Archaeological Modeling with GIS at Scales Large and Small

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Introduction

Although approaches to regional spatial analyses of archaeological distributions were possible prior to the advent of GIS technology (e.g., Hodder and Orton 1976), only very simple models of those distributions were possible. For example, an analysis might reveal that archaeological sites in a region exhibit an association with a specific soil type, or location tendencies for ridges, hilltops, or nearness to stream confluences. Before GIS it was not possible to map the intersection of multifaceted criteria over any but the smallest of regions, because all mapping had to be performed manually. With entire regions, provinces, or even countries now digitally pre-encoded within GIS-compatible databases, it is now possible to map complex models and decision rules over very large regions rapidly and accurately. Regional models of archaeological site distributions have therefore been enabled by GIS technology for nearly two decades, and many large models have been developed (see Kvamme 1990 for an overview of early approaches and Wescott and Brandon 2000 for more recent examples).

The enterprise of regional archaeological modeling has been a boon to archaeological science in a number of ways. In cultural resource management it has become a multi-million dollar industry where planning maps are produced to guide future developments (roads, bridges, buildings) away from areas predicted to be archaeologically sensitive, allowing realization of significant cost savings as expenditures for mitigating complex sites are reduced (Van Leusen and Kamermans 2005). In the United States, several large statewide models have been generated for this purpose, funded by governmental departments of transportation (e.g., Hudak *et al.* 2002). At a theoretical level, models and associated analyses can reveal important variables related to past location decisions, and GIS mappings offer a generalizing heuristic device that enables past landscape use patterns to be more easily visualized (Kvamme 1990).

Given these obvious successes and benefits, the question arises of whether models of similar form, power, and utility can be developed for within-site applications, including buried archaeological features hidden beneath the surface? Such models would undeniably be useful for management and planning purposes. It may not be surprising that little effort has been expended in pursuing models of the subsurface, for one may naturally question how one can see beneath the soil to acquire necessary data? The answer lies in archaeological geophysics, where several technologies are available that allow a range of information to be gained about subsurface conditions without excavation (Clark 2000; Gaffney and Gater 2003). GIS-driven intra-site models based on geophysical inputs are investigated here.

To form points of comparison, methodologies for modeling archaeological site distributions at the regional level are initially reviewed and a case study is presented utilizing a small number of common modeling approaches. Focus then changes to the scale of the archaeological site. A pathway to developing GIS-based models of the subsurface is followed utilizing methods identical to those applied at the regional level; only the variables and context are changed. In such a way, continuity in approach is emphasized, well illustrating that GIS is a spatial analysis and modeling engine that is scale independent (Burrough and McDonnell 1998). In sections that follow, GIS models are viewed from two perspectives. They can be *descriptive* when they are used to summarize or generalize patterns in data (useful for visualizing trends and for better understanding relationships). They may also be *predictive* when used to project from the known to the unknown, indicating the likelihood of archaeological sites at previously unexamined locations (useful as a prospecting tool for management and planning purposes).

GIS Methods for Regional Archaeological Modeling

GIS-based models for archaeological site locations have been around since the mid-1980s (Judge and Sebastian 1988). They are based on the simple assumption that patterns exist in places where people locate their activities, camps, or settlements across the landscape. Even today, when camping, we usually select locations that are on level ground, near water, that capture the sun's warmth, that have a good view, that are sheltered from the wind, and so on. So too did ancient peoples. Prehistoric farming settlements may have been located with a concern for water and good soils; hunting camps may have been sited with a preference for hunting and a view of game.

There are two ways to pursue modeling where past peoples located themselves - which translates to where the archaeological sites they left behind might be found. One approach lies in a close examination of the anthropological and historical literature of a region in an effort to *deduce* the kinds of locations that past peoples may have selected to place their camps and settlements (Judge and Sebastian 1988). In this approach, one must specify relevant variables and characteristic values of those variables, a difficult task that requires good intuition and educated guesswork, especially when working in the distant past. For instance, south-facing slopes might be preferred for warmth in the northern hemisphere, but how many degrees off south remains suitable? If good soils are required for farming, how much deviation from the ideal is allowed? Long-term villages might need to be placed near secure water, but how near? Depending on values chosen, widely different modeling outcomes can result.

A superior approach is to let the people of the past give us clues about the circumstances that were important to them. This can be accomplished through systematic field surveys that allow discovery of archaeological sites throughout a region of interest. Simply by measuring and analyzing a number of variables at known archaeological sites it is possible to ascertain ones that might have had a bearing on past site location choices. The variables selected for analysis, of course, are based on previous work, theory, or ethnography. If it is found that 25 percent of a region lies in a productive soil type, but 75 percent of known prehistoric farming villages exist in the same unit, then there is strong evidence that this variable holds a relationship with the presence of these archaeological sites (other things, such as site visibility, being equal). By examining the data in this way, variable-by-variable and site type-by-site type, it is possible to let the past speak to us, to give us clues that allow model-building. Obviously, GIS facilitates this analytical task, and a wide variety of statistical approaches have been developed that make special use of GIS capabilities (e.g., Kvamme 1996), but these methods are not the focus of this paper.

