PREDICTIVE MODELLING OF ARCHAEOLOGICAL SITES LOCATION IN MBEYA REGION, TANZANIA

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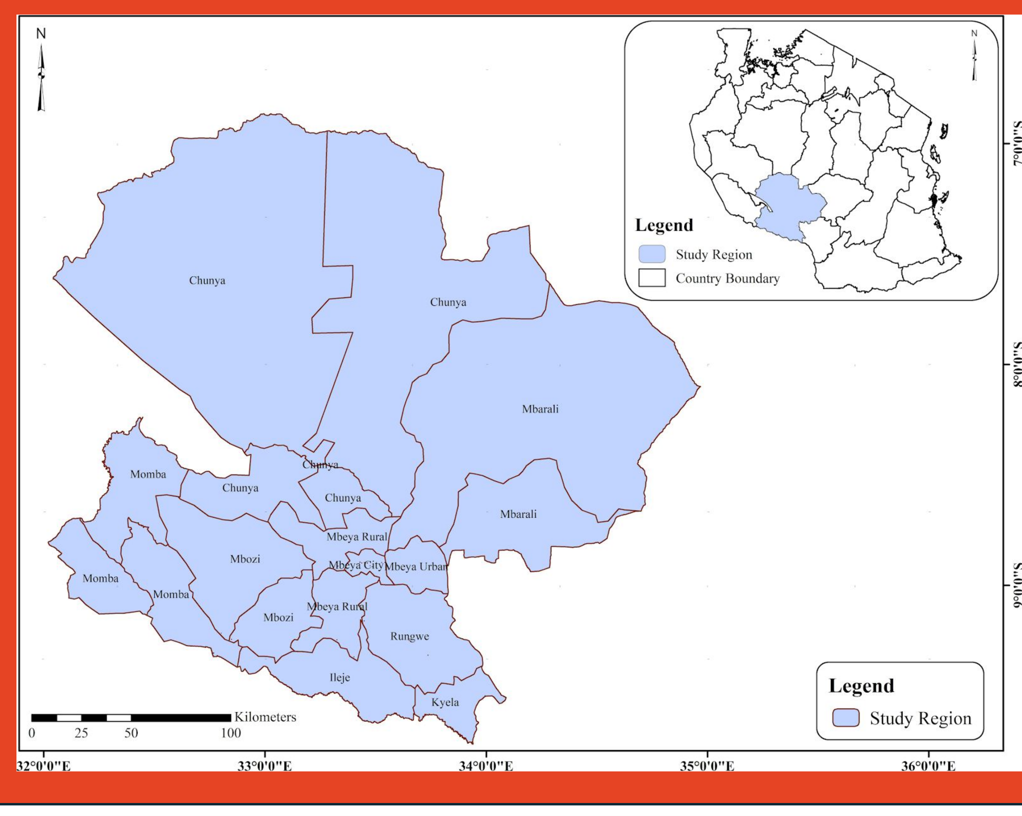
MAEASaM Mapping Africa's Endangered Archaeological Sites and Monuments

Introduction

Predictive modelling is predominantly used in archaeology to assess the likelihood of the presence of archaeological sites on the landscape. The need to model areas of maximum likelihood is imperative as archaeological survey of vast areas is time consuming and resource-intensive. Over the last 40 years, archaeological predictive modelling has been applied in contract archaeology to salvage archaeological sites which are prone to destruction. Here, we present a scenario of a predictive model of the Mbeya region in Tanzania (where few archaeological sites are known from a relatively large region) to predict where previously undocumented stone age sites may be present in the region, based on prior knowledge of existing ones.

Study Area

Mbeya region in Tanzania is located in the southwestern part of the country at an altitude of about 1700 m, characterised by a subtropical highland climate with humid summers and dry winters. The average annual rainfall is 900 mm while the temperature ranges from -6°C in the highlands to about 29°C in the lowlands (Sagamiko et al 2018). The region is famous for the Ruaha and Kitulo National Parks, Lake Nyasa, Mbozi meteorite and the Great Rift Valley viewing point, as well as some yet-to-be documented rock art sites. Within Mbeya, between Lakes Tanganyika and Nyasa, lies Lake Rukwa: a shallow soda lake with no outlet and which has occasionally dried out completely.



Materials and Methods

This study used MaxEnt (Maximum Entropy) model to predict likely areas on the landscape where archaeological sites could be found. Using SRTM DEM to extract environmental parameters associated with prehistoric archaeological sites location in addition to GIS data (geographic location of these archaeological sites), a spatial model for estimating prehistoric stone age sites was created.

