps. Firstly, GLMs in R environment (R Development Core Team 2010) with all the 11 variables were run in order to point out significant relationships according to their p values ($p < 0.05$). As is common with such data, over-dispersion was apparent and it was accommodated by using GLMs with quasi-Poisson error distributions. These models estimate the degree of over-dispersion and inflate standard errors accordingly (Zuur et al. 2009). In addition, we calculated Variance Inflation Factor (VIF) values to exclude the correlation between the remaining predictors through a stepwise procedure. We used the *vifstep* function of usdm R package (Naimi et al. 2014) which first finds a pair of variables which has the maximum linear correlation and excludes the variables which have greater VIF.

Table 1 List of variables (with abbreviations when used) applied for acquisition cost modelling and relative source: (1)Regione Autonoma della Sardegna (2009); (2)WCS and CIESIN (2005); (3)Regione Autonoma della Sardegna (2008); (4) 30 s resolution data layer retrieved from Hijmans et al. (2005)

Variables	Format	Description
Latitude (lat)	Point	UTM Y coordinate of 1 × 1 km grid centroid
Longitude (long)	Point	UTM X coordinate of 1 × 1 km grid centroid
Streets	Line	Sum of kilometres of streets(1) inside each grid
Human Influence Index (HII)	Raster	Raster dataset at 1 km spatial resolution(2), created from nine global data layers covering human population pressure, human land use, infrastructures, and human access
Land Cover (LC)	Polygon	Standard CORINE Land cover code first level categories(3)
Distance from coast (Dist)	Point	Minimum distance of each 1 × 1 km grid centroid from the line coast
Elevation (Elev)	Raster	Mean elevation obtained from a Digital Terrain Model at 1 km spatial resolution(4)
Slope	Raster	Mean slope in degrees generated from a Digital Terrain Model at 1 km spatial resolution(4)
Annual mean temperature (Bio1)	Raster	Data layer generated through interpolation of average monthly temperatures from weather stations at the time period between 1950 and 2000(4)
Temperature annual range (Bio7)	Raster	Difference between maximum and minimum temperatures of the coldest month from weather stations at the time period between 1950 and 2000(4)
Annual precipitation (Bio12)	Raster	Data layer generated through interpolation of average monthly precipitations from weather stations at the time period between 1950 and 2000(4)

Modelling real estate bids

We used the raster R package (Hijmans and van Etten 2014) for modelling real estate bids. In particular, we used the function *extract* to obtain the previously selected raster values to fit the model and the function *predict* to make a raster object with predictions from the fitted model. This approach is commonly used in ecology for species distribution modelling (e.g. Lindborg et al. 2013). Any type of model (e.g. GLM, GAM, randomForest) for which a predict method has been implemented can be used in raster R package (Hijmans and van Etten 2014); otherwise, a limitation of using several alternative models is that the coefficients become more difficult to interpret and understand (Hwang and Quigley 2004). Thus, we preferred to use for this study only the GLM approach because of its facility in understanding its fundamental modelling concept and in interpreting the relative influence of each factor (Miska and Jan 2005).

GLMs for each administrative province were separately run and results were then merged. For GLMs, the adjusted R^2 equivalent is measured by the amount of deviance accounted for (D^2; Guisan and Zimmermann 2000). D^2 values were computed for each GLM using *Dsquared*

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function in the modEvA package for R (Barbosa et al. 2014) and the independent contribution of each explanatory variable was also implemented by the hier.part package in R (Walsh and Nally 2008). A separated data set was used for a post hoc test of the models' predictive power (hereafter, Predictive Power). For this test, a number of further independent points ($N = 30\%$ of points used for GLMs) were obtained following the same methodology applied for the training ones and used for the post hoc evaluation. Such test points were considered as positive if they satisfied the prediction within a variability of 20%. In case the percentage of positive test points was lower than 50%, further training points were added to the initial model and all the procedure was repeated.

