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It must be right, GIS told me so! Questioning the infallibility of GIS as a methodological tool

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ABSTRACT

While the benefits of GIS are widely touted among archaeologists today, less attention has been paid to the potential pitfalls and drawbacks of this undeniably important methodological tool. One of the greatest challenges of geospatial modeling is unbalanced data: due to the nature of the archaeological record, we can never assume that the remnants of past behavioral processes we are working with constitute a fully representative sample. Rather, our datasets are reflective of differential social and natural preservation conditions, as well as research biases. Most regional geospatial studies must collate diverse data collected over decades by researchers with varying backgrounds and goals, using assorted spatial scales and levels of technological sophistication. Such factors contribute substantial uncertainty to our models, uncertainty that should be recognized, quantified, and mitigated. If GIS techniques are to continue shifting the way we conduct archaeology and improve our abilities to answer questions regarding past behavior, then we must question the infallibility of GIS as a methodological tool and direct more attention toward developing robust geospatial applications that can meet the idiosyncratic needs of archaeological analysis. This paper explores one example of how such uncertainty investigation can be conducted.

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1. Introduction

The advantages of Geographic Information Systems (GIS) to explore socionatural processes in the past are widely accepted by archaeologists today (with some notable exceptions, of course, both in the compliance world as well as the post-positivist, phenomenological camp); indeed, many now consider GIS a critical tool in the proverbial analytical tool kit. However, less attention has been accorded to the potential methodological pitfalls and drawbacks of this undeniably important suite of spatial-analytical tools. This scenario is to some degree related to the use of GIS by casual or novice users, who wish to employ GIS representationally to display geo-referenced data or perhaps search informally for patterns between, e.g., site distributions and ecological characteristics.

The research goals of novice users versus academic users who employ GIS with a deep understanding of the theoretical and methodological underpinnings of the tool are understandably different; indeed, one of the beauties of the software is its ability to cater to both types of operations. However, the easy-access, point-and-click functionality of most GIS software packages should not mask the fact that for powerful GIS results to be obtained, especially about past human-landscape interactions, the user must have not only a solid grasp of the underlying theoretical concepts regarding geospatial analysis and socionatural processes, but also some knowledge of the methodological functionality of the various analytic tools provided by the software package and the impact of uncertainty and bias in the overall process. In general, any use of GIS should be wary of conflating geospatial results with fact in the positivist sense, nor should these results be considered infallible and taken for granted, with self-evident benefits (Hacıgüzeller, 2012: 246). Non-critical or atheoretical uses of the technology can lead to unsatisfactory, misinformed, inaccurate or (worst of all) incorrect outputs. For GIS to become a paradigm shifter in the field of archaeology, I believe that a skeptical and theory-laden approach to GIS usage by academic users should be employed at all stages of inquiry and, as much as is possible, such high-end applications should be adopted in other segments of archaeological investigation. Below, the limitations of GIS use in archaeology are described with the aim of demonstrating that many of the methodological shortcomings of GIS can be known, quantified, and assuaged with proper user training, education, and engagement with the ongoing

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theoretical critique. Then avenues by which GIS could move beyond the classification of 'tool' are discussed.

2. Background: assessing GIS as a tool

While GIS use has become ubiquitous in most sectors of archaeology, the character of its employ varies drastically in extent, sophistication, and theoretical underpinnings. Regardless, a great many archaeologists in the US use GIS in a strictly representational manner, to display geo-referenced data with the overall positivist goal of gaining insight into past human spatial behavior and how the material proxies of these behaviors have been impacted over time through taphonomic processes. In this sense, GIS are used as an investigatory tool that help strengthen links between archaeological theories of human behavior and the observed world (i.e., the present-day archaeological record), allowing users to formulate models, or representations, of potential past experiences, attitudes, behaviors, processes, and patterns. Practitioners view these representations as heuristically useful *simulacra*, or close (although highly simplified) approximations of *portions* of past realities, regardless of the fact that ultimately, we can never fully understand what transpired in the past.

