Adaptive Behavior
XX(X):1–17
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DOI: 10.1177/ToBeAssigned
www.sagepub.com/
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A Spatially explicit ABM of Central Place Foraging Theory and its explanatory power for hunter-gatherers settlement patterns formation processes

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Abstract

The behavioural ecological approach to anthropology states that the density and distribution of resources determine optimal patterns of resource use and also sets its constraints to grouping, mobility and settlement choice. Central Place Foraging (CPF) models have been used for analysing foraging behaviours of hunter-gatherers and to draw a causal link from the volume of available resources in the environment to the mobility decisions of hunter-gatherers.

In this study we propose a spatially explicit agent-based CPF mode. We explore its potential for explaining formation of settlement patterns and test its robustness to the configuration of space. Building on a model assuming homogeneous energy distributions we had to add several new parameters and an adaptation mechanism for foragers to predict the length of their stay, together with a heterogeneous environment configuration.

The validation of the model shows that the spatially explicit CPF is generally robust to spatial configuration of energy resources. The total volume of energy has a significant effect on constraining sedentism as predicted by aspatial model and thus can be used on different environmental conditions. Still the spatial autocorrelation of resource distribution has a linear effect on optimal mobility decisions and needs to be considered in predictive models. The effect on settlement choice is not substantial and is more determined by other characteristics of settlement location. This limits the CPF models in analysing settlement pattern formation processes.

Keywords

agent-based model, hunter-gatherers, central place foraging, mobility, settlement choice

Introduction

Mobility is one of the most distinctive features of hunter-gatherer lifeways and therefore has attracted a significant amount of research. Studies of empirical material collected by ethnographers have shown that varying rates of both residential and logistical mobility, i.e. respectively settlement decisions and day to day movements to get the required resources, are related to subsistence behaviour and environmental conditions. Mobility patterns observed in ethnographic studies have been used for explaining archaeological settlement patterns using correlates between known mobility and environmental variables. This allows archaeologists to draw hypotheses about the economy and organization of past societies. (Binford 1980, 2001; Kelly, 1983, 2013; Lee and Devore, 1968)

Hunter-gatherer mobility patterns have often been explained by foraging requirements. They need good locations for foraging for resources and move when the conditions become less favourable due to diminishing foraging returns. The explanations are formalized in a number of models, mostly based on Optimal Foraging Theory (Emlen, 1966; MacArthur and Pianka, 1966; Schoener 1979) and marginal value theory (Charnov 1976). Both models were originally developed to predict animal behaviour while foraging the environment to fulfill their energetic requirements. Hunter-gatherers have more complex foraging organization than non-humans and their mobility strategy has been described as Central Place Foraging (CPF). They are assumed to set up a central base from which they make logistical forays to acquire food and other resources. In the present paper, we consider in particular the CPF mobility model of Kelly (2013, p. 96-101), which formalizes the effects of the environment on mobility and assumes that the active foragers in a group dominate the choice of residential moves.

We construct an Agent-Based Model (ABM) that builds on Kelly's work in order to test CFP model robustness and explore residential mobility in the context of heterogeneous landscapes, hence heterogeneous environment and spatially varying distributions of resources. Spatial variations in environmental conditions and its influence on hunter-gatherer mobility patterns have been analysed before, but not in the context of CPF mobility modelling. Landscape heterogeneity can result from exogenous causes such as natural variations (soils, vegetation types, proximity to water, etc.) or arise endogenously from resource depletion due to foraging habits. If the environment is the key to

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understanding mobility patterns and the spatial distribution of Central Place foragers, we question here how its spatial distribution impacts our understanding of foraging and settling behaviour. In addition, since hunter-gatherers, by their actions, change the spatial distribution of the resources through time, we think it is important to consider the impact several hunter-gatherer groups have on a given landscape.

Kelly's original model assumed homogeneous distribution of energy resources in the environment. It involves a choice between staying or moving to alternative sites and focuses on the timing of this decision and the distance between sites. We introduce these decisions in a spatio-dynamic Agent Based Model. Our framework allows for multiple locational alternatives (not only distance) to be modelled in a spatial explicit environment where there is heterogeneity in the availability of resources. The likelihood of choosing a new base site, i.e. the utility of a particular location, is deterministically defined by a measure of access to resources from the location and idiosyncratic variability among agents (hunter-gatherer groups).

We explore the new insights that the spatially explicit model could offer us regarding settlement pattern formation processes and whether the CPF model can be used as a link to empirical settlement data. Kelly's model is an aspatial model, hence moving decisions are made irrespective of the existence of alternatives. By introducing a spatially explicit landscape, we add multiple choices and an interaction between the decision to move and the choice of alternative sites. Adding spatial dimensionality allows us to understand the emergence of settlements across a given area. To do so we introduced several new components including the calculation of utility values of all locations in the environment, generalizing the foraging process without simulating individual foragers moves, depletion and recovery of resources and adaptive expectations of agents about their duration of stay in a settlement location.

The remainder of the paper is organized as follows: in the next section "Theory", we position our model within existing theories and models of hunter-gatherer mobility. In the section "Model description" we describe the components and the functioning of our model. Our experimental results are presented in the section "Simulation results" where we show the effect of varying environments on residential mobility and how this effect is mediated by two parameters of the model: the general level of resource available and the costs of moving. We then discuss the effect of heterogeneous resource distribution on mobility parameters. Conclusions follow in the last section. The details of implementation following ODD+D protocol are described in appendix of the article.

Overall, we find that the CPF model is generally robust to initial environmental conditions. But we find that the energetic resource dispersal in the environment has a significant effect on the time at which move decisions are made. Environments with more clumped energy resources lower mobility rates while a more even spatial distribution increases mobility. We also show that the settlement location choice aspect of mobility can not be well explained by just energy distribution. Placement configuration of critical resources and local affordances in space play a more significant role. We discuss the CPF mobility model as a way to explain empirical settlement patterns in a spatially explicit way and conclude that it would require including information about critical resources and local affordances required at a prospective site location.

Theory

In this section, we contextualize our work within the hunter-forager modelling literature. A comprehensive literature review is out of scope rather we bring the essential theoretical (mostly from Kelly, 2013) and empirical elements related to foraging and mobility, from which we build our model, then position it with regards to other agent-based models of hunter-gatherers' behaviour.

Central place foraging and mobility

Theories of hunter-gatherer land use are mostly based on optimal foraging theory, originally developed as a part of behavioural ecology describing animal behaviour. The anthropological version of the theory asserts that, in several domains, human decisions are made to maximize the net rate of energy gain. Together with dietary choices, foraging time, group size, residential mobility and settlement location decisions belong to those domains (Bettinger, Garvey, and Tushingham, 2015, p. 92). As mobility and settlement choice are the basic choices behind the emergence of settlement pattern formation Optimal Foraging Theory (OFT) can be used to explain at least a part of the process. According to OFT, hunter-gatherers choose their location in the environment so that they can gain maximal amount of energy with minimal effort. The choice of the location of a site is expected to be close to critical resources (eg. fuel or water) in case the resource is rare and bulky. But more generally it will be placed next to the acquisition center of food and mentioned critical resources (Winterhalder, 2001, p. 21).

The question of when a decision to move is made is addressed by the marginal value theorem, which states that optimal foragers leave a patch when its declining marginal return rate equals the average level of the environment (Charnov 1976). The timing of the move will then be determined by the gain curves of available resources. Although the theorem is originally developed for explaining animal behaviour it has been successfully applied for hunter-gatherer residential mobility (eg. Winterhalder 1981; Hames 1980; O'Connell & Hawkes 1981; O'Connell & Hawkes 1984). The empirical study of Batek showed that camp movements coincided with the point at which resource acquisition declined to a certain threshold level (Venkataramana et al 2017).

Describing the timing of residential moves leads us to the concept of mobility which has long been considered as one of the most characteristic features of lifeways of hunter-gatherers. In his influential paper "Willow smoke and the dog tails", Binford (1980) introduces a distinction between residential and logistical mobility. Residential mobility refers to the movement of inhabitants from one residential base to another. Logistical mobility is the daily mobility required for acquiring resources and transporting them to the residential base. Drawing from this distinction, Binford proposed the concept of a forager-collector continuum. Compared to collectors, foragers have higher residential mobility, i.e. moving people to resources, while collectors rely more on logistical mobility, i.e. moving resources to people.

Residential mobility and logistical mobility are interdependent behaviours: a higher residential mobility lowers the logistical mobility and vice versa. Each hunter-gatherer group can be situated on the continuum based on how much use of both types of mobility is adopted. The optimal strategy (i.e. bundle of residential and logistical mobility) is the one that provides higher net foraging returns (Binford 1980). Empirical evidence compiled by Binford (2001) from records documenting hunter-gatherers in ethnographic observations show significant variations in residential mobility. The number of residential moves per year ranges from 0 to 60 and the distance of the move ranges mostly from 5 to 10 km. In some cases residential moves go beyond 60 km (Kelly 2013, p. 80-84 Table 4-1).