Estimated land market values and endemic vascular plant species

Spatialised estimates of land monetary values were correlated with the distribution of endemic exclusive vascular plants. In particular, we used the occurrence data of 187 endemic species exclusive to Sardinia ($N = 3858$ records; see the complete list and source details in Fois et al. 2017). Three different aspects were considered: (1) species richness, (2) conservation status and (3) species altitudinal range. Each aspect was categorised and shown in box plot form. Therefore, differences among categories were tested using one-way analysis of variance (ANOVA) with Tukey's post hoc test.

In order to account species richness and acquisition cost per each grid, the 1 × 1 km grid-based matrix for all the Sardinian territory was used (data available from the appendix of Fois et al. 2017). Thus, significant acquisition cost differences were tested among six species richness categories: (1) 1 × 1 km grids with more than 20 endemic species; (2) grids with 11 up to 20 species; (3) grids with 5 up to 10 species; (4) grids with 4 or 5 species; (5) grids with 2 or 3 species; (6) grids with 0 or 1 species.

Occurrence records ($N = 1830$) of all the 89 exclusive plant species, which were already assessed according to the IUCN criteria (2001), were used to correlate their presence with the acquisition costs. Species were subdivided according to the IUCN categories (2001): (1) CR, critically endangered; (2) EN, endangered; (3) VU, vulnerable; (4) NT, near threatened; (5) LC, least concern.

Because altitude was one, if not the main factor related to the distribution of several plant species in Sardinia (e.g. Fois et al. 2017), another subdivision was implemented according to the altitudinal range, obtained using extrapolated mean values per 1-km^2 grid cell: coastal (0–150) m above sea level (m asl), plains and hilly (10–800 m asl), montane (> 800 m asl) or widespread (altitudinal range > 1000 m asl).

RESULTS

Estimated land values

The estimated average value of the overall Sardinian territory was 22.6 €/m^2. Mean, minimum and maximum values of selling offers (i.e. training points) for each province were reported in Table 2. Maximum values were recorded for the CA and OT provinces while minimum values were in OR and OG. In order to explain such differences among estimated monetary values, three anthropogenic parameters (available at the official Web site of Sardegna Statistiche; http://www.sardegnastatistiche.it) were also reported in Table 2: population density (Pop; year 2014), number of tourist presences (Tourist; year 2013) and percentage of agricultural lands (Agriculture; year 2011). The most populated province was CA, while the less populated OT province was the one with the largest number of tourist presences and percentage of agriculture lands.

The deviance explained (D^2), post hoc test and relative independent contribution of each explanatory variable previously selected, according to P values and VIFs, are reported in Table 3 for each of the eight models. The D^2 of each model was, in most cases, greater than 0.50 (excepting OR = 0.30). As supposed to be, the percentage of positive correspondence of independent test points was higher than 50% in all cases. Because of two initial percentages of positive correspondence lower than 50% (for OR and VS provinces), we had to improve the analyses by using additional training points. Besides the CI and OR provinces, the CORINE first level categories of LC

Table 2 Mean, minimum and maximum values in euro (€ per m^2) of a determined number (N) of selling offers per each Sardinian administrative province (Prov) and three respective anthropogenic parameters obtained from the official web site 'Sardegna Statistiche' (http://www.sardegnastatistiche.it): population density (Pop; inhabitants per km^2 for the year 2014), number of tourist presences (Tourist; year 2013) and percentage of agricultural lands (Agriculture; year 2011)

Prov	N	Mean (€)	Min (€)	Max (€)	Pop	Tourist	Agriculture (%)
CA	59	84.3	0.4	716	112.7	2 679 886	19.2
CI	21	44.0	1.1	220	86.0	225 825	11.3
OG	32	71.9	0.1	400	31.1	797 973	17.3
NU	41	87.6	0.5	551	40.4	1 040 775	21.4
SS	52	31.6	0.2	391	66.0	1 560 727	4.7
OR	40	74.1	0.2	708	53.8	436 637	2.9
OT	49	92.6	0.3	720	26.0	3 866 305	36.6
VS	43	37.7	0.2	177	66.4	72 500	16.9