In archaeological applications of GIS, various types and nested levels of 'models' are utilized. At the base level, each individual GIS layer (or input) can be considered a model—a simplified representation of reality that varies in accuracy, be it in the present or past. Such 'models' are usually layered within a GIS in order to search for revealing patterns or trends between human and environmental features and processes. At the higher level, there are computational models (such as agent-based models) that involve complex algorithm, environments, temporal iterations, and many base level inputs to execute. These models help to connect abstract theory to observed phenomena/systems (Brouwer Burg et al., 2016b:4). Even the simplest of these computational models have the potential to produce a rich output of behavioral data that requires thorough investigation.

While using the term 'model' seems to lend an air of technological sophistication to an analysis, the esteemed statistician George Box has noted "that all models are wrong; the practical question is *how* wrong do they have to be to not be useful" (Box, 1987: 74). And herein lies the rub of employing models, either simple or complex, atheoretical or theoretical: we can never generate a model that perfectly represents reality, especially not for past circumstances (our 'target system'). Thus, we must seek to understand, as Box indicates, how well our models approximate the target system by investigating where our models are wrong or, to use a more constructive concept, to determine where *uncertainty* enters our models. By identifying where, when, and how uncertainty is introduced into a model, the modeler can gain a deeper understanding of the strengths and weaknesses of the model.

Uncertainty, like models, also occurs in varying types and degrees. In GIS applications within archaeology, we must assume a certain type and amount of uncertainty is introduced with the addition of each individual GIS layer. These simple geospatial models of reality bring their own assumptions and biases, data collection strategies and goals. When these layers are integrated in a GIS, the uncertainty and resulting error of each layer is compounded. For the GIS user, recognizing and understanding the drawbacks of the uncertainty accompanied in this iterative process is incredibly important for determining the overall validity, or 'fit,' of the higher-level model (see definition below). The design and execution of computational models, which are often run on the platform of the composite geospatial models, also entails incorporating a certain degree and varying types of uncertainty related to theoretical assumptions about past socionatural processes and conditions. Additionally, there is the uncertainty associated with the archaeological data we select to use in our models, which are inevitably unbalanced and biased due to differential preservation of the archaeological record, research bias, etc. Finally, if we follow a non-positivist stance and assume that our own presentist biases and ontologies cannot be removed from the unavoidably subjective theoretical frameworks we impose on our data, we invite yet further uncertainty into the picture. So what's the point in trying? Laying aside more non-representational rhetoric, I argue that we *can* learn something of value by modeling the past with GIS, and that these understandings can and should be augmented by evaluating the type and degree of methodological and data-related uncertainty in our models (see Brouwer Burg et al., 2016a).

3. Materials and methods: investigating uncertainty and error

There are various ways to analytically investigate where, when, and how uncertainty is introduced to a computational model, and how it leads to error and bias propagation. For example, tests of verification and validation are regularly and systematically performed in related, geospatially-oriented fields (Geography, Geology, Ecology, etc.). For archaeological models to resonate beyond the scope of the discipline, archaeological GIS users should also consider incorporating such tests more uniformly in their analyses. A successful method I have used entails conducting a series of recursive analytical tests throughout a model's lifecycle, via the processes of verification, calibration, sensitivity analysis, and validation (Brouwer Burg, 2016a; Brouwer Burg, 2016b). To clarify, verification refers to how well a model executes the task it is designed for; calibration involves tuning input parameter values to produce model output that approximates real data; sensitivity analysis examines effects on model output of varying input parameters and their weights; and validation (or fit) assesses how well a model yields reproducible outcomes that approximate reality, while satisfying the outset objectives of the model. In archaeology, this generally involves comparing independent archaeological data to the outputs of the model. Establishing the fit of an archaeological model is necessarily very difficult, as the approximated reality or target system is a past condition or context that cannot be directly accessed by researchers in the present.

