

Satellite-based remote sensing rapidly reveals extensive record of Holocene coastal settlement on
Madagascar

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Abstract:

Despite decades of archaeological research, roughly 75% of Madagascar's land area remains archaeologically unexplored and the oldest sites on the island are difficult to locate, as they contain the ephemeral remains of mobile hunter/forager campsites. The known archaeological record is therefore biased toward later sites, especially sites dating to the second millennium AD, following the expansion of Indian Ocean trading networks. Systematic archaeological investigations are required to address these biases in the known archaeological record and clarify the island's early human history, but funding limitations, logistical and time constraints in surveying large areas and a relatively small number of active field archaeologists present substantial barriers to expansive areal survey coverage. Using theoretical models derived from human behavioral ecology (i.e., ideal free distribution, optimal foraging theory) in conjunction with freely available remote sensing data, we illustrate how archaeological survey of Madagascar's landscapes can be rapidly expanded, more effectively target early archaeological deposits, and address questions about the island's settlement. This study illustrates the potential for theoretically-driven satellite-based remote sensing analysis to improve our understanding of the archaeological record of the world's fourth largest island.

Keywords: settlement patterns; remote sensing; predictive modeling; GIS; human behavioral ecology; Madagascar; ideal free distribution; coastal foragers

Word count: 4279 (excluding captions and references)

Highlights (limit of 85 characters per highlight)

- Ideal distribution models are used to theoretically frame remote sensing analysis
- Predictive model successfully identified cultural materials in Southwest Madagascar
- Settlement distribution in Late Holocene appears to follow IFD predictions
- Method uses freely available data and provides cost effective prospection method
- Future surveys of identified areas may evidence earliest settlements on Madagascar

1.1 Introduction

The human history of Madagascar, the world's fourth largest island, is complex and involves the movement and dynamic interaction of people, plants, animals, and ideas from around the Indian Ocean (Radimilahy and Crossland 2015; Dewar and Richard 2012; Fuller and Boivin 2011). To-date, archaeological, genetic, and linguistic research have revealed the earliest known evidence of Madagascar's far-reaching connections; the island lies at the westernmost reach of the Austronesian expansion (Crowther et al. 2016) and multiple lines of evidence testify to the migration of Bantu peoples from the African mainland to Madagascar (Parker Pearson 2010; Pierron et al. 2017). Important questions, however, regarding Madagascar's human past remain poorly resolved. The timing and nature of Madagascar's human colonization continue to generate intense debate in archaeology (Douglass et al. 2019), and our understanding of subsequent social, economic, political, and ecological processes is limited, both temporally and spatially (Douglass and Zinke 2015; Dewar and Wright 1993).

Research into Madagascar's early history requires new approaches to overcome existing barriers to our understanding. These include the poorly understood remains of ancient foraging and fishing communities, and the relationship between archaeological settlement patterns, environmental conditions, and climate change (e.g., Kull 2000; Parker Pearson et al. 2010; Wright 2007; Wright and Rakotoarisoa 2003). Landscape-level approaches are critically needed to address these research lacunae. To date, landscape-level approaches are mostly absent from archaeological studies on Madagascar (for exceptions see Dewar and Wright 1993; Mills 1970; Vérin 1986; Wright 2007; Parker Pearson et al. 2010). This is partly because ground-based landscape investigations require large investments of time and resources in the field to generate sufficient information; funding, logistics and a small number of active field archaeologists have proven to be barriers to extensive areal coverage.

Here we present the first satellite-based remote sensing archaeological survey of the Velondriake Marine Protected Area of southwest coastal Madagascar. Using freely-available satellite imagery, image processing algorithms, predictive modeling derived from human behavioral ecology (HBE) theory and ground-truthing survey, our approach successfully identifies cultural deposits throughout a ~1400 km² area. The Velondriake (Figure 1) case study demonstrates how the development of a predictive model to analyze satellite imagery can rapidly expand the known record of archaeological settlements on Madagascar, filling both temporal and spatial gaps at the landscape level.

Our case study also highlights the importance of integrating theoretical models with remote sensing methods in African archaeology more broadly (Davis and Douglass, *in review*). Drawing on lessons from research conducted using HBE and related theoretical models from other regions (e.g., Baja California [Coddington and Jones 2013], the Channel Islands [Winterhalder et al. 2010], Australia [O'Connell and Allen 2016], Polynesia [DiNapoli and Morrison 2017]), we demonstrate that it is possible to use satellite-based remote sensing to test the nature of past human-environment interaction and drivers of settlement mobility. We further demonstrate that the integration of theoretical models and satellite-based remote sensing methods holds great

potential for rapidly locating previously unrecorded archaeological deposits at vast geographical scales, even when these deposits are ephemeral in nature.

