INTRODUCTION

Understanding why people choose to move from one location to another and areas of greater or lesser traffic flow can suggest the social significance of a given space as well as how transport infrastructure is used for movement. The importance of transportation for land-use, human-to-human, and human-to-environmental interactions is clearly demonstrated for a variety of spatial settings (Rapoport 1990, Johnston and de la Barra 2000, Stough 2004). Despite disparities in theoretical approaches, archaeologists and other social scientists generally agree that transport infrastructure often shapes and is shaped by significant social developments that affect how people perceive space and movement within that space (Snead et al. 2009, Wheatley and Gillings 2002, Lefebvre 1991). Given transport infrastructure's social significance, researchers need to understand both its arrangement and utility in various settings. For many cases dealing with past pedestrian transport, however, data needed in order to assess and understand what areas one may expect heavy traffic, preferences for specific routes, and decisions people make in order to move to given locations are missing. In perhaps a few historical cases, data are more easily recoverable, allowing researchers to create modeling approaches that can replicate, to a high degree of fidelity, relevant social and physical behaviors affecting human walking. Whether needed data are readily available or not, spatial approaches need to be applied by researchers in order to make assessments of traffic volume that directly affects wider social understanding.

Modeling approaches within geographic information systems for transportation (GIS-T) have been traditionally applied by analysts and researchers in order to assess transportation behavior and structure (Goetz et al. 2004). However, applying such tools can prove to be cumbersome in integrating different modeling techniques and expensive, limiting their potential for modifying assessments as new data and theoretical understanding arises. Models incorporated should allow assessments to be made by leveraging different and multiple approaches in order to provide the broadest analysis possible that is modifiable to a wide variety of circumstances and scenarios. By enabling an application to modify modeling approaches and available data, the tool becomes more feasible for analysts working with largely missing, emerging, or complete data as well as testing different theoretical assumptions.

This paper introduces an object-oriented geosimulation environment for modeling pedestrian transportation. Our approach allows users to integrate both mathematical and agent-based models (ABMs) in order to address questions dealing with pedestrian transport. The main focus of this paper is to demonstrate how our modeling approach provides reasonable assessments of past pedestrian traffic volume and allows researchers to determine areas that warrant further archaeological investigation. The primary analytical benefit of our approach is that it allows researchers to integrate multiple modeling methods that enhance archaeological understanding. For the case study, we integrate a biophysical model that enables agents to determine physical costs of travel based on how much energy is consumed in order to walk to a location. In addition, an agent-based (or individual-based) approach is used in order to provide discrete event flexibility and allow different types of individuals to be modeled. The paper begins by providing details of our modeling methodology and specific models used in addressing our pedestrian case study. The case study is then presented, detailing why the models

applied are appropriate. Applying the simulation method to the case study, results demonstrate our approach in addressing archaeologically relevant research questions. These results are then compared to fieldwork observations in order to help validate and show that the applied models provide useful insights. After this section, we discuss how modeling results and approaches are applicable to archaeological problems and research. We also present the general utility of our approach, discussing relevant modeling issues based on applying an object-oriented and multi-model method.

SIMULATION METHODS

Background of the Approach

Quantitative and modeling approaches are increasingly being used to address such topics as assessing archaeological landscape transformations and site analysis (Barceló 2009). Included within this trend, ABMs (Bonabeau 2002) are being incorporated with GIS technologies in order to provide geospatial analysis capabilities and modeling flexibility that addresses bottom-up processes over continuous and discrete time (Rand et al. 2005, Brown et al. 2005, Branting et al. 2007, Robinson and Brown 2009). Applying ABMs to pedestrian transportation is nothing new, as the approach provides benefits by allowing researchers to incorporate human decision-making, heterogeneous agents, and movement within grids or street networks (Lake 2001, Batty et al. 2003, Batty 2003). The list of current tools and approaches is extensive; we refer to Zhou (2008) in order for readers to review recent applications of ABM-GIS tools for pedestrian transportation. Few tools, however, have been developed to allow varied types of models, in addition to ABMs, to be integrated into analysis and the incorporation of new models as needed through development frameworks.