MaxEnt Model

MaxEnt model estimates a target probability distribution by identifying the probability of distribution of maximum entropy. This estimation is subject to a set of constraints that represent incomplete information about the target distribution.

Presence sites

Georeferenced archaeological sites (n=38: 29 training dataset and 9 test dataset) from the publication of Willoughby which comprises MSA sites discovered as scattered sites on river terraces along the northern Songwe River.

Environmental Predictors

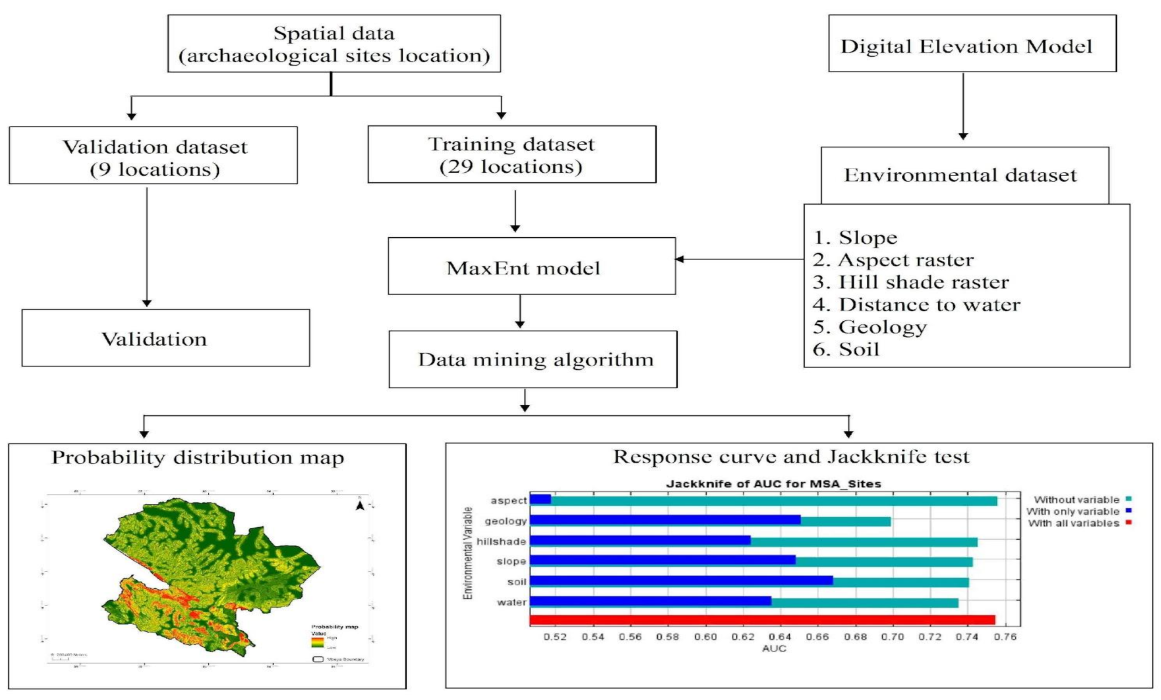
Six environmental variables grouped into two categories were employed as predictors for the model.

Model Execution

Probability distribution of stone age sites was used as presence point data and environmental variables as raster data. The result of the model is an output distribution produced as an ASCII grid.

Model Evaluation

The model was evaluated using three parameters; average test AUC output, estimates of relative contributions of the environmental variables, and the marginal and corresponding response curves.