In order to explain the observed variations in residential mobility, Kelly (2013, p. 96-104) links individual foraging to camp movements and introduces the Central Place Foraging (CPF) mobility model. The CPF itself has been considered a distinctive feature of human foragers (as opposed to other animals, eg. Washburn & DeVore, 1961; Isaac, 1978; Lovejoy, 1981) who form camps and make logistical forays around them for gathering resources. The CPF model links individual foraging decisions to settlement pattern formation as seen in the archaeological record. It helps us explain how residential bases and their choice is related to foraging preferences. Formally, Kelly defines an effective foraging radius (re) as the distance at which the net return rate of foraging satisfies the calorific requirements of the group. The net return rate itself includes the energetic value (gross calorific returns) minus the costs of processing the food and commuting between the base and the the foraging location. In the case of a homogeneous environment it is then optimal to move the residential base to a new location, at a distance of $2r_e$ rather than make foraging trips beyond the threshold distance r_e. The forager-collector continuum is then simply a function of the the effective foraging radius:higher values of r_e correspond to lower residential mobility and the collector strategy while lower r_e corresponds to higher residential mobility and the forager strategy. Variations in r_e are then crucial and may depend on the environment, especially its level of resource availability. Hence, one can move from the effective foraging radius to the mean overall return rate (r) of the environment given daily averaged trips (t), and formalize the foraging return associated with an environment. Following Kelly (2013, p.97) and assuming 8 hours of daily foraging, the daily net return (R) for foraging is:

$$R = r(8 - 2t) - (2C_m t + C_t t) \quad (1)$$

which is expressed in number of calories per day, with: r = mean overall return rate of the environment (in calories per hour of foraging) t = time of moving to foraging location (in distance / speed (km / h)) C_m = energetic costs of a foraging trip due to moving to the location (in calories) and

C_t = energetic costs of a foraging trip due to carrying the foraged food back to camp (in calories)

Obviously after foragers settle in a camp, the resources start depleting, forays get longer and returns are diminishing. As soon as the return rate (R) no longer satisfies the energy requirements of a group (ρ_a), foragers are forced to resettle. According to Sahlins (1972, p. 33) foragers don't wait for resources to deplete completely but weight the costs of remaining at a place i and foraging further out against the benefits of moving to a new location j. Therefore, following Kelly (2013, p. 97-102), the camp is moved when the return rate (R_j) of a new location j, minus the moving costs are higher than the return rate (R_j) of staying in the base for a certain time. While theoretically elegant, the timeframe hunter-gatherers use for evaluating returns as well as the perceived costs of moving to another location are however not evident from empirical observations (Kelly 2013, p. 100)

Agent based simulations of settlement choice and foraging

Our proposed conceptual framework is based on Agent-based modelling (ABM) a computational simulation method that let's us observe how the relatively simple behaviours of components of a system lead to the emergence of complex phenomena. ABM offers an opportunity to test theories based on behaviour of individuals and project them to multiple social and spatial scales (Kohler 2000) creating a means of constructing scenarios that could never normally be observed (McGlade 2005, p. 558). ABM allows us to join the analytical nature of CPF model with simulated, artificial landscapes which can include a higher complexity of problems and use local knowledge to guide agent decision making. Agent-based models have been extensively used to study residential choice in urban and land use change contexts (for a review see Huang, Parker, Filatova, and Sun, 2014). Those models generally include a decision making process and push and pull factors related to specific locations. The factors can be differentiated as coming from environmental, economic or social domains, or both of them (Thober et al 2018).

ABM simulations have also been created to model hunter-gatherer foraging processes and its implications to other aspects of their lives. Some of the models are used to develop theory of optimal foraging to implement it in archaeological inquiry (eg. Costopoulos 1999, 2001; Lake 2000; Janssen & Hill 2016). Several domains of hunter-gatherer lives have also been studied from the standpoint of OFT by ABM including social cooperation (Premo 2006, 2012), cultural transmission and diversity (Reynold 2001; Premo 2015), cooperation while foraging (Santos et al 2015; Janssen & Hill 2014).

Premo (2015) constructed a spatially explicit ABM based on aforementioned Kelly's central place foraging model and explores how effective foraging radius (r_e) affects the size of the metapopulation composed of CPF groups. The results show that higher logistical mobility can inhibit group interaction and increase effective size of population.

An agent-based model was developed by Janssen and Hill (2016) to explore Ache mobility based on explicit environmental data of their actual environment. The purpose of the model was similar to our study, namely to assess the influence of heterogeneity of resource distributions on mobility and group size. The results showed that much greater heterogeneity in resource distribution does not favour larger camp size as expected (Kelly 2013) and has a modest effect on camp mobility.

While the Ache mobility model is constructed based on ethnographical data, a similar model has also been published to reconstruct Stone Age foraging behaviour. Wren at al (2019) constructed a Paleoscape model based on the model of Janssen and Hill (2016) using explicit paleoreconstruction of the environment of the South African coastal landscape. They published several model outputs analysing proportions of food resources, effects of population size change and planning while making foraging decisions.

The inquiry behind those models is aligned with the goals of this paper, but is based on simulating individual hunter-gatherers' actions in an explicit case. Different patterns of individual food procurement activities are extremely varied. As our purpose is to create a generic model we generalize the process of individuals foraging based on CPF theory and create a decision model based on camp level without going into details about specific foraging activities. We also create a generalized model which can be used with artificial random resource distributions and measure its impact to central place foragers mobility and settlement location choice.

To our knowledge, so far no ABM s have been developed to link optimal foraging theory to settlement choices. In previous models using residential moves the location choice has been based on distance and not on specific utility of the evaluated location. An ABM model of animal foraging has been created, extending MVP into spatially explicit space with the purpose of assessing foraging effectiveness with different spatial distributions of resources (Nonaka & Holme, 2007).

To formalize the agents' residential decision process, we use the principles of a discrete choice model, often used to describe residential mobility. Discrete choice model implies the existence of a finite choice set and an abstract utility value assigned to every choice. For settlement choice the set is composed of possible locations known to an agent with abstract utility values used to quantify the attractiveness of the locations. As described before, according to CPF theory, the utility value for hunter-gatherer residential choice is based on foraging net return rates accessible from a given location.

Model description

In this section we describe the general purpose, structure and concepts behind the model. The technical overview of the implementation of the model will be given in the Appendix to the article.

Purpose The purpose of the model is to evaluate how the abundance and placement of resources in the environment affects hunter-gatherer residential mobility and settlement choice. As implied by optimal foraging theory and empirical observations we assume that settlement choice is to an extent determined by foraging conditions which in turn are shaped by access to food resources (Kelly 2013; Binford 2001). We are studying how differences in distributions of energy resources influence optimal foraging behaviour of hunter-gatherers. The simulation model is designed as an experiment to isolate the effect of energy resource topography on hunter-gatherer mobility and settlement choice and thus test the robustness of Kelly's model and CPF approach in general to spatial configurations.

Model structure The model has two kinds of entities: the environment representing the resource distribution landscape and agents representing groups of people inhabiting the landscape by forming residential camps on it.

Environment is presented as a raster grid with each cell (i) in it having a state variable representing the potential net return rate of energy (R_i). It is the amount of energy that can be foraged from it during a day by a camp of given population with available technology and social organization. As the net return rate depletes after resource use the amount of currently available energy is stored in an additional variable.

The environment is generated by an external model configuration which determines the general characteristics of it. Configuration variables are selected so that the summed energy rate of the environment will not be depleted by artificial population and will achieve a stable equilibrium state.

As the goal of the model is measuring spatially explicit mobility patterns we decided not to use a toroidal environment and thus it has a certain edge effect. The edge effect makes edge areas less desirable for habitation. As a result agents move away from it so it does not have a significant impact on the overall results of the model. The edge area is ignored while measuring spatial autocorrelation of the environment.

The model is a stylized representation of settlement pattern formation processes, not meant to be used in comparison with empirical data. But in order to draw conclusions that have meaning in empirical reality and to avoid anomalies of scale we fit it into realistic spatiotemporal frames. For this we assume that every cell in the grid has an area of one km^2 making the whole area of the landscape 10 000 km^2. Every step in the modelling process is equivalent to one week of time as being a realistic minimum time of stay (Kelly 2013, p. 88), so a run of 52 steps would be equivalent to one year.

Agents represent hunter-gatherer residential units composed of an amount of people. As every individual in the camp is having energetic needs, the population value is used for determining the energy consumption of an agent. The measure of population is included in the system as a constant agent parameter (N = 20) because the demographic dynamics are irrelevant for current research goals. Each agent in a system is located in a specific position in the environment and consumes resources it can access by logistical mobility. Agents also include a state variable representing the duration an agent is expecting to stay at it's next location.