While some high-level, mostly academic archaeological GIS practitioners are incorporating such evaluations (see Brouwer Burg et al., 2016a; Carroll, 2013, 2016; Watts, 2013, 2016; White, 2013, 2016), the importance of such measures must be disseminated to the field at large. Ongoing evaluative steps such as these serve to refine and improve models, making them less wrong but also providing modelers with enormous insight into datasets and model functionality, making more transparent the mysterious 'black box' of geospatial modeling components and mechanics (Brouwer Burg et al., 2016b:1). Further, such tests will help to build the analytical credibility of archaeological applications of GIS beyond the field itself.

4. Results

I want to mention a few key lessons learned from my own work developing a map-centric, multi-tiered, multi-criteria decision-making model to explore socionatural dynamics of hunter-gatherer land use in the post-glacial Netherlands (Brouwer Burg, 2016a; Brouwer Burg, 2013; Brouwer, 2011; Eastman, 1999). This model ("HGLUM") was built upon detailed paleolandscape reconstructions that incorporated landscape features and probability distributions of vegetation zones and faunal habitats. Decision-making algorithms derived from ethnoarchaeological sources and ethnographic correlates were applied to heuristically explore ecosystem use, human spatial patterning, and cognitive perceptions of landscape (Brouwer, 2011; Brouwer Burg, 2016a: 60–63). The goal of this modeling process was to investigate the role and impact of both natural and cultural parameters on human decision-making, as well as to analyze the effects of environmental change on adaptive strategies.

An important part of the HGLUM model's lifecycle involved recursively verifying, calibrating, and validating the functionality of the model and the model output (Brouwer Burg, 2016a: 67–76). As part of this process, the propagation of methodological uncertainty was continuously monitored. Of course, methodological uncertainty can enter a model at any stage, but the most common points of entry are in the selection of input datasets to establish boundary conditions and the determination of model fit to these datasets (Fig. 1). Thus, the first, rather obvious but largely overlooked lesson is simply that the selection of datasets is a critical step for, as the old saying goes: “garbage in, garbage out.” The uncritical use of input data has the potential to render futile the entire modeling pursuit. Regular calibration and analysis of data sensitivity are necessary steps required to adjust for uncertainty in inputs and, as difficult as it might seem, we need to be willing to entirely remove extremely sensitive or insensitive data from our models. Furthermore, we should remember the old axiom of quality over quantity, as the inclusion of more datasets or more detailed data, runs the risk of over-parameterization of our models.

As described in greater detail in Brouwer (2011) and Brouwer Burg (2013, 2016a), HGLUM is comprised of a cascading set of parameters considered essential to hunter-gatherer subsistence-settlement decision-making. Four parameter orders were established: first order parameters depicted basic model inputs of resource acquisition; second order parameters involved aggregating first order parameters under varying resource acquisition frameworks; third order parameters evaluated lower-order parameters based on

