Aiming for the Optimum: Examining Complex Relationships Between Sampling Regime, Sampling Density and Landscape Complexity to Accurately Model Resource Availability

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Research Article

Keywords: optimal sampling, landscape interpolation, heterogeneity, kriging, inverse distance weighting, nearest neighbor

Posted Date: November 3rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-1005366/v1

Abstract

Context

Obtaining accurate maps of landscape features often requires intensive spatial sampling and interpolation. The data required to generate reliable interpolated maps varies with spatial scale and landscape heterogeneity. However, there has been no rigorous examination of sampling density relative to landscape characteristics and interpolation methods.

Objectives

Our objective was to characterize the 3-way relationship among sampling density, interpolation method, and landscape heterogeneity on interpolation accuracy in simulated and *in situ* landscapes.

Methods

We simulated landscapes of variable heterogeneity and sampled at increasing densities using both systematic and random strategies. We applied each of three local interpolation methods: Inverse Distance Weighting, Universal Kriging, and Nearest Neighbor — to the sampled data and estimated accuracy (R^2) between interpolated surfaces and the original surface. Finally, we applied these analyses to *in situ* data, using a normalized difference vegetation index raster collected from pasture with various resolutions.

Results

All interpolation methods and sampling strategies resulted in similar accuracy; however, low heterogeneity yielded the highest R^2 values at high sampling densities. *In situ* results showed that Universal Kriging performed best with systematic sampling, and inverse distance weighting with random sampling. Heterogeneity decreased with resolution, which increased accuracy of all interpolation methods. Landscape heterogeneity had the greatest effect on accuracy.

Conclusions

Heterogeneity of the original landscape is the most significant factor in determining the accuracy of interpolated maps. There is a need to create structured tools to aid in determining sampling design most appropriate for interpolation methods across landscapes of various heterogeneity.

Introduction

Measurement of ecological processes at a landscape level requires a thorough understanding of spatial relationships of the target resource across landscape gradients. Originally focused within landscape ecology or biogeography (Turner and Gardner, 2015), measuring landscape heterogeneity has emerged as an important research front in movement ecology, agroecology, disturbance ecology, precision agriculture,

and other landscape-level sciences focused on ecological processes and the spatial configuration of resources (Carlile et al. 1989). For example, spatial configuration of forage mass and quality influence landscape utilization and grazing pressure by cattle (*Bos taurus*) or bison (*Bison bison*) (Kohl et al. 2013) and browse selection by moose (*Alces alces*; Balluffi-Fry et al. 2020; Leroux et al. 2017). Further, spatial sampling is commonly used in agricultural fields to identify areas which may need alternative management strategies, such as increased nutrient inputs (Franzen 1995), or designated wildlife habitat and conservation areas (Burger, 2019), which can result in economic and environmental improvements (Sun and Brus 2021). As such, a common objective of landscape-level studies is the creation of data layers or maps that accurately portray the distribution of resources, such as forage biomass and nutrient density, species distribution, habitat, and soil quality or landscape condition (Turner and Gardner 2015).

Given that complete measurement of resources across the landscape is virtually impossible, the full landscape of resource availability is often approximated by sampling predetermined locations and performing spatial interpolation to estimate resource values at unobserved locations (Li and Heap 2008). Accuracy and precision of estimated resource values generally depend upon: (1) the sampling strategy employed (Cobby et al. 1985); (2) number of samples collected (Tsutsumi et al. 2007); (3) the degree of variability among samples across the landscape (Sun and Brus 2021); (4) the interpolation method used (Li and Heap 2008); and (5) the spatial scale under investigation (Turner and Gardner 2015; Wu 2004). These effects have been individually examined, often in great detail. For example, ecologists have utilized systematic, random, stratified random, and cyclic sampling strategies in hopes of identifying some optimum strategy which efficiently and accurately describes a landscape variable (Burrows et al. 2002; Turner and Gardner 2015). Additionally, the minimum number of samples required to accurately model the landscape must be considered given that sample collection is often labor and cost intensive (Burrows et al. 2002; Tsutsumi et al. 2007; Turner and Gardner 2015). Spatial heterogeneity is driven by underlying biotic and abiotic processes and their interactions. For example, the heterogeneity of available forage can be driven by interactions between grazing patterns of herbivorous animals, soil type, moisture and infiltration, slope gradient, plant species distribution, and soil microbe populations (Barthram et al. 2005; Hirata et al. 2012). Interpolation methods provide a means of creating a continuous surface from point processes; however, selection of the best method for a specific process and sample strategy is difficult (Li and Heap 2008). Finally, defining the appropriate spatial scale matched with the correct sampling strategy and sample number is required to accurately and precisely model landscape resources (Fryxell et al. 2008; Sun and Brus 2021; Turner and Gardner 2015; Wiens 1989).

