Decomposing Habitat Suitability Across the Forager to Farmer Transition

[1], Kenneth B. Vernon[1,2], Peter M. Yaworsky[1,2], Jerry Spangler[3], Simon Brewer[4,5], and Brian F. Codding[1,2,5]

[1] *Department of Anthropology, University of Utah, Salt Lake City, UT, 84112, USA*
[2] *Archaeological Center, University of Utah, Salt Lake City, UT, 84112, USA*
[3] *Colorado Plateau Archaeological Alliance, Ogden, UT 84401, USA*
[4] *Department of Geography, University of Utah, Salt Lake City, UT, 84112, USA*
[5] *Global Change and Sustainability Center, University of Utah, Salt Lake City, UT, 84112, USA*

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Abstract

How might subsistence strategies structure the costs and benefits of habitat selection and, therefore, drive settlement patterning? We explore this question within an Ideal Distribution framework, arguing that (i) a habitat can be decomposed into its environmental covariates, (ii) their relative contributions to suitability can vary as a function of subsistence strategy, and (iii) the resulting differences will in turn lead to different population distributions across habitats. To evaluate these claims, we apply a Poisson point-process modeling approach known as maximum entropy (MaxEnt) to Archaic hunter-gatherer and Formative maize-farmer sites within the Grand Staircase-Escalante National Monument. Our results show that environmental covariates vary in their importance for each strategy and that the strategies themselves vary in their land use and habitat distribution, with Archaic foragers being widely distributed across space, Formative farmers more densely packed into areas indicative of higher maize productivity. The approach itself also has wide application to other subsistence strategies, including horticulture and pastoralism, across a range of environmental conditions.

Keywords: Ideal Free Distribution, Grand Staircase-Escalante National Monument, Subsistence-Settlement Dynamics, Poisson Point Process Modeling, Maximum Entropy, Land Use

1 Introduction

In the context of subsistence-settlement dynamics, the order in which choices are made matters, for the choice of where to live introduces new subsistence constraints and the choice of how to live introduces new settlement constraints (Binford, 1980; Bettinger and Baumhoff, 1982). While the interaction of these deserves further consideration, here we focus on the latter, on how subsistence strategies might constrain habitat selection. We argue that (i) a habitat can be decomposed into its environmental covariates, (ii) their relative contributions to suitability can vary as a function of subsistence strategy, and (iii) the resulting differences will in turn lead to different population distributions across habitats.

The analysis is largely motivated by two complementary ideas. The first is that intensification can alter the way per capita suitability responds to demographic pressure (Kennett et al., 2006). The second is that measures of subsistence efficiency can be applied not only to the behaviors of individuals, but to locations in space (Magargal et al., 2017). Drawing on spatial modeling techniques outlined by Yaworsky et al. (in review), we implement our coupled subsistence-settlement approach within an Ideal Distribution framework (Fretwell and Lucas, 1969) using a statistical method for species distribution modeling known as maximum entropy (MaxEnt) (Phillips et al., 2004, 2006; Elith et al., 2011). Archaeological applications of MaxEnt have increased over the last several years (Banks et al., 2011; d'Errico and Banks, 2013; Galletti et al., 2013; McMichael et al., 2014a,b, 2017; Kondo, 2015; d'Errico et al., 2017; Wachtel et al., 2018), so a deeper understanding of the approach is called for. To aid in this, we rely on the interpretation of MaxEnt as a Poisson point process model (Berman and Turner, 1992; Baddeley and Turner, 2000), an interpretation that has garnered a great deal of attention in the recent ecological literature (Fithian and Hastie, 2013; Merow et al., 2013; Renner et al., 2015; Phillips et al., 2017). We evaluate our claims using the extensive record of subsistence and settlement provided by the distribution of Archaic (8,500-2,500 BP) and Formative (2,000-700 BP) sites in the contested Grand Staircase-Escalante National Monument (GSENM), where individuals transitioned from foraging to farming over a roughly 1500 year period, from 3000 to 1500 BP (Spangler et al., 2019).

2 Theory, Methods, and Materials

Intuitively, people will live where they can make the best living, however they choose to do that. Consider Archaic hunter-gatherers, whose broad diets include a large variety of wild resources (Simms, 2008). Because those resources are widely dispersed, the foragers themselves should be widely dispersed, too. For those who transition to farming, however, settlement will likely be more clustered, especially in an area like the arid Southwest, where potential maize production is spatially limited (Spangler et al., 2019). Thus, the spatial distribution of their archaeological materials should

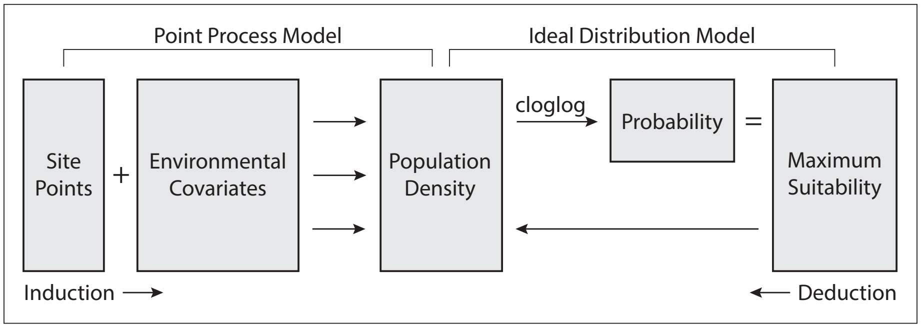

Figure 1: Methods Diagram. The conceptual relationship between Ideal Free and Point Process models. Note that the complementary log-log (cloglog) transforms an empirical density estimate into a probability of site occurrence, which we take to be an operational definition of maximum potential suitability wherever the IDM holds (discussed below and in supplement A).

differ as well, a fact that we can leverage to decompose their respective habitats into a number of environmental variables (precipitation, temperature, elevation, etc.), which are thought to co-vary with the suitability of that habitat. In this way, we are effectively walking a chain of inference from suitability, as defined by the theoretical Ideal Distribution Model (IDM), to the environmental covariates, whose contribution to suitability we measure with an empirical Poisson Point Process Model (PPM), as shown in Fig. 1. It is important to note that this interpretation of a PPM as an empirical model of suitability is only meaningful within the conceptual framework provided by the IDM; thus, it would be invalid in circumstances where individuals do not distribute themselves in conformity with that model.

2.1 Deductive Model: Suitability and Subsistence Efficiency

According to the IDM (Fretwell and Lucas, 1969), suitability should decline as a function of increasing population density. In the simplest case, this is because density leads to greater competition, which in turn reduces the benefit to the individual of occupying that habitat (Parker and Sutherland, 1986; McCool and Yaworsky, 2019). Given that individuals seek to maximize their own gains, the model predicts that they will settle the highest ranked habitat first, with subsequent infilling occurring up to the point where the next highest ranked habitat is of equal suitability, at which point individuals should settle both at an equal rate. This process will, thus, lead to an equilibrium distribution in which each individual experiences the same level of gain - the same actual suitability - regardless of the maximum potential suitability of the habitat they happen to occupy.

A simple, intuitive way to articulate these model expectations with subsistence behavior draws on Optimal Foraging Theory (Emlen, 1966; MacArthur and Pianka, 1966; Charnov, 1976a,b) to postulate an identity between the suitability of a habitat and the optimal overall caloric return-rate

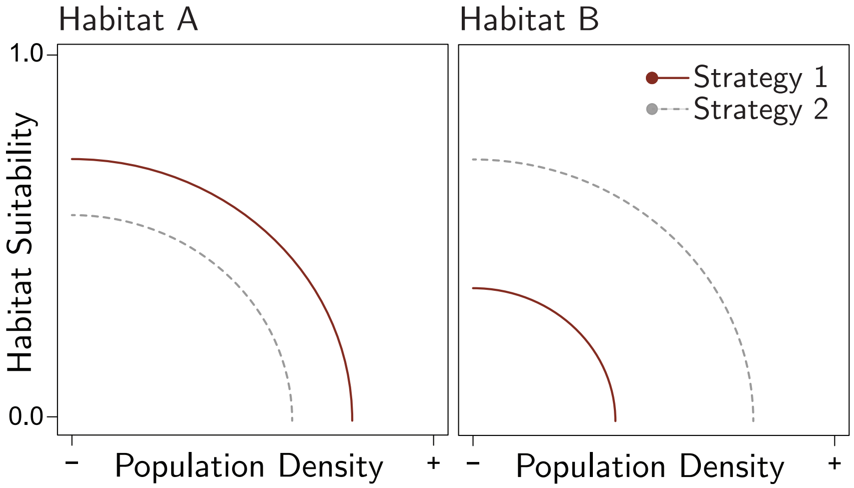

Figure 2: An IDM showing the effects of subsistence on settlement, specifically a change in the potential suitabilities and relative rankings of habitats A and B.

an individual can achieve there when pursuing a particular subsistence strategy. This identity expands on the strategy employed by Magargal et al. (2017), assigning to each habitat an estimate of expected subsistence efficiency but also allowing for foraging strategies themselves to be negatively density-dependent. The identity also provides for a number of additional subsistence-settlement dynamics. As Kennett et al. (2006) show, the transition to a farming strategy can decrease the magnitude of density's effect on suitability and introduce Allee effects, or positive contributions to suitability at low density (Allee et al., 1949; Sutherland, 1996). In addition, it suggests that subsistence transitions can lead to changes in the maximum potential suitability of habitats, which can in turn lead to changes in their relative rank.

