MODELING ARCHAEOLOGICAL SENSITIVITY FOR THE WEST MOJAVE ROUTE MANAGEMENT NETWORK PROJECT: AN UPDATE ON FIVE YEARS OF TESTING

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In 2015, the Bureau of Land Management developed a GIS-based cultural resource predictive model to assist in the management of off-highway vehicle (OHV) routes across 3.1 million acres of public lands in the West Mojave planning area. The model predicts areas of high cultural sensitivity based on various geographic, environmental, and historical factors. Over the past five years, field crews completed on-the-ground testing by conducting archaeological surveys to identify and record cultural resources along randomly selected OHV route segments throughout the planning area. Field testing resulted in a wealth of new locational data, the first two years of which were incorporated into a second run of the model in 2017. This article provides the results of five years of field testing, a summary of the second run of the model, and next steps for the model.

FIELD TESTING

Between 2015 and 2019, under the auspices of the Bureau of Land Management (BLM), field crews surveyed 25,793 acres of randomly selected off-highway vehicle (OHV) route segments within the West Mojave (WEMO) planning area. A total of 651 new sites and 309 isolates was recorded during the inventories. Additionally, 110 previously recorded resources were encountered, 30 of which were updated with new site records while 80 were monitored for changes in condition since the last site visit. These surveys produced a sample made up of 70 percent historic sites, 25 percent prehistoric sites, and 5 percent multi-component sites.

Mining sites are the most prevalent site type, making up 35 percent of the total sample, followed closely by historic refuse scatters at 34 percent. Lithic scatters are the most prevalent prehistoric site type at 15 percent, followed by habitation or temporary camp sites at 6 percent (Figure 1). Understanding the distribution of site types across the WEMO planning area helps us to select environmental predictors that address specific land-use patterns; for example, elevation profiles for mining sites may be higher than roadside dumping sites. This breakdown may also help us prioritize vulnerable site types, such as focusing future identification efforts on areas where prehistoric habitation sites are more likely to be present.

OHV IMPACTS

Field crews were instructed to note any impacts to cultural resources resulting from OHV activity, which revealed that 30percent of sites encountered during the surveys had been affected. Impacts range from the dispersal of already disturbed surface artifacts to destruction of features and vandalism. Newly encountered sites were significantly more likely (between 3 and 20 percent, $p = 0.05$) to have OHV impacts than previously identified sites. These data suggest that identification efforts are a crucial step toward protecting cultural resources, as the BLM is better able to manage impacts once identified (Figure 2).