Clearly there has been substantial attention to each of these components regarding spatial sampling; however, there is not yet a comprehensive demonstration of how these factors interact to increase the accuracy of common interpolation strategies. In keeping with recent calls for critical utilization of currently existing metrics of landscape structure and scale (Turner and Gardner 2015), herein we use well-defined metrics with clear application to commonly studied landscapes to examine the relationship among sampling strategy, sampling density, and landscape heterogeneity and, subsequently, place them in the context of scale (Wu 2004). Particularly, we focus on systematic and random sampling strategies because these are commonly used techniques for landscape sampling in agriculture and forestry (e.g.,

Jordan et al. 2003; Sun and Brus 2021; Burrows et al. 2002; Clark et al. 2008). We generate multiple simulated landscapes representing a gradient of landscape heterogeneity and perform interpolation using 3 common geostatistical techniques (i.e., Nearest Neighbor, Universal Kriging, Inverse Distance Weighting) to estimate continuous surfaces from derived samples (Li and Heap 2008). We then explicitly consider how landscape heterogeneity interacts with sample size and the interpolation method itself to determine the goodness-of-fit (R^2) between predicted and observed surfaces, and we expected that R^2 would increase with increased sampling density and lower heterogeneity (Figure 1a). Finally, we repeat these procedures using *in situ* data to validate our findings from simulation with empirical data, and to evaluate interpolation accuracy as spatial resolution decreases.

Methods

Simulated landscapes

We simulated a series of landscapes (n = 330) according to methods outlined in the appendices of Matthiopoulos et al. (2015), with landscape dimensions and average resource availability held at 600 x 600 pixels and 50, respectively. Simulated landscapes featured a range of 1 to 100 nodes of focal points for resource aggregation, which was smoothed across the landscape gradient by a defined bandwidth between 1 and 1000. For a full description of the simulation code, see Matthiopoulos et al. (2015).

We calculated three measures of landscape heterogeneity for each simulated landscape: (1) Rho (i.e., ρ ;Tsutsumi et al. 2007), (2) variation (Turner and Gardner 2015), and (3) the range from a variogram (Burrows et al. 2002; Sun and Brus 2021). Each of these is a measure of spatial autocorrelation, with higher values indicating greater landscape similarity. ρ was calculated as the squared mean divided by the squared standard deviation of the landscape resource (μ^2/σ^2; Tsutsumi et al. 2007). Variation was calculated using the *sd* function in R (R Core Team 2021). Variograms were created for each simulated landscape using the *autofitvariogram* function within the automap R package (Hiemstra 2013), which set initial values for range by multiplying 0.1 times the diagonal spatial bounding box, and nugget as the minimum value of the semi-variance of the data. The model with the lowest residual sum of squares was selected from a pool of models consisting of spherical, exponential, or gaussian models available within the gstat R package (Gräler et al. 2016). Range values were then extracted from the selected variograms.

We created sampling densities from 10 to 100 locations in 1-sample increments (range = 10 to100 samples, i.e., 0.028 to 0.28 samples/10,000 pixels). Point locations were created using the *spsample* function from R package sp (Hijmans et al. 2021). Systematic sampling points were set a specified distance apart at the intersection of evenly spaced gridlines laid across the landscape. For both systematic and random sampling strategies, and for each simulated landscape × sample number combination, we extracted resource values from simulated landscapes at each sampling location and used extracted values to estimate a raster surface using (1) Universal Kriging, using the *autokrige* function within the automap R package (Gräler et al. 2016; Hiemstra 2013); (2) Inverse Distance Weighting, which was conducted using the *idw* function also available within the gstat R package (Gräler

et al. 2016); and (3) Nearest Neighbor interpolation which was created using Thiessen polygons and identifying the closest observed point from which to interpolate (Brunson 2019) using the *whichmin* function (R Core Team 2021). In total, 27,000 landscapes were created using interpolation and compared to their appropriately paired simulated landscape, providing a robust dataset from which to make comparisons among sampling strategy, sample density, and landscape heterogeneity given the interpolation method. For all landscapes, fit between simulated landscapes and predicted layers were evaluated using R^2 from a simple linear regression between the interpolated and true surface for each interpolation method, sample density, and sampling strategy.

To better understand the relationship among the three measures of landscape heterogeneity and sampling density and accuracy, we ran a series of beta regression models using the betareg R package (Cribari-Neto and Zeileis 2010). We regressed the calculated R^2-value obtained from the interpolated vs. true surface regressions against the sample density and one of each of the 3 metrics of landscape heterogeneity (i.e., ρ, the Pearson correlation coefficient, and range from variograms of the simulated landscapes). We selected the best model from each of the 3 competing models within a given interpolation-method-by-sampling-regime combination using AIC values (Table S1). Additionally, given the large variation in raw values (Figure S1), we used the identified relationship, which included a term for sample number and the selected landscape heterogeneity (Table S1), to create 3-dimensional plot using *wireframe* within the lattice R package (Sarkar 2008) and extracted predicted values using the *emmeans* function in the emmeans R package (Lenth et al. 2018) for each value of landscape heterogeneity and number of samples ranging from 1 to 100.