In our approach, we apply an object-oriented Java-based modeling application, called SHULGI and built using Repast Simphony (Repast 2010) as the underlying modeling structure, in order to assess areas where pedestrian traffic is expected (Branting et al. 2007). The SHULGI tool only applies open source and free tools, making its methods easily accessible to others and requiring minimal financial costs to upgrade. SHULGI currently uses GeoTools as the main GIS framework (GeoTools 2010), which is directly coupled to the SHULGI application. Modeling and algorithm choices built within SHULGI relate to metabolism (McDonald 1961, Pandolf et al. 1977), velocity (Imhof 1968), least-cost route selection (Dijkstra 1959, Hart et. al. 1968), elevation interpolation through triangulation or inverse distance weighting (de Berg et al. 2008), and ABMs (e.g., Standard Decision Model).

Additional models and algorithms can be created and integrated within SHULGI using Repast Simphony's development environment (North et al. 2007, Repast 2010). Figure 1 shows a GUI model creation tool, which allows models to be created in Java and then directly coupled to SHULGI. Users can apply mathematical notation or conditional statements (i.e., if-then-else statements) within the model creation process, potentially enabling those with limited programming experience to create and apply different types of models. Models can be created using discrete events or fixed time steps, giving greater

temporal flexibility than traditional GIS modeling methods (Pawlaszcyk and Timm 2007).



Fig. 1. Model displayed using the Repast Simphony model GUI development environment within Eclipse (North et al. 2007). The model shown here is described and detailed in Section 3.1 (Standard Decision Model).

Similar to other ABM efforts that address past land use dynamics, models are not integrated directly with agent objects in SHULGI; rather, they are represented by their own simulation objects which are used by agents as needed (Christiansen and Altaweel 2006). The benefit of this approach is that it potentially allows multiple models to be concurrently applied, enabling efforts to leverage the strengths of each modeling approach for research problems. Data loaded are directly mapped by the user to specific agent and object parameters using XML or SHULGI's GUI. Outputs produced by modeling are exported via shapefiles, with these data then brought into different GIS environments (e.g., ArcGIS) for further analysis.

For the case study demonstration to be presented below, we apply models that specifically address metabolic expenditures and route decision-making. The metabolic model we use is the built-in McDonald model, which determines how much energy agents require in walking a specific street segment. We use an ABM route selection model, called the Standard Decision Model (SDM), that allows agents to determine locations to go to (see Figure 1). Our scenarios have focused on energy minimization, whereby agents choose routes that require the least amount of energy to walk. Although the selection of routes through minimal energy costs is not the only assumption one can make, it is a valid initial consideration to test in order to see if energy costs were a major

determinant in decision-making. In other words, lacking social data on how people make decisions on selecting routes, we feel a reasonable approach is to begin with known and simple factors affecting walking, primarily physical energy expenditures and the transport infrastructure, in order to identify locations where one could expect different patterns of traffic to develop. The results of modeling assumptions should then be checked with archaeologically recovered data, which we will discuss in a later section.

In scenarios, objects that are evolved by modeling include: TransportAgents that represent agents modeled, Structures which contain data about urban structures, ShuligEdges which are edges in a road network, RoadNetworkNodes that comprise the ends of road edges, a RoadNetwork which contains the ShulgiEdges and allows network analysis, and DestinationNodes that represent locations agents travel to. We have also provided SHULGI as a supplementary file to this electronic article (see Additional Files). The file provides information on objects used and SHULGI's Java code.