Of those three, the last should have the largest effect on density distributions. As shown in Fig. 2, we assume in the simplest case two habitats, H_A and H_B, and two strategies, S1 and S2. S1 has greater subsistence efficiency in H_A relative to H_B and should, therefore, rank H_A above H_B. Conversely, S2 has greater efficiency in H_B relative to H_A and should, therefore, rank H_B above H_A. All else being equal, a change in maximum potential suitability should, in turn, entail different habitat distributions for each strategy. Individuals pursuing S1 should occur at higher densities in H_A, and individuals pursuing S2 should occur at higher densities in H_B. This outcome is a simple, qualitative variation of the "input matching rule" (Parker, 1978), which states that population density should be proportional to the maximum potential suitability of a habitat.

Logically, the inverse of this matching rule should also hold, so that the observed density of individuals pursuing a subsistence strategy within a habitat indicates something about that habitat's potential suitability for the strategy. That is, if the density of individuals pursuing strategy S1 in a habitat is greater than the density of individuals pursuing strategy S2 in that habitat, then the potential suitability of that habitat for S1 ought to be greater than its potential suitability for S2, assuming at least that the strategies are at equilibrium.

Similar reasoning applies to an environmental variable's ecological utility function, where that refers to changes in the variable that increase or decrease a habitat's potential suitability (for how we specify an ecological utility function, see discussion of the marginal response below and in Supplement A). Since suitability is tied to subsistence efficiency, environmental covariates should also exhibit different ecological utility functions for individuals pursuing different subsistence strategies, which should in turn entail different habitat rankings and habitat distributions. So, just as observed population density suggests something about potential suitability, it should suggest something about these ecological utility functions, too.

Crucially, these inferences from observed density to both potential suitability and ecological utility rely on the assumption that no Allee effects have occurred, that density affects both strategies equally, and that settlement costs are the same for both. Yet, as already noted, these assumptions are almost certainly false. Thus, without suitable actualistic research to estimate settlement costs and other subsistence related constraints and trade-offs, the naïve inference from density to potential suitability is tantamount to inferring from the fact that a person occupies a low quality habitat that they must actually prefer that habitat, which is uncharitable in the extreme (Codding and Bliege Bird, 2012; Codding and Bird, 2015). Heeding this concern, we fall back on evaluating potential suitability relative to land use itself, assuming that this must in some way relate to the underlying subsistence efficiency of each strategy.

2.2 Inductive Model: MaxEnt as a Point Process

An inductive (or predictive) distribution model requires a dependent variable or response, in this case site "occurrence" data, and a set of independent variables or predictors, here environmental variables thought to co-vary with the response. Typically, archaeologists think of site occurrences as presence-absence or Bernoulli responses, thus turning to logistic regression to model the probability of each outcome, which is then interpreted in terms of habitat suitability (Kvamme, 2005; Wachtel et al., 2018). This is a somewhat awkward approach, however, for two important reasons (Warton and Shepherd, 2010; Phillips and Elith, 2013; Fithian and Hastie, 2013; Hastie, 2013; Renner et al., 2015). First, systematic inventory of potential absence locations is rarely conducted, so the data we have at our disposal is overwhelmingly presence-only. This is exacerbated by the fragmentary record of archaeological sites commonly used as a proxy for past occurrences. Second, this approach often fails to recognize that probability measures are sensitive to spatial scale. If a region consists of two habitats about whose environmental conditions we know nothing save that one has twice the area of the other, we should not assign to each a probability of settlement of 0.5, but rather 0.66 and 0.33 respectively.

To address these issues, we interpret site occurrences as counts or Poisson responses per unit area, in short, as densities (Warton and Shepherd, 2010; Fithian and Hastie, 2013; Renner et al., 2015). More precisely, we assume that archaeological sites are independent and identically distributed point locations $s_p = \{s_1, ..., s_N\}$ occurring within a larger project window W. While this assumption of independence is almost certainly unrealistic, it does allow us to treat the density distribution of sites as a Poisson point process and thereby formulate expectations regarding that distribution using a point process model (PPM).

A Poisson point process can be either homogenous or inhomogenous (Baddeley and Turner, 2000; Baddeley et al., 2015). For a homogenous process, the point pattern exhibits “complete spatial randomness,” so there will be variation around the mean, but not variation whose direction away from the mean we can estimate. Thus, our expectation regarding a habitat i's density (denoted $\lambda(s_i)$ in the PPM literature) is just the average density of W:

$$\lambda(s_i) = \frac{N}{area_W} \tag{1}$$

This serves as a null model. It is equivalent to the hypothesis that individuals do not differentiate habitats with respect to their land use, so that we have no reason to expect sites to occur more often in one habitat as opposed to another.

For an inhomogenous process, the point pattern does not exhibit complete spatial randomness, so the density within any habitat can be modeled as a log-linear response to a vector X of environmental covariates $\{x_1, ..., x_j\}$:

$$\lambda(s_i) = \exp(\beta_0 + \beta_1 X(s_i)) \tag{2}$$

where β_0 is the intercept, β_1 a vector of coefficients, and the error a Poisson distribution. A fitted PPM model can be used to estimate the population density in each habitat based on its environmental conditions, which is equivalent to estimating site occurrence probability for every habitat size (Fithian and Hastie, 2013). We emphasize that this is only an estimate of the relative density (referred to as the relative occurence rate), as we cannot measure the total prevalence of points within the window without true absence data (Fithian and Hastie, 2013; Hastie and Fithian, 2013; Phillips and Elith, 2013).

One popular form of PPM is MaxEnt (Fithian and Hastie, 2013; Merow et al., 2013; Renner and Warton, 2013; Renner et al., 2015; Phillips et al., 2017), which estimates β-coefficients for Eq. 2 subject to the constraint that the geographic probability distribution be as close as possible to absolute entropy (Jaynes, 1957). For the sake of clarity, we use 'MaxEnt' in this paper to refer to a particular software implementation for training a PPM and 'entropy' to refer to a particular concept in information theory (Shannon, 1948). In terms of point patterning, absolute entropy is equivalent to homogeneity or complete spatial randomness, or a geographically uniform probability distribution. Formally, MaxEnt estimates β-coefficients by maximizing the penalized log-likelihood of the following:

$$P_i/B_i = \exp(\beta_0 + \beta_1 X(s_i)) \tag{3}$$

where P_i is the probability density of covariates at presence locations and B_i is the probability density of covariates across the research area, typically estimated using background or quadrature points, also known as pseudo-absence points (Elith et al., 2011; Merow et al., 2013). The ratio is equivalent to point density in ecological as opposed to geographic space (across habitats, that is, as opposed to coordinate locations). The distance between them is the relative entropy of the point process (also known as the Kullback-Leibler or KL divergence) (Elith et al., 2011; Merow et al., 2013). Minimizing relative entropy in ecological space is equivalent to maximizing absolute entropy in geographic space, for smaller values of relative entropy suggest less differentiation in land use, which in turn entails greater homogeneity in the resulting point pattern.

One can also think of the ratio P_i/B_i as a means of controlling for a covariate's prevalence (Elith et al., 2011; Merow et al., 2013). The reason for doing so is straightforward. Though many sites may occur at some value of an environmental covariate, if that value is ubiquitous, it should be given less weight in fitting the final model, for it becomes that much harder to discern whether individuals have arrived at that value because they chose to or simply as a matter of chance.