Application to in situ data from pastoral landscape

Following our simulation exercise, we applied the same approach to remotely sensed data collected from an experimental grazing facility in Starkville, Mississippi, USA (33 26’07N 88 48’03W; Figure 1b) in June 2019. The pasture was ~9.35 ha and consisted primarily of a mixture of tall fescue (*Festuca arundinacea*), bermudagrass (*Cynodont dactylon*), and annual ryegrass (*Lolium multiflorum*), which was inter-seeded across one-half of the pasture in fall 2018. Remotely sensed imagery was collected using a Red Edge MX hyperspectral camera (MicaSense®, Seattle, WA, USA) mounted on a Matrice 100 unmanned aerial system (DJI, Shenzhen, Guangdong, China). The camera collected reflectance in the green, blue, red, near-infrared, and red-edge spectral bands at 8.5 cm resolution from a flight altitude of 122 m above ground level with 80% overlap. After imagery was collected, individual pictures were mosaiced utilizing Pix 4D software (Pix 4D Inc. Prilly, Switzerland) and we calculated the normalized difference vegetation index (NDVI) at each pixel following standard procedure Huete et al. (2002).

Finally, we conducted an identical analysis as used in the simulated landscapes, increasing resolution from 0.085 to 100 m at 1-meter increments using R^2 to observe the consequences of decreasing the measured heterogeneity on the landscape (Wu 2004). At each resolution, resampling was conducted at increasing rates of sample density, ranging from 1 to 185 samples per hectare (equating to 0.003 to 0.49 samples/10,000 pixels at a 0.085-m to 100-m resolution), and collected using systematic and random

sampling designs. Interpolation techniques identical to those used in simulated landscapes were applied to each combination of landscape resolution, sampling strategy, and sample density, and compared to the original landscape to measure interpolation accuracy. All simulations and applications of simulation methods to real data were performed in R version 3.6.3 (R Core Team 2021).

Results

Simulated landscapes

Beta regressions of goodness-of-fit (R^2) between interpolated and true surfaces against sample density and one of each of 3 competing metrics of landscape heterogeneity (ρ, standard deviation, and the variogram range)., indicated that ρ consistently returned higher values for R^2 compared with other metrics of landscape heterogeneity in all comparisons (Table S1). As such, we report only findings for ρ. For simulated landscapes, measures of heterogeneity ranged from 0 (most heterogeneous) to 1600 (least heterogenous; Figure 2). Simulated landscapes indicated all interpolation methods, except for random sampling under Universal Kriging, performed similarly given the distributions in R^2 values across sampling densities and landscape heterogeneity (R^2 = 0–0.98; Figure 3). We found the highest R^2 occurred at low levels of heterogeneity, as values beyond 10 resulted in a 1:1 relationship (Figure 3). For Universal Kriging, gridded samples consistently achieved higher R^2 values compared to randomly collected samples at all sampling densities and heterogeneities; at sampling densities below 15 samples per landscape, Universal Kriging failed to interpolate successfully (Figure 3). Additionally, Universal Kriging yielded a convex relationship with accuracy under random sampling compared to all other interpolation by sampling strategy combinations, staying low before increasing as sample number increased (Figure 3).

Application to in situ pastoral landscape

The pasture featured moderate levels of heterogeneity (ρ = 34 – 110) compared to simulated landscapes. Decreased landscape heterogeneity (accomplished by decreasing resolution of the original raster; Supplementary Figure 1) and increasing sample density were associated with more accurate interpolation outcomes for all interpolation techniques (Figure 4). Gridded sampling resulted in the highest accuracy values for Universal Kriging, and this performance was matched in random sampling for Nearest Neighbor and Inverse Distance Weighting (Figure 4). Decreasing landscape heterogeneity increased the accuracy of both Inverse Distance Weighting and Nearest Neighbor interpolation (Figure 4).