The practical problem in archaeological modeling over large regions has always rested in its application. What was needed was a means to map all locations with, for example, level ground, good soils, that are close to water, with south-facing slopes, and so on, according to variables shown to be important by analysis, over tremendously large regions. It was not until the mid-1980s that this was accomplished using Geographical Information Systems (GIS) computer technology (see Kvamme 1990, 1999 for reviews). GIS allows virtually any sort of map variable to be computer-encoded and combined with other variables to yield complex modeling outcomes over large areas - even across an entire states or countries!

Case Study: the Region and Data

The Pinon Canyon study area may be characterized as a broad, arid (less than 25 cm annual precipitation), high altitude (1,500 m), short-grass plain, dissected by a number of deeply entrenched canyons around tributaries of the Purgatoire River, in the southern Colorado Great Plains, USA. The area is completely undeveloped because it lies within the U.S. Department of Defense Pinon Canyon Maneuver Site, used primarily for armored vehicle training. The prehistoric archaeology of Pinon Canyon is characterized predominantly by open-air lithic scatters, consisting of chipped-stone tools, ground stone, debitage, and occasional ceramics, deposited by hunting-and-gathering cultures. Numerous "tipi ring"sites dot the plains (five-meter diameter circles of head-size stones used to hold down the leather

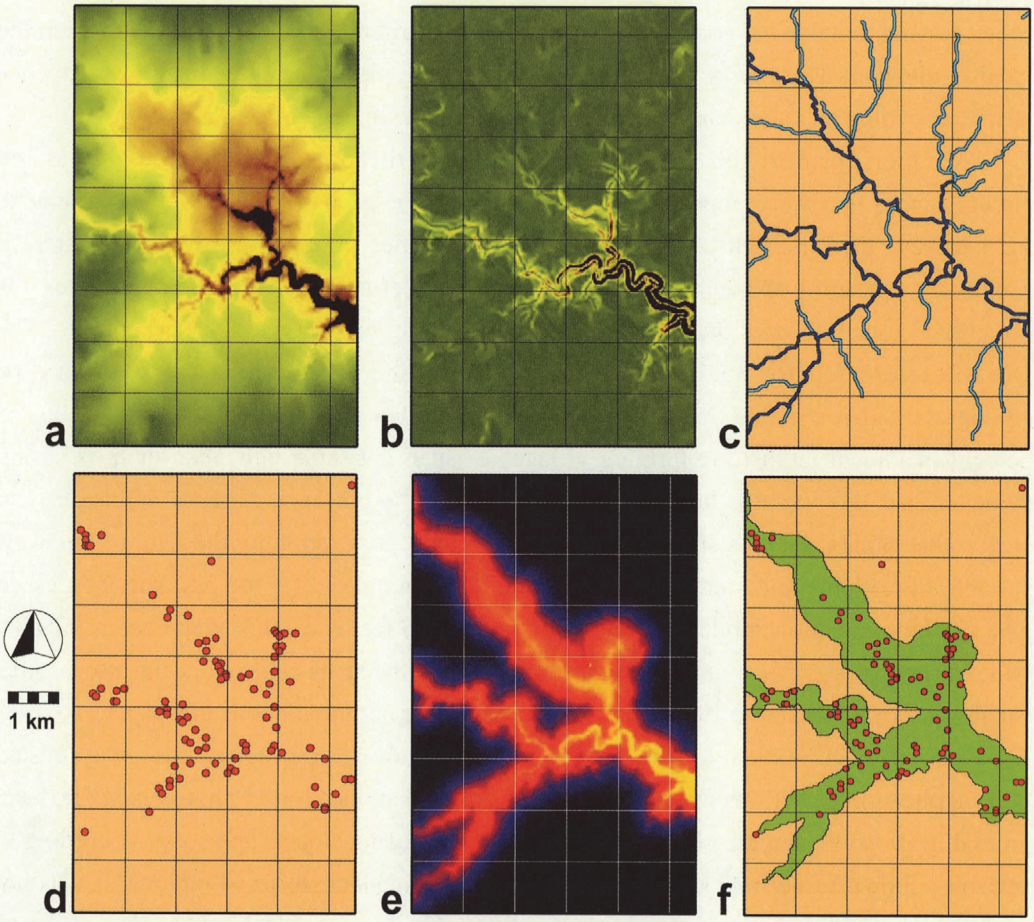

Fig. 1 GIS layers from Pinon Canyon, Colorado, USA: a) DEM, b) slope, c) permanent and ephemeral streams, d) known archaeological sites, e) probability surface model for site presence, f) classified model with sites overlaid.

edges of native tents, known as tipis). The bulk of the occupation of this region seems to have been between 200-1400 A.C.E., although earlier Paleoindian and Archaic sites have also been identified (Kvamme 1992).