But even standard linear PPMs account for the background distribution, so why use a MaxEnt PPM? This is a complicated question involving a number of modeling trade-offs. By default, MaxEnt transforms the set of covariates X into a larger set of *features* including product, quadratic, and hinge terms (described in Supplement A) (Phillips and Dudík, 2008; Elith et al., 2011; Phillips et al., 2017). It then reduces that set through regularization, which also limits overfitting by penalizing the log-likelihood (Dudík et al., 2004; Phillips et al., 2004; Elith et al., 2011). This process has the advantage of capturing complex multi-modal responses unavailable to a simple linear PPM. It also increases the model's predictive power (Elith et al., 2006; Phillips and Dudík, 2008; Wachtel et al., 2018; Yaworsky et al., in review). Unfortunately, the price of this gain in predictive power is a loss of interpretability (Phillips et al., 2006), specifically with respect to covariate importance, where linear models can leverage standardized coefficients and model diagnostics like the Likelihood Ratio Test. MaxEnt does provide alternative measures (described below), but these must be read with caution, for the underlying Poisson probability distribution is less transparent and the subsequent statistical inference more opaque. Thus, MaxEnt faces a familiar modeling trade-off between prediction and

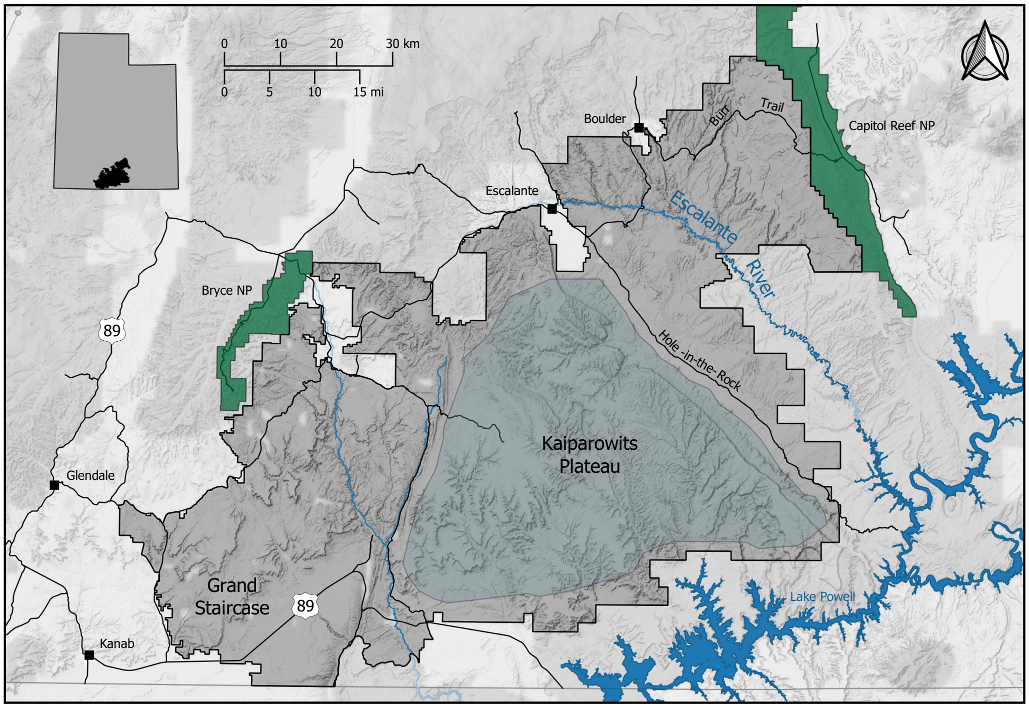

Figure 3: Reference Map for the Grand Staircase-Escalante National Monument. Includes nearby national parks, major water features, and the original boundary designation, which defines the current project window.

interpretability. To get some handle on this trade-off, we compare the results of a feature-restricted MaxEnt and linear PPM.

2.3 Archaeological Point Patterns (λ)

The project window from which we draw environmental and archaeological information is the GSENM, an area in south-central Utah along the western most extent of the Colorado Plateau. When these data were collected, the monument consisted of some 1.9 million acres (7.6 thousand km^2) commonly subdivided into three major regions including the Grand Staircase, the Kaiparowits Plateau, and the Canyons of the Escalante, as shown in Fig 3. While mostly uniform with respect to their aridity, these regions do exhibit dramatic variation in topography and vegetation.

Here we focus on Archaic (AR) and Formative (FO) economies within the GSENM as they present a fairly stark contrast in their respective subsistence strategies. From roughly 8,500 to 2,500 BP, the former involved a broad-spectrum foraging strategy including everything from large game animals to less profitable resources like nuts and seeds (Simms, 2008). Beginning around 2,000 BP and

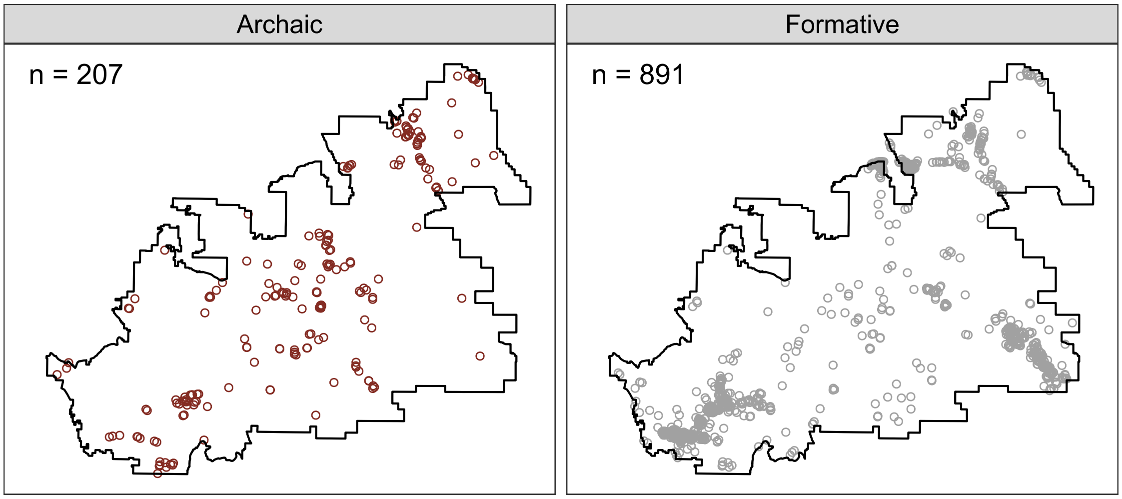

Figure 4: Point Patterns. The distribution of Archaic and Formative Sites.

persisting for nearly 1,300 years, the latter involved a small-scale, agricultural strategy highly reliant on maize (Coltrain et al., 2007). Importantly, Formative maize farming is a form of intensification (*sensu stricto*, Morgan, 2015), whereby higher energetic yields are gained at the expense of diminished efficiency (Barlow, 2002), producing more food per unit area (Boserup, 1965) and increasing the carrying capacity of occupied habitats. This is reflected in the relative abundance of observed residential sites associated with each time period (AR=207, FO=891).

Spatial data for archaeological sites and information required to associate each with Archaic and Formative time periods are drawn from records curated by the Bureau of Land Management (BLM) and the Utah State Historic Preservation Office (SHPO). These records contain field notes detailing the presence and number of formal diagnostic materials. The rules we use to infer time period affiliations from those diagnostics are outlined in detail in our report to the BLM GSENM district office (Spangler et al., 2019). We then select only residential sites (as opposed to temporary camps) defined as places of long-term habitation and indicated archaeologically by the presence of either deep hearths, habitation features, which are too costly to build when stays are short, or heavy groundstone, which are too costly to transport (Beck et al., 2002). The resulting point patterns are shown in Fig. 4. These represent spatial patterning in prehistoric foraging and farming strategies within the GSENM.

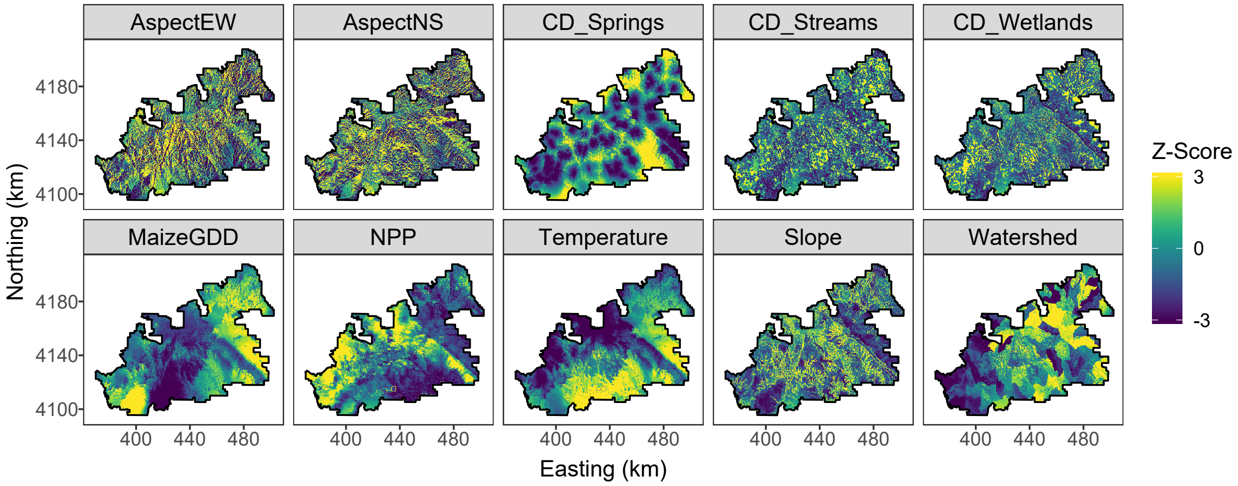

Figure 5: Environmental Covariates Projected in Geographic Space. For visualization purposes, the z-values of these covariates were compressed into a -3 to 3 range.

