

The Effect of Spatial Clustering on Stone Raw Material Procurement

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Abstract—Brantingham [1] proposes a neutral model to explain observed data on stone tool raw material procurement. Here we provide the results of investigating how real source locations, and their spatial clustering affect the raw material pattern outcome of the neutral model. Our initial findings are that spatial distributions mimicking empirical data challenge the validity of the neutral model. More specifically, increasing the source clustering increases the amount of time where the forager is without raw materials. In terms of foraging behavior, it is not realistic to expect that foragers go extended periods of time without raw materials to create and repair tools.

I. INTRODUCTION

The archaeological record shows that foragers varied the stone tool raw material preferences, even when several types of stone materials were available. The changing use and co-use of different stone tool raw materials is well known from a wide range of environmental and climatic contexts, time-periods, and cultures (e.g., [2], [3]). What explains this changing raw material preference is a question of great interest, and it is debated whether changes in stone tool raw material frequencies could be considered a reliable proxy for human forager adaptive variability (e.g., [4], [5]). Explanations for change in raw material usage frequency include climate/environmental change and its co-variability with mobility and procurement strategies [6], selection of certain raw materials for their physical properties [7], changes in demography [3], the preference for appearance or color [8], symbolic value [9], and style [10].

Brantingham [1] challenges these explanations, providing a neutral model that can explain some of the observed patterns. Brantingham [1] argues that in order to demonstrate the deliberate selection of raw materials, patterning must be shown to be different from the results of the neutral model, which provides a baseline for comparison where archaeologists can be certain that observed raw material patterns is not the result of strategic selection.

We agree with Brantingham's sentiment [1]. However, the neutral model in its original form has two major limitations. To be able to make better comparisons with archaeological raw material frequencies these two limitations need to be explored

and corrected: 1) the raw material sources are distributed randomly without any clustering across the model landscape, which is not the case on a real landscape where potential raw material source locations are controlled by the underlying geological structure and geophysical processes; and 2) each raw material location in the model represents a unique raw material, which is not realistic. Five thousand raw material sources are possible over an extended landscape but not 5,000 unique raw materials. It is more likely that a smaller amount of different raw materials, say 1-25, are represented by the 5,000 source locations. In addition, the 1-25 unique raw materials are not randomly distributed in isolation away from same type raw materials. As discussed under limitation 1, not only are source locations clustered due to the underlying geological structure and geophysical processes but also depending on the geological formation (several sources of the same material can be available in a cluster).

The overall question we address is how does the structure of a real landscape and real source locations affect the output of the neutral model? We specifically address a question related to the first limitation: What is the effect of spatial clustering of raw material sources on the model raw material procurement output?

II. EMPIRICAL DATA

The test case is the landscape around the town of Mossel Bay, Western Cape, South Africa. The Mossel Bay region has several archaeological sites that, combined, offer a long sequence of change in raw material selection [11], [12]. The local geology is well understood [13], and thorough surveys for potential raw material sources have been undertaken. In total, 38 potential stone tool raw material sources have been discovered, which is likely an underestimate. These sources ranges greatly in size (Figure 1), are clustered according to geological structures and geophysical processes, and only 6-7 raw materials are represented among the 38 sources.

III. MODEL DESCRIPTION

Brantingham [1] created a simple model of one agent with a mobile toolkit of fixed capacity that is randomly placed on the environment. At each time step, the agent moves to

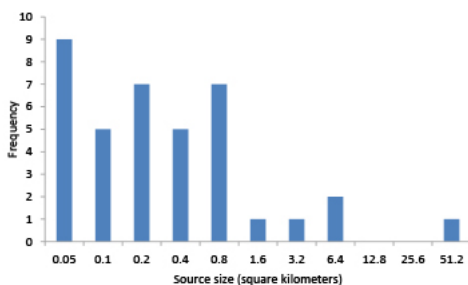


Fig. 1. Frequency of stone tool raw material source by size bin in the Mossel Bay area.

one of the nearest eight neighboring cells or stays in the present cell, with equal probability ($= 1/9$). Each time step a fixed amount of raw material is consumed dependent only upon its frequency in the mobile toolkit. If a raw material source is encountered, the toolkit is re-provisioned up to its maximum capacity before moving again at random. If no raw material source is encountered, the forager moves immediately at random. Simulations are run until 200 unique raw material sources are encountered, or the edge of the simulation world is reached. The model is replicated in Netlogo by Janssen and Oestmo [13].

For our analysis we use a maximum capacity of the tool kit equal to 100, the environment is 500x500 cells and consist 5,000 unique material resources. When we include clustering of resources, we include a probability p_r . When we place the 5,000 material resources on the landscape there is a probability p_r where the new material resource is placed on a randomly chosen empty cell. With probability $1 - p_r$ the new material resource is placed on a randomly chosen empty cell that has at least one neighbor (one of 8 neighboring cells) that already contains material resources (see Figure 2 for an example landscape).

