2020 IMEKO TC-4 International Conference on
Metrology for Archaeology and Cultural Heritage
Trento, Italy, October 22-24, 2020

Investigation of archaelogical sites with species distribution models and satellite data

Noviello Mariangela[1], Cafarelli Barbara[2], Calculli Crescenza[2], Sarris Apostolos[3], Mairota Paola[1]

[1] *Department of Agro-Environmental and Territorial Sciences, University of Bari'Aldo Moro', Via Orabona 4, 70125 Bari, Italy, paola.mairota@uniba.it;*

[2] *Department of Economics, University of Foggia, Largo Papa Giovanni Paolo II, 1, 71100 Foggia, Italy, barbara.cafarelli@unifg.it;*

[3] *Laboratory of Geophysical-Satellite Remote Sensing and Archaeo-environment (GeoSat ReSeArch Lab), Institute for Mediterranean Studies, Foundation for Research & Technology, Hellas (IMS/FORTH), Crete, Greece, asaris@ims.forth.gr*

Abstract – **The combined use of probability distribution models and remote sensing data can benefit the study of archaeological landscapes in the perspective of both archaeological risk impact assessment and scientific field surveys planning. A multiscale comparison between two predictive models a Geographical Information System (GIS) based multiparametric spatial analysis (MPSA) and the Maximum Entropy Model (MaxEnt) is presented. Both response (presence only) and independent variables included attributes derived by cartographic sources and satellite data. Best model selection (Akaike's Information Criterion) and Receiving Operator/Area Under the Curve analysis indicated a better performance of MaxEnt with respect to the GIS-MSPA model. Insights on pitfalls and potentials for the progress of this kind of approach in the archaeology operational context are described.**

I. INTRODUCTION

Many present landscapes bear the imprint of pre-historical and historical human activities in the form of artifacts. The study of their spatial distribution in geographical areas of interest can benefit cultural heritage protection policies, archaeological risk impact assessments inherent in infrastructural planning as well as effective scientific field surveys planning. In this perspective, probability distribution models are becoming an investigation method for archaeological landscapes [1, 2, 3]. Likewise, the use of remote sensing data in archaeological studies and ecological contexts, is gaining momentum [e.g., 4].

II. METHODS

Two predictive modelling approaches, a Geographical Information System (GIS) based multiparametric spatial analysis (MPSA) [5]. and the Maximum Entropy (MaxEnt) approach [6] were contrasted and their performance evaluated for archaeological applications in a case study area of the Tavoliere Plain (Southern Italy). Both modelling approaches rely on presence only data as response variables and on environmental attributes as independent variables. For the scopes of this study presence data included artifacts identified by means of both archaeological survey techniques [7] and remote sensing [8, 9]. Environmental variables included topographic, geomorphological attributes in the form of raster maps chosen among those traditionally guiding field archaeologists in their preliminary assessments of artifacts presence (e.g., altitude, slope, aspect, river banks) and remote sensing derived attributes (e.g. vegetation indices) known to provide information on the structural and physiological state of crops which can be altered by the presence of buried constructions [10, 11].

The same data conditions were ensured to the models which assume a different representation of input data (i.e., polygons in GIS_MPSA vs. points MaxEnt). This was achieved by creating two series of environmental variable maps at two different scales (low resolution and high resolution) approximating the average extent of the polygons delimiting the presence sites.The low-resolution map (pixel size 200x200 m) corresponds to a 1:400,000 map scale (coarse scale, high map ratio), and the high-resolution map (pixel size 8x8 m) corresponds to a 1:16,000 map scale (fine scale, low map ratio). Non redundant environmental variables were selected by applying two alternative criteria (i.e. correlation coefficients combined with MaxEnt ranking of the importance of variables and spatial Principal Component Analysis (sPCA) [12]. The Akaike's Information was Criterion [13] with a correction for a small sample size (AICc) [14] was used to select the most parsimonious model configurations and the Receiving Operator/Area Under the Curve (ROC/AUC) analysis was adopted for model comparison.

The minimum number of occurrence data required for modelling the distribution archaeological site in the study area and the optimal proportion of survey vs remotely senses occurrence data were assessed by means of a threshold analysis of the presence data (Scheldeman & van

Zonneveld, 2010, p. 148) on the best MaxEnt model at the high resolution scale.

III. RESULTS

MaxEnt models outperform GIS_MSPA ones, at both spatial scales as indicated by the value of AUC (low resolution 0.75 vs 0.51; high resolution 0.75 vs 0.64). Scale also affects the effectiveness of sPCA ws MaxEnt ranking of environmental variable importance for the objective selecting non-redundant input variables and thus the construction of more parsimonious model configurations.

To improve and stabilise the performance of the model the combination of density of 0.2 presence sites/km^2 and 45% of remotely sensed sites resulted optimal to improve a stabilise the performance of the model in the case study.