2.4 Environmental Covariates (X)

For this analysis, we decompose suitability into a set of ten environmental covariates (5), which we derive from a larger set through Principal Component Analysis to reduce spatial covariance (Yaworsky et al., in review). These group roughly into landscape attributes, climate values, environmental productivity, and resource distribution. Landscape attributes include aspect (both east-west and north-south), slope, and watershed size, with the first two being extracted from a digital elevation model (U.S. Geological Survey, 2019) and the latter provided by Utah's Automated Geographic Reference Center (AGRC Staff, 1984). Our sole climate covariate is thirty-year average temperature (PRISM Climate Group, 2019). Indicators of environmental productivity include maize growing-degree days (GDD) (Coop, 2014) and net primary productivity (NPP) (Numerical Terradynamic Simulation Group, 2013). Finally, we define resource distributions as cost-distance to water features computed using Tobler's hiking function (Tobler, 1993), specifically cost-distance to springs, streams, and wetlands. The rasters encoding these covariates are projected to a 50-m x 50-m resolution. For more details regarding these covariates, see supplement B.

Climate and productivity covariates in our dataset are measures of modern variation within the GSENM, so we must assume that the relative differences across space for each category are largely representative of relative differences in the past. For example, if it is hotter in the eastern part of the GSENM today, then it was hotter in the eastern part of the GSENM during the times in question. While further work is required to test this assumption, we proceed with this analysis without introducing additional bias that would come with using spatially-explicit reconstructions of past climate and environment (Codding and Jones, 2013).

2.5 Hypotheses

We argue that these environmental covariates will contribute differentially to suitability as a function of subsistence strategy - in this case, Archaic foraging and Formative farming - and that this will lead to differences in the downstream distribution of those strategies. Transposed into the language of point processes, these claims amount to the following null and alternative hypotheses:

H_0 Archaic and Formative point patterns are homogenous.

H_1 Archaic and Formative point patterns are inhomogenous.

H_2 Archaic and Formative subsistence strategies differ significantly in (a) the ecological utility of covariates, (b) the potential suitability of habitats, and (c) the spatial clustering of sites.

We stress that we are evaluating these hypotheses relative to land use as we have no independent control on subsistence-settlement constraints and trade-offs. In general, however, we expect that environmental covariates more conducive to maize agriculture will play a greater explanatory role in Formative site patterning. Because individuals pursuing a more intensive farming strategy have more to gain by reducing handling rather than search costs (Bettinger and Baumhoff, 1982; Kelly, 1992; Hawkes and O'Connell, 1992; Morgan, 2015; Parker et al., 2018), we also expect that Formative individuals will be more sedentary, with residential sites exhibiting greater levels of clustering around maize-promoting covariate values. Conversely, those pursuing a more general and less intensive Archaic foraging strategy should be more mobile, with residential sites trending toward a homogenous point pattern spread out across a wider range of covariate values.

2.6 Analytical Methods

To test these hypotheses, we center and scale our covariates, subtracting by the mean of each and dividing by their standard deviations, which makes estimated β-coefficients directly comparable. To estimate the background distrubtion of these covariates for model training, we generate a spatially uniform or gridded quadrature scheme of 100,000 points based loosely on a rule recommended by (Renner et al., 2015) (for more details, see Supplement A).

We then use the spatstat package in R (Baddeley et al., 2015) to fit three linear PPMs: (a) a stationary or homogenous PPM that measures the average density for each strategy; (b) a strategy-insensitive, inhomogenous PPM of all the points, both Archaic and Formative; and (c) a strategy-sensitive, inhomogenous PPM that treats time period as a categorical interaction term with two levels, Archaic and Formative. These are nested models, allowing Analysis of Variance (ANOVA) to evaluate whether each model is significantly better than its simpler alternative. The results will tell us whether the respective point patterns are different than a homogenous point process (H_0 and H_1) and whether they are different than each other (H_2). PPM (iii) also provides a de facto Wald test of signficant differences in the linear importance of each covariate for each subsistence strategy (H_2a). A graphical Ripley's L test (Ripley, 1977) accompanied by a Maximum Absolute Deviation (MAD) test (Baddeley et al., 2014) evaluates potential for significant clustering in foraging and farming point patterns (H_2c) (further details in Supplement A). These will give us an idea of their "notional" habitat size as well as their density of occupation within it.

Next we use the dismo package in R (Hijmans et al., 2017) to fit a MaxEnt PPM for each subsistence strategy, restricting its default feature expansion to hinge and quadratic terms so that only the additive contributions of each covariate are measured, which eases interpretation of MaxEnt's estimates of covariate importance. Through iterations of fitting a PPM, MaxEnt tracks changes in the empirical log-loss associated with changes in each feature, which is assigned to the corresponding covariate. Once a model is fitted, the total contribution to the log-loss for each covariate is divided by the sum of all covariate scores, and then multiplied by one hundred to give a percent contribution score (Phillips, 2017). MaxEnt then randomly permutes each covariate and evaluates the loss in model performance, measured using the area under the receiver operating characteristic curve (AUC) (for a discussion of the AUC, see Yaworsky et al., in review). Again, these measures are divided by the total loss across all covariates, and then multiplied by one hundred to give a permutation importance score (Phillips, 2017). Together these measures provide some indication as to the importance of each covariate to the final model and by extension to the corresponding subsistence strategies (H_2a). To validate these scores, we also conduct a spatial random bootstrap and fit MaxEnt PPMs to the resulting data. This includes building ten models for each time period and in each case removing approximately one quarter of the presence and background points within spatially defined quadrats (further details in Supplement A). An ANOVA tests whether the results are significantly different.

We generate marginal response plots (Fig. 8) for each covariate by holding all other covariates at their zero-centered means and predicting the density from a MaxEnt PPM using all the data. That is then converted into a probability using the complementary log-log transform (cloglog) (Baddeley et al., 2010; Phillips et al., 2017). The marginal response shows how potential suitability (operationalized as probability of occurrence) responds to changes in a covariate within the average habitat as represented in ecological space and relative to a subsistence strategy, so they are graphical representations of strategy-specific ecological utility functions (see Supplement A for the actual formulas estimated by MaxEnt). We compare these plots to probability density functions for covariates at Archaic and Formative presence locations and background locations to show how MaxEnt's probability estimates

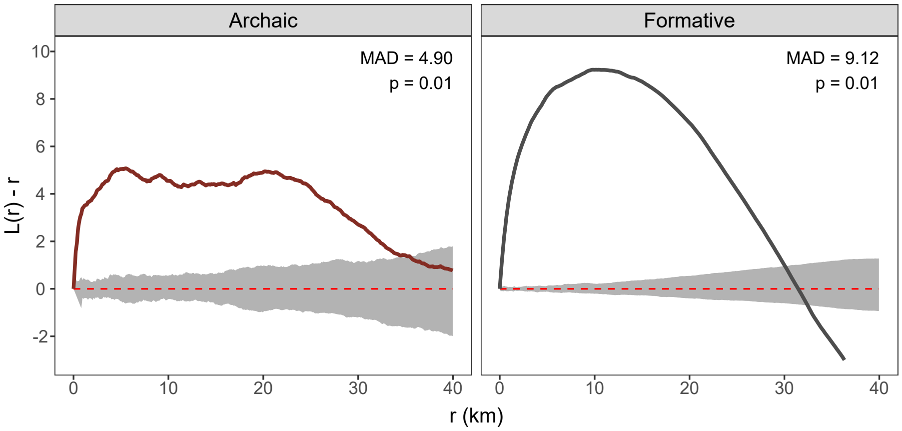

Figure 6: Ripley's *L* Test. Values greater than expected by the null mode (represented by the red dashed line) indicate spatial clustering. Values less than expected by the null model indicate spatial repulsion. The gray ribbon represents Monte Carlo simulations of the null mode. Where the line enters the gray ribbon, it is no longer significantly different than complete spatial randomness. The MAD statistic measures the maximum distance between observed values and the null model.

relate to the ratio P_i/B_i, with B_i being estimated using the quadrature points.

Finally, we use a MaxEnt PPM (iii) to estimate the density at each geographic location within the GSENM. MaxEnt's raw predictions are point density estimates standardized by the total number of occurrence locations. Although we do not know the true prevalence of each strategy, to get a sense of the difference in population density distributions we take the product of MaxEnt's raw output and the total number of sites for each strategy. Again, the standardized estimates are converted into probabilities using cloglog. Being transformations of the underlying density, these probability estimates are not susceptible to issues of scale (Fithian and Hastie, 2013) and thus provide a suitable means for operationalizing habitat suitability. Although they are not observations, strictly speaking, they are pair-wise estimates, so we can use a Wilcoxon Signed-Rank Test to see if the model suggests significant differences in the spatial distribution of potential suitability (with respect to land use) between Archaic hunter-gatherers and Formative maize-farmers (H_2b). While there are more sophisticated techniques for map comparisons (Wilson, 2011), this test is sufficient for current purposes.

All statistical analyses are conducted in the R programming environment (R Core Team, 2019) with code and further discussion reported in the supplementary material.