Discussion

Our objective was to evaluate the ability of different interpolation strategies to produce accurate representations of a known landscape under variable landscape heterogeneity, sampling regime, sample density, and spatial scale. Our simulations showed that, while there was limited influence of the interpolation method on sampling strategy (except in one case: random sampling for Universal Kriging),

there was a consistent effect of increased sampling density on goodness-of-fit, as would be expected (Tsutsumi et al. 2007). However, the effect of sampling density was overshadowed by the effect of landscape heterogeneity, which increased accuracy considerably as the landscape became less heterogeneous. Trends in sampling density and heterogeneity indicate there are threshold levels of sampling given the heterogeneity encountered (Figure 3). Additionally, we found similar results for field estimates of NDVI, showing increased accuracy as sampling density was increased (Figure 4). When we manipulated heterogeneity in the NDVI layer by decreasing resolution, we found that decreased heterogeneity caused an increase in accuracy of all interpolation methods.

We demonstrated that there was limited influence of sampling strategy on accuracy estimates across sampling densities and heterogeneities in our simulations (Figure 3). This is surprising given it has been shown in other landscape simulations that random sampling is superior for estimating forage biomass on the landscape (Tsutsumi et al. 2007) and more accurately captures the necessary lag distance within a pine wood stands (Burrows et al. 2002). However, other authors used stratified random sampling which weights spatial sampling to areas of particular interest. Our results confirm the increased consistency and accuracy of gridded sampling when paired with Universal Kriging, which agrees with Burrows et al. (2002) and our simulation results suggest a systematic approach to landscape sampling better captures landscape structure than does a random sampling strategy.

In addition to the limited influence of sampling type on accuracy, we also showed consistent results across interpolation techniques in our simulations, except in the case of Universal Kriging under random sampling (Figure 3). This is again inconsistent with other studies; it has been shown that Inverse Distance Weighting and Universal Kriging can have a greater ability to capture landscape heterogeneity, particularly at lower sampling densities within more heterogenous landscapes, compared to other interpolation methods such as Nearest Neighbor (Coelho et al. 2008). Our use of random sampling with no prior attention given to matching sampling point distance to an expected variogram, inhibited Universal Kriging as we failed to capture the appropriate lag distance. Under these conditions, we would recommend a systematic sampling strategy using Universal Kriging if the sample point distance captured the appropriate lag as demonstrated by the variogram.

Our simulations show that, while there was a positive linear relationship between accuracy and sample density, this effect was relatively small compared to the increases in accuracy when landscape complexity diminished (Figure 3). While it is known that sampling density can increase accuracy (Jordan et al. 2003; Tsutsumi et al. 2000), this relationship is often described as asymptotic, which assumes that ever increasing numbers of samples will continue to push accuracy ever closer to 1:1 match at some diminishing rate. In our case, sampling never achieved an asymptote, which is most likely due to the low sampling densities explored within our simulations given the size of the simulated landscape. However, it is notable that even if our simulated data approached an asymptote, the increased level of accuracy (up to 20%) was inconsequential compared to the effect of landscape complexity (Figure 3). Indeed, a moderate sampling strategy is typically sufficient to accurately measure landscape mean and accuracy in creating interpolated maps of forage quality (Jordan et al. 2003), and simulation exercises within

grasslands of varying levels of heterogeneity demonstrated a similar phenomenon (Tsutsumi et al. 2007). Like sample density, we observed a positive quadratic relationship between accuracy and landscape heterogeneity for most sampling strategies and interpolation methods. This is in line with our predictions, given that as the landscapes became more heterogenous, the distance over which self-similarity occurs increases; therefore, decreasing the total variability within the landscape while increasing the number of samples required to detect small or spatially isolated differences. These relationships were further emphasized when we applied the same techniques to real world data where we observed a decrease in the rate of return as heterogeneity diminished (Figure 4). While adequately measuring heterogeneity can be a complex endeavor in both cases, it is worthy of increased attention given its influence on accuracy.

We further demonstrated the relationship between data resolution and landscape heterogeneity. As the resolution decreased, the measured heterogeneity of the NDVI landscape also decreased, which indicates a loss of information (Supplementary Figure 1). Indeed, decreased resolution caused dominant values on the landscape to become more dominant with continued aggregation (Turneret al. 1989), effectively causing a reduction in the total observed plant productivity. This effect is driven by how dispersed the variation is across the landscape (Turner et al. 1989). Clearly, changing the resolution has dramatic impacts on the information available at that scale (Turner et al. 1989), and should be carefully considered with respect to meeting the needs and objectives of the analysis (Reynolds et al. 2016).