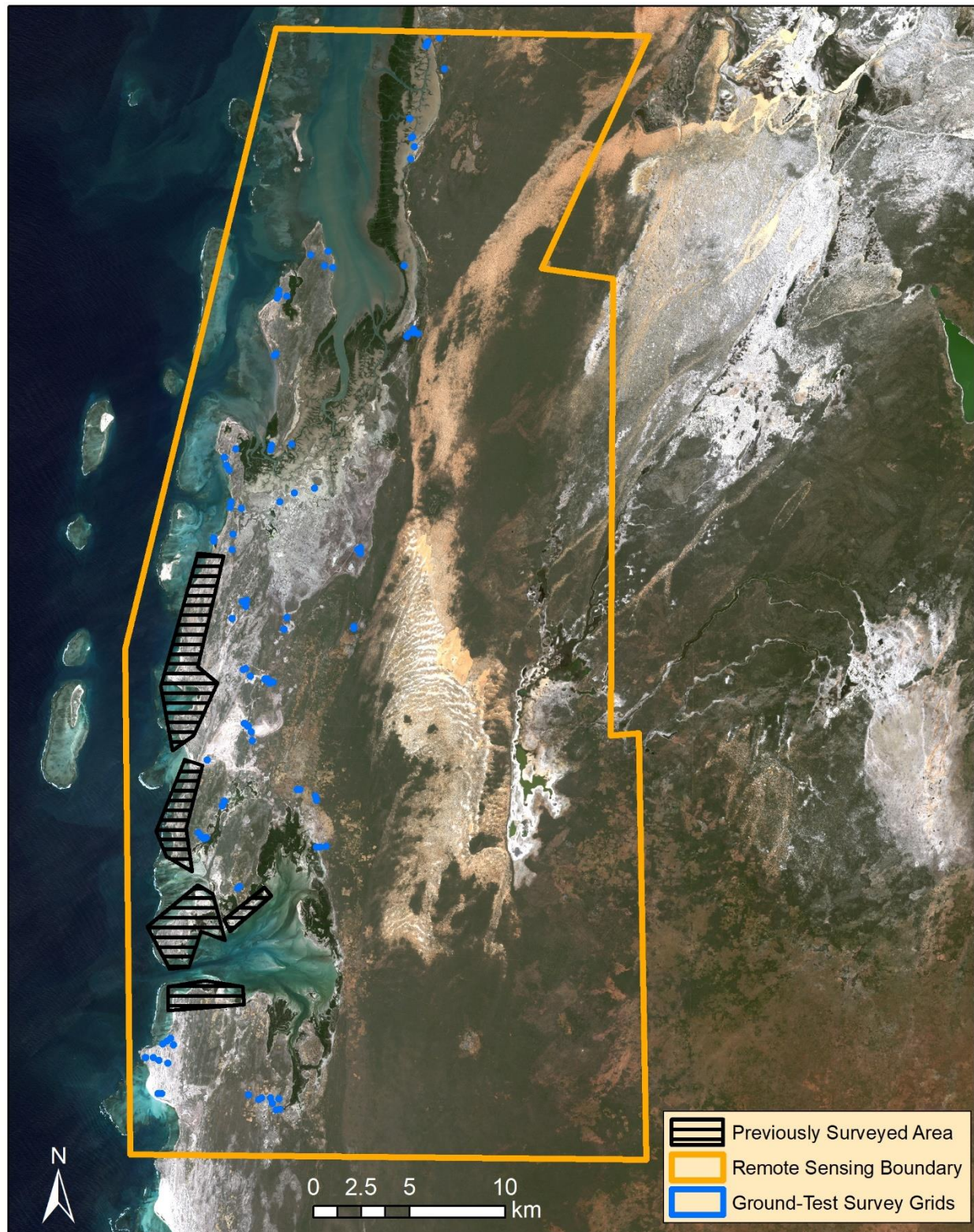


Figure 1: Map of study area. Full coverage pedestrian transect survey of a portion of the research area by the Morombe Archaeological Project (MAP, 2011-2017) generated preliminary data used to build a theoretically-driven remote sensing procedure. Previously unexplored areas were then surveyed using our remote sensing imagery and the results of our predictive model of site location were then assessed using ground-truthing survey (Satellite image: Sentinel 2; Inset map source credits: Esri, GEBCO, NOAA, National Geographic, Garmin, HERE, Geonames.org).

2.1 Previous Landscape-Level Investigations on Madagascar

Most landscape-level archaeological investigations on Madagascar center on the second millennium AD and highlight important demographic and political processes during this period, including the overall increase in size and number of settlements and the rise of centers of political power (Parker Pearson et al. 2010; Wright 2007). Although the reliability of chronometric determinations for early periods has been questioned (e.g., Anderson et al. 2018; Mitchell 2019), evidence of far earlier occupations exists on Madagascar, extending the island's human record as far back as the Early Holocene (Hansford et al. 2018). Recent systematic assessment of Madagascar's radiocarbon chronology supports the possibility of an Early Holocene human presence on Madagascar, despite a lack of contextual information on the nature of such an early presence (Douglass et al. 2019). Given the evidence for Early Holocene human activity on Madagascar and the taphonomic and sampling challenges inherent in studying Madagascar's ephemeral early forager sites (Douglass and Zinke 2015), new approaches are urgently needed to record and assess over 90% of the span of time for which human presence has been recorded on the island. Landscape-level approaches, in particular, will be critical to understanding the evolution of settlement patterns and human-environment dynamics during early periods of human occupation. A diversity of landscape-level approaches has proven useful for understanding the interplay between human behaviors and environmental contexts in other parts of the world (e.g., Coddington and Jones 2013; DiNapoli and Morrison 2017; Jazwa et al. 2017; Winterhalder et al. 2010).

Despite the critical temporal gaps in landscape-level archaeological investigations to-date, understandings of landscapes from the 10th century onwards (Crossland 2001; Pearson 1992; Sussman et al. 1994; Tucker 2004; Wallace et al. 2016) have illuminated connections between humans and their environmental surroundings. Theory from human behavioral ecology (HBE) and historical ecology have been used recently, but such approaches are still scarce (e.g., Douglass et al. 2018b; Tucker 2004, Tucker et al. 2010). For example, Tucker (2004) demonstrates how Mikea (inland forest dwellers in Southwest Madagascar) food-sharing practices are dictated by economic factors, reciprocity, kin selection, and tolerated theft. In another study by Tucker et al. (2010), HBE is used to understand risk mitigation via the practice of mixed subsistence strategies.

With recent advances in remote sensing methods and datasets (e.g., Davis et al. 2019; LaRocque et al. 2019; Thabeng et al. 2019) the time is ripe for new applications of remote sensing approaches that promise to advance and expand our understanding of the island's archaeological record, particularly with regard to early and ephemeral sites. On Madagascar, previous studies using aerial imagery successfully revealed the locations of tens-of-thousands of

fortification sites (Mille 1970). Most recently, Clark et al. (1998) illustrated the potential of multispectral and radar instruments for recording landscape patterns that could reveal the locations of archaeological deposits. Our study demonstrates the potential of this remote sensing to clarify diachronic landscape changes and their human dimensions on Madagascar, as has been achieved in other world regions (e.g. Carlton and Collard 2019; Davis 2019b; Stephens et al. 2019)

3.1 Methods

Here, we outline a preliminary study that combines HBE modeling with remote sensing survey to predict the distribution of archaeological sites on southwest Malagasy landscapes. The approach is based on ideal free distribution (IFD) models (see Fretwell and Lucas 1969). These models assume that individuals settle areas with the best overall suitability (with regards to available resources) and that, as population density and resource consumption increase, settlements shift to areas with lower resource suitability. Because the current study lacks temporal control, the assumption is made that the earliest sites will be located in “high” suitability areas. Confirmation of this hypothesis requires further testing. Here we focus on the density and variability of cultural materials present in different suitability locations. Furthermore, we assess whether ethnographically and historically important resources (e.g. coral reefs, vegetatively productive land, distance to the coast, etc.) are good predictive variables for locating archaeological sites in southwest Madagascar.