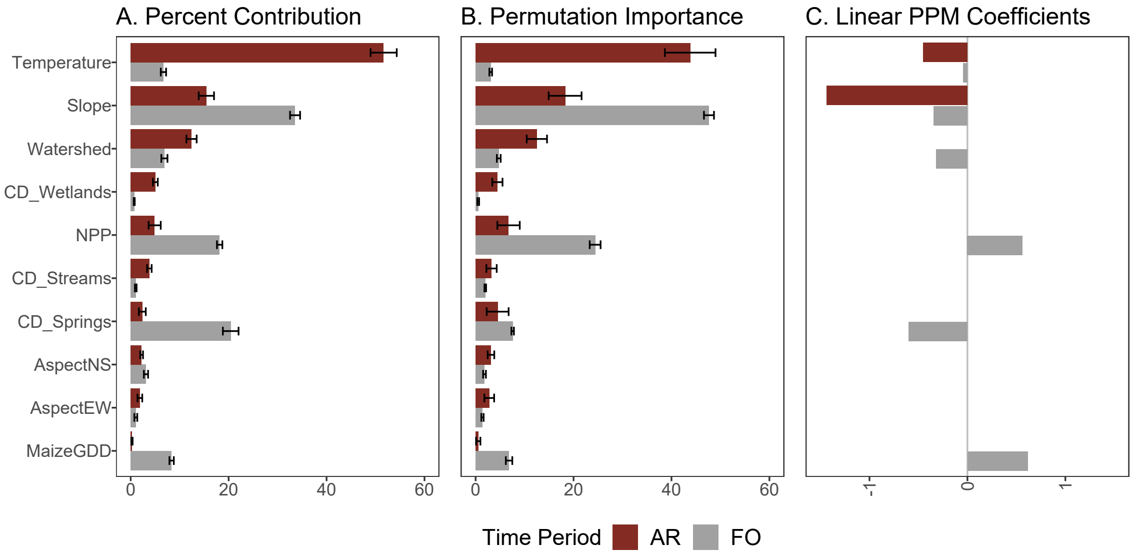

Figure 7: MaxEnt and Linear PPM Measures of Covariate Importance. These are estimated for both Archaic (AR) and Formative (FO) subsistence strategies. (A,B) ANOVAS indicate that all differences between strategies are significant. (C) For comparitive purposes, the log-β's for linear PPM (c) are reported. In general, (A) and (B) speak to the magnitude of importance, (C) to its direction.

3 Results

The results of the ANOVA show significant improvement in model fit for each incremental increase in model complexity, from stationary (a) to strategy-insensitive (b) ($\chi^2(10) = 960$, $p < 0.0001$) and from strategy-insensitive (b) to strategy-sensitive (c) ($\chi^2(11) = 642$, $p < 0.0001$). This shows that there are significant differences in land use patterns between the two strategies (H_2 is true), and that they are not homogenous (H_0 is false and H_1 is true). Results of the graphical Ripley's L and MAD tests are shown in Fig. 6. Together, these indicate that Archaic hunter-gatherers and Formative maize farmers exhibit clustering over the same range of approximately 30 kilometers, which is suggestive of their notional community size. Over that range, however, Formative maize farmers exhibit higher densities than Archaic hunter-gatherers (MAD FO = 9.12, MAD AR = 4.90).

Spatial bootstraps of MaxEnt measure spatial variation in percent contribution and permutation importance scores for each covariate, as shown in Fig. 7. Relatively speaking, temperature appears to be most important to Archaic hunter-gatherers, followed by slope and watershed size. For Formative maize-farmers, it is slope followed by NPP, cost-distance to springs, and maize GDD. ANOVAs comparing the distributions of percent contribution and permutation importance for each covariate and time period suggest that all are significantly different. As evidenced by the linear coefficient, Archaic individuals gravitate towards PRISM temperatures below the mean ($\mu = 10.77°\text{C}$).

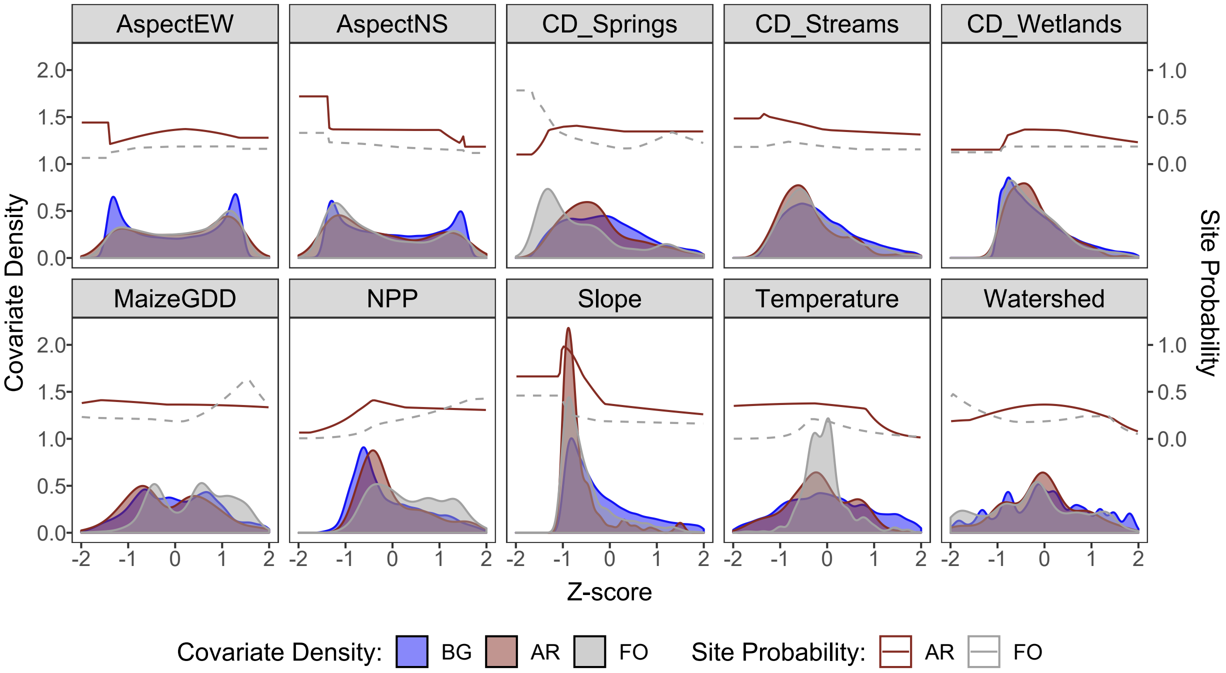

Figure 8: Covariate Density and Marginal Response Plots in Ecological Space. MaxEnt models P_i/B_i, the ratio of covariate density at presence locations (AR and FO) to covariate density at background locations (BG), with regularization to avoid over-fitting. MaxEnt then converts that ratio into a probability using the cloglog transform. The result is a margial response plot, a line showing the response of each subsistence strategy (solid red for AR and dashed gray for FO) to change in the covariate at the margin, the "average" habitat in this case, or the point at which other covariates are held at their zero-centered mean.

Higher values of NPP ($\mu = 1325.29$ kg-C/m^2/year) and Maize GDD ($\mu = 2896.54$°F-sum) attract agriculturalists.

Probability density functions and marginal response plots are shown together in Fig. 8. In general, the greater the relative entropy (i.e., the greater the KL divergence between the probability densities of a covariate at presence and background locations), the greater the probability of occurrence. For instance, Formative sites tend to be closer to springs than the average background location within the GSENM, as shown by the gray spike around -1.1 standard deviations from the mean. That fact also corresponds to the change in MaxEnt's modeled response, with higher probabilities of a Formative site occurring at the same z-score value of the covariate, as shown by the grey line. The overall trend is also indicated by the negative log-β in linear PPM (c).