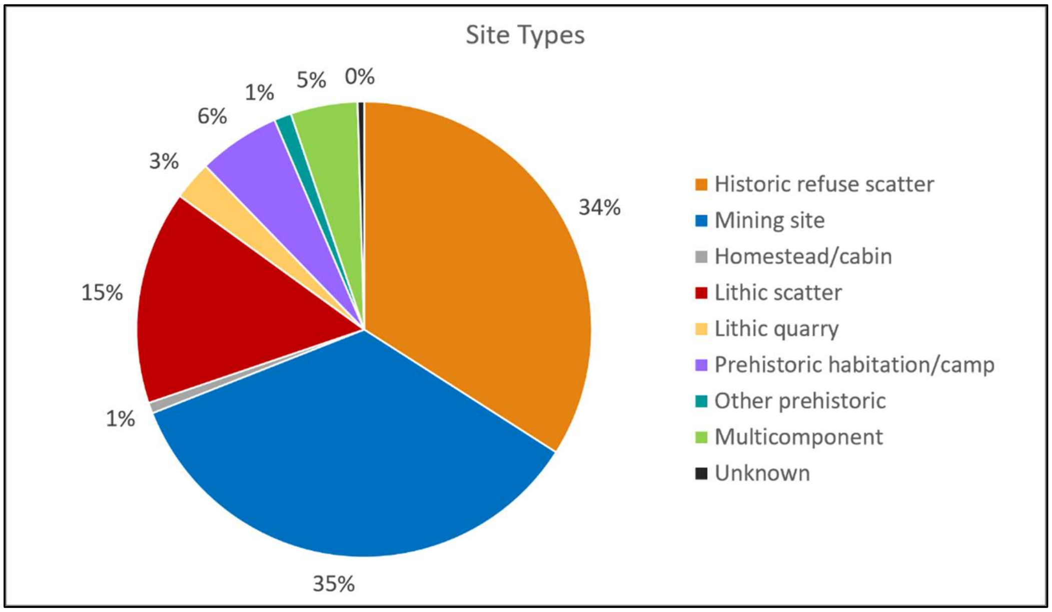


Figure 1. Breakdown of site types for newly identified sites in the WEMO planning area.

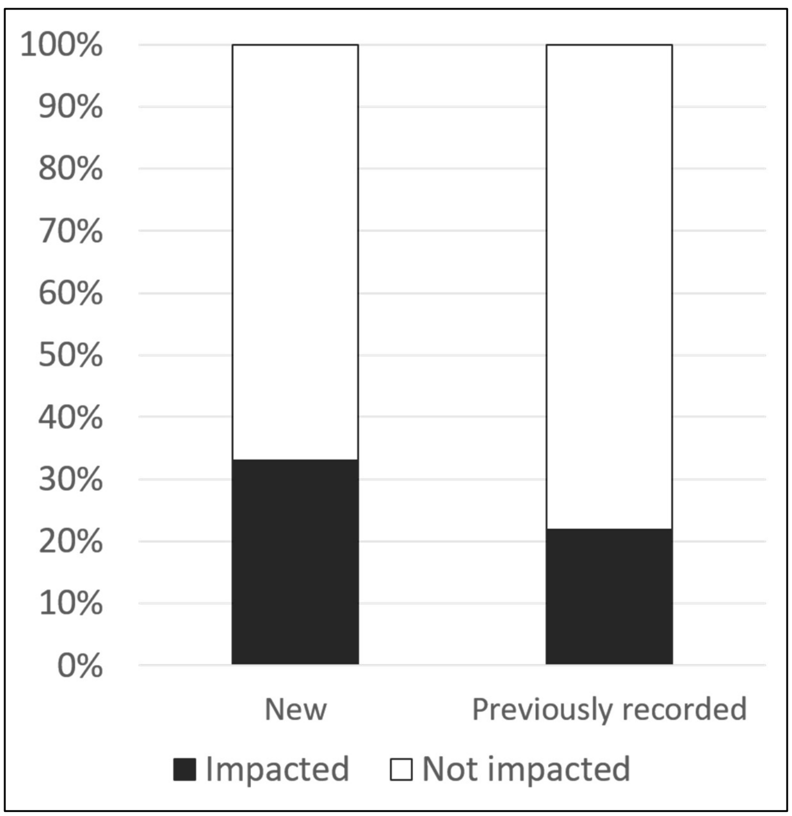


Figure 2. Sites impacted by OHV activity. Impacts were observed at 22 percent of previously recorded sites and 33 percent of newly identified sites.

SECOND MODEL RUN

In the second run of the WEMO model in 2017, the BLM had two goals: (1) to attempt to replicate the low, medium, and high probability results of the 2015 iteration with a different individual running the model (2017-Iteration A); and (2) to change the parameters from the 2015 iteration to get low, medium, and high probabilities with an emphasis on landscape suitability towards prehistoric habitation sites (2017-Iteration B).

2017-Iteration A

In 2017-Iteration A, the GIS specialist (J. Sahagún) who ran the model attempted to closely follow the weights assigned to the environmental factors and tracks in the 2015 iteration, without having knowledge of these weights, to determine if the 2015 iteration could be replicated. The model-builder found that replicability was difficult to achieve due to the built-in subjectivity of how different GIS specialists from different backgrounds assign weights to the environmental factors and tracks (Figure 3, Table 1).