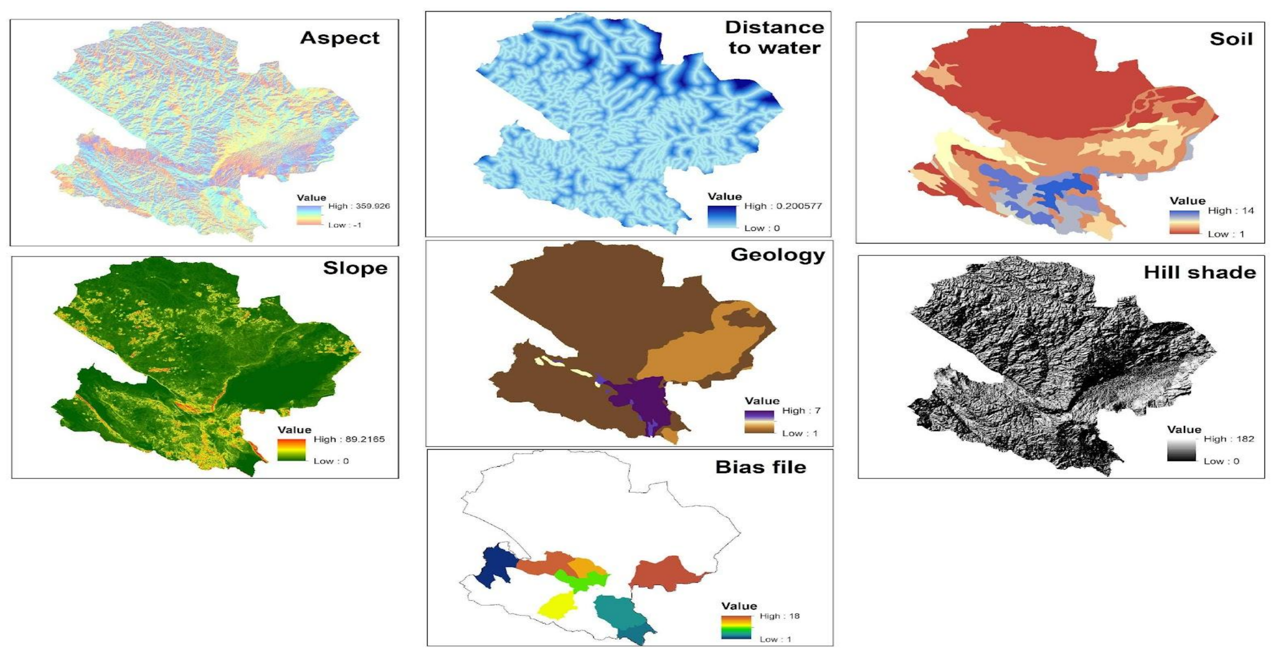


Flowchart of the analyses

Table 1. Environmental layers used for the predictive model, along with source and GIS processing.

ENVIRONMENTAL LAYER	SOURCE (TYPE)	GIS PROCESSING	RASTER VALUE
Digital Elevation Model (DEM)	Copernicus-DEM 1 arc second (raster).	Raw data. Clipped to extent and pixel size and converted to .asc.	Meters above sea level.
Slope	Derived from DEM (raster).	r.slope.aspect	Degrees
Aspect	Derived from DEM (raster).	r.slope.aspect	Degrees
Geology	USGS (vector).	r.watershed	TWI
Drainage network	USATC (vector).	Euclidean Distance (r.grow.distance).	Normalized matrix (0 to 1).
Soil	IGAD (vector).	Euclidean Distance (r.grow.distance).	Normalized matrix (0 to 1).
Bias file	Derived from DEM (raster).	Euclidean Distance (r.grow.distance).	Normalized matrix (0 to 1).