Although the full study area comprises nearly 1,000 km^2, a smaller 5.5 x 8.5 km^2 region is examined here, in which 95 prehistoric archaeological sites are located. These sites were discovered through a random sampling program that guided pedestrian survey of the surface, where visibility of surface artifacts and archaeological sites is very high owing to the region's aridity and limited vegetation cover. The data available for modeling include these 95 open-air lithic scatters, a digital elevation model (DEM) of the topography, and water sources, classified as permanent and ephemeral. GIS terrain processing and other methods were then employed to generate a suite of other variables of relevance to the archaeological distribution, including slope, aspect, terrain curvature, a local relief measure,

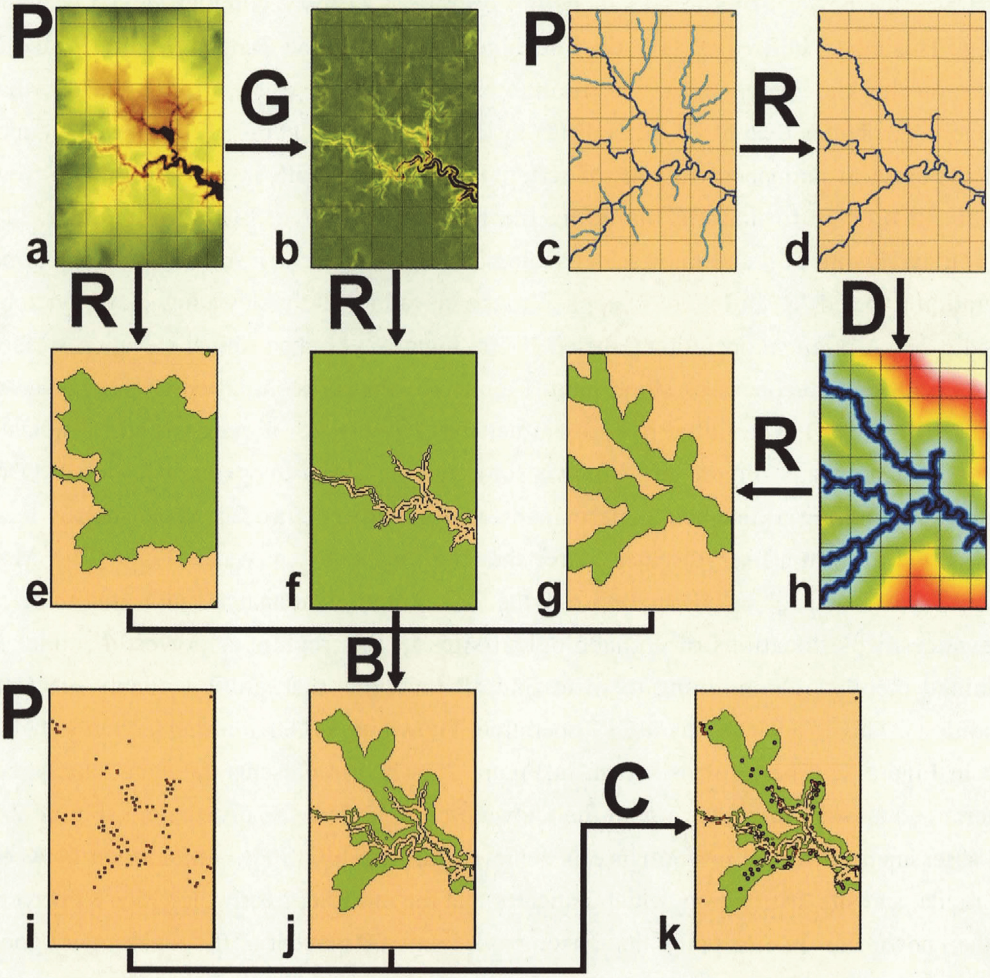

Fig. 2 GIS operations necessary for simple Boolean model of archaeological site location at Pinon Canyon: a) DEM, b) slope, c) all streams, d) permanent water, e) low elevation, f) level ground, g) locations near permanent water, h) distance to permanent water, i) known archaeological sites, j) Boolean intersection model of e-g, k) sites overlaid on model in j. KEY: P=primary layer; G=gradient operation; R=reclassification; D=distance operation; B=Boolean intersection; C=cover operation.

vertical and horizontal distances to secure and ephemeral water sources (see Kvamme 1992). These data are held within a GIS at a spatial resolution of 30 m. Some of the data layers are illustrated in Figure 1.