Applied Agent-Based Model Detail

We developed the SDM model in order to allow all modeled urban structures to be visited by each agent (i.e., TransportAgents) once; when all Structure objects have been visited then the simulation ends. Agents move from a starting center point location in a structure by selecting a route to another structure. Agents then go back to the initial start location. This process is repeated until all structures are visited. The model, in summary, attempts to find which routes become significant if one were to attempt to access all structures within the spatial setting. The intent of our modeling is to show the potential of the approach applied to realistic archaeological problems. To do this adequately, we have chosen to apply a model that addresses a reasonable research goal and that can be validated to some extent, showing the research approach's utility. Other ABMs we have applied, in fact, have not produced results that we have been able to validate to any extent, as the results of these simulations did not match empirical data collected in the field. To keep this paper relatively short, we have chosen not to discuss in detail those other models applied. To summarize these attempts, however, the other models applied include those that allow agents to choose routes that are the shortest based on time or distance. In addition, SDM, using a non-agent-based variation, has been applied to modern urban settings and shown to correctly forecast pedestrian movements for different age and sex cohorts (Branting 2004). Steps involved in SDM are described in greater detail using mathematical notation.

As the first step, prior to the simulation starting, edge weights are parameterized using the metabolic model, which uses agent velocity, based on average walking speed for the given agent type, and slope gradient of the walking surface. This is expressed as:

$$\forall (p \in N) w_{pt} = M(v_t, g_t) \tag{1}$$

where w_{pt} is the edge weight of a ShulgiEdge p for agent type t, N is the RoadNetwork object, M is the McDonald model function (McDonald 1961), v is velocity, and g is the gradient of the given terrain. The agent type (t) encapsulates both the sex and age category (i.e., young, middle, and old) of the agent, which is used by the McDonald model in order to determine energy consumption for individuals. When each agent (i) traverses a specific road link, *w* is checked by that agent's type. The weight function is used for an undirected RoadNetwork object, prompting the weight calculation to be determined for both directions of each ShulgiEdge object. This step is not repeated again, as edge weights stay constant throughout the duration of the simulation. In essence, the McDonald model determines how much energy is necessary for an agent to walk through a specific edge.

After edge weights have been initialized, agents decide which node they should go to. This is determined by the following function:

$$if (l_i \neq h_i) d_i \leftarrow h_i;$$

else { $a_i \leftarrow \delta(r, l_i);$ while $(n \notin V_i \land n \neq null) d_i \leftarrow \min(n \in a_i)$ } (2)

where *l* is the current location for agent *i*, *d* is the desired DestinationNode *i* wants to go to, *h* is the start location of *i*, δ is a function for finding the nearest DestinationNodes, *r* is the set of all DestinationNodes, *a* is a sorted set of possible locations to visit, *n* is a destination (i.e., a DestinationNode instance) *i* may want to go to, and *V* is the set of all DestinationNodes visited previously. This function, in summary, returns the agent to his/her start location if he/she is not there, but if the agent is at the start location then the next node that the agent will visit is the nearest (i.e., the minimum value of *a*) DestinationNode not previously visited. The function locating the nearest DestinationNodes is defined as:

$$\delta(r, l_i) \coloneqq \forall (n \in r) \theta(|n - l_i|) \tag{3}$$

with $(|n-1_i|)$ representing a sort function that orders DestinationNodes *n*, from nearest to farthest, using a three-dimensional Euclidian distance calculation determining distance between each *n* instance and the current location (*l*) of *i*. To find the shortest path from 1_i to the chosen destination d_i , the least-cost Dijkstra algorithm (alternative models applied include using A*) is called:

$$S_i = D(l_i, d_i) \tag{4}$$

where S is the set of ShulgiEdges that is the least-cost path based on the Dijkstra algorithm (D) that takes the start location (l) and chosen destination (d). Rather than strict distance, the weight between the two locations, as determined by (1), is used to find S in the Dijkstra implementation. After this function, agents move along the chosen path based on their walking velocity. This is simply expressed as:

$$l_{ix} \leftarrow \forall (s \in S_i) T(\frac{|s - l_i|}{v_i})$$
(5)