Fig. 9 shows the geographic distribution of probability estimates, which serves as a proxy for the potential suitability of each location with respect to the Archaic and Formative. The Wilcoxon Sign-

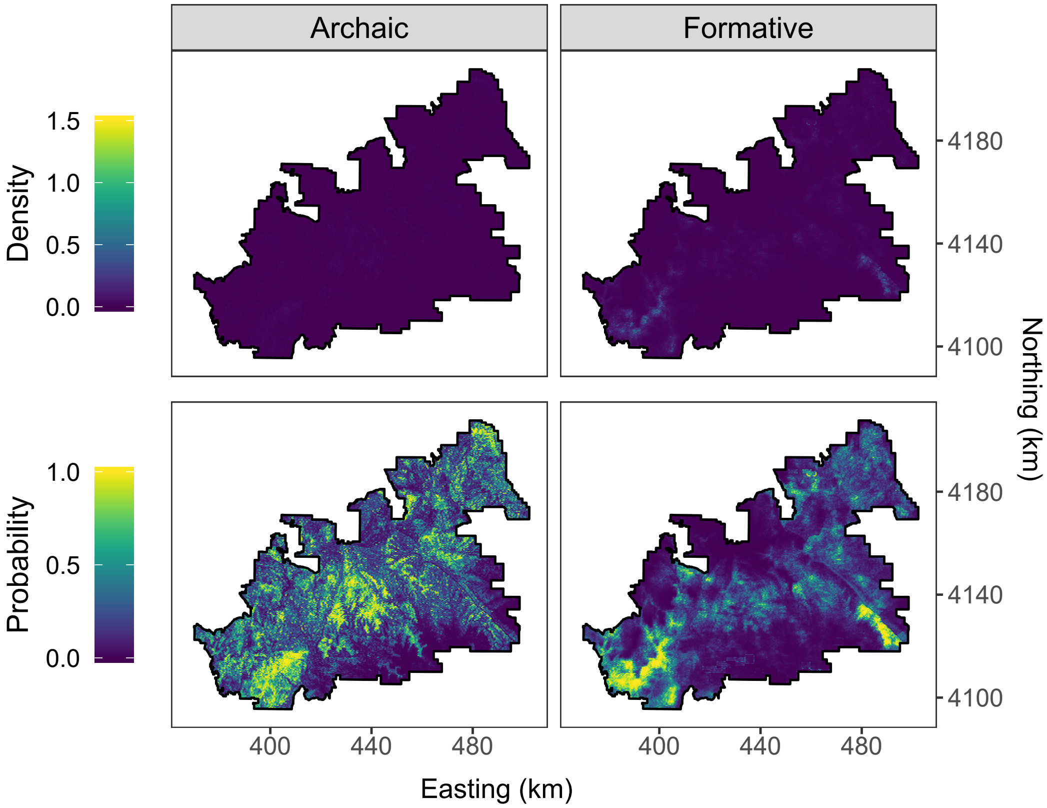

Figure 9: Site Density and Site Probability in Geographic Space. MaxEnt's raw output is a density estimate standardized by the total number of points in the project area, so these density maps were produced by first multiplying by the total number of points for each time period. The probability at each location represents the potential suitability of that habitat, interpreted as its importance to land use behavior.

Ranked Test indicates that the probability maps exhibit significantly different spatial distributions ($p < 0.0001$). The dispersed area in the central monument along the northwestern most extent of the Kaiparowits Plateau appears to be highly suitable to Archaic individuals, as is the area around the Escalante River, the Burr Trail, and Capitol Reef in the northeast of the monument. Values of PRISM temperature are high in this area, with springs and streams cost-distance evidently being highly variable. The concentrated area of high probabiliy along Fiftymile Mountain in the southeast of the monument is evidently highly conducive to maize agriculture. The Vermillion Cliffs area in the southwest of the monument looks to be a high suitability area across the range of subsistence strategies explored here. This region is high in Maize GDD, low in levels of slope and cost-distance to springs and wetlands, and average in conditions for all other covariates.

4 Discussion

Our results show that Archaic hunter-gatherers and Formative maize farmers differ significantly with respect to their land use patterning in the GSENM. Not only are their point patterns not spatially random, they are also significantly different from each other. These two facts together allow us to leverage the spatial distribution of observed density for each strategy to assess the relative importance of environmental covariates (percent contribution, permutation importance, and linear βs) as well as the potential suitability of locations within the GSENM, at least with respect to land use. Presumably, high probability areas for the Formative are also those most conducive to maize agriculture. This may be because lower values of slope and cost-distance to springs indicate ease of irrigation and maize GDD, obviously, more opportunities for production.

Our results also have important implications for the region's archaeology. Here we note two. First, according to the Ripley's L test, Formative maize farmers and Archaic hunter-gatherers exhibit clustering at the same range, but at different densities. This seems to be slightly at odds with regional trends, as well as theory, where we expect farmers to be more concentrated in a smaller area owing to their reliance on a single crop and hunter-gatherers to be more dispersed over a larger area owing to their less restrictive dietary requirements. This may be a result of the landscape imposing constraints on neighborhood size, in which case the different strategies are only reflected in the densities within those neighborhoods. In this case, "neighbors" are sites that occur closer together than one would expect by chance, and the "neighborhood" is the spatial extent of that clustering. A landscape constraint then would be something like a canyon that sets an upper limit on the size of a neighborhood, but still allows for different numbers of neighbors within it. Alternatively, this result could be a limitation of the Ripley's L statistic, which does not account for potential differences in the underlying processes generating the spatial patterning we see (Baddeley et al., 2000).

Second, reconstructing habitats for each strategy offers an additional avenue to investigate the transition from foraging to farming, allowing us to say with greater confidence whether an "Early Agricultural" site (Spangler et al., 2019; Geib, 1996; McFadden, 2016) is affiliated with a more foraging-like or more farming-like economy. In this case, if we know where Archaic sites are more likely to occur, then absent other dating methods, the occurrence of a site there would suggest an Archaic affiliation; similarly, for the Formative. An example of this would be the Kaiparowits Plateau in the central area of the monument. As shown in Fig. 9, this is a high probability area for the Archaic, but not the Formative; hence, a site there is more likely to be associated with hunting and gathering rather than farming.

MaxEnt's marginal response plots in Fig. 8 provide a graphical illustration of the ecological utility function for each covariate and subsistence strategy, showing how suitability varies as a function of the covariate, though importantly without the costs explicitly measured. Note, too, that the probability density function for the covariate at presence locations is analogous to the resource-utilization niche as defined by MacArthur and Levins (1967). The marginal response is, thus, that niche weighted by the background density, which allows us to consider land use choices within the range of alternatives actually available. The probability maps are then those niches projected into habitats found in geographic space, which gives us an idea of their potential suitability.

We may also interpret the marginal response as a background-weighted representation of niche-breadth, overlap, and divergence (MacArthur and Levins, 1967). Temperature, for example, shows a unimodal response for both the Archaic and Formative. However, the temperature niche-breadth – the range of the covariate where the probability of occurrence is above a certain threshold – is much narrower for the Formative than it is for the Archaic. As the peaks are centered near zero, this suggests greater sensitivity among agriculturalists to deviations from the mean. Niche-overlap – here defined as the range of the covariate where each strategy has a probability of occurring above a certain threshold – and its complement, niche-divergence, can also be extracted from these results. NPP is a good example of the former, with Archaic and Formative niches overlapping at high values. Watershed size is an interesting example of the latter, with Archaic centered around the mean and flanked by two Formative niches. Were these contemporaneous strategies, niche-overlap and divergence would point to potential locations of resource competition.

These points serve as well to highlight an important cautionary tale, that inferences regarding land use will be spurious when insensitive to differences in subsistence efficiency. As Fig. 9 shows quite clearly, individuals who practice different subsistence strategies will use land differently and thus distribute themselves differently across the landscape. This is reinforced by the ANOVA comparing strategy-sensitive and insensitive PPMs. Thus, archaeological applications of the IDM may need to alter proxies of suitability when evaluating settlement across subsistence transitions.

We have also shown that modeling the spatial distribution of the density within a Poisson point process framework sheds light on the underlying environmental features composing a habitat and that measures of their importance provide a means of estimating the potential suitability of those habitats. In this sense, PPM is the inductive arm of the deductive IDM. Where the latter structures our expectations regarding optimal settlement behavior, the former tests our hypotheses regarding important constraints and trade-offs. In a related way, the cloglog transform serves as our mathematical inference from density to potential suitability, with the important caveat that these are restricted to land use patterning.

With few exceptions (Winterhalder et al., 2010) most ethnographic (Moritz et al., 2013), historic (Yaworsky and Codding, 2017), and archaeological (Kennett, 2005) applications of the IDM begin by establishing proxies of habitat suitability *a priori* and then evaluate qualitative model predictions using settlement data. Here instead we begin by assuming that settlement behavior conforms to the IDM, which is reasonable given broad empirical support (Codding et al. this issue; Weitzel et al. this issue, Jazwa et al. this issue), and then leverage this assumption to decompose suitability into its environmental covariates. Future studies could expand on this Poisson point process approach by evaluating population-suitability dynamics in archaeological contexts iteratively over time (Winterhalder et al., 2010), and further validating its use with ethnographic cases where individual return rates (E/T) are known, as others have called for (Codding and Bird, 2015).

Before concluding, we emphasize several important confounds that may bias this analysis. First, we constrain our sample of the archaeological record to Archaic and Formative residential sites defined by the presence of certain costly architectural features and heavy groundstone. Obviously, this is an imperfect definition, as it obscures differences in mobility between foragers and farmers, which biases our estimate of the true population density for each strategy. Related to this is the fact that we have flattened variation in the rate of occupation across time, assuming in other words that all sites affiliated with a specific strategy are occupied at the same time. Since the Archaic lasted nearly 6000 years, the Formative only 1500, this is almost certain to further bias our estimate of the true density. To mitigate these worries, we suggest that these would not change the differences we have found, only their magnitude, in fact, exaggerating the differences, with Archaic sites being less densely packed and more dispersed, Formative site more densely packed and less disperseed. Nevertheless, additional empirical work is needed to evaluate that claim.