Regional Descriptive Models

Numerous methods and algorithms have been developed for modeling archaeological site distributions (Kvamme 1990). An initial and simple model of archaeological location illustrates the power of basic GIS modeling operations; a more complex model is given below. This model utilizes some of the foregoing data from Pinon Canyon (Figure 1), and is based on the knowledge, achieved through statistical analyses mentioned earlier, that archaeological sites tend to be located: (1) in low elevation locations, (2) on level ground, and (3) close to permanent sources of water. Three primary GIS layers are utilized from which all other information, including the model, is derived: elevation (Figure 2a), hydrology (Figure 2c), and known archaeological sites (Figure 2i). A GIS *reclassification* operation (labeled "R" in Figure 2) applied to the elevation data yields a low elevation zone (Figure 2e). A *gradient* operation (labeled "G" in Figure 2) on the original elevation surface yields a ground steepness or slope map (Figure 2b) that is reclassified to portray level ground (Figure 2f). The initial hydrologic network (Figure 2c) is reclassified to indicate only permanent water (Figure 2d), which is subjected to a *distance* operation (labeled "D"in Figure 2), yielding a distance to permanent water result (Figure 2h). This map is then reclassified to form a fixed-distance buffer showing locations near water (Figure 2g). Map layers "e," "f," and "g" in Figure 2 portray the three criteria that analysis indicated to be of relevance to the locations of archaeological sites in this region. A powerful model is obtained merely by combining them to find all locations that simultaneously meet all conditions. This is achieved by a GIS operation, known as a *Boolean intersection* (labeled "B" in Figure 2). The result is shown in Figure 2j, which represents the stated analytical criteria and appears to conform with the known archaeological site distribution (Figure 2i). An assessment of model performance is achieved through a GIS *cross-tabulation* between the model and site distribution, which indicates that the model correctly classifies 89 percent of the known sites in a mapping that encompasses only 30 percent of the region, very good performance. The fit of the model may also be visually evaluated, simply by comparing maps in Figure 2i and Figure 2j, or by implementing a GIS *cover* operation (labeled "C" in Figure 2), which drapes the known sites over the model showing how well they agree (Figure 2k).

A model such as that in Figure 2j can be viewed as a *description* of an archaeological location pattern. This kind of model is useful because it generalizes the data to make distribution patterns easier to visualize and understand. GIS model mappings may be compared against primary data (e.g., Figure 1) to better recognize contexts that might relate to archaeological site locations, and individual sites may be assessed to ascertain how well they conform to the overall pattern. Knowledge of variables that make up a model contributes to a growing body of theory pertaining to human spatial behavior.

Regional Predictive Models

From another point of view, a model such as that in Figure 2j forms a *predictive* model. This circumstance arises when a model is applied to areas not yet field-surveyed to indicate the likelihood of archaeological site presence or absence. It assumes that yet-undiscovered archaeological sites in the region will follow a pattern of location similar to those sites used to develop the model (random sample surveys for site discovery insure that patterns in samples will be representative of other sites in the population). In other words, if the archaeological sites in Figure 2i are only a sample from the region, then the model represents a prospecting tool for making predictions of archaeological site location in areas not yet surveyed.

In practice, actual model development is typically much more complicated than the approach illustrated above, using many more variables and complex multivariate statistical functions that are optimized to characterize patterns in the data. Supervised classification methods, where results are developed from statistical characteristics of samples provided by a supervisor, include a large number of powerful algorithms in satellite remote sensing (Schowengerdt 1997). Locations of known class membership (i.e., archaeological site present and absent locations) provided to the algorithm are referred to as "training sites," because they are used to train the algorithm to recognize patterns in the samples. The model used here is logistic regression, a particularly robust technique widely used in archaeology (Kvamme 1990; Wescott and Brandon 2000). A simple binary logistic regression model is pursued here to produce a probability surface for archaeological site presence (where low probabilities point to site absence). In order to develop a more robust model than the one illustrated in Figure 2, GIS terrain processing and other algorithms (Burrough and McDonnell 1998) were employed to create additional variables that were subsequently analyzed and shown to be relevant to the presence or absence of sites in the region. The following function was derived:

$$L = -0.9425 + .00122*aspect - .0239*slope + .00277*local\_relief + .00181*rim\_index - .00404*terrain\_curvature - .00204*horizontal\_water\_distance - .000636*vertical\_water\_distance$$

where *aspect* is a north-south directional index, *slope* is gradient, *local relief* is an elevation range within 300 m of a locus, *rim index* quantifies the sharpness of canyon edges, *terrain curvature* measures surface convexity, and the remaining variables measure horizontal and vertical distances to nearest secure water. All parameters in this model are statistically significant contributors (at α=.05). Positive coefficients indicate that high values of the corresponding variables are related to the site-present class while negative coefficients link low values of a variable with that class. Thus, high values of *aspect* (pointing to south-facing), *local relief* (places close to large elevation changes), and the *rim index* (vertical canyon edges) tend to be associated with the archaeological site locations. The model also indicates that the sites tend to occur at locations with low values of *slope* (level ground), and horizontally and vertically close to water sources (see also Kvamme 1992). Map algebra operations available in GIS were used to map this function, after application of the logistic transformation, $p=(1+exp(-L))^{-1}$, which scales the result to vary between 0-1 allowing interpretation as a probability surface for archaeological presence (Hosmer and Lemeshow 2000). This predictive model is illustrated in Figure 1e. For comparison with the previous model, the continuous probability surface may be reclassified to indicate most likely regions of site presence and absence (Figure 1f). GIS cross-tabulation with the known sites indicates that approximately 97 percent of the known sites are correctly classified by the model in a mapping that also covers only 30 percent of the region, indicating improvement over the previous model.

GIS Methods for Intra-site Archaeological Modeling

Foregoing sections have illustrated GIS-based models that *describe* regional archaeological distributions, and that *predict* favorable loci of archaeological sites when such models are applied to locations not yet field inspected by archaeologists. But how can such modeling approaches be applied to map the locations of buried archaeological features within a site-the loci of walls, floors, hearths, pathways, graves, and the like? In other words, how can one predict, or indeed even model, what lies hidden beneath the surface?