3.2 Ideal Free Distribution Modeling

Within HBE, there are a series of different optimality models which try to predict decision making of individuals based on costs and benefits of different actions (e.g., Blurton Jones 1986; Charnov 1976; Fretwell and Lucas 1969; MacArthur and Pianka 1966; O’Connell and Hawkes 1981). Such modeling approaches have proven useful in exploring the rationale behind observed phenomena in anthropology, including archaeological evidence of behavior and choice (e.g., Bird et al. 2016; Codding and Bird 2015; Jazwa et al. 2017; Robinson et al 2019; Tucker et al. 2010). Despite criticisms of optimality models (see Zeder 2012), the explicit framework offered by such approaches provides a heuristic device for exploring factors that may influence settlement choice in human populations (e.g., Stiner and Kuhn 2016).

IFD models have been applied in various settings around the world for identifying temporal and ecological trends in population settlement distribution (see Winterhalder et al. 2010; Codding and Jones 2013; Yaworski and Codding 2018). IFD stems from the work of Fretwell and Lucas (1969) and operates on the principle of negative density dependence (Winterhalder et al., 2010; Yaworsky & Codding, 2018). As population pressures increase, the overall resource quality of that area will degrade, thereby lowering the suitability of that habitat and its likelihood of being settled.

Furthermore, the IFD model is simplistic, and there are biological principles that often violate its assumptions. For example, the Allee effect accounts for temporary improvements in

habitat suitability caused by immigrating populations (Fretwell & Lucas, 1969, 19). One example of Allee-effect IFD comes from Neolithic farmers who modified their landscapes to increase agricultural production by clearing forestland (McClure et al. 2009). IFD-Allee models predict that individuals settling lower ranking habitats attract others to follow, thereby abandoning higher suitability areas (Winterhalder et al., 2010, 473). As such, the highest suitability areas will have a slightly lower population than medium suitability locations.

There is also a variant of IFD for when access is restricted, and people establish certain controls over resources – ideal despotic distribution (IDD). IDD accounts for differences in competitive ability and resource control (Jazwa et al., 2017). In an IDD model, the opposite pattern of population distribution is expected from IFD, wherein the highest density of individuals will inhabit lower suitability habitats.

Since we currently lack substantive information about the resource management and land-use practices of these communities or changes in their demography at a fine resolution, we cannot definitively assess whether land-use practices led to degradation of environments as the model posits. IFD models, therefore, are used as a theoretically framed starting point, so that we may begin to address this information in a theoretically sufficient manner (*sensu* Lewontin 1974).

3.3 Remote sensing and predictive modeling

For this study we use freely downloadable satellite imagery from the European Space Agency Sentinel-2 satellite (<https://scihub.copernicus.eu/dhus/#/home>). This satellite has proven useful for a wide range of disciplines, including archaeology (Agapiou et al. 2014), but its medium-to-low resolution (10m visual and NIR, 20m NIR and SWIR) constrains its applicability, including for the documentation and preservation of cultural heritage. Because archaeological deposits on Madagascar's southern coasts are often subtle artifact scatters, Sentinel-2 data do not have the spatial resolution necessary to directly identify these features. However, its resolution is conducive to developing a predictive model of site locations using the theoretical assumptions of IFD. While similar predictive measures have been used by other scholars (e.g., Agapiou et al. 2014; Bennett et al. 2012; Kirk et al. 2016; Lasaponara and Masini 2007), most rely on interpreting vegetative indices for soil and vegetative anomalies, and do not always utilize explicit theoretical models from anthropology.

If our method is successful – and the data conform to an IFD – we expect: 1) that high value areas will contain the greatest proportion, density, and variety of artifacts; 2) these amounts will decrease steadily in Medium, Low, and Null probability areas; and 3) that the settlements located in high probability areas will be older than those in other locations. This third hypothesis is beyond the scope of the current paper and will be the focus of future research once temporal data becomes available.

3.4 Processing steps of predictive modeling analysis

1. Based on a review of available archaeological and ethnographic data, we developed a list of important resources and landscape features for communities of the southwest coast (e.g.,

Douglass 2016; Douglass et al. 2018; Gommery et al. 2011; Pearson 1992, 1997; Tucker 2004, Tucker et al. 2010). These data include locations of coastal archaeological sites identified by surface survey and excavation (Douglass 2016; MAP 2011-2017). Important variables that influence human settlement include: distance from the sea shore; distance from offshore coral reefs; distance from paleodunes; and the vegetative productivity of specific locations.

2. Training samples were created using the 2-D scatterplot function in ENVI to develop a total of 6 landscape classes (Figure 2): water, coral, bare soil, shrubs, paleodunes, and dense vegetation (i.e., mangrove forests). This method was used for training sample collection to ensure a minimal amount of spectral overlap between each land class. An initial assessment of the spectral properties of the study area led to the decision to use the NIR, Red, and Green bands (RGB 843) in order to capture the most information pertaining to vegetative health and moisture properties for landscape classification.

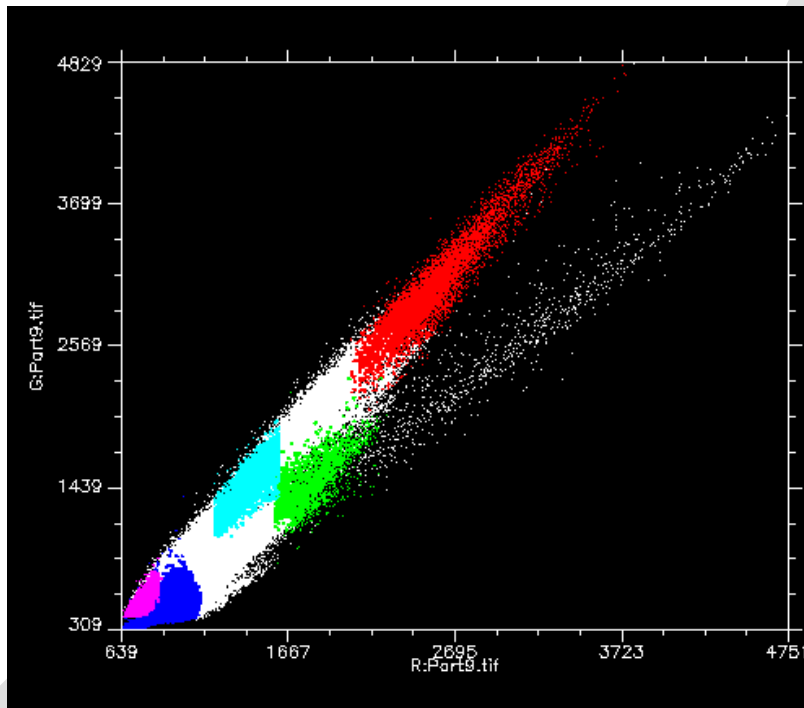


Figure 2: A 2-D scatterplot function in ENVI. Each land-class can be identified by spectral values and overlaps can be minimized. Red: paleodunes; Green: coral; Cyan: shrubs; Blue: water; Magenta: dense vegetation. All white space is unclassified spectral values within the satellite image.