Process overview All agents are selected in random order and their tasks are then executed. The first agent action is evaluating the costs of staying at its current location as opposed to the best alternative location for a base. As a result the agent then either moves or stays depending on the choice.

As agents needs to satisfy an energy consumption rate determined by their population, the agents first harvest cells around it. We generalize the process without explicitly simulating the activities of individual foragers as done in OFT simulations presented in the previous chapter. A number of adjacent cells are selected and their return rate is decreased in proportion to required energy.

Over a specified time period the resources recover and original rate is restored. The resource and recovery processes are described in the submodels section.

Theoretical and Empirical Background of the Conceptual Model The essential component in agent based models involving discrete choice is a currency or utility which an agent tries either to maximize or to satisfy it's requirements. In this section we discuss the construction of such an utility value.

Any mobility theory based on depletion of resources implies that agents have certain required resources that are depleted during the usage. The current model is based on food resources, namely how much energy hunter-gatherers can obtain from the environment during a period of time, a measure which is called the net return.

The net return rates in particular cases have been estimated by ethnographers, and vary to large extent. For example the Ache are estimated to gain 1115 kcal/h from hunting with foraging offering even higher returns (Kelly 2013 p. 52). On the other end of the spectrum Smith (1981) estimated hunting Inukjuak obtaining only 1700 kcal per hunting party member per day with 2000 kcal per day usually considered to be minimal energy requirement for adults.

The return rates depend on specific resources, ease of access, technology of their procurement and a lot of other details. Also an area usually includes a variety of resources eg. small game animals and plant food for foraging. As we are creating a generalized model we don't take into account the huge variety of circumstances affecting the rates. In our model the rate R_i represents aggregated rates of resources at a given cell i including local searching, harvesting and handling costs. As R_i stands for a local potential it does not include costs of moving from base camp to a given area.

Our implementation of Kelly's model (2013, p. 97102) involves settlement choice. The original is explained using an environment with a homogeneous energy distribution. Although it has a sound analytical meaning we want to test it's applicability with different and dynamic energy distributions.

Before we do so we simplify the model and remove individual foragers energy expenditure of logistic mobility from the formula determining range size. The energy expenditure would be important if an individual forager would be foraging for itself, social sharing mechanism would be implemented or if foraging would use significantly more energy than other activities. In the current model energy requirements will be satisfied and there is no intra-group sharing implemented. Also we consider individual foragers requirements as part of the requirements of the whole camp population. It has been argued that an individual spends more energy while procuring a resource, for example Grimstead (2010) has provided model calculating energy expenditure of long distance hunting. However some recent studies contradict it by showing that energy expenditures and thus requirements of hunter-gatherers are not significantly dependant on their activities (Pontzer et al 2015), but are more dependant on their personal features. Thus we consider individual energy expenditure during foraging insignificant in the scope of the model and remove it from the formula without contradicting the original CPF model.

For our model we create environment configurations where every cell is assigned a local energy rate R_i that would result in foraging at the location for a fixed period of time (details explained in environment generation section the Appendix). As we are currently building a stylised theoretical model we use the human daily energy requirement (2000 kCal / day) as a unit of variable R_i.

This rate is obviously not enough to rank the location as a potential place for settlement. Hunter-gatherers move around in the landscape as part of their logistical mobility and thus other cells in the logistical range of the camp are also used for food procurement. To calculate the energy rate accessible from a base positioned at given cell i, assuming an 8 hour working day as was done in Kelly's original model (Kelly 2013, p. 99), we calculate accessible return rate P_i:

$$P_i = \sum_{n=1}^{|N|} R_n = \sum_{n=1}^{|N|} (r_n * (8 - 2\frac{d}{s})) \qquad (2)$$

where: N is the set of neighboring cells around i in a maximum logistic range (12 km from base in case of speed of 3 km/h); s is the speed of moving to the foraging location, we use 3 km/h which is measured foraging speed as used by Kelly (2013, p. 97); d is the distance between base i and cell n and has a maximum value of 12 km with used movement speed; r_n is the local hourly energy rate for location n in vicinity N.

As we can calculate both P_i and R_i for all the cells in the environment we get two distributions local return rate distribution (S_r) and accessible return rate distribution (S_p) that can be used for describing the current environment.

For formulating settlement choices we need to relate accessible energy rates of cells (P_i) to agents a, which are defined by their location and energy requirements. For this we define a function U_i that returns an utility value cell i has for an agent.

Kelly's model and empirical data suggest that a forager's goal is to maximise foraging return rates (Kelly 2013). For central place foragers it implies that the purpose is to minimize travel time (Orians & Pearson 1979). Our goal is to create an abstract model and not to solve an explicit problem using any energy data, therefore it proved to be more straightforward to use time costs as a reversed utility value to be minimized instead of energy rate.

The marginal value theorem is based on the concept that while resources are foraged their amount in the environment is reduced leading to diminishing returns. Empirical equivalents of the decline of energy rates are hard to study.

Venkataramana et al (2017) evaluated asymptotic, sigmoidal and linear functions for describing gain curves based on data collected while observing Batek foraging activities by Kirk and Karen Endicott. They found that some of the resources were not depleting before the move, but the best fitting depletion models for the remaining cases were based on firstly sigmoidal and secondly asymptotic functions. The dataset used was not big enough to create any data calibrated functions but the shape of the depletion curve is enough to use in our current stylized model. Although the sigmoidal curve starts collection of resources slower in the long run the general shape is very similar to asymptotic function, which we simulate in our energy depletion function.

The declining returns according to MVT have been defined by Charnov and Parker (1995) as a negative exponential function of acquired energy at a given moment:

$$g_t = G(1 - e^{-ct}) \tag{3}$$

where c is a scaling factor and G is the initial energy.

In the current model we also want to isolate the rate of the energy needs of the population and relate it to the rates at a given location. We assume that the depletion process lowers the return rate by a similar scaling factor, D. We also take into account ρ_a which is the energy requirements of an agent (a) as calculated by the population multiplied by the energy requirement of one person.The agent with smaller requirements deplete a plot in a longer time period. For this we multiply D with $\frac{\rho_a}{P_i}$ multiplied by the requirements of agents ρ_a relation to environmental rate. We use a simple step function to describe the depletion of a cell with calculating it's current accessible return at time step t:

$$P_{it} = P_{i(t-1)} - \frac{DP_{i(t-1)}\rho_a}{P_{i(t-1)}} = P_{i(t-1)} - D\rho_a \tag{4}$$

where D is the depletion rate after the foraging event of the cell and Pi(t-1) is the the rate before the current time step. We notice that as the requirement grows relative to the remaining resource rate the function takes a linear form.

To get time the costs of the agents fulfilling their needs we write a differential equation so that:

$$\frac{dP_i}{dt} = -D\rho_a \tag{5}$$

The differential equation is solved as:

$$P_{it} = P_0 - (D\rho_a t) \tag{6}$$

As we are interested in the inverse gain function - time costs used for foraging to satisfy need during a specified time period (T_t), we can use the formula

$$T_t = \frac{\rho_a}{P_{it}} \tag{7}$$

and write it as a differential equation

$$\frac{dT_t}{dt} = \frac{\rho_a}{P_0 - t\rho_a D} \tag{8}$$

which could be solved as a time costs function, used as a costs function for agents

$$U_{ait} = T_t = \frac{\log(P_0)}{D} - \frac{\log(P_0 - tD\rho_a)}{D} \tag{9}$$

with boundary conditions of $tD\rho_a < P_0$ and $P_0 > 0$.

Time variable t in the function is the considered time frame for staying in one location. The function returns time costs of foraging to satisfy the energy needs of the population of an agent for a given time period t assuming depletion at rate D.

Decision-Making of Agents At every iteration of the model every agent chooses its next place of residence. The choice can be broken down into two decisions of when and where to move. According to Kelly's theory the central place foragers decision to move is based on optimizing the workload of individual foragers with food procuring. We deduce from his model that if the foraging time expenditures of the current location grow higher than the foraging costs plus the costs of moving to the new location, the foragers move. In addition to just mobility costs the costs of moving involve camp breakdown, setup and movement of populations and belongings from one site to another. In archaeology those fixed costs are brought together under the umbrella term of site investment. We include those fixed costs in our implementation as a separate global variable (MOVE-START-COST). In the agent based simulation for every agent all cells j in the vicinity are evaluated so that V is the time effort put into foraging in order to satisfy the needs of agents (a) population during given time frame t including the moving costs C_{ij} to a new base location including fixed costs.

$$V_{jt} = U_{jt} + C_{ij} \tag{10}$$

C_{ij} are the moving costs from agents' current position i to j. The best alternative location is selected, which has a minimal V value. If

$$U_{jt} + C_j < U_{it} \tag{11}$$

the decision is made to move to the best alternative location j. In the reverse case, the agent stays at the current position. The agent decision described here includes the anticipated timeframe (t) of staying at a new location. In Kelly's model the timeframe of stay is not specified as there is no empirical evidence to back it. For our ABM model we create a simple agent learning process for finding an optimal timeframe of consideration.