The approach taken here relies on knowledge gained from archaeological geophysics combined with common GIS modeling tools. It is well known that geophysical methods-magnetometry, ground-penetrating radar (GPR), electrical resistivity, and other methods-allow the identification and mapping of subsurface archaeological features (Clark 2000; Gaffney and Gater 2003). Each technique does so imperfectly, however. Electrical resistivity might well identify stone walls and floors; magnetometry might locate such burned features as hearths or kilns; and GPR might show packed trails or post holes. To successfully model the subsurface based on these data, whether descriptively or predictively, a holistic approach must be utilized. The geophysical data must be integrated through a "data fusion" that effectively combines the multidimensional information. Various GIS methods readily offer this capability, and several are explored here.

Case Study: the Site and Data

Army City, Kansas, was a privately owned commercial center established in 1917 to provide goods and services to troops at Camp Funston (now Fort Riley) in the era of World War I. The town declined after the close of the war in 1918, and a fire that devastated its commercial core in 1920 contributed further to its demise. It was abandoned soon afterward with its remaining structures dismantled, sold as scrap, or moved to another town (Hargrave et al. 2002). Army City now rests under a hayfield with few indications of its presence although significant architectural and other remains lie buried only 30 cm below the surface.

In order to better understand the condition and organization of Army City, six geophysical surveys were undertaken in a 100 x 160 m (1.6 ha) region centered over its commercial core. These surveys included ground-based magnetic gradiometry, electrical resistivity, GPR, magnetic susceptibility, and soil conductivity; thermal infrared data were obtained from the air in a low-flying ultra-light aircraft (Kvamme 2006a). All of the ground-based data were collected within 20 x 20 m survey units, allowing their automatic co-registration within a locally established coordinate system. The data were acquired at various spatial resolutions, however, depending on the technology used. Most of the measurements were sampled in the field every 1 m on the x-axis by .5 m on the y-axis, although magnetic gradiometry was sampled every .25 x 1 m and GPR at .025 x .5 m. For the aerial thermal infrared data, still frames were extracted from digital video that showed ground control markers placed over the 20 m survey block corners of the ground-based data collection units. These images, with spatial resolutions of about 10 cm, were subjected to standard affine transformations available in GIS to rectify and register them to the coordinate base of the study area (Burrough and McDonnell 1998:128). All of the ground and aerial geophysical data were then resampled to a uniform .5 x .5 m to facilitate subsequent GIS manipulations and modeling (Kvamme 2006a).

Extensive processing of the geophysical data was required to remove unwanted trends, reduce noise, and enhance culturally generated anomalies. This demanded use of specialized algorithms, many of which were performed with GIS. High-pass filters were employed to remove regional data trends caused by underlying geology or broad soil changes. Adaptive box filters were employed to remove data "spikes" (extreme measurements) caused by poor electrical contacts in resistivity surveys or the effects of metallic artifacts in others. De-striping algorithms were applied to remove instrument drift and imbalances caused by parallel transect survey methods. Low-pass filters allowed consolidation of weak features of interest and noise reduction. These methods are described in several sources, including Gaffney and Gater (2003). The six processed data sets are illustrated in Figure 3a-f.

Intra-site Descriptive Models of the Subsurface

Useful geophysical results are obtained when an archaeological feature possesses physical properties different from the surrounding matrix and instrumentation detects a contrast against this natural background. These contrasts are referred to as "anomalies." By definition, anomalous measurements are extreme in value and differ from "normal" data from undisturbed deposits. Analysis of the six geophysical data sets allowed definition of anomalous conditions in each data distribution. It was learned that high electrical resistivity, thermal, and GPR amplitudes best defined walls and floors; high magnetic susceptibility showed burned areas and deposits of magnetically enriched topsoil along street gutters; large magnetic gradiometry and negative conductivity measurements located iron water and sewer pipes; low thermal infrared measurements corresponded with street gutters, pipe trenches, and cellars (Kvamme 2006a). Based on these findings, thresholds were defined on each geophysical data distribution that best defined robust anomalies. These binary data sets are illustrated by the small inset maps in Figure 3a-f.

The binary mappings of Figure 3 were derived through GIS reclassification operations that assigned a "1" to signify the presence and a "0" the absence of robust anomalies. Binary data allow Boolean methods to be applied for the simultaneous integration of all six data sets into a single composite. The Boolean union is revealing because it shows the loci of all significant anomalies from all sources, offering a comprehensive description of the subsurface (Figure 4a). Much like the foregoing Boolean model at the regional level that describes the pattern of archaeological site location (Figure 2j), this intra-site Boolean model describes the overall distribution of subsurface content- the layout of archaeological features and the overall structure of Army City. (A Boolean intersection was also computed, but was not informative because a total of only 11.5 m^2 out of the study area's 16,000 m^2 - .07 percent- simultaneously shows anomalies in all six dimensions, an unsurprising result given the large number of geophysical surveys.)