Our results indicate that it is critically important to carefully consider landscape heterogeneity and understand how heterogeneity is influenced by landscape-level processes in order to construct a useful sampling design. While we showed that capturing landscape-level heterogeneity can occur irrespective of most sampling regimes and interpolation methods, exploring how sampling density and heterogeneity perform under other sampling regimes may be useful. For example, cyclic sampling may provide yet another way to reduce sampling effort by applying prior knowledge of the landscape autocorrelation structure to the sampling design (Burrows et al., 2002; Turner and Gardner, 2015). Further, it is also expected that relationships between sampling density and heterogeneity may change with different metrics. This was demonstrated in the wide variation of samples required to predict within crop variation in nitrogen, phosphorous, potassium, and sulfur (Jordan et al. 2003). Thus, spatial sampling should be structured to capture the most heterogenous variable of interest to ensure adequate sampling of all variables given their heterogeneity within the landscape. Finally, while we look at the spatial relationships among sampling density, landscape heterogeneity, and accuracy, it is likely that these relationships also change temporally. Indeed, we examined these relationships at the height of the growing season, a time when factors affecting landscape heterogeneity, such as resource restriction and grazing pressure, are likely less influential (Cid and Brizuela 1998). We would expect sampling requirements to vary based on plant phenology and abiotic factors such as rainfall. For example, the sample number required to precisely measure silage production and plant nutrient values varies between cuttings over the summer and by metric of nutrient density (Jordan et al. 2003). As a result, more work on temporal changes in resource distribution is needed to accurately predict the level of heterogeneity to be expected within a given landscape; such an investigation is likely critical to target areas of rapid change.

Conclusion

Landscape ecology requires mapping resource distribution across the landscape. Thus, a thorough understanding of spatial relationships allows for selection of the appropriate sampling structure and interpolation method to arrive at accurate and meaningful results (Reynolds et al. 2016), though landscape heterogeneity may be an underlying driver of mapping accuracy. The current body of knowledge offers less than desired guidance for selection between methods. This and future work should lay foundations for a structured decision-making process which will allow researchers and managers to clearly identify sampling strategies and interpolation prediction methods to meet their specific objectives in a resource efficient manner.

Declarations

The authors declare no conflict or competing interests.

This work is supported by Thinking Like a Mountain to Improve Animal Production Systems Ecology, Energy Budgets, and Mechanistic Models, grant no. 2018-67016-27481/project accession no.1014926] from the USDA National Institute of Food and Agriculture, Mississippi Agriculture and Forestry Experiment Station (MAFES), and Noble Research Institute, Inc.

Acknowledgements

We thank Jane Dentinger and members of the QuEST lab for valuable feedback and discussion. We also thank the farm crew of the H.H. Leveck Animal Research Center for their professional support.