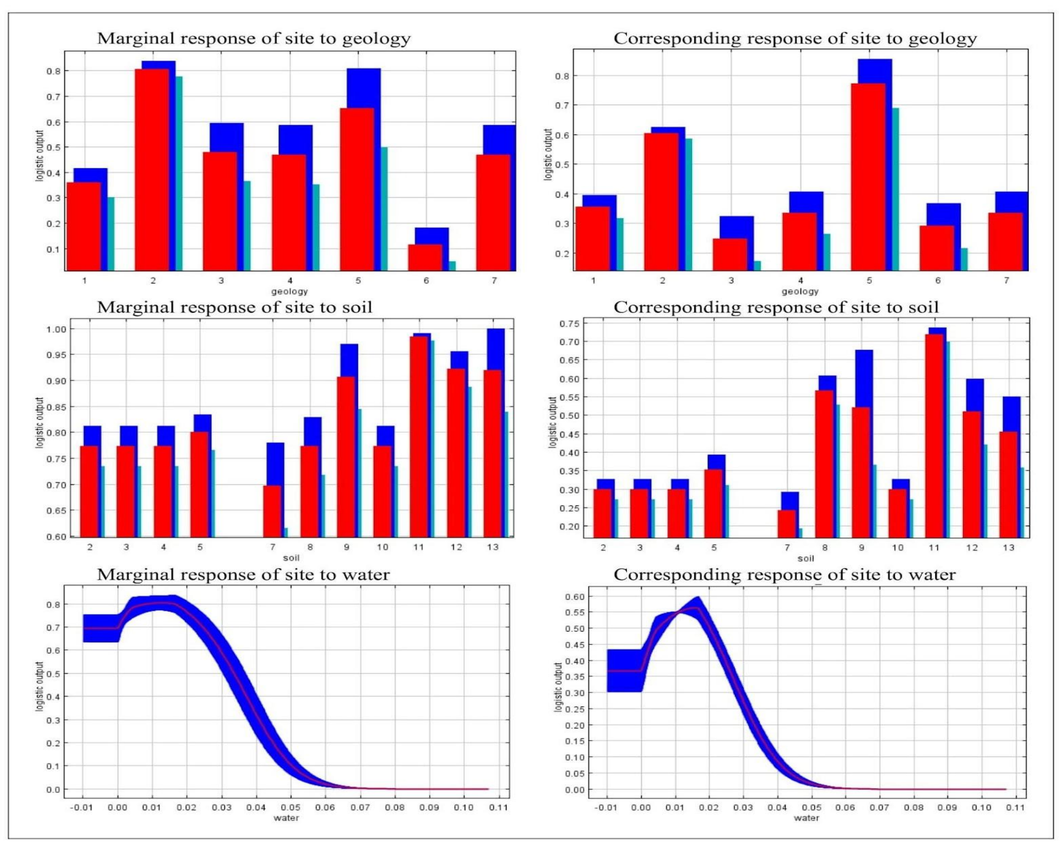
Environmental variables



Environmental raster layers and bias grid

Results

Response curves



Marginal curves (above left) assess how each environmental variable influenced the prediction of the presence of a site. **Corresponding curves** (above right) show Maxent prediction as it reaches the peak and then decreases as the values for each environmental variable go up. For the continuous data types, the results are shown as curves while the categorical data types are shown as bar charts. The y-axis of the response curves is the probability of stone age site presence while the x-axis signifies the cell values for the environmental variables (slope, aspect, hillshade, and distance to water).