Intra-site Predictive Models of the Subsurface

As in regional applications of archaeological models, the element of prediction occurs in within-site models when patterns from known circumstances are applied to the unknown. Such a model is pursued at Army City through use of a supervised image classification algorithm where samples of known identity are used to train functions to recognize other members of classes of interest. Just as a model can potentially be developed for individual types of archaeological sites at the regional level, so too can models be created for specific classes of archaeological features at the intra-site level.

Over 100 small excavations were placed throughout Army City in an archaeological testing program designed to evaluate and ground-truth anomalies indicated by the geophysical surveys (Figure 3). Excavation units were placed by random sampling, stratified by general classes of anomaly types that included a "background" class devoid of anomalous indications (Kvamme 2006b). Twenty-two of the excavation units identified buried concrete or masonry representing floors, walls, and footings associated with former structures.

Another nine units revealed pipes and 16 crossed former street gutters. Two additional classes were necessary. One was a single class representing all other anomalous locations of identifiable archaeological type in 26 excavation units (i.e., archaeological features that represented neither concrete nor masonry nor pipes nor gutters). Anomalous data indications within these units, plus adjacent areas of the *same* anomalies outside the units, were employed as training sites for these archaeological classes. Finally, a reference class is statistically required against which characteristics of these four archaeological classes could be contrasted. Eleven excavation units from the background class represented loci without anomalous geophysical indications of any kind; their areas plus an adjacent two-meter radius were used to represent this class. The training locations are indicated in Figure 4b.

Logistic regression was again selected as the modeling algorithm (Hosmer and Lemeshow 2000). In the present case with multiple classes, the goal is a probability surface for the presence of each archaeological class, requiring a multinomial model. The four derived regression functions are presented in Table 1. These functions offer considerable interpretive potential. Prior to the analysis, each data distribution was standardized with a mean of zero and variance of unity, allowing comparisons of the regression coefficients. Table 1 indicates that resistivity and magnetic susceptibility carry most weight in the "concrete-masonry" model; that magnetic gradiometry and susceptibility most influence the "pipes" model; and that magnetic susceptibility, resistivity, and GPR are best related to street gutters. These findings agree well with data patterns in corresponding imagery (Figure 3), and make sense geophysically. Concrete and masonry are high resistance features, iron pipes possess a high level of induced magnetism, in-washed topsoil filling street gutters tends to be more magnetic, and rubble filling gutters exhibits high resistivity and generates pronounced GPR reflections.

A probability surface for any class can be generated by:

$$p_k = exp(L_k) \,/\, [\, 1 + \Sigma_i exp(L_i) \,]$$

where p_k is the probability of membership in class k, L_k is the linear regression function for that class (Table 1), "*exp*" is the exponential function, and the summation is over all classes (Hosmer and Lemeshow 2000). When mapped on a per-pixel basis through GIS map algebra methods, a probability surface for each class is achieved.

All four probability models are simultaneously portrayed in Figure 4c, through use of different colors. These probability surfaces represent prospecting models for specific archaeological classes lying beneath the surface- pipes, street gutters, concrete-masonry features, and other archaeological features as a class. The success of these models arises

