Using MaxEnt to predict landscape preference: A case study in Madrid

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Abstract.

Cultural ecosystem services (CES) can be defined as "non-material benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation and aesthetic experiences" [1].

Despite their relevance, CES evaluation remains disregarded and poorly understood in

comparison with the other material ecosystem services [2]. Landscape photographs available on social media have opened up the possibility of quantifying landscape values and ecosystem services that were previously difficult to measure. Thus, a new research methodology has been developed based on the spatial distribution of geotagged photographs that, based on probabilistic models, allows us to estimate the potential of the landscape to provide CES.

Maxent is a software based on machine learning technique called the maximum entropy approach, used as a CES supply potentiality tool by several researchers. [3,4]

This study tests the effectiveness of predictive models from MaxEnt, a software based on a machine learning technique called the maximum entropy approach, as tools for land management and for detecting CES hot spots.

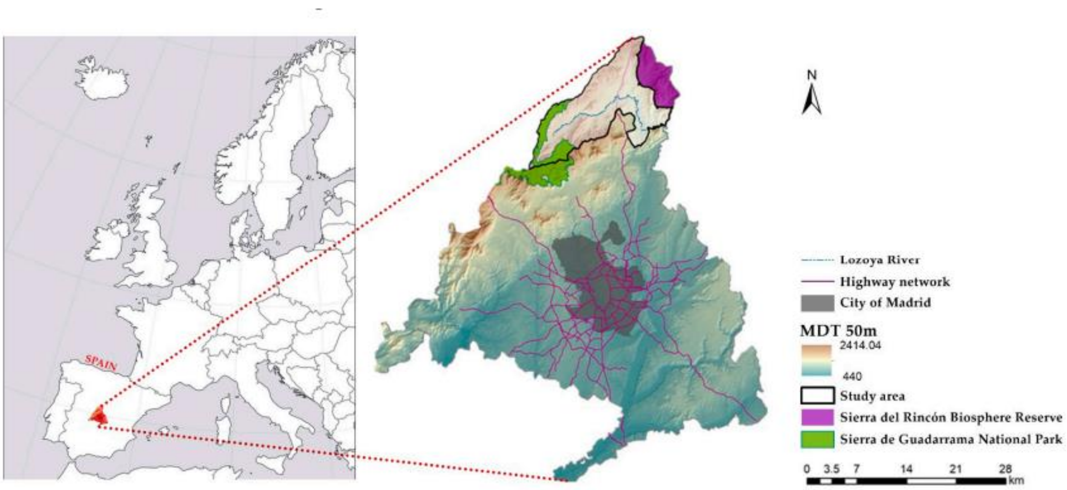

Figure 1. Map of the Madrid Region with the Lozoya Valley area of study in the north.

The study area is Lozoya Valley (Figure 1.), located in the northern Sierra de Guadarrama in the Lozoya river basin (Madrid, region, Spain). The Lozoya Valley is a heterogeneous landscape with forest, settlements, water bodies and a mosaic of traditional land uses containing pastures, meadows, hedgerows and riparian forest due to a continuous change in land uses and rural activities over the centuries, which have shaped the landscape and their traditional way of living that have resulted in a region of great socio-ecological value. Currently, this heritage landscape is under several categories of protection [5].

This study compares the prediction of potential demand of CES in an area, calculated by MaxEnt, with the actual demand, measured based on photo density. To do so,

it was used a sample of photographs from Panoramio network, taken between 2007 and 2008 in Lozoya Valley, to develop a future prediction of CES distribution and then, compared it with the real distribution of photograph from 2009 to 2015.

First, the images were classified according to a series of categories link to CES and the most represented elements in six categories: natural system, urban system, rural system, water bodies, recreational activities and cultural activities. Once classified, a sieve was applied to the collection of images to remove unwanted tendencies. Given that there are also methodologies that consider this type of reduction in the original sample to be negative [33], and that this paper is oriented towards a critique of an established method, the analysis is carried out with two samples: the original, with 1728 photographs, and the PUD, with 709 photographs.

To calculate the actual distribution of CES (for the original sample and PUD), five environmental factors were added to Maxent: land cover, altitude, average atmospheric temperature, distance to road and distance to cultural assets.

Finally, to test the correlation between the future distribution of CES an its actual demand it was conducted a photograph point density study using the Kernel tool in ArcMap 10.5.1. which computes covariance and correlation matrices.

There is little variation between the predictive model of both samples. The AUC, the standard measure of model reliability, is 0.755 in the case of the original sample and 0.908 in the case of the PUD sample. In both cases, it is much higher than 0.5, indicating reliability of the model. In the PUD sample, it is very close to 1.