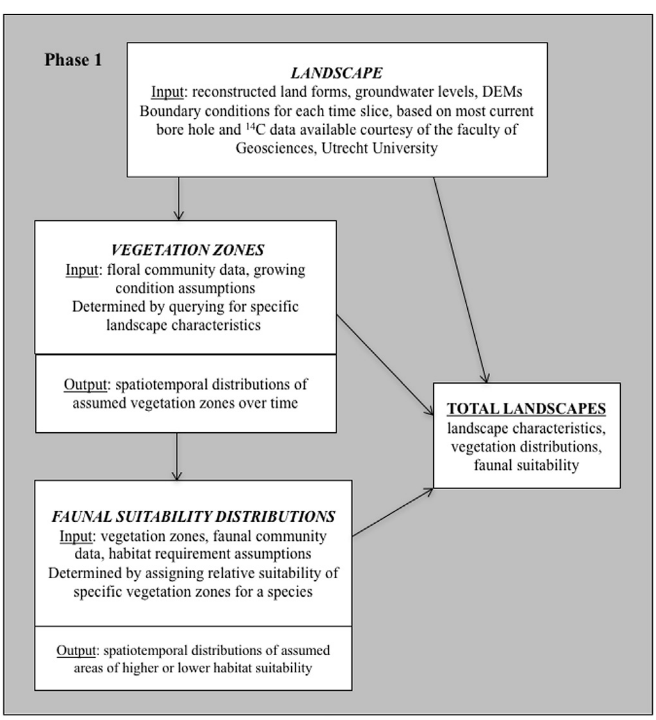

Fig. 1. Data Inputs for Paleolandscape Reconstructions (adapted from Brouwer, 2011: 350).

the presence/absence of landform features; and fourth order parameters entailed harnessing composite third order parameters to specific settlement and mobility preferences (Brouwer Burg, 2016a: 68). Obviously, any uncertainty or error inherent in the lower-order components would become compounded within higher-order analyses. Thus, all initial and secondary input datasets were continuously evaluated and re-evaluated based on comparability between scale, granularity, and collection strategy. In some cases, datasets had to be geospatially transformed in order to enhance or improve this comparability. For example, the basal peat deposition within core profiles was used as a proxy to indicate sea-level transgression, and interpolation was used to approximate sea-level rise surfaces (Brouwer Burg, 2013:2309–2311).

Further, sensitivity analyses (SA) were carried out on parameters from all four orders, specifically extreme multiway or corner-test and design of experiments (DOE) SA (for a full discussion of these recursive tests, see Brouwer Burg, 2016a: 67–76). Using the corner-test SA, first order parameters were identified that were extremely sensitive, meaning that the presence or absence of these parameters could greatly skew the overall output of the geospatial model. In addition, unique parameters leading to very similar outcomes could be collapsed and redundancy in the model removed (this also helped to improve the efficiency of running the model). An iterative DOE SA was also used to determine which parameters had the greatest net impact on model outputs. Going forward, these parameters were accorded special attention as to their incorporation, and in some cases were not included at all given their reactionary presence within the overarching model.

Dismissal of this first lesson (the uncritical use of input data) is tantamount to selecting an unfit or mis-fit model, which brings me to the second lesson: that model selection, development, and execution is also a process that should be approached skeptically, with the goal of minimizing uncertainty and error propagation (Fig. 2). When establishing differential valuations of the overall modeling schema, the potential for uncertainty has to be weighed against the benefits of including certain parameters and criteria.

In my work, model outputs constituted probability surfaces reflecting gradations of uncertainty about the suitability of locations for carrying out specified activities (Fig. 3). This particular form of output was selected intentionally as the best way to acknowledge and incorporate uncertainty in the datasets and model function. This form of output is also well-suited to sensitivity analysis as described above, whereby the impact of varying the number, type and weight of input parameters on model output can be evaluated and optimized. Further, model output could be cast against independent archaeological data to determine the degree of ‘fit’ of the model (‘best fit comparison’ in Fig. 2; see Brouwer, 2011 for more detailed discussion). When no fit or mis-fit was found between model outputs and the archaeological record, further investigation into the verification and calibration of the model parameters, properties, and functionality were carried out.

The overall take-home message here is that if we want to be successful practitioners of GIS, and communicate with others in related fields, then we must scrutinize all aspects of our methodological approach, actively engaging with the implications of our data, methods, and models (Hacıgüzeller, 2012: 248). The all too common approach of ‘plugging and chugging’ geospatial data into GIS software can do far more damage than good, leading us down uncertain routes of investigation, laden with error, and moving quite frankly in the wrong direction. And, as we all know, adding more data, more types of data, or more complexity to the model will not necessarily improve model output. Further, can we be sure that a direct tradeoff exists between uncertainty and certainty? If we can identify and mitigate readily observable sources of uncertainty, does that necessarily make our models more certain? These