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Table 3 Estimated results from the GLM models for each Sardinian administrative province. Deviance explained (D^2) and proportion of positive correspondence of test points (Post hoc) of all the eight models (one per administrative province) are also reported. Directions of each correlation are also indicated with + for positive and − for negative ones

	Coeff	SE	Dev. (%)
Model CA ($N = 59$; $D^2 = 0.55$; Post hoc = 0.55)			
Intercept	+ 7.134***	0.963	
Land Cover (LC)	− 2.104**	0.003	− 66
Human Influence Index (HII)	+ 0.214**	0.014	+ 19
Slope	− 0.177*	0.026	− 12
Distance from coast (Dist)	− 0.026*	0.003	− 3
Model CI ($N = 21$; $D^2 = 0.58$; Post hoc = 0.71)			
Intercept	− 3.068**	0.951	
Streets	+ 0.435**	0.003	+ 39
Annual precipitation (Bio12)	− 0.474**	0.014	− 36
Elevation (Elev)	− 0.267**	0.026	− 25
Model OG ($N = 32$; $D^2 = 0.57$; Post hoc = 0.80)			
Intercept	+ 7.608***	0.640	
Land Cover (LC)	− 1.819***	0.003	− 86
Streets	+ 0.015*	0.014	+ 11
Model OR ($N = 40$; $D^2 = 0.30$; Post hoc = 0.58)			
Intercept	+ 0.02*	0.001	
Human Influence Index (HII)	+ 0.044*	0.026	+ 50
Land Cover (LC)	− 0.899*	0.511	− 44
Annual Mean Temperature (Bio1)	+ 0.024*	0.020	+ 6
Model OT ($N = 49$; $D^2 = 0.55$; Post hoc = 0.66)			
Intercept	+ 1.915***	0.424	
Land Cover (LC)	− 1.008***	0.258	− 41
Bio7	− 0.580**	0.196	− 23
Streets	+ 0.714**	0.668	+ 20
Elevation (Elev)	− 0.711*	0.2833	− 16
Model NU ($N = 41$; $D^2 = 0.68$; Post hoc = 0.70)			
Intercept	+ 4.101*	2.269	
Land Cover (LC)	− 1.790***	0.373	− 66
Streets	+ 0.201**	0.007	+ 28
Longitude (Long)	+ 0.078*	0.006	+ 4
Model SS ($N = 52$; $D^2 = 0.85$; Post hoc = 0.69)			
Intercept	− 17.285***	1.278	
Land Cover (LC)	− 2.104***	0.003	− 71
Bio7	+ 0.133**	0.049	+ 12
Human Influence Index (HII)	+ 0.025*	0.011	+ 9
Annual Mean Temperature (Bio1)	+ 0.020*	0.016	+ 8
Model VS ($N = 43$; $D^2 = 0.64$; Post hoc = 0.54)			
Intercept	+ 7.112***	0.486	
Land Cover (LC)	− 2.104***	0.003	− 90
Elevation (Elev)	− 0.003*	0.002	− 10

Statistical significance denoted as follows: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

explained the most of variance, while other factors, such as the Human Influence Index (HII), Slope and climatic ones (Bio1 and Bio7), differently influenced the acquisition cost in each province. The differences on the estimated land values, ranging from zero to 900 euros (€), among the administrative provinces of Sardinia (Fig. 2) reflected the variability in the anthropogenic influence of each province (Table 2) and the different interactions among predictor variables (Table 3).