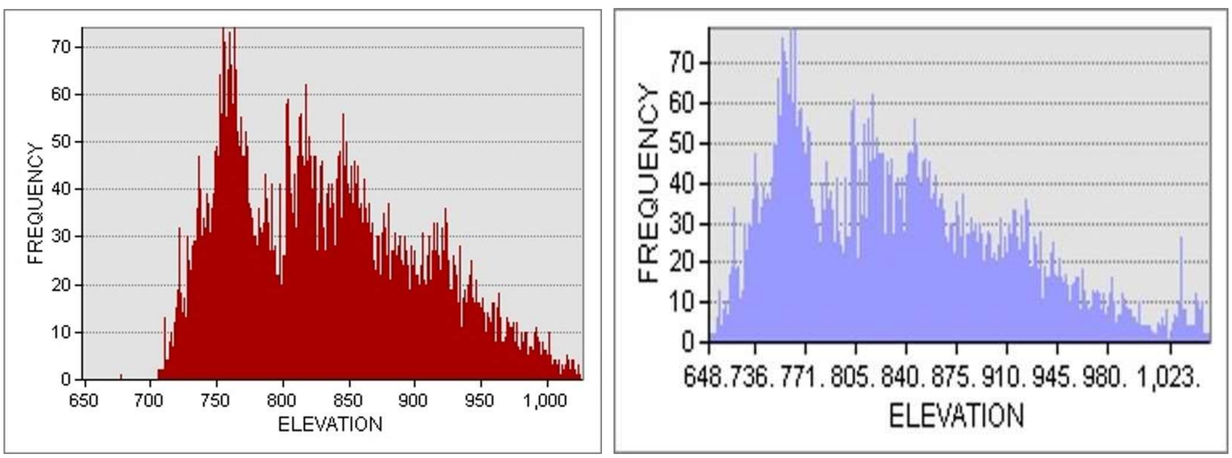


Figure 3. Frequency data for elevation from 2015 (left) and 2017 (right) appear similar, but differences in interpretation may ultimately affect model results.

*Table 1. Differences in Assigned Weights for Elevation Between the 2015 and 2017 Iterations.**

Assigned Weights for Elevation			
2015		**2017**	
Range (ft)	**Weight**	**Range (ft)**	**Weight**
642-733	1	642-750	3
734-876	3	751-790	7
877-925	6	791-945	4
926-1,032	10	946-1,000	2
1,033-1,165	4	1,001-1,570	1
1,166-1,563	2	--	--

* Reflecting decisions made by the model builders.