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Figures

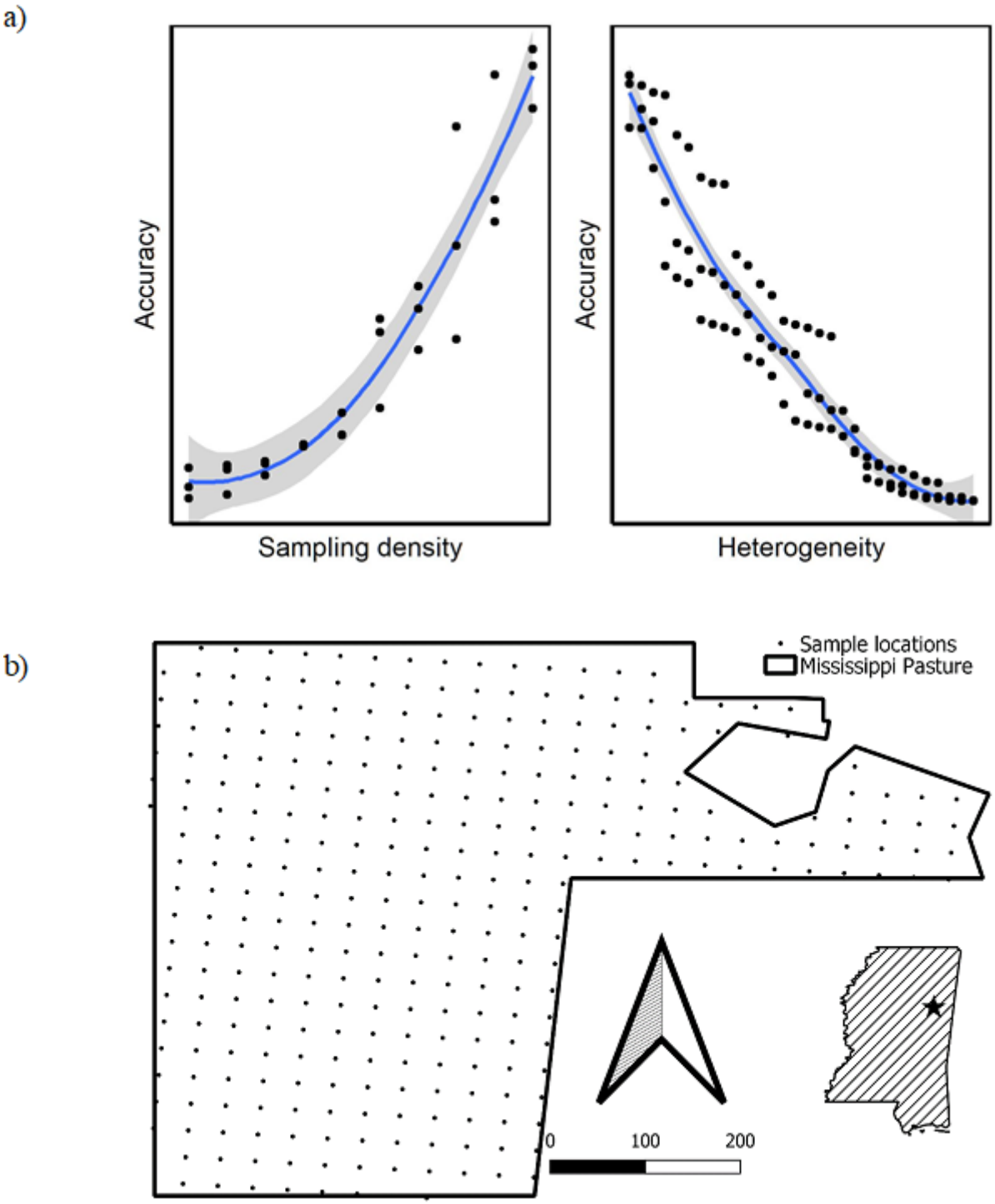

Figure 1

a) Conceptual representation of the expected accuracy (R2) due to (left) sampling density and (right) an increase in landscape heterogeneity. b) The 307 forage sampling locations (equating to a sampling density of 32 samples/ha) used to collect forage samples during an 11-month grazing study in 2019 in a pasture in Starkville Mississippi, USA (inset).