Estimated land values and endemic vascular plant species: Giving a monetary value to biodiversity

Tukey's post hoc tests revealed significant differences ($p < 0.001$) among species richness and altitudinal ranges categories, while differences among IUCN categories (Fig. 3b) were not significant ($p > 0.05$). In particular, 1 × 1 km grids with one or no endemic plant species

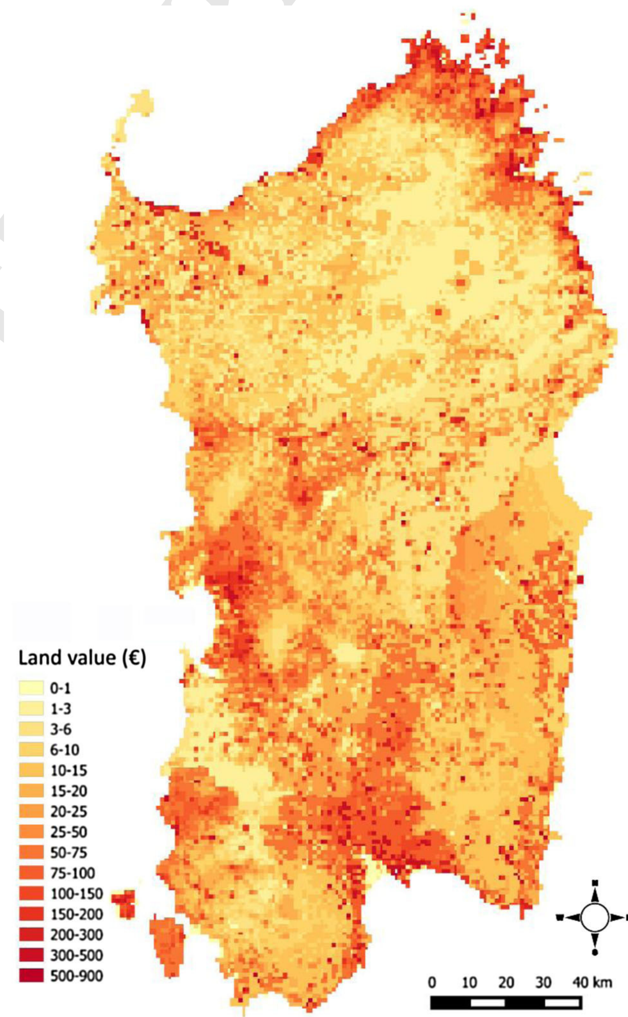

Fig. 2 Estimated land value map of the territory of Sardinia at a scale of 1 × 1 km. Prices (in euro, €) are plotted in a yellow–red scale and ranged from 0 (slight yellow) to 900 € (red)

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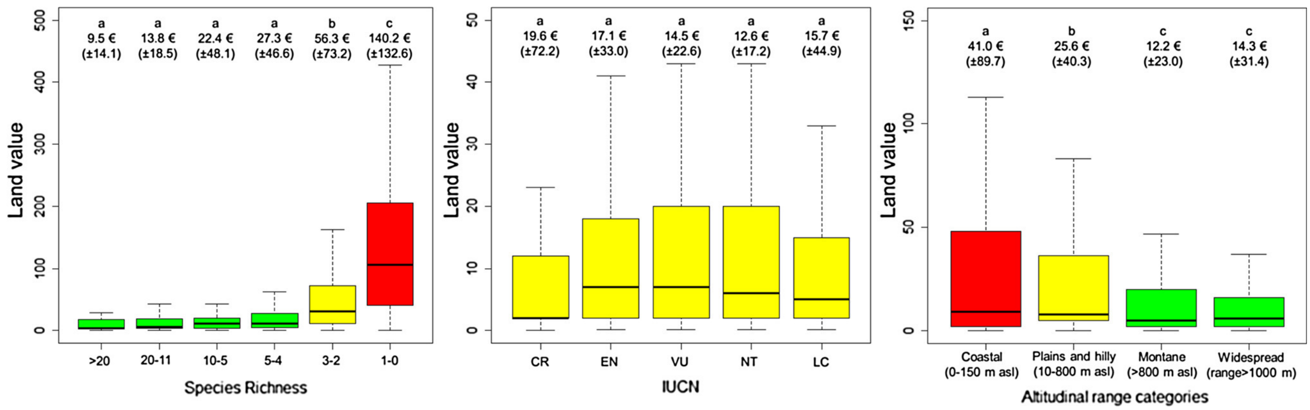