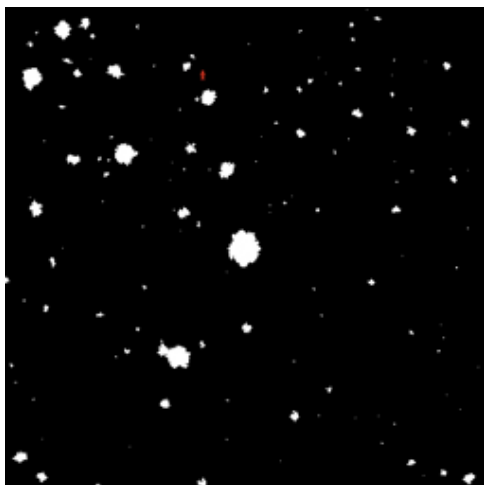


Fig. 2. Distribution of material resources (white) when $p_r = 0.01$.

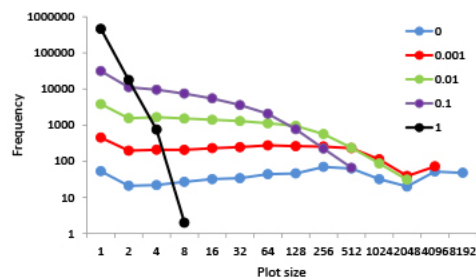


Fig. 3. Distribution of sizes of material resources in generated landscapes.

IV. MODEL ANALYSIS

When we simulate the model 1,000 times for different clustering of material resources, we derive different outcomes on the metrics of raw material procurement. We consider different values of p_r (Figure 3) and see that a more clustered environment leads to a much larger tail of richness of material in the toolkit (Figure 4). The continuous refilling of the toolbox when the agent is moving on a large cluster of materials is causing this richness of materials. However, the richness value is inflated because it is assumed that each source is a unique raw material.

The distance that material resources are moved after collection remains similar (Figure 5) throughout the random landscape. We see that clustering leads to much longer times in which the agent has no materials. With $p_r = 0$ the average time agents look for resources is 3,700 steps, while it drops to 1,600 steps when $p_r = 0.01$ and to 107 steps when $p_r = 0$ (Figure 6). If resources are more clustered than simulated in the original model, we can expect that foragers will run out of materials for longer periods of time. If we calculate the percentage of time the agent is without materials we find this to be 14% for $p_r = 0$; 63% for $p_r = 0.001$; 83% for $p_r = 0.01$ and 0.1; and 34% for $p_r = 1$. Hence, the original neutral model might not be an appropriate model for landscapes with raw material sources clustered like empirically observed. It is not realistic to expect that foragers will go extended periods of time without raw materials to create and repair tools.

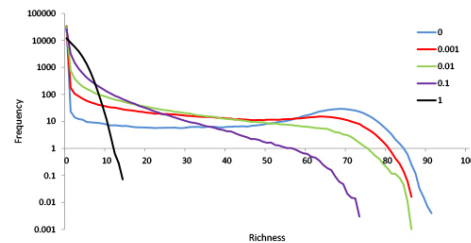


Fig. 4. Distribution of richness (number of unique material sources).

V. OPEN ISSUES

By the conference in September, we will have extended the analysis for different p_r values over more simulation runs. We would also like to address limitation 2, to test the effect if we

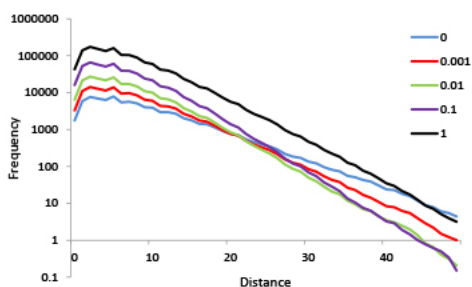


Fig. 5. Distance that material is moving until discarded.

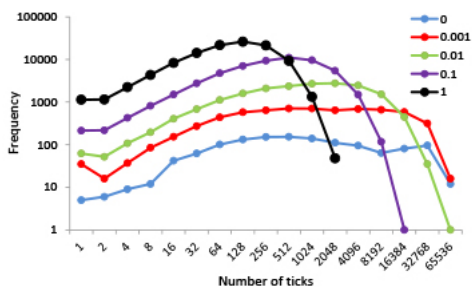


Fig. 6. Distribution of the number of steps that agents make when toolkit is empty.

assume that locally clustered materials are represented by the same raw material and not different raw materials. Finally, we would like to test the effect of different random walk implementations.

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