with each element *s*, or node location along the *S* path, reached based on the scheduling of time (*T*) by dividing the link distance between *s* and l_i (i.e., *s*- l_i) by the velocity (*v*) in which *i* moves over a given terrain (see Table 1). In SHULGI, velocity can be determined through the Imhof model or loaded static values. In any case, the current location (*l*) of *i*

is then only true at a specific time (x). Then, the agent simply checks to see if the desired node has been reached (i.e., $l_i = d_i$). The agent also checks:

$$if(d_i \neq h_i) \Longrightarrow d_i \in V_i \tag{6}$$

so that locations that are not the same as the initial home location (h) are added to the previously visited set (V). After this step, (2) is called again until all locations have been visited by the agent. The agent always returns to his/her initial location after going to a new destination. After all locations have been visited by all modeled agents, the simulation ends.

SIMULATION RESULTS

Case Study: Kerkenes Dağ

The example case study in which we apply our integrated modeling methodology is the archaeological site of Kerkenes Dağ, which is a large Iron Age site in Turkey dating to the 6th century B.C. (Summers 1997). Despite the age of this site, virtually the entire plan and street network is known through surface mapping, with structures and streets clearly visible in aerial photography. The site was occupied for a short period, perhaps less than 100 years, which has enabled many of the visible structures to survive and the assumption can be made that many of the visible structures were contemporary. Elevation on the site varies up to approximately 100 m. Nevertheless, because this case study has no or little historical data associated with it, we cannot easily determine route selection decisions made by its past pedestrians. In this case, we want to know what the likely relative traffic volume was given the street layout. Specifically, the research goal is to determine which streets and neighborhoods may have had more traffic volume in contrast to other parts of the ancient city. Knowing traffic volume within the city may provide clues as to possible social functions and status for given neighborhoods. Given the limitations of our research budget, the entire site cannot be explored through excavations in order to determine areas of relatively greater or lesser traffic volume. This necessitates a research approach that provides a reasonable assessment of traffic volume and could be validated to some extent using a sampling excavation strategy that investigates soil properties.

First, we define what factors and data we know. We divide the modeled population into six different agent cohorts that are derived based on age and gender. These agent types, as we refer to them, are referenced as: young men (aged 10–34), young women (aged 10–34), middle-aged men (aged 35–55), middle-aged women (aged 35–55), older men (aged 56–75), and older women (aged 56–75). Rather than modeling the exact population, we modeled each agent type, or expected age and sex cohorts for Kerkenes Dağ, that likely made up the majority of the pedestrian population. This is done because the past population is uncertain and the intent of the models applied is to determine route selection patterns and relative traffic volume based on varying types of agents that would have been found throughout the modeled city. Distributing the number of agents unevenly across the city landscape is a possibility, but this is speculative and only justifiable if modeling results suggest such distributions. In any case, each agent type is

modeled in scenarios by creating one agent for each building structure, initially placing that agent at the center point of structures. For each scenario, there are 758 agents.

Street edges in Kerkenes Dağ are divided based upon stride lengths of the different agent types modeled. In other words, for each agent type the street network is unique as average stride lengths vary for different agent categories. This approach allows one to factor elevation changes and energy expenditure by stride length for agents. In addition to stride lengths, average body weight and average walking velocity for the agent types are applied, with these data derived from multiple studies investigating age and sex cohorts (Fulwood 1981, Kawamura 1991, Sun et al. 1996). Age and sex cohorts in our model are defined as such because people within these groups have similar walking behaviors. Elevation data for Kerkenes Dağ's streets, taken from GPS and derivable from Delaunay triangulation, are included in the street network and used in distance and slope calculations. Visible remains of building structures that were mapped are represented as shapefiles in the model; in total there are 758 structures in Kerkenes Dağ. Table 1 summarizes the applied stride velocity, stride length, and weight values used for agent types modeled.