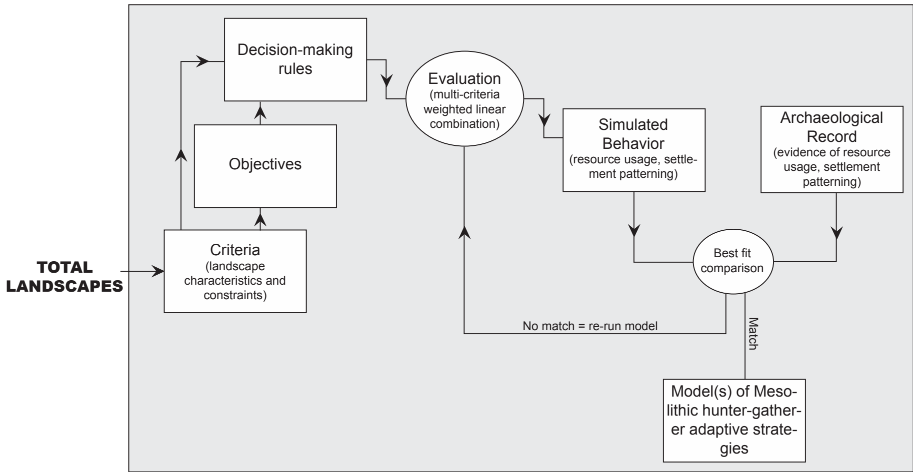

Fig. 2. Decision-Chain Formula Used in the HGLUM Model (adapted from Brouwer, 2011: 202).