Fig. 3 Boxplot (middle line = median; upper edge = 75th percentile; lower edge = 25th percentile; lines = variability outside the quartiles) showing land values of each category divided per **a** endemic plant species richness, **b** IUCN and **c** altitudinal range categories. The letters refer to the results from ANOVA and Tukey post hoc tests for each treatment (similar letter indicates non-significant differences among categories; $p > 0.001$). The average land values and the standard deviations are also reported for each category

showed an averaged predicted monetary value of about 140 euros, while areas with four up to more than 20 plant species showed an average acquisition cost of about 9 up to 27 euros (Fig. 3a). Significant differences among species with different altitudinal distribution range categories evidenced that coastal plants live in areas with higher estimated market value (average of 41 euros) while montane and widespread species live in areas with a lower value (average of 12.2 up to 14.3 euros).

DISCUSSION

Estimating land values

Using Sardinia as an example, this study also offers an exploratory perspective on the challenges of adopting a correlative modelling approach to extrapolate useful but often unobtainable or hardly achievable information about land economic values. In order to consider this necessity, different surrogates of influential factors, such as Human Influence Indices (Sanderson et al. 2002), have been proposed. According to other authors (e.g. Balmford et al. 2003; Lindborg et al. 2013), we also modelled our cost depending on such anthropogenic drivers but we integrated them with other factors which could also influence field values. In particular, Elevation was likely to be indicative of the agriculture economic activity, while climate factors (i.e. Bio1, Bio7) were more correlated with tourism; this last is in line with another a recent research where a dependency between tourism demand and several climatic factors (e.g. number of ‘wet’ days or ‘too hot’ days) was proved in Sardinia (Köberl et al. 2016). Returning to our case, if we consider the VS province, a relatively poor region in terms of tourist presences but rich in terms of agricultural activities, the Elevation was the only driver which contributed with LC. Contrarily, the SS province, with a low percentage of agricultural areas and a high number of tourist presences, showed a great proportion of the deviance explained by climate factors.

Stochasticity of our models was tried to be reduced by subdividing the Sardinian territory into a reasonable quantity of subsets and by evaluating their predictive power with independent data. As far as the administrative provinces are concerned, we argued that, following their definition baseline, this subdivision was matching our scope. According to it, our results were reflecting the different environmental and socio-economic conditions of the eight provinces. Indeed, we found that the acquisition cost of a Sardinian field varies enormously from 0.1 to 900 € per m^2. It is an example of how much field market values could influence a conservation planning. Most expensive lands were the ones designated for urbanizations along the heaviest populated and touristic areas (i.e. cities in CA, OR and SS provinces and the tourist coast of OT). Intermediate values corresponded to scattered cheapest urban areas and to the expensive agricultural fields of the most populated provinces (CA, CI), fertile (alluvial plain of CA, OR, SS and VS provinces) and near the tourist coast of OT province. Steep, semi-natural areas and small uninhabited satellite islets were the low-priced ones.

Land values and endemic vascular plant species: One good and one bad news

A necessary premise is that even if there have been several attempts of putting monetary values on environmental ones, such as the Economics of Ecosystems and Biodiversity (http://www.teebweb.org/), environmental values have not yet received full economic recognition, and can

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thus not be directly used in economic transactions (Dalerum 2014). Additionally, several scientists criticised the common assumption that the natural environment can best be safeguarded by valuing and managing ‘nature’s services’ as tradable commodities (Turnhout et al. 2013 and references therein). In this sense, an economic perspective may frame biodiversity in too specific reductionist terms and may then provide the basis of enabling the commodification of biodiversity, by incorporating it in systems of exchange (Turnhout et al. 2013). Accordingly, it is important to highlight that, in this study, we did not try to capture the value of the endemic species, but rather a proxy for the difficulties connected with how to convert the land into profit yielding units.