Tab. 1. Average velocity (km/h) of agent types are indicated with the numbered values in the Category column indicating the nearest surface slope (in degrees) for street edges walked by agents. Average stride length (m) and weight (kg) are included for each agent type.

Category	Young	Young	Middle	Middle	Old	Old
	Men	Women	Men	Women	Men	Women
12	7.01	6.16	6.84	5.35	4.97	4.75
11	7.40	6.50	7.22	5.65	5.25	5.01
10	7.40	6.50	7.22	5.65	5.25	5.01
9	7.40	6.50	7.22	5.65	5.25	5.01
8	7.56	6.65	6.89	6.60	6.28	5.36
7	7.36	7.04	6.99	6.42	5.86	5.41
6	7.31	7.30	7.27	6.62	6.18	5.57
5	7.46	6.48	7.21	7.34	5.81	5.48
4	7.65	6.84	7.21	6.74	6.02	5.65
3	7.94	7.21	7.05	6.72	6.43	5.88
0.5	7.77	7.58	7.47	7.03	6.65	6.08
0	8.61	8.10	7.81	7.16	6.85	6.16
-0.5	8.03	7.82	7.26	6.57	6.47	5.78
-3	7.19	6.66	6.85	6.61	5.44	5.76
-4	7.70	7.23	7.28	6.81	6.02	5.58
-5	7.55	7.32	7.07	6.54	5.55	5.29
-6	7.62	7.31	7.67	5.76	5.36	5.37
-7	7.69	7.11	6.95	6.31	5.51	5.37
-8	7.22	6.93	6.84	6.55	5.68	4.81
-9	8.50	8.30	7.34	6.64	5.86	4.36
-10	8.50	8.30	7.34	6.64	5.86	4.36
-11	8.50	8.30	7.34	6.64	5.86	4.36
-12	7.48	7.31	6.46	5.85	5.16	3.84

Stride Length	0.68	0.63	0.65	0.58	0.57	0.51
Weight	68.89	72.19	71.39	55.05	59.02	58.79

Simulation Outputs

Each scenario, in which there are six, consists of one agent type (e.g., young men) for all modeled TransportAgents. Although we are aware that among the benefits of agent-based modeling is its ability to integrate heterogeneous agent types into a given simulation environment, for the purpose of presenting results we have divided modeled groups. However, we also present the results of all the scenarios integrated together, which represent results of a heterogeneous mixture of cohorts. Overall, there are 758 agents per scenario, which is also the same number of structures in Kerkenes Dağ. Each scenario is modeled once since the applied models are deterministic. The outputs that our simulations have focused on include expected street traffic volume on road edges (i.e., ShulgiEdges) as well as expected traffic volume passing by specific urban structures. The second output is determined by aggregating the road edge traffic volume that surrounds a modeled structure; this is done for all structures. The results are then exported to shapefiles for statistical analysis.

Scenarios 1-6

From the six scenarios modeled, results can be summarized statistically, with information focusing on street traffic volume as measured by the number of times a street is walked on. Table 2 provides comparisons between the distributions of the number of times streets are traversed in each scenario as well as the mean and standard deviation of this measure for each agent type. We apply a Kolmogorov-Smirnov (K-S) two-sample test on traffic volume for all edges to indicate if there are significant (p-value < .05) street traffic volume for road links in all the scenarios. We also applied an Anderson-Darling test, but qualitatively the results produced by this test are comparable to the K-S test and are not presented here. As Table 2 shows, the scenarios with the greatest distribution differences are the young men and old women scenarios. In all scenarios, the distribution patterns for the number of times streets are traversed cannot be considered significantly different from each other.