3. Sentinel-2 images were classified using a support vector machine (SVM) classifier in ENVI 4.7 (Exelis Visual Information Solutions 2009). SVM is a non-parametric classification technique that has gained popularity due to its ability to produce highly accurate classifications using limited training datasets (Mountrakis et al. 2011). The method works by identifying optimal separations between classes and can handle multiple classes simultaneously (Pal and Mather 2005).

4. Coral reefs in some instances were not reliably classified using pixel-based methods (i.e., SVM). We therefore used an object-based image analysis (OBIA) approach with threshold classification (see Davis 2019a; Sevara et al. 2016). Unlike pixel-based methods, object-based methods take shape, texture, and morphology into account to classify image components (Blaschke 2010; Davis 2019a; Hay and Castilla 2008). This same procedure was used to classify the locations of offshore islands, which serve to extend fishing grounds and offer safe-havens for coastal fishers during periods of political instability (Cripps 2009; Douglass 2016:72). OBIA was used to generate shapefiles of offshore island and coral locations using eCognition 9.0.1 (Trimble 2014). Multiresolution segmentation was conducted using a scale parameter of 60, shape parameter of 0.7, and compactness factor of 0.6. Following this step, pixel brightness thresholds were used to extract all image objects located in areas covered by or immediately adjacent to water (as identified by SVM) that matched threshold values for coral or offshore island features. Corals within this region contained brightness values between 600 and 1150 and offshore islands contained values of 1200 or greater. The OBIA results were then assessed manually to eliminate the few errors present throughout the study region.

5. Data generated from the SVM and OBIA classifications were imported into ArcGIS 10.6.1 (ESRI 2018) and underwent several processing steps (Figure 3). The water and paleodune classes were extracted into their own raster layers in ArcMap and subjected to Euclidean distance tests. Euclidean distance produces a raster of distance measurements between the input (i.e., water and paleodunes) and the surrounding pixels in an image. Euclidian distance is appropriate, as opposed to a cost-distance analysis, because of the gradual landscape elevation changes in this region. While hills and other topographic features are present, there are no extreme elevation changes within the study region.

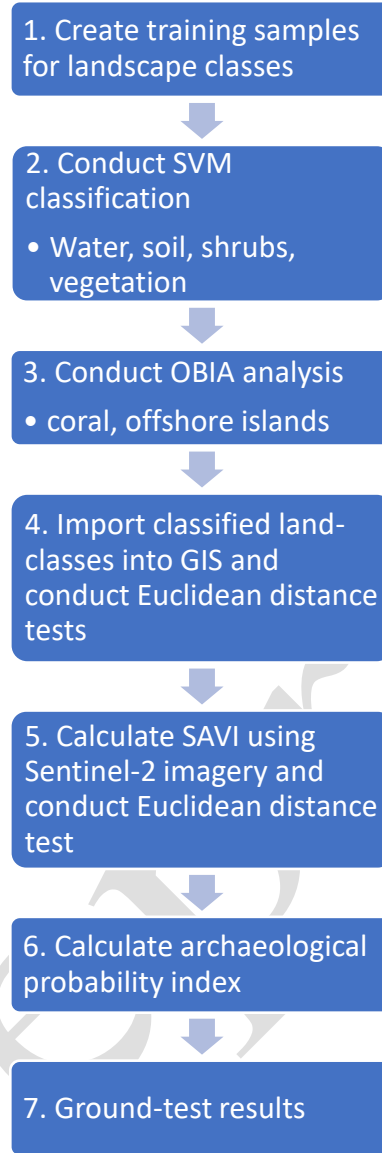


Figure 3: Processing steps of predictive modeling analysis

6. The final variable incorporated is vegetative productivity. To measure vegetative productivity a SAVI (soil adjusted vegetative index) was used, which takes into consideration soil properties, including moisture content (Huete 1988). Given the extreme variance in soil reflectance characteristics on Madagascar (see Clark et al. 1998), SAVI was chosen as the most appropriate index, as opposed to NDVI and others that decrease in accuracy over large geographic areas with high vegetative diversity (Jensen 2007). SAVI is calculated using the formula:

$$SAVI = \frac{NIR-red}{NIR+red+L} \times (1 + L). \quad \text{Equation 1}$$

where the NIR and red bands are used, and L represents the soil adjustment factor. The best soil adjustment has been demonstrated around $L = 0.5$ (Huete 1988; also see Jensen 2007) and was

chosen for this study. Once calculated, SAVI indices that contained values associated with the presence of shrubs and other vegetation were extracted and we conducted another Euclidean distance function to produce a distance raster of vegetative areas.

7. With all these variables together, we used the following formula to calculate overall probability of early forager settlements in ArcGIS using the raster calculator:

$$P_{Arc} = \left(\frac{1}{d_w} + \frac{1}{d_c} + \frac{1}{d_p} + \frac{1}{d_v} + \frac{1}{d_i} \right) \times 100 \quad \text{Equation 2}$$

Where P_{Arc} is the probability of archaeological deposits, d_w is distance from water, d_c is the distance from coral beds, d_s is the distance from paleodunes, d_v is the distance from land with SAVI index values of .35 or better (this value represents the minimum value for shrubland), and d_i represents the distance to offshore islands. Each distance raster was inversed to produce the highest values for the lowest distance from each resource type. Once the index was calculated, we used inverse-distance weighting (IDW) interpolation to fill in gaps in the probability raster up to 100 meters using the elevation void fill function in ArcMap 10.6.1 (ESRI 2018).

8. Following the development of our predictive model, we assessed the model's ability to detect *prerecorded* archaeological sites (MAP 2011-2017) and established a sampling strategy for field tests to assess the model's ability to predict the location of *previously unrecorded* cultural deposits. To accomplish this, we first compared the locations of prerecorded sites to the probability values generated by the algorithm. Then, to assess the algorithm's ability to detect previously unrecorded materials, we created a grid of 50m x 50m squares throughout the entire study area (~1400 km²). Each grid was assigned a unique identification number by ArcMap. In Excel, we randomly selected 600 ID numbers using the "randbetween" function. These 600 areas were then checked to ensure they were accessible on foot. Ultimately, a total of 145 areas were selected on the basis of proximity to other points, accessibility, and feasibility of visitation during the 2019 field season. Among the randomly selected grids, 73 contained "high" probability zones, 31 contained "medium probability", and 27 had "low" probability. Table 1 shows the quantitative breakdown of these qualitative categories. The remaining 14 areas had null probability values and were chosen to assess false negative results.