Another potential confound concerns the fact that data are provided by archaeological records generated from surveys which exhibit bias in sampling effort and detection. Fortunately, ecologists have methods for handling these biases (Warton et al., 2013; Fithian et al., 2015), and those should be applied in future work. Finally, there is the issue of interactions in the point process, where the occurrence of an individual in one location serves either to attract or repel others from distributing themselves in proximity, both spatially and temporally. This is a violation of the independence requirement in the Poisson process, and is highly likely to have occurred given our social tendencies. PPMs have sophisticated tools for accommodating these interactions (Baddeley and Turner, 2000; Baddeley et al., 2015), and future studies should investigate their potential.

5 Conclusion

The Ideal Distribution Model is a deductive framework within which to investigate variation in prehistoric settlement decisions. When alternative strategies exhibit differences in their efficiency across habitats, those habitats will also differ in their ecological utility and potential suitability, here interpreted as measures of importance for overt land use behavior. Those differences will in turn lead to downstream differences in the spatial occurrence of individuals pursuing different strategies, as well as the distribution of their respective archaeological materials. As it models the distribution of populations across habitats, a Poisson point process approach like MaxEnt provides a sophisticated set of tools for applying these and other extensions of the IDM framework to actual empirical cases, such as the forager to farmer transition in the GSENM.

References

AGRC Staff (1984). Utah Automated Geographic Reference Center. Data retrieved August 2019.

Allee, W. C., Park, O., Emerson, A. E., Park, T., and Schmidt, K. P. (1949). *Principles of animal ecology*. W.B. Saunders Company, Philadelphia, PA.

Baddeley, A., Berman, M., Fisher, N., Hardegen, A., Milne, R., Schuhmacher, D., Shah, R., and Turner, R. (2010). Spatial logistic regression and change-of-support in poisson point processes. *Electron. J. Statist.*, 4:1151–1201.

Baddeley, A., Diggle, P. J., Hardegen, A., Lawrence, T., Milne, R. K., and Nair, G. (2014). On tests of spatial pattern based on simulation envelopes. *Ecological Monographs*, 84(3):477–489.

Baddeley, A., Rubak, E., and Turner, R. (2015). *Spatial Point Patterns: Methodology and Applications with R*. Chapman and Hall/CRC Press.

Baddeley, A. and Turner, R. (2000). Practical maximum pseudolikelihood for spatial point patterns. *Australian & New Zealand Journal of Statistics*, 42(3):283–322.

Baddeley, A. J., Møller, J., and Waagepetersen, R. (2000). Non-and semi-parametric estimation of interaction in inhomogeneous point patterns. *Statistica Neerlandica*, 54(3):329–350.

Banks, W. E., Aubry, T., d'Errico, F., Zilhão, J., Lira-Noriega, A., and Peterson, A. T. (2011). Eco-cultural niches of the badegoulian: Unraveling links between cultural adaptation and ecology during the last glacial maximum in france. *Journal of Anthropological Archaeology*, 30(3):359 – 374.

Barlow, K. R. (2002). Predicting maize agriculture among the Fremont: An economic comparison of farming and foraging in the American Southwest. *American Antiquity*, 67:65–88.

Beck, C., Taylor, A. K., Jones, G. T., Fadem, C. M., Cook, C. R., and Millward, S. A. (2002). Rocks are heavy: transport costs and paleoarchaic quarry behavior in the great basin. *Journal of Anthropological Archaeology*, 21(4):481 – 507.

Berman, M. and Turner, T. R. (1992). Approximating point process likelihoods with glim. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 41(1):31–38.

Bettinger, R. L. and Baumhoff, M. A. (1982). The Numic spread: Great Basin cultures in competition. *American Antiquity*, 47:485–503.

Binford, L. R. (1980). Willow smoke and dogs' tails: Hunter-gatherer settlement systems and archaeological site formation. *American Anthropologist*, 45:4–20.

Boserup, E. (1965). *The Conditions of Agricultural Growth: The Economics of Agrarian Change under Population Pressure*. Aldine, Chicago, Illinois.

Charnov, E. L. (1976a). Optimal foraging: attack strategy of a mantid. *The American Naturalist*, 110(971):141–151.

Charnov, E. L. (1976b). Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, 9:129–136.

Codding, B. F. and Bird, D. W. (2015). Behavioral ecology and the future of archaeological science. *Journal of Archaeological Science*, 56:9–20.

Codding, B. F. and Bliege Bird, R. (2012). Should I stay or should I go now? the spatial dynamics of foraging and diminishing returns. *Australian Archaeology*, 74:18–19.

Codding, B. F. and Jones, T. L. (2013). Environmental productivity predicts migration, demographic and linguistic patterns in prehistoric California. *Proceedings of the National Academy of Sciences*, 110:14569–14573.

Coltrain, J. B., Janetski, J. C., and Carlyle, S. W. (2007). The stable- and radio-isotope chemistry of western basketmaker burials: Implications for early puebloan diets and origins. *American Antiquity*, 72(2):301–321.

Coop, L. (2014). US Degree-Day Mapping Calculator. Data retrieved August 2017.

Dudík, M., Phillips, S. J., and Schapire, R. E. (2004). Performance guarantees for regularized maximum entropy density estimation. In Shawe-Taylor, J. and Singer, Y., editors, *Learning Theory*, pages 472–486, Berlin, Heidelberg. Springer Berlin Heidelberg.

d'Errico, F. and Banks, W. E. (2013). Identifying mechanisms behind middle paleolithic and middle stone age cultural trajectories. *Current Anthropology*, 54(S8):S371–S387.

d'Errico, F., Banks, W. E., Warren, D. L., Sgubin, G., van Niekerk, K., Henshilwood, C., Daniau, A.-L., and Goni, M. F. S. (2017). Identifying early modern human ecological niche expansions and associated cultural dynamics in the south african middle stone age. *Proceedings of the National Academy of Sciences*, 114(30):7869–7876.

Elith, J., H. Graham, C., P. Anderson, R., Dudík, M., Ferrier, S., Guisan, A., J. Hijmans, R., Huettmann, F., R. Leathwick, J., Lehmann, A., Li, J., G. Lohmann, L., A. Loiselle, B., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., McC. M. Overton, J., Townsend Peterson, A., J. Phillips, S., Richardson, K., Scachetti-Pereira, R., E. Schapire, R., Soberón, J., Williams, S., S. Wisz, M., and E. Zimmermann, N. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 29(2):129–151.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., and Yates, C. J. (2011). A statistical explanation of maxent for ecologists. *Diversity and Distributions*, 17(1):43–57.

Emlen, J. M. (1966). The role of time and energy in food preference. *The American Naturalist*, 100(916):611–617.

Fithian, W., Elith, J., Hastie, T., and Keith, D. A. (2015). Bias correction in species distribution models: pooling survey and collection data for multiple species. *Methods in Ecology and Evolution*, 6(4):424–438.

Fithian, W. and Hastie, T. (2013). Finite-sample equivalence in statistical models for presence-only data. *Ann. Appl. Stat.*, 7(4):1917–1939.

Fretwell, S. D. and Lucas, H. L. (1969). On territorial behavior and other factors influencing habitat distribution in birds I. theoretical development. *Acta Biotheoretica*, 19:16–36.

Galletti, C. S., Ridder, E., Falconer, S. E., and Fall, P. L. (2013). Maxent modeling of ancient and modern agricultural terraces in the troodos foothills, cyprus. *Applied Geography*, 39:46 – 56.

Geib, P. (1996). Early agricultural period: Transition to farming. In Geib, P., editor, *Glen Canyon Revisited*, volume 119 of *University of Utah Anthropological Papers*, pages 53–77.

Hastie, T. (2013). Generalized additive models. v1.09 http://cran.r-project.org/web/packages/gam.

Hastie, T. and Fithian, W. (2013). Inference from presence-only data; the ongoing controversy. *Ecography*, 36(8):864–867.

Hawkes, K. and O'Connell, J. F. (1992). On optimal foraging models and subsistence transitions. *Current Anthropology*, 33:63–66.

Hijmans, R. J., Phillips, S., Leathwick, J., and Elith, J. (2017). *dismo: Species Distribution Modeling*. R package version 1.1-4.

Jaynes, E. T. (1957). Information theory and statistical mechanics. *Phys. Rev.*, 106:620–630.

Kelly, R. L. (1992). Mobility/sedentism: Concepts, archaeological measures, and effects. *Annual Review of Anthropology*, 21:43–66.

Kennett, D. J. (2005). *The Island Chumash: Behavioral Ecology of a Maritime Society*. University of California Press, Berkeley.

Kennett, D. J., Anderson, A. J., and Winterhalder, B. (2006). The ideal free distribution, food production, and the colonization of oceania. In Kennett, D. J. and Winterhalder, B., editors, *Human Behavioral Ecology and the Origins of Agriculture*, pages 265–288. University of California Press, Berkeley.