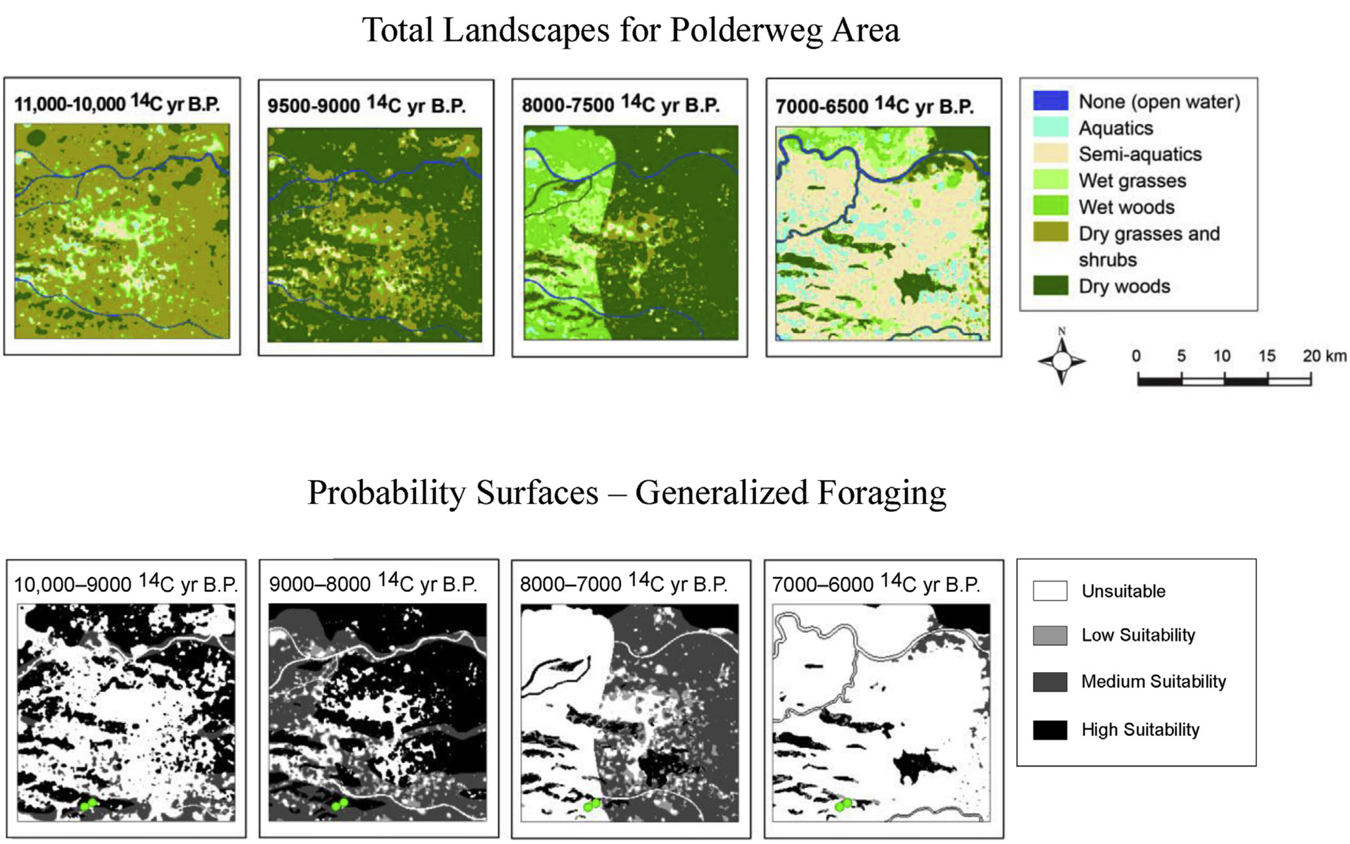

Fig. 3. HGLUM Model Output (Total Landscapes and Probability Surfaces for Generalized Foraging; adapted from Brouwer, 2011: 166, 485).

issues can be succinctly demonstrated by the *Bias Variance Tradeoff* (Fortmann-Roe, 2012; Hastie et al., 2009) (Fig. 4). Here, the overall error (or mis-fit) of model output to a target system is related to bias (degree to which outputs differ from the expected range) and variance (degree to which outputs vary from each other). Model bias decreases with model complexity, as presumably additional parameters and criteria are incorporated to deal with some of these biases, while the reverse is true of model variance. For archaeological purposes, we cannot know what the expected range is, and thus it is more useful to focus on obtaining model output with lower variance, establishing model robusticity through reproducibility. There is a 'sweet spot' here that we should shoot for, where bias, variance, and overall error are minimized; finding this spot via sensitivity analysis is critical for determining optimal complexity for our models. The tradeoff also highlights the parabolic nature of error: while seemingly elegant, very simple models are often riddled with it, and so too are overly complex models.

The last factor contributing methodological uncertainty to model outcomes and subsequent interpretations is that of equifinality (Brouwer Burg et al., 2016a; Hole and Heizer, 1969; Lyman, 2004; Premo, 2010; von Bertalanffy, General system theory 1956; von Bertalanffy, Problems of organic growth 1949), the principle

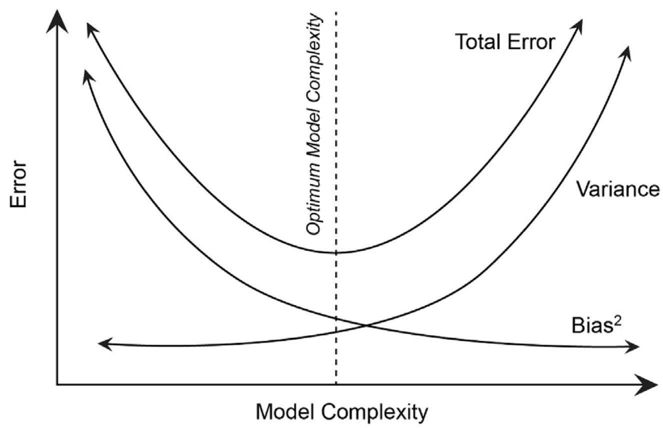

Fig. 4. Bias-Variance Tradeoff, adapted from http://scott.fortmann-roe.com/docs/docs/BiasVariance/biasvariance.png.

stating "that in open systems, any given final state, result, or outcome can be reached by more than one path and/or from more than one set of initial conditions or starting points" (Premo, 2010: 31). For the archaeological record, I define these differing 'starting states' as cultural and natural processes in the past, which may lead to the creation of similar to identical 'outcome states,' or archaeological signatures in the present. When equifinality is considered as a possible mechanism influencing the archaeological record, it can undermine strong positivist approaches where material remains are assumed to be reflective of specific behaviors and processes that occurred in the past. The ability of GIS to incorporate diverse datasets using an array of spatial and statistical transformations endows this technology with great potential for exploring questions of equifinality in the archaeological record.