Adaption process of timeframe t The agents' learning process considers finding an optimal time of stay (t) while evaluating alternative locations for the next settlement. To illustrate this we describe the optimal time frame problem. If the time frame is very small then moving costs (C_j) are relatively high in comparison to time used for harvesting leading to small returns. For example when considering the time costs of only one day and moving costs of 6 hours, it is not worth moving because the day will be lost on just moving. This leads to a situation where moving does not offer any gains until the resources are completely depleted and the move will be made after a period of time longer than one day. Conversely, when the group plans a longer time period, the residential move becomes profitable relatively quicker, meaning that the in case of a homogeneous environment there is an optimal duration somewhere in between.

Although there is no empirical evidence, we assume that hunter-gatherers evaluate the length of stay by the timeframe set by their previous experience. The timeframe of stay is optimized by an adaptive process so we assign the t variable a mean value of the two last durations of residential stay. In this way the t reaches an optimal value for a given environment by the choice process and should approximate an average length of residential stay. In our model implementation the agents will get a stochastic number of turns as a starting t value and although no collective learning is included the standard deviation of the considered timeframes decrease quickly as the simulation progresses.

Information in the model Agents in the model have complete information about the R_i values of each cells in their residential range. This information is used to calculate the utility which is based on the location choice. Effectively though as the moving costs grow the cells further away are not evaluated just because of their significantly lower return rates considering the costs of moving.

Although having information on the current status of all locations is never the case in real-life situations, hunter-gatherers had an impressive knowledge of their surrounding landscapes. For example according to Binford (Binford 1983, p. 206) Nunamuit maintained general knowledge of 250000 km^2 and Pintupi had knowledge of 52000 km^2 (Long 1971).

Individual agents don't process any information about other agents as direct interactions between agents are not in the scope of the current model.

Agents don't have direct interactions in the model, site selection and resource depletion processes imply that competition rises between agents sharing a territory. An agent already depleting an area will make it less attractive for others who tend to choose their next residential site further away from depleted areas. Therefore, competition creates a spatial dispersal force for agents' placement.

Implementation and experiments

Implementation and variables To introduce a spatially explicit heterogeneous space and control the generation of environments we introduce two variables: the mean energy rate of the cells in the environment (MEAN-ENERGY-RATE-KM) and the standard deviation of energy rate distributions (STD-ENERGY). We process those randomly generated environments with a smoothing algorithm with differing diffusion strength, resulting in energy rate distributions having different spatial autocorrelations.

To study the effect of environment to mobility we observe two groups of variables first containing information about environment and second collecting information about formed mobility patterns.

The first group contains I-RESOURCE and I-UTIL, the Moran's I spatial autocorrelation coefficients of the raster of energy distribution S_r and accessible energy distribution S_p (determined by access to adjacent resources) of the environment. For randomly generated landscapes, the Moran's I value ranges from 0 to 1, with 0 having the most rough and 1 having most evenly distribution of values.

The observed variables describing mobility are a subset of mobility measures defined by Kelly (1983): MOVESPERYEAR number of residential moves per year (mean of all agents); MOVELEN mean length of a residential moves during the model run by all agents; MOVELEN-STD standard deviation of the length of a residential moves during the model run by all agents; LOGMOBTURN length of the logistical foray per residential stay (mean of all agents).

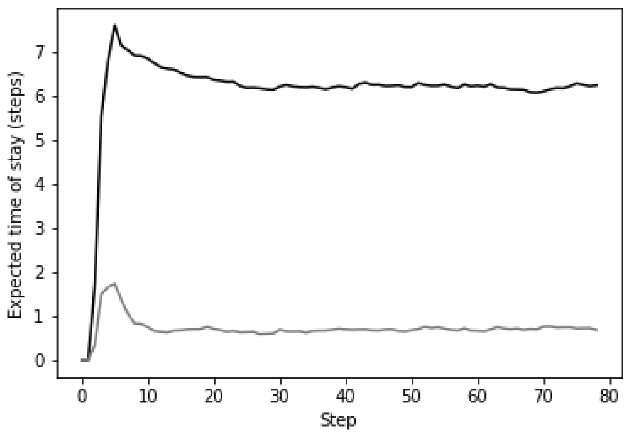


Figure 1. Achieving equilibrium of expected time of optimal expected stay (t) in one settlement location. Darker line is the mean value of all agents (10) over runs (n = 41), and the lower line is standard deviation of those values.

Although the calculation of the first two variables is straightforward and can be quite similar to the empirical observation, the length of logistical forays is hard to measure as logistical mobility is not really simulated by agents. So it is calculated as a sum of distances to locations of resources made during a residential stay. The results emerging while observing the parameters are described in section (4).

Experiments We present three experiments that we conducted with our ABM implementation of the CPF model. The first experiment was run for face validation of the new mechanisms added into Kelly's interpretation of CPF.

To show how logistical mobility and residential mobility are influenced by the spatial heterogeneity of the landscape we conducted two ABM experiments.

To verify whether the classic CPF results still hold in the spatially explicit model we tested whether it responds to global parameters the mean environmental return rates and the moving costs as assumed by CPF. In experiment 2 we vary the environmental variable MEAN-ENERGY-RATE-KM and the fixed costs variable MOVE-START-COST for different environments (see submodels section in the Appendix for description of environment generation) resulting in varying values of I-UTIL and I-RESOURCE. Other values in the model were held constant and the correlation between the mentioned variables and the variables defining mobility (MOVESPERYEAR, LOGMOBTURN, MOVELEN) were studied.

We conducted experiment 3 to assess the model's sensitivity to spatial autocorrelation of resource and utility destribution. We varied the landscape generation parameters smoothness and standard deviation, and held other variable constant. We measured spatial autocorrelations of both energy distribution in the environment (I-RESOURCE) and the utility distribution measured by the access every location has to energy resources (I-UTIL). We analyse changes in the 3 variables describing mobility(MOVESPERYEAR, LOGMOBTURN, MOVELEN) along changes of the spatial autocorrelation of the landscape and global parameters of STD-ENERGY.

Simulation results

Experiment 1: base model evaluation

Adapting to optimal duration of a stay at one location The adaption mechanism of calculating the optimal time range of a stay at one location is required to run original Kelly's model as a simulation. To solve this currently lacking mechanism, we use agents experience for predicting their time of stay by calculating the mean values of their previous stay durations. Results of the simulations showed that the strategy quickly leads to an equilibrium optimum value. Here we illustrate this convergence (Figure 1) with the standard deviation of the return rate of environment being set to 1. The simulations start with all agents having a time span of planning for just one turn. Given this time span it makes it worthwhile at step=1 to move only after local resources have been depleted, which results in a longer period of stay in the beginning of the simulations which peaks at about step=7 of the current simulation. Then the time span of planning lowers slowly and achieves an equilibrium of optimal value (around value t=6.5). The values relate to the given particular example but it illustrates simple, intuitive logic of planning future behaviour using previous experience. Although it has not been empirically documented it is obvious that hunter-gatherer cultures have a more complex memory process of predicting conditions. Our simple solution can be used as an heuristic for current purposes, but it must be taken into account that optimal choices for a given environment might start to be taken only after certain number of steps (about 25 with current model configuration)

Resource depletion process The process of resource use and depletion significantly changes the characteristics of the environment itself. The change is illustrated in figure 2 showing the depletion process impacting the initially relatively homogeneous return rates distribution. In figure 3 it can be seen that the spatial clustering of return rates of environment (I-RESOURCE) decreases significantly while the accessible returns distribution (I-UTIL) remains almost the same. We can observe a declustering of the landscape until approaching equilibrium. It illustrates the significant change of resource distribution on the landscape in the case of mobility driven by depletion.

As utility is calculated as a sum of neighboring energy rates it functions as a smoothing function. Though the available energy in the environment decreases the utility values of the landscape, in general it remains relatively constant. Thus the depletion process is not significantly influencing the settlement location choice.

While every agent is depleting resources around itself it makes the area less attractive to other agents which in turn creates a force of dispersal for agents. This leads to a more dispersed form of the settlement pattern which in turn impacts the pattern of depletion. Note that the dispersal of agents may be balanced by social and cooperative interactions in reality but these are not incorporated into this model.

Experiment 2

The second simulation experiment demonstrated that resource abundance of the environment and moving costs have a significant effect on the mobility patterns. Figure 4 illustrates the inverse non-linear relationship between yearly residential mobility (MOVESPERYEAR) and mean return rate of the environment (MEAN-ENERGY-RATE-KM) and cost of residential moves (MOVE-START-COST). We find negative exponential relationships with a much lower range of variation in yearly mobility by the move cost as compared to the environmental return rates. The increase of the environmental return rate can lead to sedentism while the residential move costs can become extremely large but agents are still forced to move when the resources in the environment are depleted.