Category	Young Men	Young Women	Middle Men	Middle Women	Old Men	Old Women
Young Men		0.47	1.00	0.72	1.00	0.08
Young Women	0.47		0.27	1.00	0.80	0.23
Middle Men	1.00	0.27		0.49	0.94	0.11
Middle Women	0.72	1.00	0.49		0.97	0.36
Old Men	1.00	0.80	0.94	0.96		0.27
Old Women	0.08	0.23	0.11	0.36	0.27	

Tab. 2. Comparisons (p-value) between age and sex cohorts as well as the means and standard deviations of each cohort for the number of times street segments are traversed. A Kolmogorov-Smirnov test was applied to test for differences between the distributions.

Mean	3835.71	3805.67	3844.75	3809.15	3830.92	3804.20
S.D	8357.07	7923.92	8437.07	8015.06	8265.38	8017.25

Figure 2 shows modeled spatial output for the young men scenario. Overall, streets indicated by the numbers 1-5 and the lettered structures are areas where the most traffic is discernible. The streets designated as 1-5 are ordered from the greatest to the least traffic volume among the top five traffic volume streets. Ordering the top five passing traffic volume structures, from greatest to least volume, yields the following result: A, B, C, D, and E.



Fig. 2. Modeling results from the young men scenario showing streets with the most traffic volume (numbered 1-5 with 1 having the most traffic) and structures with the most passing traffic volume (lettered). Street traffic and passing structure volumes, using standard deviation, are indicated by the thickness of lines and polygon shades respectively.

Since both statistically and qualitatively most of the scenario results are similar to each other, we find it necessary to only show one other scenario, the old women scenario, as this case differed the most from the young men scenario (Figure 3). The other cases, however, are used as a part of the aggregate results that will be presented. In the old women scenario, some different patterns of traffic volume are observed. Nevertheless, even in this case the results are qualitatively similar to the young men scenario. The same five streets have the most traffic volume, with the order from greatest to least also being the same. Similar structures to the young men scenario (i.e., structures that are nearby to those in the young men scenario) are passed by the most in the old women scenario, but some differences are noticeable. The order in which structures are listed from greatest to least passing traffic volume in the scenario is: A, C, D, B, and F.



Fig. 3. Modeling results from the old women scenario showing streets with the most traffic volume (numbered streets 1-5 with 1 having the most traffic) and structures with the most passing traffic volume (lettered).

If we assume that all agent types were present at any given moment during the history of Kerkenes Dağ, then all agents should be investigated together to determine the overall route selection pattern. In other words, aggregating the results from the different scenarios allows us to determine which streets enable the easiest access to different structures and the overall passing traffic volume for structures in all agent types. Figure 4 provides the cumulative results for the six scenarios, showing streets we expect to have the most traffic and structures that have the most surrounding traffic volume. As in the other scenarios, the same five streets have the greatest expected traffic volume. The total passing volume results for structures are very similar to the young men scenario, with the same order, from greatest to least, for the five structures that have the greatest passing volume: A, B, C, D, and E.



Fig. 4. Aggregate simulation output for all agent types. As before, the five streets with the most traffic volume (1-5 with 1 being the most) and structures with the most surrounding traffic (lettered buildings) are shown.

Comparing Modeling Results to Fieldwork

Methods of validation are critical in order to demonstrate that an approach has at least some merit in addressing real-world phenomena. Although social models likely cannot be definitively proven for all possible cases, validation indicates if an approach is able to produce results that match empirical data to some extent (North and Macal 2007). For archaeological problems, validation is often difficult because models cannot be easily tested against empirical data due to difficulties in recovering various types of information and limited sample sizes. Nevertheless, we believe it is necessary to conduct modeling approaches on problems in which some level of validation is possible, as this helps to support arguments made via modeling.