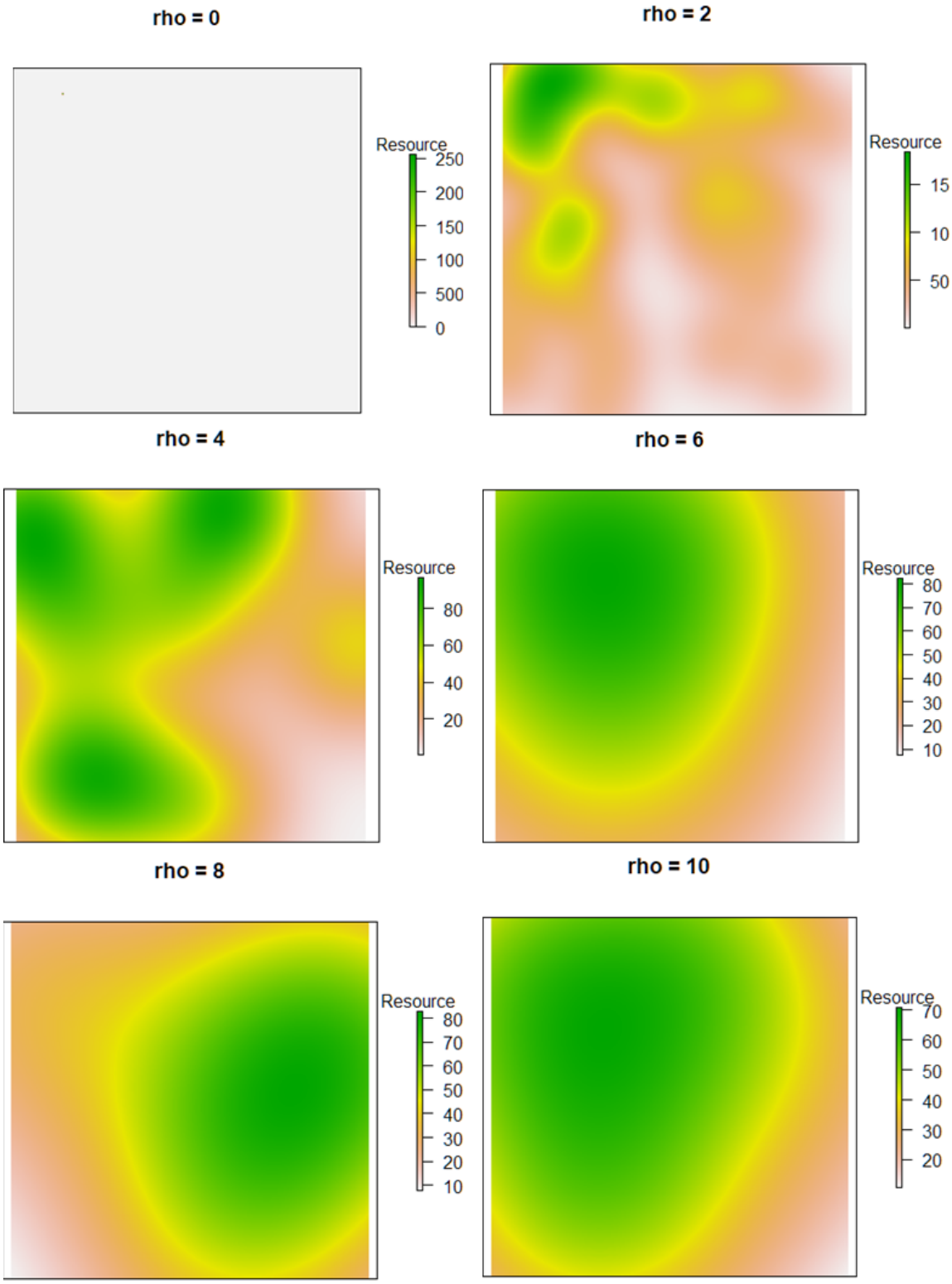

Figure 2

Examples of simulated landscapes, each containing the same volume of resources, but with varying gradients and number of focal aggregation points resulting in heterogeneities ranging from 0 (most heterogeneous) to 10 (least heterogeneous).

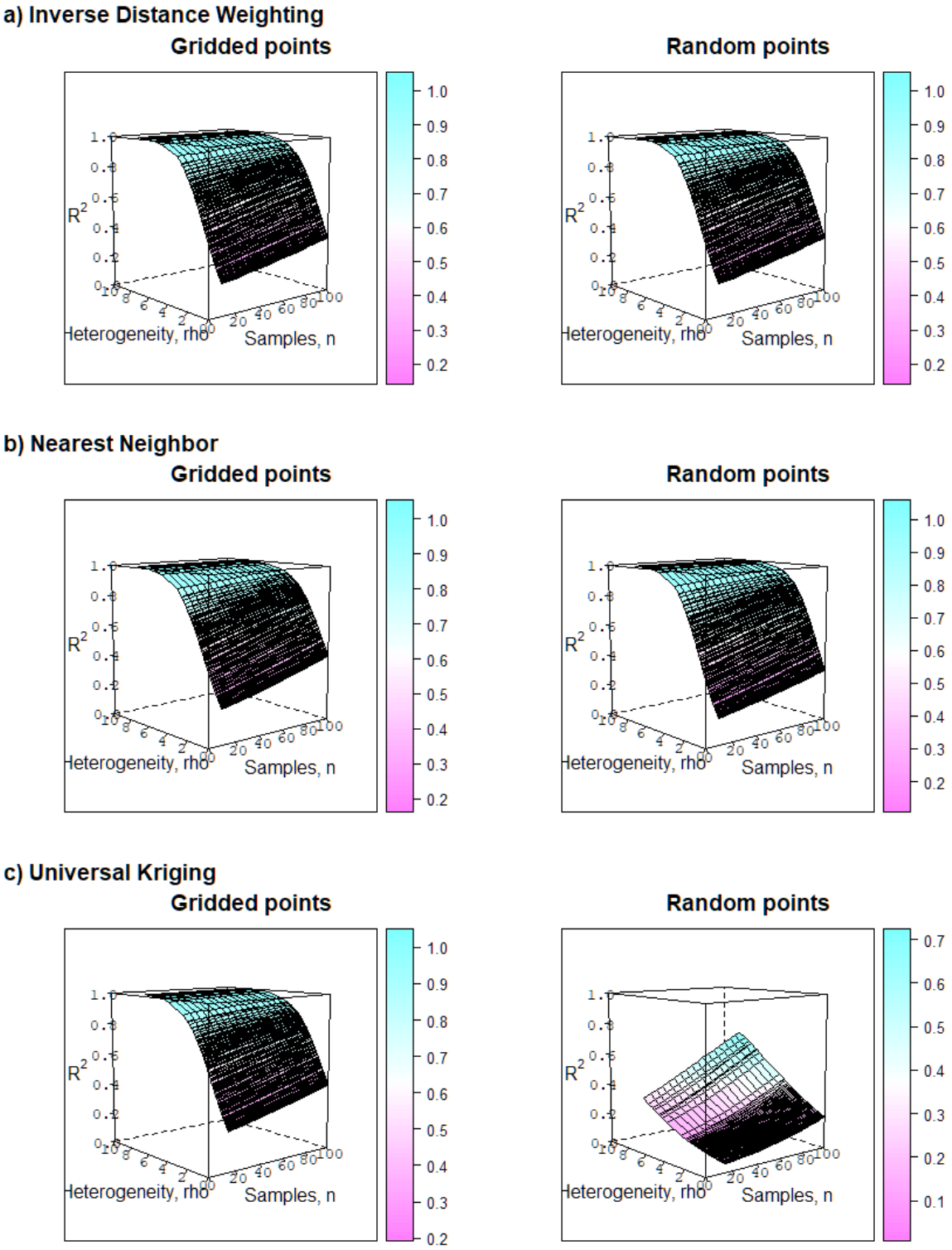

Figure 3

Accuracy (R2) of a) Inverse Distance Weighting, b) Nearest Neighbor, and c) Universal Kriging interpolation at increasing sample densities and landscape heterogeneities (with 0 being more heterogeneous) using a systematic or random sampling strategy. Raw values are provided in Supplementary Figure 2 and Supplementary Tables 2-7.