Similarly the effects of MEAN-ENERGY-RATE-KM and MOVE-START-COST on logistical mobility (measured by LOGMOBTURN) are illustrated in figure 5. The results show that the mean environmental return rate has a negative exponential effect on the effort put into logistical mobility, but the cost of theresidential move has a modest positive linear effect.

The results were expected by both analytical predictions which serves as an internal validation of the spatial CPF model. It has also been shown in the empirical observations that high abundance and accessibility of resources is negatively correlated with residential mobility rate, in the case of terrestrial foragers (Kelly 2013, p 88; Kelly 2013 p. 103, 104).

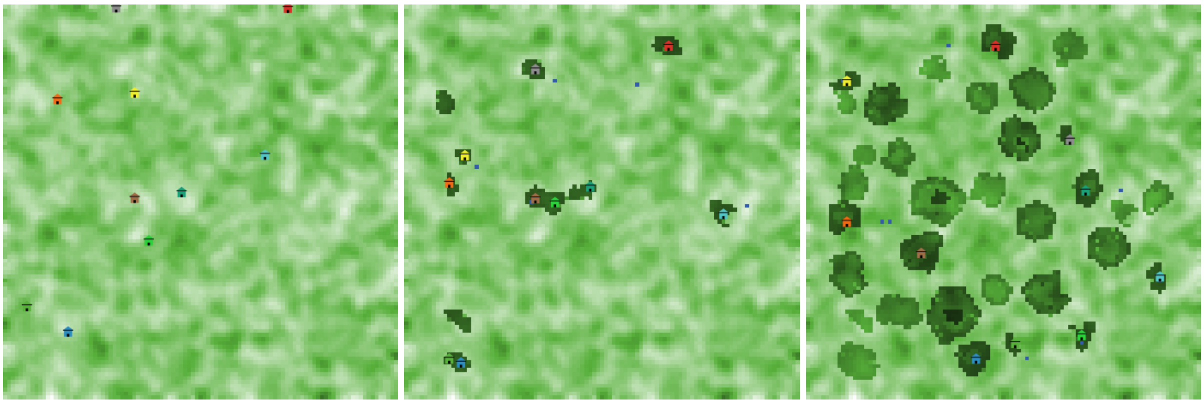
The positive correlation between residential move cost and logistical mobility can be explained intuitively. In the case of higher costs of moving to another camp it is preferable to put more effort into local forays before undertaking the costly move. The influence is modest compared to the influence on residential mobility which can be explained by the impact of environmental configurations influencing the effort put into logistical mobility.

Finally, residential move length is another important characteristic especially because of its potential for explaining past settlement processes. Surprisingly there is no correlation between MEAN-ENERGY-RATE-KM and mean residential move length over the runs as seen in figure 6. But there appears to be an increase in the standard deviation of residential move length with higher MEAN-ENERGY-RATE-KM values. This implies that environments with high returns support variance in mobility strategies and perhaps more freedom in location choice.

The positive correlation between residential move costs (which does not include moved distance) and move length is a spatial nature of depletion processes. Increased costs force a longer stay and results in extended depletion area which requires agents to move further away from their previous location.

Experiment 3

The third simulation experiment was conducted to measure the sensitivity of the CPF model to initial spatial configurations by varying environments and measuring mobility. For fixed MEAN-ENERGY-RATE-KM random environments were generated and diffused at different levels. The variables STD-ENERGY, I-RESOURCE and I-UTIL were then measured and used for describing the spatial configurations. During simulation runs characteristics of



(a) Initialized map. **(b)** 5 steps. **(c)** 30 steps.

Figure 2. Netlogo model running process with energy distribution and agent locations (colored markers) visualized. Lighter green pixels have more available energy and the darker less energy. A declustering of the landscape can be observed until reaching an equilibrium. We can see different equilibrium states with and without agents.

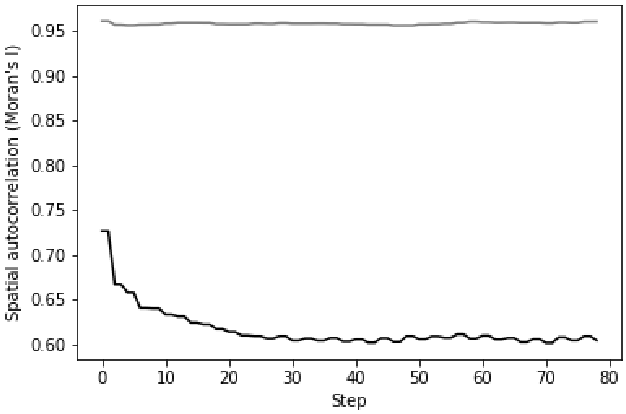


Figure 3. Moran's I autocorrelation value dynamics of resources (dark gray) and utility (light gray) based on access to them

residential and logistic mobility (MOVESPERTURN and LOGMOBTURN) were measured.

The experiment showed that the tested variations spatial configurations influence mobility patterns. There was a weak correlation between I-RESOURCE and MOVESPERYEAR (r=-0.19) and LOGMOBTURN (r=0.36) so spatial clustering in itself does not have a significant effect on mobility. But by isolating the standard deviation of the energy rate STD-ENERGY (figure 7 ;figure 8) we can see that the clumpedness, measured as a combination of STD-ENERGY and I-RESOURCE, reduces residential mobility, n.

In figure 7, three regression lines illustrate the effect of standard deviation of energy distribution on residential mobility. The environment with a high standard deviation and high spatial clustering represent clumped environments and leads to a decrease in residential mobility. The result is in line with the experiment of Janssen and Hill (2014) who, by simulating individual hunters' movements, concluded that clumped habitats favour lower residential mobility. Similar empirical conclusions have been proposed for patchy environments (Binford 1980; Fitzhugh & Habu 2002, p. 261) but not explained as a spatial effect on settlement choice but by predicting more complex hunter-gatherer procurement strategies.

Counterintuitively, any relation between spatial clustering of return rates and logistical mobility is weak and environments with higher I-RESOURCE lead to higher mobility costs. The pattern is caused by different residential strategies adopted in those case, which result in longer stays and thus longer overall logistical activity in one camp.

Overall it has to be concluded that the mobility model is less sensitive to spatial distribution of return rates over the environment than mean overall return rate. For example in the current simulation, the variance of MOVESPERYEAR while modifying environment configurations is just 5, while modifying the overall mean rate covered the whole range of the experiment of 1 to 25 moves per year. This shows that the CPF model is generally robust to initial spatial configurations in spite of some influence from spatial clustering of the environment.

It must be considered though that the model is only manually calibrated to variables and we have no information on the spatial structure of hunter-gatherer energy resources in empirical data. This might lead to lack of coverage of output space, thus for analysis of real life situations variables should be calibrated based on empirical data.

The relations between utility distribution I-UTIL (figures 7, 8) and residential and logistical mobility (MOVESPERTURN and LOGMOBTURN) are significantly weaker. The reason for it lies in the nature of the two spatial distributions used. As explained above, the utility value describes a locations access to resources in the logistical range. As the access is calculated by summing values of other locations in the vicinity it works as an averaging filter kernel with the size of the logistical mobility range. Because of its effect as a smoothing function it increases spatial autocorrelation of the original energy distribution with Moran' I values in range of 0.925 0.981. The range is about 10 times smaller than the spatial autocorrelation of energy distributions (with Moran' I values in range of 0.023 0.948) from which it is calculated by.

The smoothing function has a higher access range of results in a greater degree of spatial autocorrelation and thus smaller significance for any location choice. As the

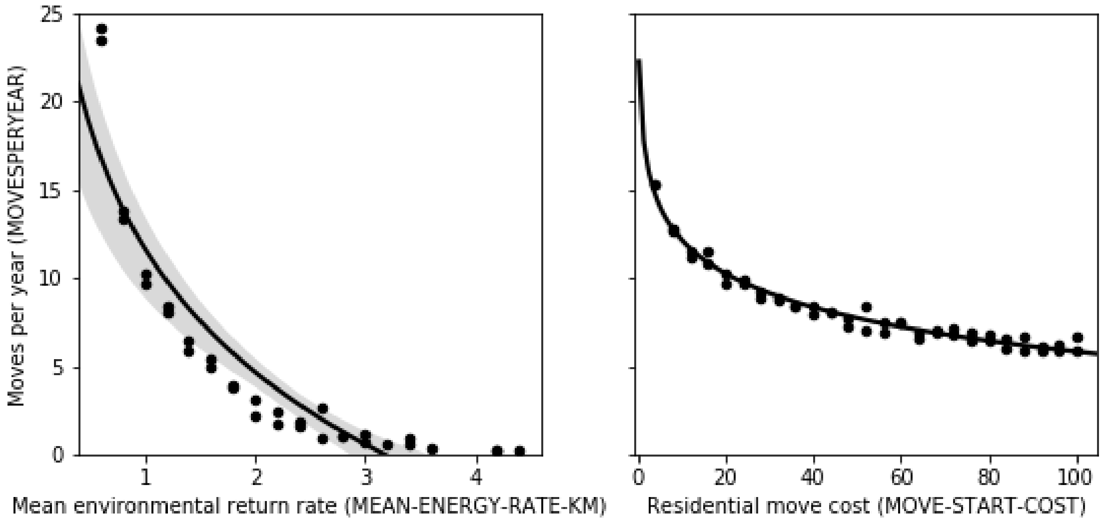


Figure 4. Influence of variance of residential move cost and mean environmental return rates to residential mobility while varying one variable and keeping the other fixed. MOVE-START-COST is fixed to value 20 and MEAN-ENERGY-RATE-KM is fixed to 1 accordingly.