We present our approach to model validation by showing how fieldwork complements our simulation methods. As far as we know, our approach to validation has not been conducted in previous similar studies, particularly cases in which modeling is directly integrated with the type of fieldwork we apply, making our validation approach relatively novel. The intent of validation in this section is to show that our research methods produce outputs useful for addressing relevant scientific questions. In the current case, comparisons between simulation output and collected data indicate if results obtained from simulations correspond to evidence for greater or lesser street traffic volume as well as demonstrate that the case study applies appropriate models for the research topic. Recent sample excavations using small test trenches have focused on determining the size of soil particles from street networks. The size and compaction of soil particles indicates the relative amount of trampling that occurred on a given street.

Soils with larger and less compact particles have been walked on less; soils with smaller and more compact particles have been walked on more (Burden and Randerson 1972).

A total of sixteen separate street trenches have been sampled so far, with more currently being planned. These trenches are located in streets that have been modeled to show relatively greater or lesser traffic volume. From current results, average particle sizes, from all tests conducted on each trench sample, are the smallest for the street that had the most aggregated simulation traffic (i.e., Street 1 in Figure 4). This street (Trench TT25) averages roughly 450 µm soil particle size based on samples taken from different locations, including above, below, and from the street level (Figure 5). The street with the third greatest simulated traffic volume (i.e., Street 3; Trench TT24) averages roughly 800 μ m soil particle size. Other streets (e.g., Trench TT23), that in the simulations have relatively low traffic volume, range up to 1400 µm soil particle size. Although current fieldwork does not prove definitively that the streets with the greatest simulated traffic volume did have the most traffic in the past, what the field collected results indicate is that at least two of the simulated streets do appear to have evidence for greater relative traffic than other archaeologically sampled streets. This suggests that these two streets may have been more central or significant in connecting different parts of Kerkenes Dağ's street network. Further fieldwork will help to show if simulation results are consistently linked with archaeologically collected data. For now, because our modeling output appears to match relatively well with data collected in the field, the models applied are deemed appropriate in addressing how traffic volume may have been distributed. Because the goal of this paper is to demonstrate our methodology, current validation demonstrates that so far our methods produce reasonable outputs. We recognize that further data are needed to better validate our presented approach; however, if new data show that our modeling method is not valid then new models, representing different behavior than agents selecting street networks based on minimum energy expenditure, need to be built. In addition, with further data collected, more meaningful statistical comparisons can be done to investigate model output against empirical data.



Soil Particle Sizes from Trenches

Fig. 5. Graph showing three of the sixteen trench samples (TT23-25) with soil particle sizes measured from different locations (Above, Surface, or Below) in the trenches.

Trench TT25 (Street 1) has the smallest particle sizes. Trench TT23's results are from a street with low simulated traffic volume.

DISCUSSION

Benefits for Archaeology

Among the benefits of our approach to archaeology is that it enables different case studies, where traffic patterns are likely to be unknowable from data sources, to apply quantitative methods, including metabolic and agent-based modeling, that can then be validated through some level of fieldwork. Such benefits are extendable to a variety of case studies, where models are modifiable and applied as appropriate based on available field observations that best match applied model results. Archaeological investigations within a site are often limited by funding and time constraints. Techniques that can enable valid assessments of past traffic patterns and likely areas of movement are able to provide some understanding of transport infrastructure within archaeological sites even in cases where limited site investigation is possible. Such quantitative approaches potentially enable researchers to better understand the significance of social spaces by providing insights as to how areas within sites were accessed, used, or potentially culturally perceived by inhabitants (Myers 2000, Snead et al. 2009). In the case study presented, streets in the central and parts of the eastern areas of the site, as seen on Figures 2-4, appear to have the most simulated traffic volume. The results show that many structures closer to the central part of the site have the most simulated traffic passing by them. These high traffic volume areas could have been likely markets and important government or public buildings that required more general access. In contrast, structures on the periphery around the site could have been private residences, which may imply that privacy and/or less central habitation were important social constructs to inhabitants.