Probability map

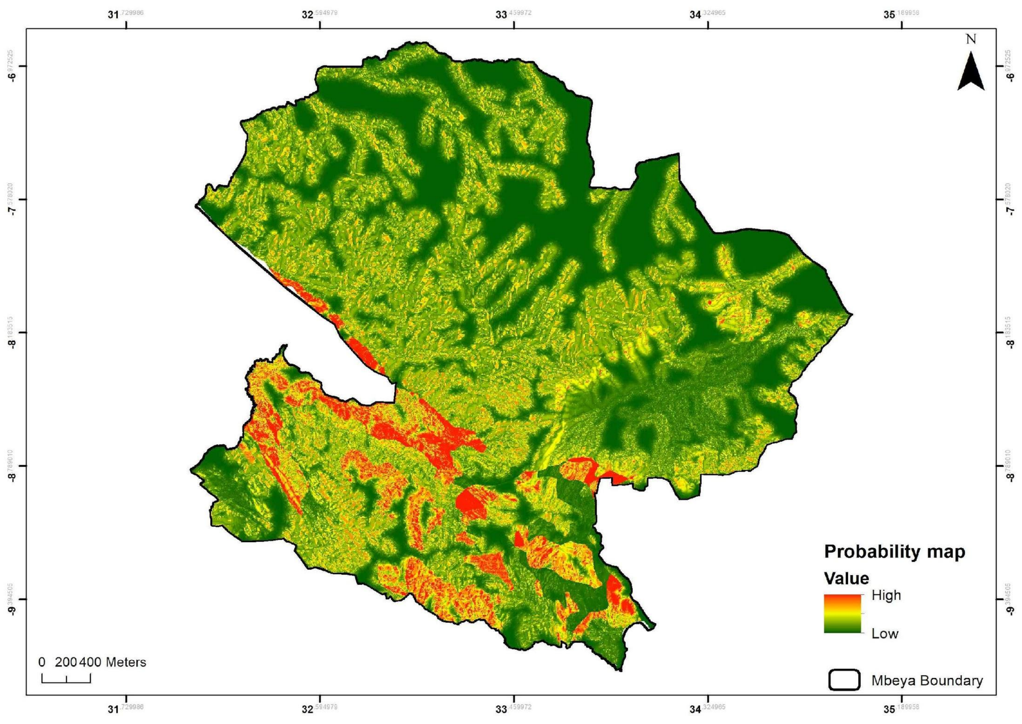
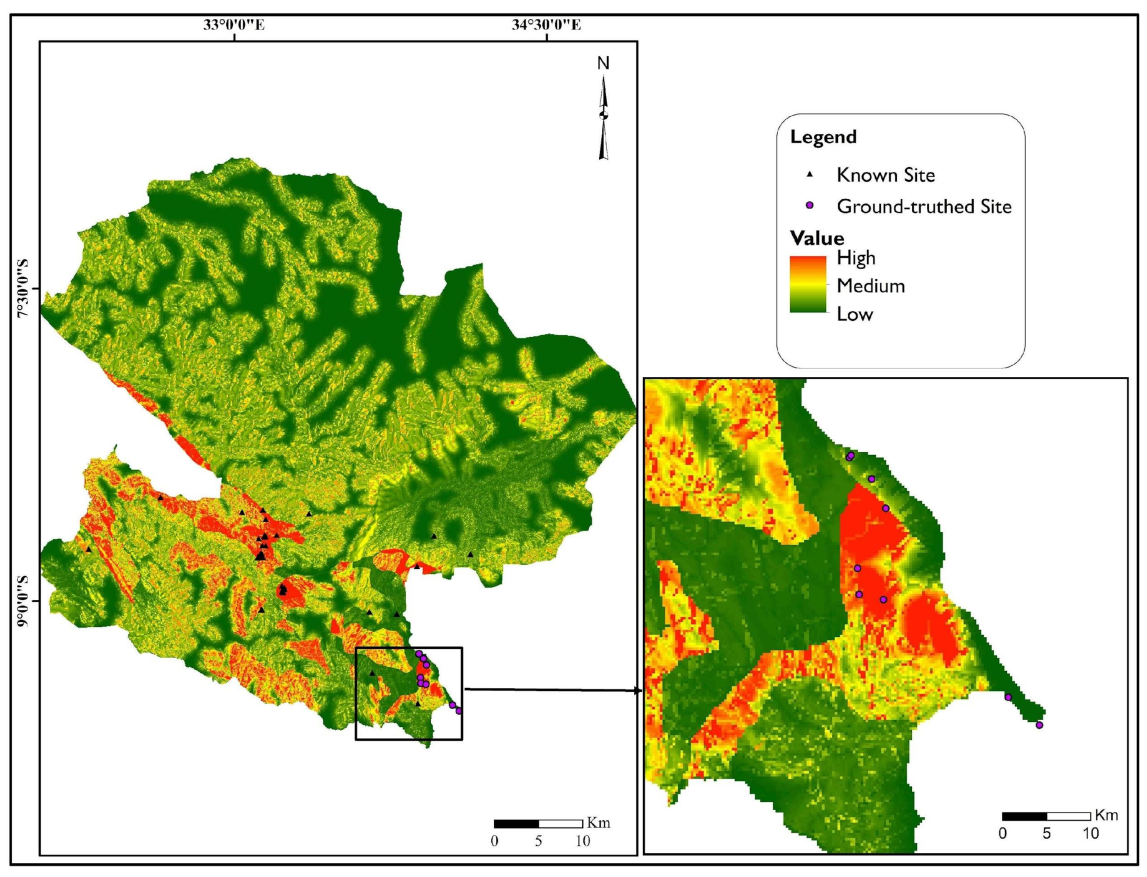


Table 3. Estimates of relative contributions of the environmental variables to the Maxent model.

S/N	Environmental Variable	Contribution %	Permutation importance %
1	Geology	31.3	27.2
2	Soil	24.1	22.5
3	Hillshade	22.1	17.2
4	Slope	12.9	10.1
5	Water	8.2	20.8
6	Aspect	1.4	2.1

The map (above) shows areas with different degrees of probability of site presence, should a survey be carried out in the area. Analysis of environmental variables determined how the variables influenced the location of sites. Table 3, above, shows the percent contribution of environmental variables. The environmental variable that has the highest contribution is Geology (31.3% contribution), followed by Soil (24.1%) then Hillshade raster (22.1%). Slope contributed 12.9% and Distance to Water 8.2%. Aspect was the lowest contributing variable at 1.4%. According to the results, **the Geological characteristic of the test area is the most important; this speaks to the fact that lithic raw materials sources which are a product of the geology of an area played an important role in raw materials sourcing for stone tools production.**

Ground truthing map



Ground truthing survey following the result of the model was carried out between February and March 2023 by postgraduate students and staff of the Department of Archaeology and Heritage Studies, University of Dar es Salaam, Tanzania. **During the survey, 19 new sites which include caves, rock shelters, surface scatters of lithics and pottery ranging from the Middle Stone Age to Historical Period were identified.**

Acknowledgments

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