Kondo, Y. (2015). An ecological niche modelling of upper palaeolithic stone tool groups in the kanto-koshinetsu region, eastern japan. *The Quaternary Research (Daiyonki-Kenkyu)*, 54(5):207–218.

Kvamme, K. L. (2005). There and back again: Revisiting archaeological locational modeling. In *GIS and archaeological site location modeling*, pages 23–55. CRC Press.

MacArthur, R. H. and Levins, R. (1967). The limiting similarity, convergence, and divergence of coexisting species. *The American Naturalist*, 101(921):377–385.

MacArthur, R. H. and Pianka, E. R. (1966). On optimal use of a patchy environment. *The American Naturalist*, 100:603–609.

Magargal, K. E., Parker, A. K., Vernon, K. B., Rath, W., and Codding, B. F. (2017). The ecology of population dispersal: Modeling alternative basin-plateau foraging strategies to explain the numic expansion. *American Journal of Human Biology*, 29(4):e23000–n/a. e23000.

McCool, W. C. and Yaworsky, P. M. (2019). Fight or flight: An assessment of fremont territoriality in nine mile canyon, utah. *Quaternary International*, 518:111 – 121. SI: Territorial Behavior and Ecology.

McFadden, D. A. (2016). *Formative Chronology and Site Distribution on the Grand Staircase-Escalante National Monument*, volume 28 of *The Utah Bureau of Land Management Cultural Resource Series*.

McMichael, C. H., Palace, M. W., Bush, M. B., Braswell, B., Hagen, S., Neves, E. G., Silman, M. R., Tamanaha, E. K., and Czarnecki, C. (2014a). Predicting pre-columbian anthropogenic soils in amazonia. *Proceedings of the Royal Society B: Biological Sciences*, 281(1777):20132475.

McMichael, C. H., Palace, M. W., and Golightly, M. (2014b). Bamboo-dominated forests and pre-columbian earthwork formations in south-western amazonia. *Journal of Biogeography*, 41(9):1733–1745.

McMichael, C. N. H., Matthews-Bird, F., Farfan-Rios, W., and Feeley, K. J. (2017). Ancient human disturbances may be skewing our understanding of amazonian forests. *Proceedings of the National Academy of Sciences*, 114(3):522–527.

Merow, C., Smith, M. J., and Silander Jr, J. A. (2013). A practical guide to maxent for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography*, 36(10):1058–1069.

Morgan, C. (2015). Is it intensification yet? current archaeological perspectives on the evolution of hunter-gatherer economies. *Journal of Archaeological Research*, 23(2):163–213.

Moritz, M., Scholte, P., Hamilton, I. M., and Kari, S. (2013). Open access, open systems: Pastoral management of common-pool resources in the chad basin. *Human Ecology*, 41:351–365.

Numerical Terradynamic Simulation Group (2013). MODIS Global Evapotranspiration Project (MOD16). Accessed August 2017.

Parker, A. K., Parker, C. H., and Codding, B. F. (2018). When to defend? optimal territoriality across the numic homeland. *Quaternary International*.

Parker, G. and Sutherland, W. (1986). Ideal free distributions when individuals differ in competitive ability: phenotype-limited ideal free models. *Animal Behaviour*, 34(4):1222 – 1242.

Parker, G. A. (1978). Searching for mates. In *Behavioural Ecology*, volume 1, pages 214–244. Oxford, UK: Blackwell Scientific.

Phillips, S. (2017). A brief tutorial on maxent. Available from url: http://biodiversityinformatics.amnh.org/open_source/maxent/. Accessed on 2019-6-13.

Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E., and Blair, M. E. (2017). Opening the black box: an open-source release of maxent. *Ecography*, 40(7):887–893.

Phillips, S. J., Anderson, R. P., and Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, 190(3):231 – 259.

Phillips, S. J. and Dudík, M. (2008). Modeling of species distributions with maxent: New extensions and a comprehensive evaluation. *Ecography*, 31(2):161–175.

Phillips, S. J., Dudík, M., and Schapire, R. E. (2004). A maximum entropy approach to species distribution modeling. In *Proceedings of the Twenty-first International Conference on Machine Learning*, ICML '04, pages 83–, New York, NY, USA. ACM.

Phillips, S. J. and Elith, J. (2013). On estimating probability of presence from use–availability or presence–background data. *Ecology*, 94(6):1409–1419.

PRISM Climate Group (2019). Parameter-elevation Regressions on Independent Slopes Model (PRISM). Data retrieved August 2019.

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Renner, I. W., Elith, J., Baddeley, A., Fithian, W., Hastie, T., Phillips, S. J., Popovic, G., and Warton, D. I. (2015). Point process models for presence-only analysis. *Methods in Ecology and Evolution*, 6(4):366–379.

Renner, I. W. and Warton, D. I. (2013). Equivalence of maxent and poisson point process models for species distribution modeling in ecology. *Biometrics*, 69(1):274–281.

Ripley, B. D. (1977). Modeling spatial patterns. *Journal of the Royal Statistical Society, Series B.*, 39:172–212.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, 27(3):379–423.

Simms, S. R. (2008). *Ancient Peoples of the Great Basin and the Colorado Plateau.* Left Coast Press.

Spangler, J. D., Yaworsky, P. M., Vernon, K. B., and Codding, B. F. (2019). *Hisatsinom of the High Plateaus: A Class I Overview of Prehistoric Cultural Resources in Grand Staircase-Escalante National Monument.* Bureau of Land Management.

Sutherland, W. J. (1996). *From Individual Behaviour to Population Ecology.* Oxford University Press, New York, NY.

Tobler, W. R. (1993). Three presentations on geographical analysis and modeling: Non-isotropic geographic modeling, speculations on the geometry of geography and, global spatial analysis. Technical Report 93 (1), National Center for Geographic Information and Analysis.

U.S. Geological Survey (2019). The national map, 3dep products and services: The national map, 3d elevation program web page. accessed 2019.

Wachtel, I., Zidon, R., Garti, S., and Shelach-Lavi, G. (2018). Predictive modeling for archaeological site locations: Comparing logistic regression and maximal entropy in north Israel and north-east China. *Journal of Archaeological Science*, 92:28 – 36.

Warton, D. I., Renner, I. W., and Ramp, D. (2013). Model-based control of observer bias for the analysis of presence-only data in ecology. *PLOS ONE*, 8(11):1–9.

Warton, D. I. and Shepherd, L. C. (2010). Poisson point process models solve the "pseudo-absence problem" for presence-only data in ecology. *Ann. Appl. Stat.*, 4(3):1383–1402.

Wilson, P. D. (2011). Distance-based methods for the analysis of maps produced by species distribution models. *Methods in Ecology and Evolution*, 2(6):623–633.

Winterhalder, B., Kennett, D. J., Grote, M. N., and Bartruff, J. (2010). Ideal free settlement of California's Northern Channel Islands. *Journal of Anthropological Archaeology*, 29:469–490.

Yaworsky, P. M. and Codding, B. F. (2017). The ideal distribution of farmers: Explaining the euro-american settlement of utah. *American Antiquity*, page 1–16.

Yaworsky, P. M., Vernon, K. B., Spangler, J. D., Brewer, S. C., and Codding, B. F. (in review). Advancing predictive modeling in archaeology: An evaluation of regression and machine learning methods on the grand staircase-escalante national monument. *PLOS ONE.*

Author Biographies

Kenneth Blake Vernon is pursuing a PhD in Anthropology at the University of Utah and is the assistant director of the University of Utah Archaeological Center. His research explores variation in human behavior within the framework of behavioral ecology. Currently, he is using geographic and spatial modeling techniques to investigate the nexus of climate, conflict, and human migration in the prehistory of the American Southwest. In addition, he is working to advance data management and data science in archaeology. \

Peter M. Yaworsky is a Ph.D. candidate in Anthropology at the University of Utah. His research uses insights from behavioral ecology to explore the variation in both past and present human behavior. Peter is particularly interested in decisions people make regarding land use on regional scales. His current research focuses on the distribution of archaeological sites in the Grand Staircase-Escalante National Monument, Utah and the site placement of early agriculturalists in Nine Mile Canyon, Utah as a function of risk mitigation. \

Jerry Spangler is the Director of the Colorado Plateau Archaeological Alliance. He specializes in the prehistoric archaeology of the Colorado Plateau and has extensive experience synthesizing records across the region. His current research includes the compilation of a comprehensive radiocarbon database for the Basin-Plateau region. \

Simon Brewer is Assistant Professor of Geography at the University of Utah. He specializes in understanding past and present climate and vegetation change through the application of paleoecological methods and environmental modeling. Current research explores the functional diversity of past ecosystems relative to climate and fire regimes. \

Brian F. Codding is Associate Professor of Anthropology and Director of the Archaeological Center at the University of Utah. His research examines human-environment interactions in the past and present through the lens of behavioral ecology. Current research is focused on explaining the dynamics structuring subsistence and land use decisions, and the feedbacks these decisions have on social and ecological systems and across western North America.