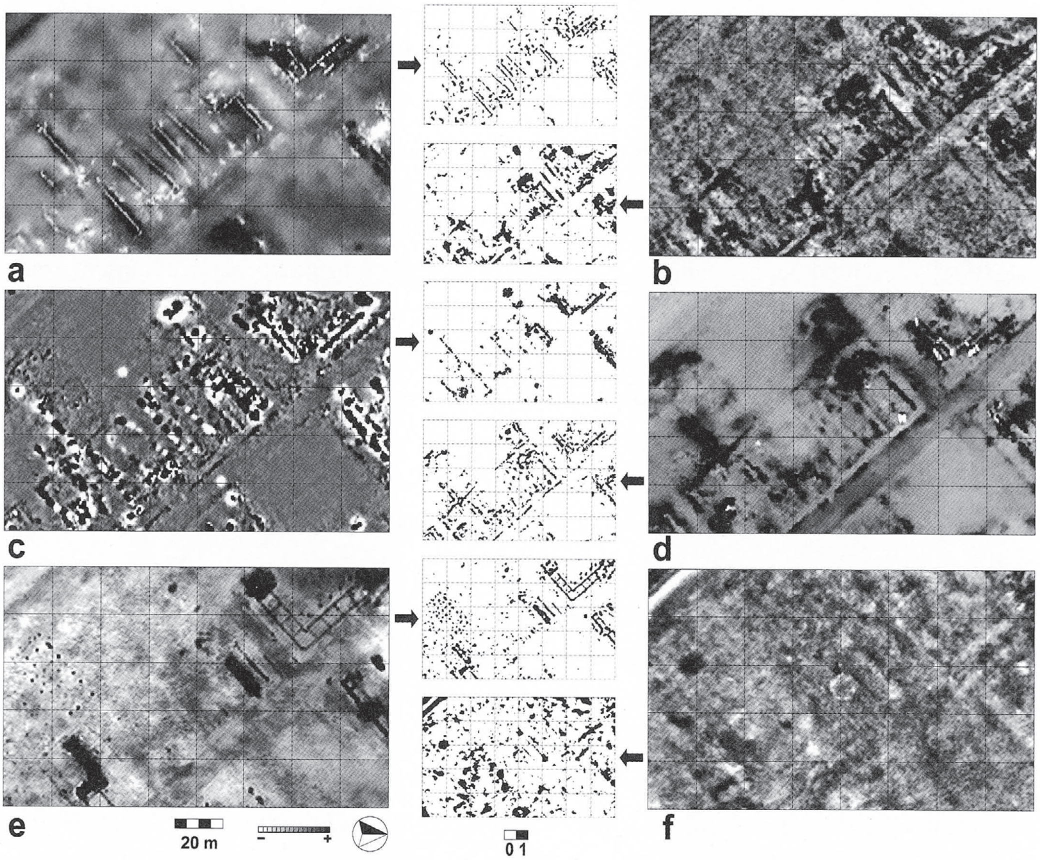

Fig. 3 Geophysical data sets from Army City, Kansas, USA: a) EM conductivity, b) GPR time-slice (20-40 cm below surface), c) absolute magnetic gradiometry, d) absolute magnetic susceptibility, e) electrical resistivity, f) thermal infrared. Small inset figures represent binary mappings of principal geophysical anomalies.

because they are based on multidimensional geophysical data that combine information from all inputs. Each model contains a predictive element because it maps localities beyond those indicated in the training data (Figure 4b). In other words, locations are identified that possess characteristics similar to these known site features, but that might not be seen as strongly anomalous in the raw data. In this way, the GIS-derived models become predictive because they extend the prospecting capabilities of geophysics, by indicating potentially new and unknown anomalous locations associated with specific classes of archaeological features.

While illustrating good performance, these models do not perform perfectly. Each probability surface also indicates locations not of the appropriate class. These errors can be assessed quantitatively by assigning each training pixel to its highest probability class of membership according to the models (Table 2). Although accuracies vary between 41-91 percent, it is clear that for each actual class the models assign the majority of pixels to the correct class (Table 2). Most of the errors appear to be associated with the "other" class, but that is to be expected. That class, after all, holds a wide variety of anomalies representing many types of archaeological features, including subtle walls, floors, street components, burned areas, and other disturbances. It is therefore unsurprising that the wide variation of this class appears very similar to other classes of interest. Additional work will be necessary to refine these results.

Conclusions

GIS-based algorithms have been presented for modeling distributions of archaeological sites at the regional level, and for modeling subsurface features at the intra-site level. It has been shown that nearly identical methodologies are possible, only the nature of the variables examined and the scale of results are different. In each case, powerful descriptive models are possible that combine available information to generalize archaeological patterns. When these models are applied to unexplored areas they offer a predictive or prospecting capacity. At the regional level, archaeological predictive models have been important to cultural resource management allowing significant cost savings to be realized in project planning and site discovery. The potential impact of the intra-site models explored here is unknown, but based on the results it can be argued that a clearer picture of the subsurface is realized, compared to the individual geophysical maps. Consequently, such models might potentially be used to target precision excavations over predicted archaeological features of potential importance, thereby making excavations more efficient and cost-effective. By more clearly imaging the totality of information about the subsurface from all sources, a better understanding of site content, structure, and organization may also be achieved.