Considering the intrinsic uncertainty of our market values extrapolation, this kind of results can be roughly used at fine scale and for specific economic purposes (Shaw and Wlodarz 2013). Nonetheless, biologists could consider them as a reliable tool for the conservation strategies evaluation at regional scales and for planning further and more concrete actions. As previously suggested (e.g. Degteva et al. 2015; Mendoza-Fernández et al. 2015), the management of a territory must be adjusted according to the anthropogenic demand. For instance, the development of a sustainable tourism have been proposed for the management of areas of the south-western coast of Sardinia (Ioppolo et al. 2013) while the integral protection of meso-micro-reserves was proposed for rocky places (Fois et al. 2018b) and uninhabited satellite islets (Fois et al. 2016).

Following this line of reasoning, we presented an explorative use of estimated land market values for planning the conservation of all vascular plant species exclusive to Sardinia; accordingly, we have one good and one bad news. The good news is that values of lands with more than four endemic species are significantly less high than areas with at most one species. Although further aspects, besides the abundance, should be taken into account when spatially prioritising (e.g. redundancy or complementarity), our information suggests that protecting most interesting areas from a plant conservation point of view is not unfeasible since direct (e.g. land acquisition) or indirect costs (e.g. presence of other economic interests and/or difficult acceptance of protection measures by local communities) are less high than in those areas poor in endemic plant species.

On the other hand, the bad news is that, if we consider the IUCN conservation status, no significant differences among areas with threatened (CR, EN or VU) and no threatened (NT and LC) plant species were found. This is explained by the presence of endangered coastal plants and plants living at low elevations in areas which have significantly higher economic interests than the rest of the territory. In addition, the same coastal areas were reported facing a high rate of plant population extinctions (Fois et al. 2018a).

CONCLUSIONS

There is an ongoing debate within the biodiversity conservation research community on how natural resources are to be economically valued. According to the most common viewpoint (e.g. Brooks et al. 2006; Naidoo and Ricketts 2006; Turnhout et al. 2013), the field market prices are only one of many values that should be considered at the time of planning conservation measures. Otherwise, the importance of such economical parameter, also in terms of communication power, is undeniable. The map of estimated land monetary values of Sardinia was developed in this sense: it would improve a tool for conservation planners in order to better address limited financial resources and more clearly inform how they would be spent. For instance, this information could be also used for cost estimation of projects funded by the LIFE EU Nature programme, since land acquisition is a one of the most common long-term investments for such projects (Andersen et al. 2017). In addition, this practical and cost-effective methodological framework permitted to point out an index of cost, which was valued in monetary terms and is thus more comprehensible to a large audience.

This study also offers an exploratory perspective on the challenges of adopting a correlative modelling approach to extrapolate useful information, which is often unobtainable or expensive to achieve. Following our proposal, a biologist could integrate a broader information provided by real estates with freely available anthropogenic and environmental global datasets.

As usual, there are pros and cons of applying our method, which is to our knowledge for the first time reported in the literature. Even if in some way inspired by them, we were not able to claim to have a picture of the hedonic prices, since standard methods were not used. For instance, we used offering prices and not actual sale prices, which gives us only a sellers’ valuation. Nonetheless, this approach allows gathering free and easily available data, in many cases already georeferenced through Web facilities. Also, this method was presenting a simplification of the more complex and complete standard procedures for hedonic pricing; indeed, we limited calculations on marginal values and presence of spatial dependency. Nonetheless, we were not pretending to replace hedonic pricing methods, since we agree that these would be better and more precise solutions to estimate monetary values. What we tried to do was to transfer methods commonly used by biologists for species distribution modelling to estimate a proxy of conservation cost that, for its

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complexity, is often unfortunately unviable (Sutton et al. 2016). The policy implications of this output are clear if they are viewed from a biodiversity conservation perspective rather than only economic. Indeed, the spatialised map of land values shows in a simplified but clear way where the hardly measurable environmental goods have no reason not to be preserved, or where land values are high and the protection of nature might be more conceived as integrated with other interests.

This said, we would like, in conclusion, to share our information, by making available to anybody that could be interested in the estimated land value map of Sardinia as a usable raster (by requesting to the corresponding author).

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