IV. DISCUSSION

This work, based on an illustrative case study, demonstrates that niche-based presence only species distribution modelling approaches can be applied with greater confidence than GIS based multiparametric ones.

However, no generalisation is possible about scales, minimum densities of presence sites and proportion or RS derived response variables as these aspects appear to be strongly landscape and archaeological context specific. need to be specific

Scaling issues, in particular should be carefully considered due to the inherent scale dependence of the MaxEnt modelling approach [16] and this principally concerns the method used to adjust the grain of the environmental variables maps to that of an area corresponding to the average size of the presence polygons.

The work also demonstrates the relevance of remote sensing for this kind of studies as both response and predictor variables can be derived from these sources. Harnessing the advances in both airborne and satellite (optical, radar, LiDAR) technologies would boost the investigation of archaeological landscapes.

V. ACKNOWLEDMENTS

This work is dedicates to the memory of Prof. Marcello Ciminale. M.N. received financial support by the DiSAAT-University of Bari (overhead funds from the project Biodiversity Multi-Source Monitoring System: From Space To Species, BIO SOS G.A. 263435 - EUFP7/SPA. 2010.1.1–04: “Stimulating the development of GMES services in specific areas”).

REFERENCES

[1] Franklin, J., Potts, A. J., Fisher, E. C., Cowling, R. M., Marean, C. W. 2015. Paleodistribution modeling in archaeology and paleoanthropology. *Quaternary Science Reviews* 110: 1-14.

[2] Galletti, C. S., Ridder, E., Falconer, S. E., & Fall, P. L. (2013). Maxent modeling of ancient and modern agricultural terraces in the Troodos foothills. Cyprus. Applied Geography, 39, 46–56

[3] Howey, M. C., Palace, M. W., & McMichael, C. H. (2016). Geospatial modeling approach to monument construction using Michigan from AD 1000–1600 as a case study.Proceedings of the National Academy of Sciences, 113(27), 7443-7448

[4] Lasaponara, R., Masini, N. (2011). Satellite remote sensing in archaeology: Past, present and future perspectives. Journal of Archaeological Science, 38 1995e - 2002.

[5] Noviello, M., Chliaoutakis, A., Ciminale, M., Donati, J. C., & Sarris, A. (2015). Neolithic settlements in the Tavoliere plain (Apulia, southern Italy): Predictive probability maps. Archaeologia Polona, 53, 239–243.

[6] Elith, J., Graham, C. H., Anderson, R. P., Dudík, M., Ferrier, S., Guisan, A., et al. (2006). Novel methods improve prediction of species' distributions from occurrence data. Ecography, 29, 129–151.

[7] Barbanente, A., Volpe, G., Annese, C., Buglione, A., Di Zanni, A., Goffredo, R., et al. (2010). The “cultural heritage map of Apulia” project. In S. Campana, M. Forte, & C. Liuzza (Eds.). Space, time, place, third international conference on remote sensing in archaeology, Oxford (pp. 201–209).

[8] Gallo, D., Ciminale, M., Becker, H., & Masini, N. (2009). Remote sensing techniques for reconstructing a vast Neolithic settlement in Southern Italy. Journal of Archaeological Science, 36, 43–50.

[9] Noviello, M., Ciminale, M., & De Pasquale, V. (2013). Combined application of pansharpening and enhancement methods to improve archaeological cropmark visibility and identification in QuickBird imagery: Two case studies from Apulia, southern Italy. Journal of Archaeological Science, 40, 3604–3613.

[10] Agapiou, A., & Lysandrou, V. (2015). Remote sensing archaeology: Tracking and mappingevolution in European scientific literature from 1999 to 2015. Journal of Archaeological Science: Report, 4, 192–200.

[11] Ciminale, M., Becker, H., & Gallo, D. (2007). Integrated technologies for archaeologicalinvestigation; the Celone Valley project. Archaeological Prospection, 14, 167–181.

[12] Demšar, U., Harris, P., Brunsdon, C., Fotheringham, A. S., & McLoone, S. (2013). Principalcomponent analysis on spatial Data: An overview. Annals of the Association of American Geographers, 103(1), 106–128.

[13] Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B.

N. Petrov, & F. Caski (Eds.). Proceedings of the second international symposium on information theory (pp. 267–281). Budapest: Akademiai Kiado.
[14] Burnham, K. P., & Anderson, D. R. (2002). Model selection and multimodel inference: A practical information-theoretic approach. New York: Springer-Verlag.
[15] Scheldeman, X., & van Zonneveld, M. (2010). Training manual on spatial analysis of plant diversity and distribution. Rome: Bioversity International.
[16] Renner, I. W., & Warton, D. I. (2013). Equivalence of MAXENT and Poisson point process models for species distribution modeling in ecology. Biometrics, 69(1), 274–281.