Table 1: Quantified thresholds of probability index and their qualitative equivalent classifications.

Quantitative Values	Qualitative Ranking Equivalent
Null/Blank	Null
0-5.5	Low
5.5-11.4	Medium
>=11.5	High

Together, these methods produced information needed to calculate overall habitat suitability, and by extension, probability of settlement for coastal communities. Based upon the expectations of IFD, the highest suitability (and hence probability) locations will hold the greatest number of archaeological deposits, with lower suitability areas containing fewer archaeological assemblages.

4.1 Results

SVM resulted in 93.6% accuracy (KIA = 0.931) (see Tables 2-4) and OBIA attained an overall accuracy of 97.7% (KIA = 0.914) for the classification of the chosen environmental land-types (Tables 5 and 6).

Table 2: Confusion Matrix for SVM classification

Class	Dunes	Coral	Water	Shrubland	Mangrove	Bare Ground	Forest
Dunes	89.45	0	0	0.01	0	3.76	0
Coral	0	99.95	0.01	0	0	0	0
Water	0	0	99.99	0.01	0	0	0
Shrubland	0	0.04	0	82.35	0.001	0.86	3.36
Mangrove	0	0	0	0	95.5998	0	0.21
Bare Ground	10.54	0	0	8.684783	0	95.11134	0.001
Forest	0	0	0	8.95	4.39	0.26	96.42
Total	100	100	100	100	100	100	100

Table 3: Commission and Omission Error for SVM classification

Class	Commission (%)	Omission (%)
Dunes	4.17	10.54
Coral	0.04	0.04
Water	0.01	0.01
Shrubland	5.41	17.64
Mangrove	0.37	4.40
Bare Ground	25.83	4.88
Forest	8.94	3.57

Table 4: Producer and User Accuracy for SVM classification

Class	Producer Accuracy (%)	User Accuracy (%)
Dunes	99.64	99.92
Coral	100	100
Water	100	100
Vegetation	98.41	99.99
Shrub	99.99	98.44
Bare Ground	99.92	99.64

Class	Producer Accuracy (%)	User Accuracy (%)
Dunes	89.45	95.82

Coral	99.95	99.95
Water	99.99	99.99
Shrubland	82.35	94.58
Mangrove	95.59	99.62
Bare Ground	95.11	74.16
Forest	96.42	91.05

Table 5: Confusion Matrix for OBIA classification. Numbers reflect amount of training objects.

Class	Islands	Coral	Total
Islands	795	8	803
Coral	14	141	155
Total (%)	809	149	958

Table 6: User's and Producer's Accuracy for OBIA classification

Class	Producer's Accuracy (%)	User's Accuracy (%)
Islands	98.3	99.0
Coral	94.6	91.0

4.2 Prediction of pre-recorded site locations

Within the entire dataset of prerecorded sites, we find that only 5 previously surveyed deposits do not fall within areas identified by the algorithm (Figure 4). All of these deposits are located on paleodune features, however, suggesting a strong relationship between this environmental context and human settlement. The model thus reliably predicts the location of *pre-recorded* deposits.

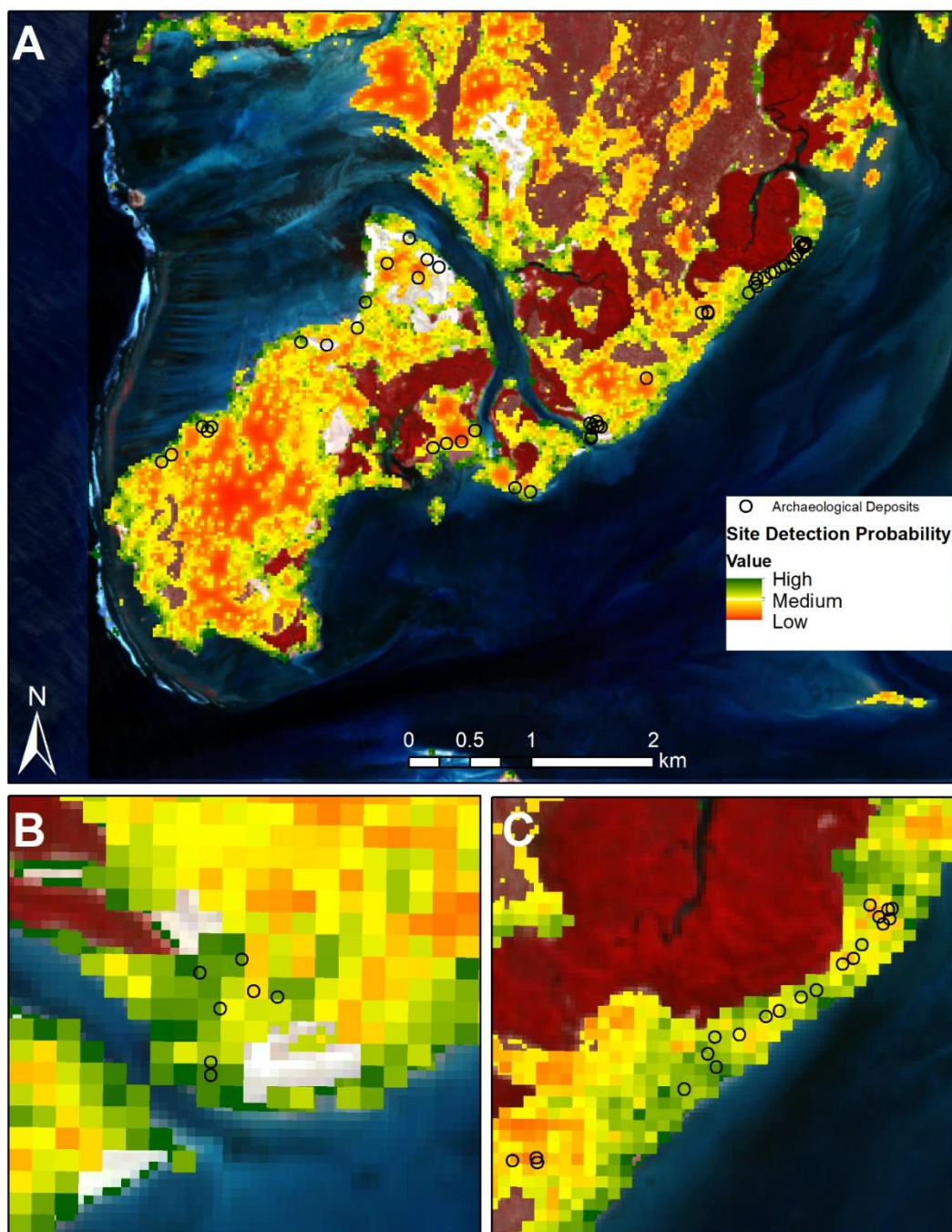


Figure 4: Preliminary results of Archaeological Probability Index. Sites represent those recorded by recent survey work between 2017 and 2018 and earlier surveys recorded by the MAP between 2011-2018 (see Douglass 2016).