5. Conclusions: becoming more than a tool?

These are difficult and time-consuming issues to grapple with; overworked compliance archaeologists can hardly be expected to take the time and resources necessary to conduct the kind of critical investigation of theoretical frameworks, input data, model functionality, and outcomes suggested above. However, the non-critical application of GIS analysis practiced in the field of archaeology is something to be wary of; just because anyone *can* collect a carbon sample does not mean they should also attempt to date that sample in an amateur laboratory. There would be no oversight of the testing procedure, and the validity of obtained date ranges would be uncertain at best. We don't do this, because although we may have provisional knowledge of issues of contamination and sources of uncertainty and error, we agree that the rectification of these considerations and standardization of analysis procedures is something better left to specialized laboratories staffed by professionals who keep abreast of theoretical and methodological developments in the field of radiocarbon dating.

The widespread availability of evermore powerful personal computers and the growing accessibility (in terms of user-friendliness) of GIS software has led to the notion that anyone can sit down and "teach themselves GIS" in a day or two. This approach to what is, in reality, an incredibly complex technology supported by a rich and complicated theoretical corpus is perhaps most responsible for the apparent dissatisfaction with the technology in some sectors, and perhaps also the disconnect between compliance and academic applications of GIS. Increased collaboration between archaeologists and spatial experts from related disciplines is one way such issues may be overcome, as there is much to be learned from the theoretical and methodological ideas and expertise of researchers asking similar questions from differing perspectives and drawing upon distinct theory and data. Another avenue could entail training and educating more full-time GIS "experts" (or power users) in the field of archaeology, people who straddle archaeology and GIS science, critically engaging in the theoretical and methodological aspects of GIS, and producing research on best applications in archaeology. In related scientific disciplines and industries, such GIS experts have been charged with creating subject-area specific toolboxes that help novice and academic users alike work through modeling projects in a step-by-step fashion. Such toolboxes would be incredibly useful for the field at large, as they could also establish a set of procedural guidelines or best practices that mitigate non-critical and atheoretical uses of GIS to answer archaeological questions.

In my last word on uncertainty and error, I would like to point out that, in addition to methodological uncertainty, more must be done to critically problematize theoretical uncertainty, in terms of addressing broader epistemological and representational concerns of post-modernist theorists. We may scrutinize our data and our models sufficiently, but if we are not also reflexively scrutinizing ourselves and the ontological frameworks from which we conduct our analyses, then we will continue to miss a large chunk of the story, by preferencing the male gaze (Wickstead, 2009) and by couching our investigations in dualities of nature/culture, objectivity/subjectivity (Brück, 2005; Hacıgüzeller, 2012). In particular, we need broader consideration of *who* we are modeling. What gender, age, and ethnicity are the people whose lived realities we are trying to understand? How might these identities impact the spatial patterns and relationships we produce with our models? To investigate these questions would not require collection of new data, but rather a re-interpretation of existing data from different frameworks of inquiry along with clear acknowledgement of our ultimate inability to replicate human experience in the past, recalling George Box's quote that all models are wrong. However, if as GIS practitioners we continue to broaden our scope toward understanding more of the humanistic dimensions of space or better yet 'place,' we may be able to heuristically explore the past realities of traditionally overlooked and under-represented identities. We must expand the ways we conceptualize, apply, and perform GIS (to borrow a term from P. Hacıgüzeller). Only then can we start to think of GIS as a driver of paradigmatic change.

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