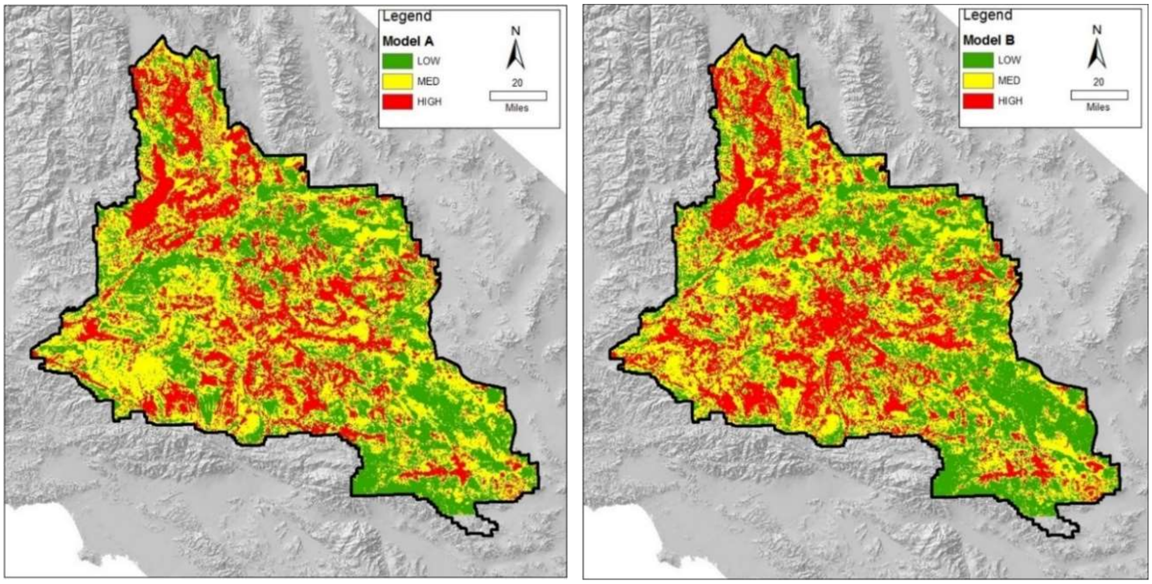


Figure 4. High, medium, and low probability areas identified by 2017-Iteration A (left) and 2017-Iteration B (right).

2017-Iteration B

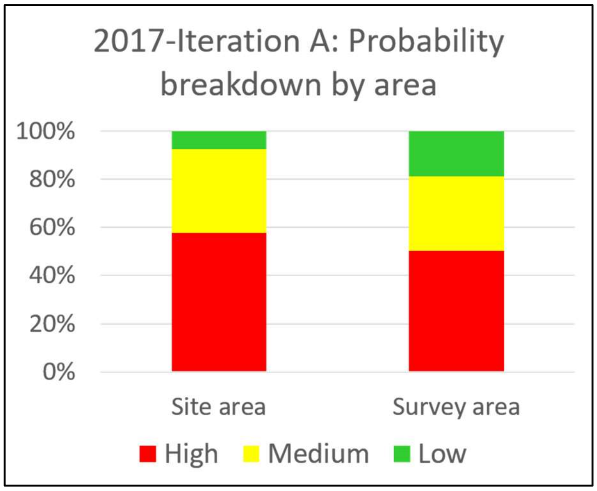
In 2017-Iteration B, the GIS specialist (J. Sahagún) who ran the model came from an archaeological background, so weights were assigned with archaeological biases in mind; for example, people tend to live for extended periods of time on near-level ground, somewhat close to water and food sources, on north-facing aspects in the summer and south-facing in the winter. Elevation also comes into play, especially for people who follow a seasonal travel pattern (i.e., lower elevations in the winter and higher in the summer). These parameters were assigned higher importance in 2017-Iteration B by increasing the weights applied to slope, aspect, elevation, and proximity to water. This iteration produced a raster with noticeable differences from 2017-Iteration A (Figure 4).

RESULTS

While sites recorded during the first two years of field testing were incorporated into the second run of the model, the remaining sites form a test sample that can be compared against the model results. The test sample consists of 16,308 acres surveyed between 2017 and 2019, resulting in the identification of 262 new sites. Preliminary statistical analysis was conducted to assess the performance of both 2017-Iteration A and 2017-Iteration B in predicting the location of cultural resources in the planning area. 2017-Iteration B was also assessed for its ability to predict prehistoric habitation sites.

Overall Model Performance

For both iterations of the model, high and medium probability areas were overrepresented in the sample surveys. Despite this bias, a Pearson chi-squared test showed significant differences in distribution patterns, indicating that site probability levels are not solely a result of initial survey locations (Figure 5). For both model iterations, the ratio of site area to surveyed area was significantly higher ($p < 0.05$) for high probability areas than for the total sample area. However, neither iteration shows a significant difference between high and medium probability areas, suggesting the cutoff point between these categories could be fine-tuned.



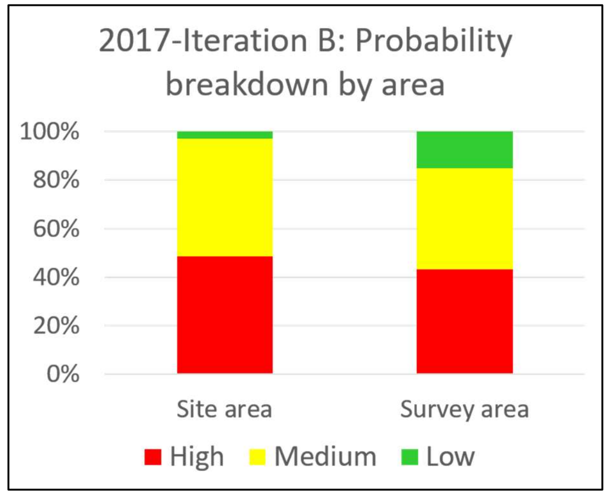


Figure 5. Probability distributions for site areas are significantly different (p < 0.01) for 2017-Iteration A (left) and 2017-Iteration B (right).