4.3 Prediction of previously unrecorded site locations

To assess the ability of the model to locate *previously unrecorded* cultural materials, ground surveys were carried out on 71 of the 145 selected sites during the summer of 2019

(Supplemental Table 1). A variety of different materials were recovered during surveys, ranging from ceramics and beads to elephant bird eggshell and marine shells (Table 7). The results largely fit the hypothesis that high suitability areas will contain the greatest proportion, density, and variety of artifacts and that these amounts will decrease steadily in Medium, Low, and Null probability areas. However, there is a slight increase in the density of artifacts within medium probability zones, suggesting a possible fit with an IFD with Allee effect model (see Fretwell and Lucas 1969; Figure 5).

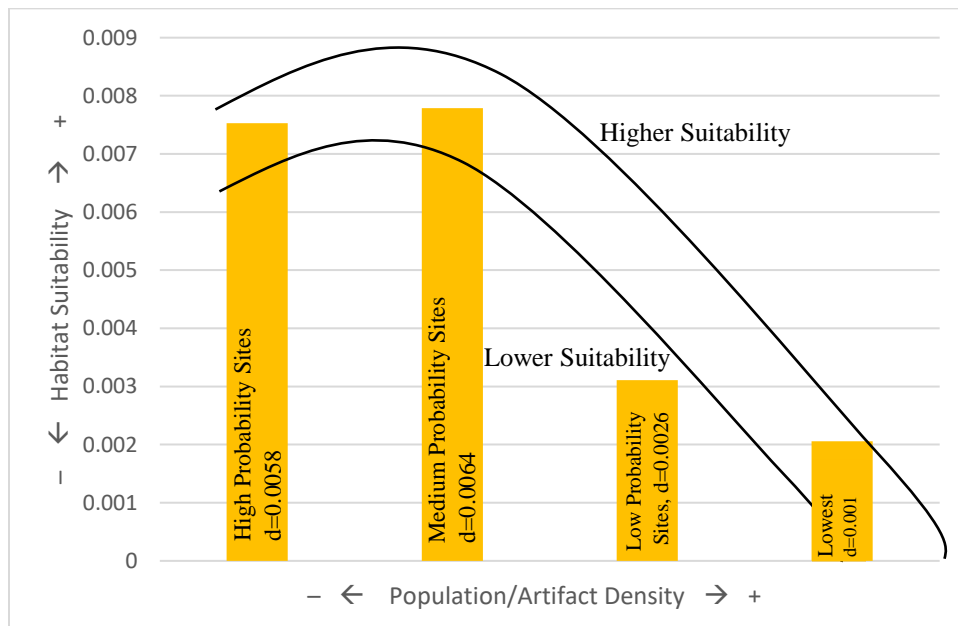


Figure 5: Density distribution of artifacts recovered from different probability locations. Black lines represent the IFD-Allee curves, with the top line representing population thresholds for the best habitats, and the second line showing thresholds for less suitable habitats. Temporal data is still needed to confirm conformity to an ideal distribution.

Table 7: Sum of survey results by grid probability value. Note, the amount of material increases between each level, with the greatest increase for high probability locations. Lower probability areas still produce artifacts, which is expected, but at lower densities and amounts, as predicted by an ideal free distribution model. The variety of artifacts also decreases with probability.

Grid Probability	Types of artifacts	Charcoal	Eggshell	Marine Shell	Faunal	Ceramics	Beads	Lithics	Botanicals	Glass	Metal	Burnt Stones	Coral	Total Materials Collected
High	9	6	186	204	35	193	26	0	0	0	1	7	1	659
Medium	8	1	88	102	6	129	3	0	0	1	0	1	0	331
Low	5	1	54	41	5	39	0	0	0	0	0	0	0	140
Null	3	0	22	13	1	0	0	0	0	0	0	0	0	36

Grid probability values are an average of raster pixel data. As such, even “high” probability grids may contain values that are lower in likelihood. Therefore, we investigated the precise locations where materials are present to see if individual materials are also accurately predicted by the model. When examining the locations of individual artifacts, we once again find a strong clustering in high probability areas (Table 8; Figure 6).

Table 8: Descriptive statistics of probability values for specific points within survey grids where materials were recovered. The average and most frequently occurring values are high probability, thus coinciding with the grid-level data. Note, these calculations ignore null values.

Statistic	Quantitative Value	Qualitative Value
Minimum	1.69	Low
Maximum	22.96	High
Mode	16.33	High
Mean	12.71	High