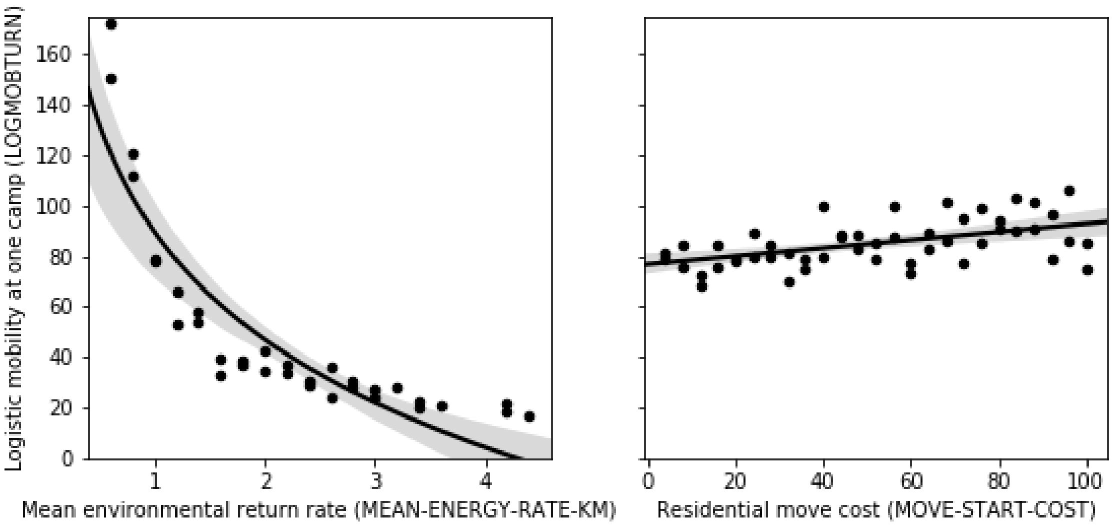


Figure 5. Influence of variance of residential move cost and mean environmental return rates to logistic mobility while varying one variable and keeping the other fixed. When not varied on the diagram MOVE-START-COST is fixed to value 20 and MEAN-ENERGY-RATE-KM is fixed to 1 accordingly.

difference is dependant on the logistical range of a given resource it can be said that the effect of settlement choice on mobility patterns decreases as the possible range of access grows. Therefore the effect of the spatial configuration of the accessible energy rate distribution is significantly smaller than the spatial distribution of resources that require direct access. As the utility which measures access to resources is used for evaluating settlement location choice we can conclude that the energy rate distribution in the environment has a modest effect on it.

Spatial configuration of return rates is closely related to the timing of mobility, as it determines foraging process at a local level. Spatial configuration of utility based on access to resources, on the other hand, is more related to the choice of new settlement locations.

From this we can conclude that the environmental energy return rate distribution is not enough for simulating settlement choices in a spatially explicit setting eg. in case of solving archaeological problems. Kelly (2013, p. 100) discusses the issue as the stay length is also related to move distance which is not only determined by energy. The ethnoarchaeological studies show that settlement site locations are determined by direct access to critical resources like water and firewood (eg. Kelly 2013, p. 90, 100, 126). Foragers always stay close to water resources, for example it has been documented that Hadza carry water to camp from a maximum distance of 700 m. Archaeological data also shows that hunter-gatherer settlement sites were positioned close to water and additionally had a preference for other geological features such as sandy soil which can drain water or a

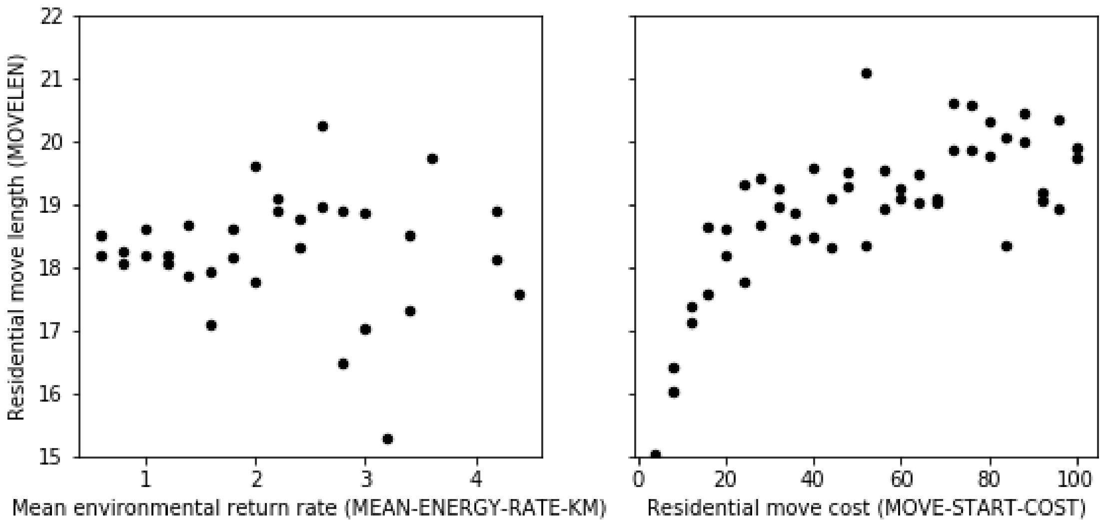


Figure 6. Influence of variance of residential move cost and mean environmental return rates to residential move length

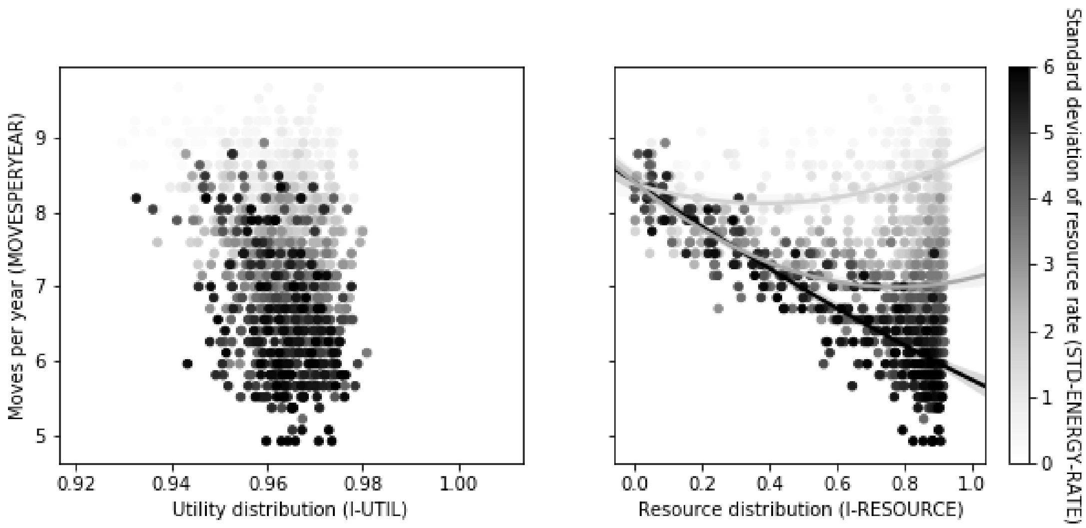


Figure 7. Influence of energy and utility distributions to residential mobility. As utility is a result of accessibility to resources it's distributions in only in Morans I spatial autocorrelation range of 0.93 .. 0.98 while energy distribution is in range from 0 .. 1. To illustrate combined influence of clumpyness of the environment (I-RESOURCE and STD-ENERGY-RATE) three second order regression lines are drawn with colors corresponding to STD-ENERGY-RATE