The photo density from the actual demand provides similar results for both the original

sample and the PUD (Figure 2). In both cases, there is a high concentration of photographs in the southwest area, although there is a proportionate distribution of lower concentrations throughout the rest of the Lozoya Valley.

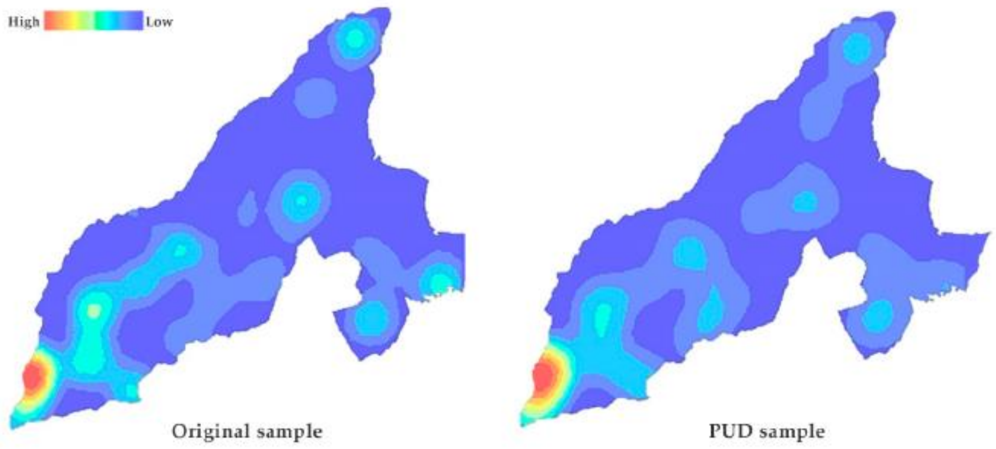

Figure 2. Density of photographs taken between 2009.2015 in both samples.

The correlation matrix between these maps and their corresponding MaxEnt models gives a value of 0.30940 in the case of the original sample and 0.435 in the case of the PUD sample. That is, in both samples there is a low correlation (<0.5) between the actual demand and the potential demand determined by the MaxEnt.

Since the closest correlation occurs in the photographs of the PUD sample, we study the correlation of the photographs on the basis of the different categories (Table 1). It is observed here that the highest correspondence occurs in natural systems (65%) and outdoor activities (64%), being the only ones with a correspondence in the variation of more than 50%. Urban systems, however, maintain a negative correlation, meaning that the actual demand has more variation in intensity than the MaxEnt model.

Table 1. Correlation between MaxEnt model and actual demand by category in PUD sample.

PUD Sample	Natural System	Urban System	Rural System	Water Bodies	Recreational Activities	Cultural Activities
Correlation Base Demand and Actual Demand	0.651	−0.07	0.204	0.246	0.642	0.244

Thus, the results highlight a low correspondence between the prediction of supply of CES and its real demand, which indicates that Maxent is not a useful predictive tool in changing and complex landscapes such as the studied here.

References

1. Leemans, R.; De Groot, R.S. Millennium Ecosystem Assessment: Ecosystems and Human Well-Being: A Framework for Assessment, (2003). *Island Press*, Washington, DC, USA.

2. Cheng, X.; Van Damme, S.; Li, L.; Uyttenhove, P. (2019). Evaluation of cultural ecosystem services: A review of methods. *Ecosystem Services*., 37, 100925. Available at: https://doi.org/10.1016/j.ecoser.2019.100925

3. Clemente, P.; Calvache, M.; Antunes, P.; Santos, R.; Cerdeira, J.O.; Martins, M.J. (2019). Combining social media photographs and species distribution models to map cultural ecosystem services: The case of a Natural Park in Portugal. *Ecological Indicators*, 96, 59–68. Available at: https://doi.org/10.1016/j.ecolind.2018.08.043

4. Arslan, E.S.; Örücü, Ö.K. (2021). MaxEnt modelling of the potential distribution areas of cultural ecosystem services using social media data and GIS. *Environmental, Development and Sustainability*, 23, 2655–2667. Available at: https://doi.org/10.1007/s10668-020-00692-3

5. Sarmiento-Mateos, P.; Arnaiz-Schmitz, C.; Herrero-Jáuregui, C.; Pineda, F.D.; Schmitz, M.F. (2019). Designing Protected Areas for Social–Ecological Sustainability: Effectiveness of Management Guidelines for Preserving Cultural Landscapes. Sustainability, 11, 2871. Available at: https://doi.org/10.3390/su11102871