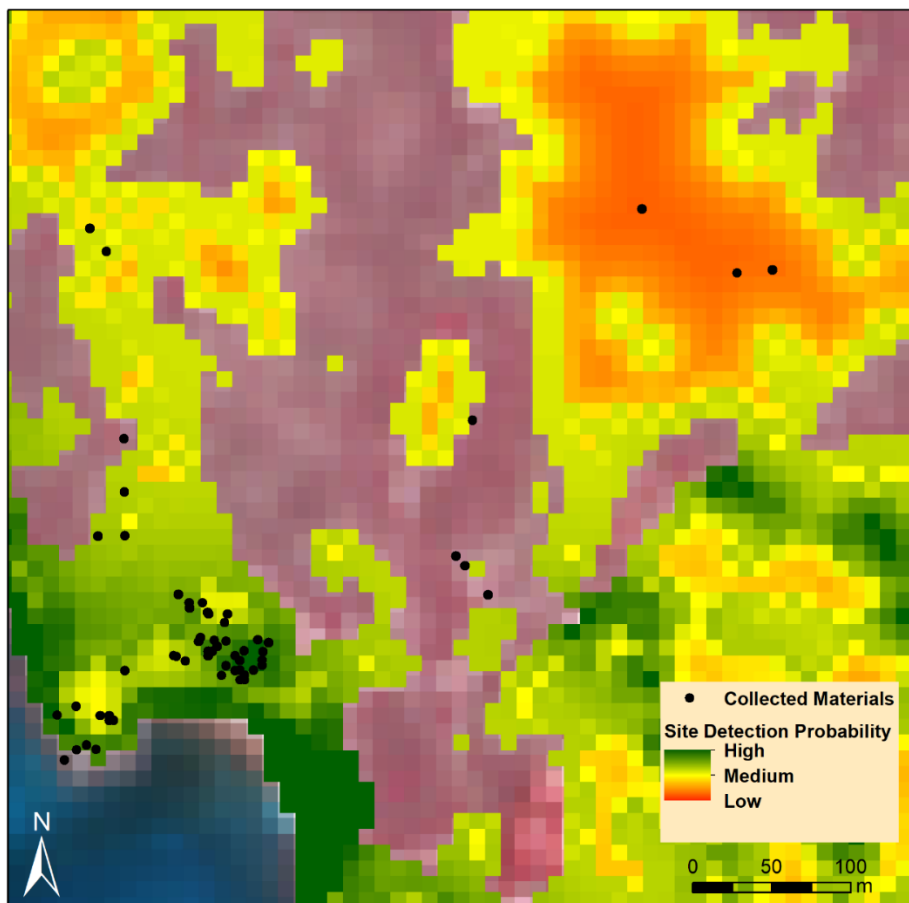


Figure 6: Shows the points of some specific materials collected during survey. Note how the greatest clustering takes place on the highest values, and as values decrease the number of materials follows suit.

5.1 Discussion

The distribution of materials recovered during pedestrian survey, suggests that the immediate coastline is the most densely inhabited area of the study region (Fig 1), with material culture abundance (i.e., ceramics, beads, modified shells, etc.) steadily decreasing as one moves inland (Figure 7).



Figure 7: Shows the locations of artifacts (and clusters of artifacts) recovered from grids visited throughout the study area during July and August of 2019. Definitive human presence is signified by beads, ceramics, and burnt/worked marine shells. Potential human presence is signified by the presence of shells and faunal remains that are not worked or modified, and an absence of ceramics or beads.

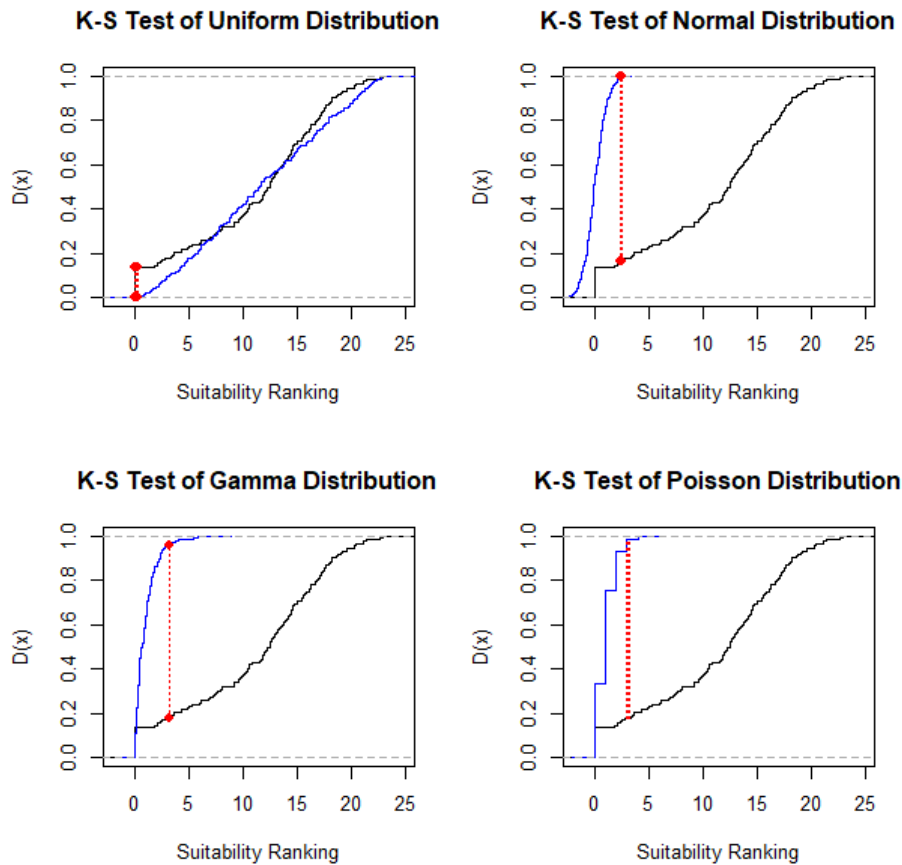
This preliminary landscape analysis illuminates several possibilities to understand settlement patterns. Archaeological deposits identified here all fall within the expectations of optimal foraging and IFD modeling frameworks. Populations settling the coast of southwest Madagascar appear to have prioritized shoreline ecosystems with ready access to resources that are still valued today. Cultural deposits found further inland are often within flood-zones during the wet season. This, coupled with the dearth of cultural materials exceeding 5 km from the modern coastline suggest that settlements are greatly influenced by natural resources. Furthermore, a seeming resemblance to an Allee effect distribution suggests that coastal foraging populations may have: a) actively changed and improved the suitability of the areas they inhabited; and/or b) that social networks were strong unifying factors that led to significant population movements as environmental resources shifted. This remains a hypothesis, however, as it rests on the assumption that the data conform to an Allee effect distribution, which needs further testing.

Additional support for an idealized distribution comes from Kolmogorov-Smirnov distribution tests which reveal distinct differences between the archaeological data and continuous distributions, but only a slight difference compared to a uniform distribution (Table 9; Figure 8). These results indicate that archaeological distributions are closer to a uniform dispersal; this fits within the context of an IFD where individuals position themselves with equal densities relative to the suitability of a given area.

Table 9: Results of Kolmogorov-Smirnov tests between archaeological probability distribution and randomly generated probability distributions. All tests run in R (R Core Team 2018) using the *stats* package.

Compared Distribution	D-value	P-value
Normal	0.83673	0.0000
Gamma	0.80823	0.0000
Poisson	0.81229	0.0000
Uniform	0.13469	0.02438

Figure 8: Graphical representation of K-S test results reported in Table 9. Archaeological data is represented by the black line. Simulated distribution is represented by the blue line. The red dotted line shows the greatest degree of difference between the observed and simulated distributions.