Although quantitative techniques alone do not provide a full explanation of theory regarding movement, such modeling as discussed here does provide some clear presentation of social or physical behavior that can then be placed within a broader theoretical context. Pedestrian modeling provides a quantitative capability in explaining qualitative understanding of past walking behaviors or serves as a heuristic methodology testing theoretical constructs. Quantitative approaches are also measurable and should be compared to empirical data recovered from fieldwork. Based on this, the results show that archaeological investigations applying modeling approaches should attempt to closely couple their fieldwork with modeling. Results obtained in the field should assist in model creation and validation. This suggests that archaeologists should design their fieldwork, when models are used, that enables model testing and validation, while models applied to scenarios in which fieldwork does not support validation will likely produce simulation results that are more tenuous in supporting theoretical arguments made.

The methods advocated here may also be applied to cases in which archaeologists seek to find new areas for further archaeological investigation. In other words, archaeologists can investigate, through excavations or other exploratory methods, areas that appear to be potentially significant based on simulation results of pedestrian traffic volume. This form of archaeology enables projects to better utilize project resources by determining which areas necessitate more focused investigations. This type of modeling, however, should only be applied after model validation. In other words, if a model is constructed and it appears to produce outputs that match data collected in the field, then this indicates that the model could be used to guide researchers to investigate unexplored locations where pedestrian traffic volume produced via simulation suggests new areas of interest.

Broader Benefits

We recognize that alternative modeling approaches could have been applied to the scenarios presented. However, this paper demonstrates why researchers may find it necessary to integrate a methodology that enables multiple modeling approaches and different tools in addressing scientific problems. One advantage is that we have only used open source tools in our coupled metabolic and agent-based modeling application. This demonstrates the cost effectiveness and accessibility of our method in contrast to more expensive and less accessible methodological tools such as proprietary GIS-T software. Proprietary software can be difficult to verify (i.e., determine that model algorithms perform according to desired requirements), hindering one's ability to certify important modeling aspects such as numeric precision.

The main methodological advantage advocated in this paper is that the applied technique provides software flexibility. An approach that can couple multiple modeling techniques is more flexible in integrating alternative models and behaviors, as models do not need to be directly coupled to agent or software objects. By integrating different modeling methodologies, the strengths of each approach can be utilized as needed. Agent-based models allow simple rules and operations to function from a bottom-up level incorporating heterogeneous agents, while the metabolic model applies a numeric method for determining route energy costs. In other words, agents operate using their simple rules by interpreting the results, in this case edge weights, from the numeric approach. In the approach presented, models can operate using a constant time step (i.e., equal time intervals) approach or discrete events that trigger model processes at potentially varied time scales. In the SDM model, agents arriving at specific locations trigger searches for new paths that agents select, making these search actions dependent on arrival events. By enabling constant time steps and discrete events, simulation techniques are able to incorporate a wider variety of models. Alternatively, traditional GIS software is generally not conducive for designing models that operate at variable temporal scales, limiting their utility in integrating multiple simulation methods.

CONCLUSION

In this paper, we apply an integrated approach that couples metabolic and agent-based modeling used for determining past pedestrian route selection. For the given scenarios, we feel this is a useful technique since lacking detailed social rules requires that we investigate route selection based on transportation costs as determined by physical energy expenditures for individuals. Although different models could be applied in our use case, the intent of this paper is to demonstrate an emerging technique that reveals the utility of applying multiple modeling methods, including ABMs, to geospatial problems in

archaeology. This includes determining areas of past pedestrian traffic and areas that may warrant further archaeological investigation. We are not purporting that other techniques, such as GIS-T, should be discarded; rather, we take the position that integrating advantages described in this paper can enhance overall modeling approaches and help to address archaeologically relevant problems. We believe that the integration of multiple modeling approaches, such as described here, should be a major area of active development within GIS applied to past social systems.

For our own efforts, if further data become available from fieldwork conducted, we will test and modify the current model as needed. For future studies, we seek to apply a valid model in guiding new and targeted archaeological investigations on past pedestrian transportation at Kerkenes Dağ and other sites.

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