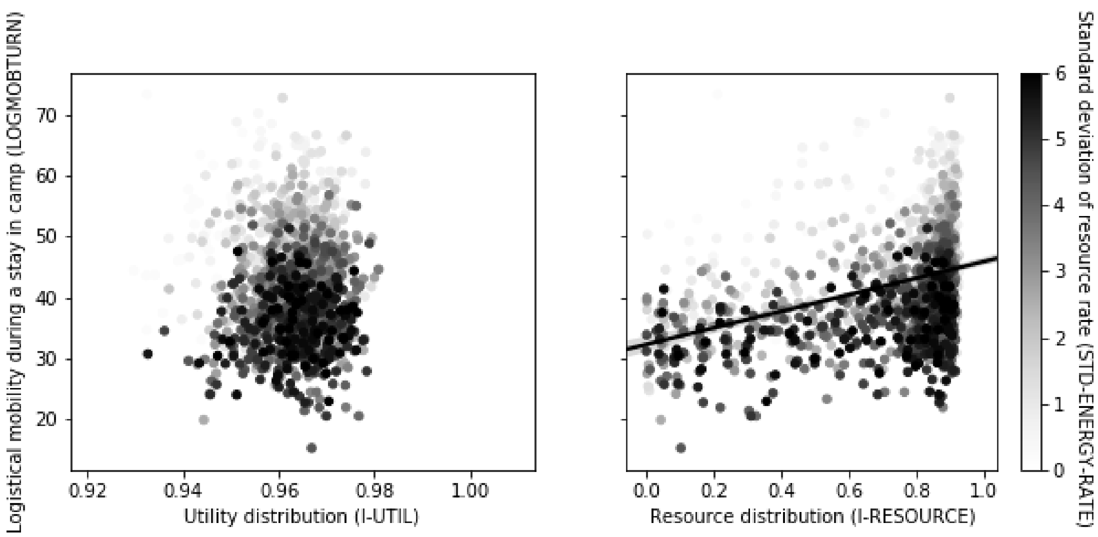
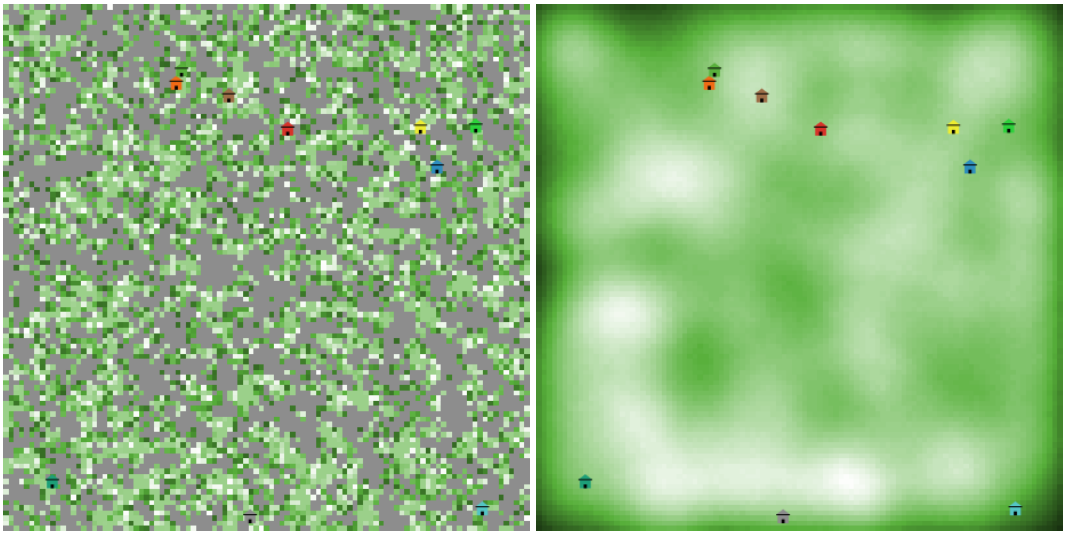


Figure 8. Influence of energy and utility distributions to logistical mobility



(a) Initialized map. **(b)** 5 steps.

Figure 9. Energy distribution and utility value distribution in the same artificial environment. Lighter green has more energy than darker and gray has zero energy.

specific elevation. In real life situations the set of possible alternatives is reduced to locations having requirements for a campsite. This reduction of alternatives might only have a moderate dispersing impact on mobility choices, but could completely change the influence the environment has on settlement choice.

To further study the landscape effect on settlement location choice using the CPF model the distribution of local features required for setting up a residential base should be included. Archaeological predictive models of settlement locations can potentially be used to describe the distribution of suitable places on the landscape and its relation to residential mobility. Combining settlement choice models with energy availability, the CPF model could potentially be used for describing mobility, settlement choice and therefore settlement pattern formation in general.

Conclusion

We proposed an agent based model to explore the effect of heterogeneous environments on hunter-gatherer mobility choices built upon Kelly's (2013) CPF model. The first goal of the model was to test the robustness of the CPF approach to spatial conditions and measure the effect of spatial autocorrelation of the environment to mobility. The second goal was to explore the possibilities of agent-based spatial CPF model for exploring mobility and settlement choice as ABM opens new possibilities in addition to analytical methods.

The original model was an aspatial model assuming a homogeneous environment. A major addition was the introduction of explicit geographical space with a heterogeneous resource distribution. The model includes abstracted agency and, alternatively to most CPF ABMs where individuals are modelled, the agent is a whole community. This enabled us to build a model based on the abstract CPF theory and avoid going into details of individual behaviours which are more complicated to link to empirical data.

We introduced the generation of energy distribution on artificial landscapes, generalizing the foraging process without simulating individual foragers' moves. It widened the residential choice set from two choices to a wider range of alternatives and hence adding settlement location choice to agents. For simplicity we modified the concept of utility not to be the energy taken from the environment but the time costs used for various tasks. The change is based on principles of CPF and thus has no functional impact on the model. To experiment with a spatial heterogeneous environment we introduced a discrete choice simulation model, which required additional adaptations of the CPF model and the addition of two new mechanisms.

The original analytical model missed an important variable of a timespan of planned stay for evaluating potential residential locations. By using ABM simulation we could create an iterative optimization process so that the variable was modified by agents' previous experience and achieved an optimal value. The adaptation mechanism achieved an equilibrium state which responded to global configuration variables.

To model the dynamics of human-environment interaction we created a mechanism of depletion and recovery of resources. Although we have no empirical data on the depletion rate we manually calibrated its values based on theory and known empirical ranges of mobility parameters. The depletion mechanism caused a significant alteration of the resource distribution in the environment. This in turn resulted in competition between agents creating a population dispersal force in the model.

We conducted three experiments. The first experiment served as a face validation for the mechanisms described above.

The second experiment confirmed the previous analytical results of the original model and served as an internal validation of the spatial model. The mean return rate of the environment had a significant impact on measures of mobility shown by a negative exponential correlation. Residential movement costs on the other hand had a small positive correlation to logistical mobility. Residential move length was also measured and surprisingly had no correlation with the energy rate in the environment but was related to fixed costs of moving.

The third experiment was conducted on the model's sensitivity to the spatial configuration of the environment. To analyse the effect of the environment on mobility we measured the spatial autocorrelation of return rates of cells in the environment and the utility values calculated by the access every cell has to adjacent energy resources. More smooth return rate distributions resulted in higher mobility while more clumpy environments had it reduced. Although the effect was present it was significantly smaller than the effect of the mean return rate. The effect of utility values based on cells access was primarily in determining alternatives for settlement location choice. As the utility distribution had a very high autocorrelation compared to return rate distribution by definition the effect was virtually non-existent.

Those results show that the CPF model is generally robust to initial environment configurations, however spatial autocorrelation of the resource distribution has a certain effect on optimal mobility decisions.

We also questioned the usability of a spatially explicit CPF model for explaining settlement pattern formation. As discussed above, according to CPF, the environment has a strong influence on the mobility, which is one cause behind settlement pattern formation. It became apparent that in CPF models the settlement location choice is not determined by energy dispersal at least at the given scale of observation. Based on empirical material we know that critical resources like water and firewood and other local affordances like shelter and geological features determine specific site locations. For modelling settlement choice a submodel of those resources should be incorporated as they might have more significant effects on formed patterns than access to energy.

Also it must be taken into account that the current model used an artificial environment with mean known energy return rates of environment where the variance was generated by a stochastic Monte Carlo process without any specific spatial structure. Hunter-gatherer energy resource distributions in the real landscape and their spatial configurations, which have not been researched so far, would be needed for validating models to data. For solving explicit archaeological problems an environment generation process should then be based on calibration and structured based on empirical material.

Acknowledgements

The authors acknowledge funding from the FNR under the PRIDE scheme.