Consistent with findings by Douglass (2016), this study suggests a relationship in the Velondriake area between possible elephant bird (*Aepyornithidae*) nesting grounds and human settlement locations. Elsewhere on Madagascar associations between cultural contexts and elephant bird eggshell have also been noted (e.g. Parker Pearson et al. 2010; Radimilahy 2011; Battistini and V  rin 1972). *Aepyornis* eggshell remains are often located in ancient paleodunes which are present along the coasts of southern Madagascar and are easily visible from medium-to-course resolution satellite imagery (Clark et al. 1998). The identification and survey of paleodune features is likely to yield exciting new information regarding the interaction between humans and these large avifauna, and the investigation of paleodunes should be prioritized to better understand the processes that contributed to the birds' decline.

5.2 Future Work

While the results are highly positive, there is room to improve the predictive power of the algorithm developed here. Future work will look to improve the method by incorporating additional ethnographic and environmental variables that were potentially overlooked, such as groundwater levels. Looking at the results, the greatest density clusters of materials seem to occur in areas closest to offshore islands and on coastlines that contain coves sheltered by rocky coastal barriers. Conducting spatial-statistical tests can reveal the most significant variables for predicting archaeological material and will be the focus of future work.

Furthermore, the results of the surveys carried out under the direction of this remote sensing model will be used to address larger questions concerning human-environmental interaction through time. In particular, future work will integrate settlement pattern data with high resolution paleoecological and paleoclimate records, to enable modeling of human response to climate and environmental change. As fieldwork continues, temporal data will become available for many of these newly identified deposits. To date, we know that several previously excavated sites dating to ~2500 B.P. (see Douglass 2016) were identified as “high” likelihood by our algorithm. This suggests that other contemporaneous – and possibly earlier sites – will emerge as our ground surveys continue.

6.1 Conclusions

The case study above illustrates the utility of HBE theory for framing predictive remote sensing analysis on Madagascar. The protocol described here evaluated the probability of cultural activity at an average rate of ~50 km² per hour of processing time.¹ With greater processing power, this rate can be increased further, saving time, money, and resources by targeting high probability areas for ground survey. Additionally, all the analyses conducted here use freely available satellite imagery and can be analyzed using open-source software, including QGIS (QGIS Development Team 2018) and R (R Core Team 2018). With greater access to geo-spatial and statistical training, this work can be greatly expanded by other researchers, particularly in regions that are understudied in archaeology.

The acquisition of remote sensing datasets at higher spatial and spectral resolutions will allow researchers to directly identify archaeological deposits on Madagascar, rather than assign general probabilities for where these features are located (e.g. Calleja et al. 2018; Davis et al. 2019; De Laet et al. 2007; Guyot et al. 2018 Lasaponara and Masini 2007; LaRoque et al. 2019; Traviglia and Torsello 2017; Trier et al. 2009; Thabeng et al. 2019). Because remote sensing surveys can often only identify locations of the largest-scale features – and thereby bias our understanding towards specific activities, the use of theoretical models can help to direct ground survey efforts in conjunction with remote sensing data to reduce some of these biases by identifying a greater variety of cultural activities. The method developed here makes it possible to identify early deposits on Madagascar which are currently at risk of disappearing due to erosion and sea-level change. We must act quickly to uncover the fragile remains of the earliest settlers of Madagascar, as these components represent an actively disappearing cultural landscape. Threats to cultural heritage from environmental factors such as erosion and sea level

¹ This ratio was calculated on the basis of the average time allocation for each section of the study area. The region was divided into 3 parts totaling ~1400 km², with each section requiring approximately 6-8 hours of computer processing time for the SVM classification and another 2 hours of manual processing time to create the final probability map. Total, this procedure can be achieved with high levels of time- and cost-efficiency which can be cut down even further depending upon computing power and processing speeds. Computer used for analysis had an Intel® Core™ i7-4790 CPU @ 3.60 GHz Processor with 32.0 GB of RAM.

rise, are exacerbated by urban development and other anthropogenic factors (Douglass 2016; Parker Pearson et al. 2010; Wright 2007; Wright and Rakotoarisoa 2003).

Preserving this history requires an expansion of remote sensing surveys – via satellites, drones, and other instruments – to rapidly and systematically survey vast geographic space. There have been calls in recent years to expand systematic survey of Madagascar’s landscape (Parker Pearson et al. 2010; Douglass and Zinke 2015), including the often-neglected areas inland from the immediate coastline (Douglass et al. 2018a). While our study looks at coastal areas in the Southwest, the method can easily be expanded to inland regions of Madagascar.

Supplemental Data (upload to Penn State’s repository and link to publication)

- Extended Abstract in French and Malagasy
- ENVI generated ROI files
- Results of segmentation procedure (shp conversion)
- Probability rasters for study area
- Sentinel-2 image(s) used for this study

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Changes from Preprint to Accepted Version

We have added a discussion of research avenues that can be improved using our method and explained why Madagascar is particularly relevant for the methods developed in this paper. We also added a paragraph to the conclusion returning to some of these research developments.

We added a description of how qualitative ranks of our predictive models were quantified. Quantitative ranks were classified using a natural breaks (Jenks 1967) method, and qualitative values followed those breaks, but with class names rather than number values. This was added to the caption of Table 1.

We added more discussion of artifact types recovered during surveys and their relationship with probability rankings.

Our discussion of OFT has been more clearly linked to IFD as suggested by reviewers.

We have revised Figure 1 to include an inset map and changed the color for the ground-test survey grid points.

The approximate cutoff at 10,000 B.P. has been added when discussing Early Holocene and the Hansford et al. study for those unfamiliar with the timeframe being discussed. To this end, we also include a brief (and very preliminary) discussion of the relative chronological information that we have analyzed in this paper with some identified sites dating to ~2500 BP.

In discussing fortification sites, we have added the earliest dates for these fortification sites (~600 B. P.).

We specify the number of prerecorded archaeological sites in this area used to validate our procedure, which total 756 individual deposits.

We have included a brief discussion of the materials recovered during surveys and the link between shells and human occupation (relating to definitive vs. possible human presence). We have described the difference between our “definitive” and “possible” human sites by clarifying that unmodified shells (but which are associated with burning and other cultural activities) can evidence human occupancy.

We have added a longer discussion of Allee effects. Allee’s principle holds that community formation (aggregation of individuals) produces an increased fitness for survival in a population. As such, social ties can act as Allee effects, in so much as they can foster cooperation between individuals (and different groups) and allow for resource acquisition to be shared, thereby limiting the burden on smaller groups or individuals.

Inconsistencies with the terms “site”, “cluster”, “settlement”, etc. have been corrected. We have defined “site” for the purposes of this manuscript clearly at the beginning of the paper as “any area containing two or more artifacts during ground surveys. Sites thus encompass artifact clusters, settlements, and any other cultural materials present in an area”.