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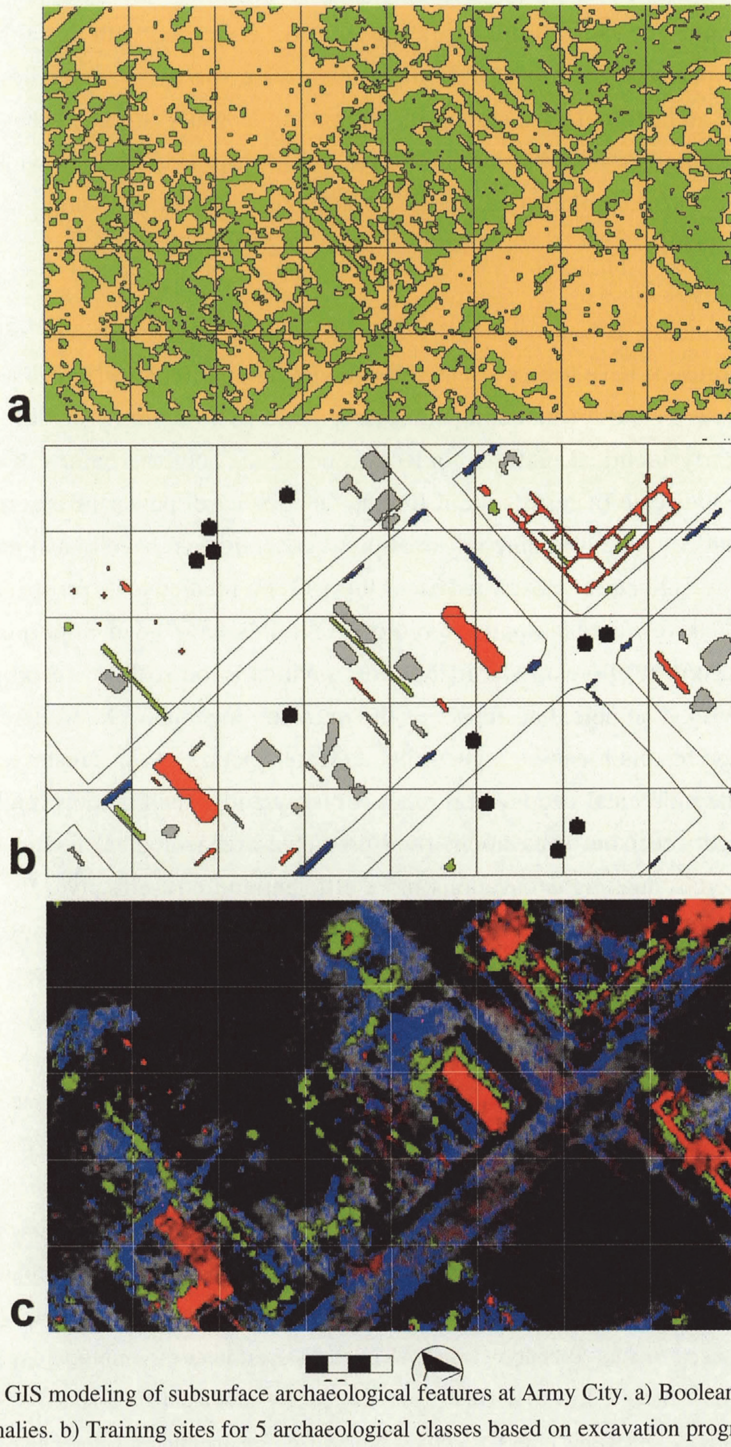

Fig.4 Intra-site GIS modeling of subsurface archaeological features at Army City. a) Boolean union model for all robust anomalies. b) Training sites for 5 archaeological classes based on excavation program with outlines of streets and alleys (from historic map). c) Probability surface models for specific archaeological features. KEY (for b, c): Black=background featureless locations; Green=pipes; Blue=street gutters; Red=concrete & masonry;Gray=all other archaeological features.

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Table 1 Parameter estimates for the four Army City logistic regression functions: $L_k = \alpha_k + \Sigma_{i=1,6} \beta_{ki} X_i$ applied to each pixel. All data are standardized.

	MODEL CLASS (k)			
PARAMETERS	Pipes	Gutters	Concrete	Other
Intercept (α)	-.733	-.121	-1.465	.414
Conductivity (β1)	.173*	.546	.754	.162*
GPR (β2)	.634	1.368	.972	.928
Magnetometry (β3)	2.152	.008*	.479	.656
Mag.Susceptibility (β4)	2.684	3.385	3.002	3.008
Resistivity (β5)	.607	1.924	3.496	1.778
Thermal (β6)	.273	.227	.515	.377

*Parameters not significant at α=.05

Table 2 Classification accuracies of the Army City models applied to the training data.

	TRUE TRAINING CLASS						
PREDICTED CLASS	Background	Pipes	Gutters	Concrete	Other	TOTAL	%
Background	459	16	10	24	218	727	63.1
Pipes	0	330	27	54	156	567	58.2
Gutters	5	28	273	121	372	799	34.2
Concrete	0	5	17	1156	184	1362	84.9
Other	42	43	122	75	650	932	69.7
TOTAL	506	422	449	1430	1580	4387	
%	90.7	78.2	60.8	80.8	41.1		

Overall accuracy: 65.4%; Average accuracy (columns): 70.3%

GISを用いた考古学モデリング
－大規模にも小規模にも－

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遺跡周辺に関する地域GISモデルが、20年間にわたって検討されてきた。各種の空間分析によって、発見されるかあるいは理解されるかもしれない遺跡分布の環境のパターン化（遺跡分布と周辺環境のパターンとしての認識）に依存している。それを受け、GISアルゴリズムはより大きなエリアにわたる遺跡分布モデルを生成できるように、様々な手法で開発あるいはバージョンアップされる。多くの場合、そうしたモデルは適用事例を通じて、強固で信頼できることが示されてきた。そして、これらの方法は世界中の文化資源のマネジメントとプランニングにおいて顕著な傾向となってきた。

だが、同様のGISを用いた手法で、遺跡内の地表下（の様相）をモデル化することができるのだろうか？

地球物理学的な多次元の属性データを利用するアプローチが採用され、地表下の異なった特徴をそれぞれのセンサーが明らかにする。GISを用いた手法は、同時性をともなって情報を複合イメージに結合するよう開発される。この複合イメージは、地表下の様相の示す多くのデータセットに関する記述を提供する。地域的な考古学モデリングと関連する方法論は、同じように遺構を表現するアルゴリズムの遺跡内モデリングを可能とする。コンピュータグラフィックや単純な数学的操作、そして統計学的アプローチなどについて、遺跡内の地表下の様相をモデル化しあるいは記述するために検討する。