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Appendix: ODD+D protocol overview of the ABM model of CPF settlement choices

I **Overview**

i **Purpose**

a **What is the purpose of the study?** To test the robustness of CPF model to initial spatial configuration and evaluate its theoretical explanatory power of settlement pattern formation processes.

b **For whom is the model designed?** For archaeologists and other scientists studying hunter-gatherer mobility.

ii **Entities, state variables and scales**

a **What kinds of entities are in the model?** The agents in the model are human groups. The environment represents a resource distribution landscape.

b **By what attributes (i.e. state variables and parameters) are these entities characterised?** Agents in the model have an explicit location and a population, which is constant (20) in the presented simulation experiments. They possess a state variable for the time an agent is expecting to stay at its next location (EXPTIME). Each cell (i) in the environment has a state variable ENERGY which represents the potential net return rate of energy (R_i). It is the amount of energy that can be foraged from it during a day by an agent. As the net return rate depletes after resource use we store an additional ACTIVE-ENERGY variable to store currently available energy. The model includes global variables which are used during the simulation. The first one is the fixed time costs of disassembling the old and setting up the new camp. It does not involve the moving process itself and thus is not related to distance. It is a defined separate global variable (MOVE-START-COST). Another global variable used for generating the environment is the mean energy rate of the environment (MEAN-ENERGY-RATE-KM), which defines the abundance of energy available.

c **What are the exogenous factors / drivers of the model?** The environment is generated by an external model configuration which determines the general characteristics of it. Configuration variables are selected so that the summed energy rate of the environment will not be depleted by an artificial population and will achieve a stable equilibrium state.

d **What are the temporal and spatial resolutions and extents of the model?** The environment is represented by 100x100 grid, each of which is equivalent to 1 square kilometer. One step in the model run is the equivalent of one week.

e **If applicable, how is space included in the model?** Environment is presented explicitly in space and agent decisions take into account distances in space.

iii **Process overview and scheduling**

a **What entity does what, and in which order** In the beginning the environment is created based on a Monte-Carlo process and is then calibrated to match the configuration variables. At every turn agents consume resources around them, which changes the ACTIVE-ENERGY variable of the environment. At every four turns resources are restored at a certain rate. At every turn agents evaluate the time costs of meeting requirements at the current location during an expected duration of stay and weight it against similar costs in alternative site locations. If any alternative location offers more optimal time use the agents moves to best (least time costs) alternative location.

II **Design Concepts**

i **Theoretical and empirical background**

a **Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?** The energy return rates in the environment are based on environmental data and ethnographic observation. The depletion of resources in the environment is mostly based on theory but also on some ethnographic studies. As the data is not sufficient the mechanism is not calibrated to it. The environment configurations are generated using Monte-Carlo methods and are not calibrated to resemble real landscape configurations as the data is not available. Every location has an utility value assigned, which comes from Central Place Foraging theory (Kelly 2013). Every cell has an utility value - an energy rate which can be accessed from a cell both locally and by logistic mobility to other cells in the logistic range.

b **On what assumptions is/are the agents' decision model(s) based?** The decision model of mobility and settlement choice is based on mobility theory from the Central Place Foraging model (Kelly 2013) which is a special case of Optimal Foraging theory. The theory asserts that a human group moves its settlement if it finds an alternative location which promises better returns during a certain period of time.

c **Why is /are certain decision model(s) chosen?** The goal of the model is to test a given decision model in a heterogeneous environment.

d **If the model / submodel (e.g. the decision model) is based on empirical data, where do the data come from?** The model is not based on empirical data.

e **At which level of aggregation were the data available?** The model is not based on empirical data.

ii **Individual Decision Making**

a **What are the subjects and objects of the decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision making included?** Agents decide on the location for their settlement site.

b **What is the basic rationality behind agent decision-making in the model? Do agents pursue an explicit objective or have other success criteria?** Agents select a site location with maximum returns by means of logistic mobility during a fixed period of time including movement time to new location.

c **How do agents make their decisions?** Agents compare the time costs of satisfying their needs by staying at one location and choose the optimal location.

d **Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?** The environment configuration and other agents' locations determine agents' decisions.

e **Do social norms or cultural values play a role in the decisionmaking process?** No

f **Do spatial aspects play a role in the decision process?** Energy resources are spatially explicitly distributed. The concept of distance is used in calculating mobility costs.

g **Do temporal aspects play a role in the decision process?** The expected time of stay at one location has significant impact on the decision-making.

h **To which extent and how is uncertainty included in the agents' decision rules?** Uncertainty is not included in the decision rules.

iii **Learning**

a **Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?** The agents' learning process considers finding an optimal time of stay (t, agent variable EXPTIME). The time is calculated as a mean of durations of two previous stays. The durations are the result of considering local conditions better than any alternatives.

b **Is collective learning implemented in the model?** Collective learning is not implemented.

iv **Individual Sensing**

a **What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?** Agents in the model have complete information about the ENERGY and ACTIVE-ENERGY values of each cells in their residential range.

b **What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?** Agents do not sense any state variables of other agents.

c **What is the spatial scale of sensing?** The spatial scale is residential move range.

d **Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?** Agents are assumed to know variables.

e **Are the costs for cognition and the costs for gathering information explicitly included in the model?** Cognition costs are not included in the model.

v **Individual Prediction**

a **Which data do the agents use to predict future conditions?** Agents use variable ACTIVE-ENERGY for predicting future energy rates.

b **What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?** Agents are using a model of resource depletion for predicting future conditions.

c **Might agents be erroneous in the prediction process, and how is it implemented?** Agents' predictions are correct only assuming their own resource use, but they don't predict activities of other agents.

vi **Interaction**

a **Are interactions among agents and entities assumed as direct or indirect?** Agents directly interact with the environment and indirectly with each other: two agents can't occupy the same cell.

b **On what do the interactions depend?** Interactions depend on spatial proximity of agents and environment cells.

c **If the interactions involve communication, how are such communications represented?** Entities don't use communication.

d **If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?** Model does not have interaction network.

vii **Collectives**

a **Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?** Collectives are not included in the model.

b **How are collectives represented?** Collectives are not included in the model.

viii **Heterogeneity**

a **Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?** Entities are heterogeneous having different expectations of length of stay at one location.

b **Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?** Decision-making is heterogeneous depending on the EXPTIME variable and on agents' location.

ix **Stochasticity**

a **What processes (including initialisation) are modelled by assuming they are random or partly random?** Environment generation and spatial placement of agents is partly random.

x **Observation**

a **What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected?** During every simulation run the variables I-UTIL and I-RESOURCE which represent the spatial autocorrelation of respectively utility value and resource distributions are collected. Agents' expected duration of stay at one location is collected and statistics about mobility are collected (MOVESPERYEAR, LOGMOBTURN, MOVELEN).

b **What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)** Model run shows that mobility characteristics have a non-linear relation with mean energy rate of the environment and moving costs of a settlement. Spatial autocorrelation of the environment has a modest impact on mobility.

III **Details**

i **Implementation Details**

a **How has the model been implemented?** The model has been implemented in Netlogo version 6.04 (Wilenski 1999) modelling environment.

b **Is the model accessible, and if so where?** Model will be published in github and request from the author.

ii **Initialisation**

a **What is the initial state of the model world, i.e. at time t=0 of a simulation run?** Environment is generated as a Monte-Carlo process and calibrated using configuration variables and agents are placed at random spatial positions in the environment.

b **Is the initialisation always the same, or is it allowed to vary among simulations?** Initialization process is the same.

c **Are the initial values chosen arbitrarily or based on data?** Initial values are chosen arbitrarily.

iii **Input Data**

a **Does the model use input from external sources such as data files or other models to represent processes that change over time?** The model does not use input data.

iv **Submodels**

a **Environment generation** A surface of normally distributed cell values (ENERGY) was generated through a Monte-Carlo process using standard deviation given as a input parameter (STD-ENERGY). The surface was then smoothed to increase autocorrelation according to an input smoothing parameter using the diffuse function of NetLogo. As the STD-ENERGY value is sometimes bigger than MEAN-ENERGY-RATE-KM the values of cells are cut off at minimal and maximal threshold values and the whole distribution is normalized so that the mean energy rate still corresponds to the global configuration variable.

As a result an environment is generated and variables I-RESOURCE and I-UTIL are calculated as global Moran's I values of local and accessible return rate distributions. The four variables describing environment are used for comparison with observation variables of mobility. During experiments the initial input configuration variables are chosen so that the overall energy of the environment is not depleted by agents but agents still have a reason to move.

b **Resource depletion** The process of resource depletion has not been studied in enough detail to create an empirically calibrated model. Only work analysing the diminishing return of hunter-gatherer foraging processes informs us that the gain curve has a general sigmoid or asymptotic shape (Venkataramana et al 2017).

To reproduce a similar dynamic we created the following heuristic process. Every agent has to satisfy its need for resources, so at every turn a cell which has the best return rate from the base will be used for foraging. During the process the ACTIVE-ENERGY variable is decreased by the depletion rate (D) times energy taken from the cell. The depletion rate configuration variable used in the system is set to a constant value of 2/3. The experiments showed that using the value of the mobility results are in the same range as empirical observations, helping us avoid anomaly of scale.

Experiments also confirm that the depletion dynamics created in this way is a close enough approximation to the differential equation that agents use for predicting utility values for potential locations.

c **Resource recovery** Over time energy rates of cells gradually recover. As there is no data to base recovery rate on, we assume that the resources will recover over one year. Although in practice recovery rates in different resources are obviously different we consider this to be a usable heuristic in our system as it is a period during which nature completes a seasonal cycle and we can also observe hunter-gatherer mobility cycles.