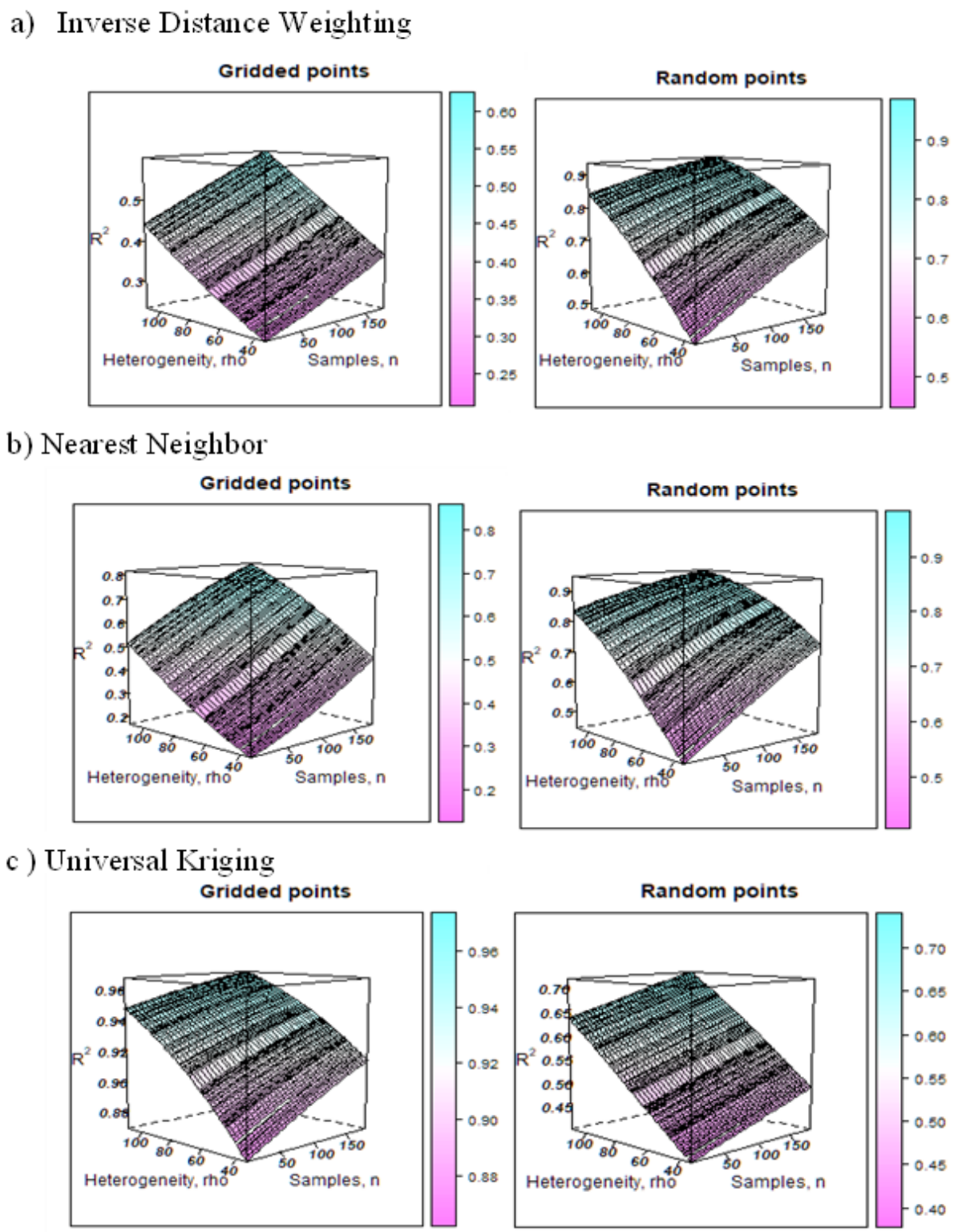

Figure 4

Accuracy (R2) of a) Inverse Distance Weighting, b) Nearest Neighbor, and c) Universal Kriging interpolation NDVI values at increasing sample densities and decreasing landscape resolution to reduce heterogeneity (with 0 being more heterogeneous) using a systematic or random sampling strategy.

Supplementary Files

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