This study concluded that high-probability areas for both 2017-Iteration A and 2017-Iteration B are statistically significant at the 95 percent confidence level. However, the expected improvement over random sampling only lies between 10 and 20 percent for 2017-Iteration A and between 0 and 20 percent for 2017-Iteration B ($p = 0.05$). Using different environmental variables or weighting strategies may help improve these metrics. The model will be used to inform the inventory strategy for the WEMO planning area.

Predicting Prehistoric Habitation

Environmental predictors for 2017-Iteration B were selected to target prehistoric habitation sites. The small sample size for prehistoric habitation sites ($n = 18$) poses challenges for statistical analysis, but comparing the prediction rate of 2017-Iteration B against 2017-Iteration A as a control model shows that 2017-Iteration B performs marginally better (Figure 6). For both iterations, the ratio of prehistoric habitation sites to surveyed area is not significantly higher for high probability areas than for the total sample area. However, the high probability areas identified by 2017-Iteration B will likely yield between 30 and 240 percent more habitation site acreage ($p = 0.05$) than low and medium probability areas. In contrast, there are no significant differences across probability levels for 2017-Iteration A.

In conclusion, 2017-Iteration B does not predict prehistoric habitation sites better than a random sample at the 95 percent confidence level. However, the high probability areas in this iteration perform significantly better than the remaining areas. 2017-Iteration B is better suited to predict habitation sites than 2017-Iteration A.

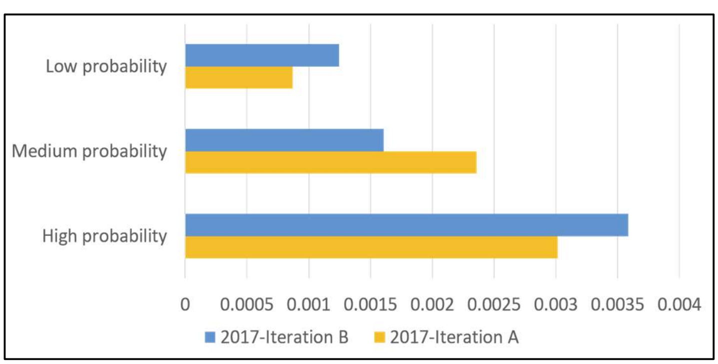


Figure 6. Habitation site acreage per surveyed acre. High probability areas for 2017- Iteration B perform significantly better than low and medium probability areas, while the difference is not significant for 2017-Iteration A.

NEXT STEPS

This model is currently in peer review, and these recommendations will be incorporated into future iterations. Based on preliminary feedback, several options for improving the model include:

1. Statistical analysis: The significance of environmental variables and their respective weights can be determined by statistics. Using statistics will help remove the biases of the GIS specialists running the model and ensure that the model is replicable in future iterations.
2. Temporal resolution: Given the heavy bias towards historic sites in the sample inventory, separating historic from prehistoric sites will lead to more effective predictions targeting different land-use patterns. The types of environmental factors that influence site location differ between historic and prehistoric sites.
3. Spatial resolution: The model currently uses point data to identify landscape trends. Using polygon data rather than point data may help preserve the spatial resolution of the initial site recordation.

Given that human behavior is inherently difficult to predict, this model reflects certain assumptions and decisions made by the model-builders regarding the importance of various landscape features. Our next steps forward involve taking account of these biases. While such biases can never be fully eliminated, even by statistical analysis, we hope to improve the model's effectiveness by balancing the knowledge of archaeologists and GIS specialists with the need for replicability in the future.