Virtual Neanderthals : a study in agent-based modelling Late Pleistocene hominins in western Europe
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PART ONE: THE LAY OF THE LAND

"…*the explosion in the number of simulation models, which taken together with their output utility, suggests that simulation really has finally come of age as part of the archaeological toolkit*."

(Lake 2014, 277-278)

2. AGENT BASED MODELLING

2.1 Introduction

The use of computer systems is today well established for solving problems of interest in archaeology. Increases in computer power have added to administrative facilities like database, spreadsheet and word processing capabilities, to the application of Geographical Information System (GIS) techniques, and the creation of large simulations implementing dynamic models and solving huge numbers of complex calculations in real-time. This chapter introduces HomininSpace; an agent based modelling and simulation system to explore hominin dispersal in a landscape through time. Modelling involves abstraction, simplification, and formalization in order to better understand how the world works. As such each model is a simplified reflection or representation of reality (Castle and Crooks 2006). Building and disputing models is fundamental to science and scientists often debate which one is the more accurate model. Models are typically used when it is either impossible or impractical to create measurable experiments (Section 2.2).

Simulations are run to model and reproduce parts of some natural, ethological, social or conceptual process (Drogoul and Ferber 1994). The design of a model usually starts with a problem definition, then the identification of the desired features of the system to be modelled, followed by a definition of possible system representations. Then the model is implemented within a modelling environment according to the design specifications and at the required abstraction levels. This also involves selecting the best simulation tools for the needed features and conversion of data into usable formats. The simulations are run using selected input data in defined scenarios. Section 2.3 will discuss different modelling techniques and motivates the selection of a particular tool.

Section 2.4 gives an overview of the development history of HomininSpace. The implementation of the underlying model in HomininSpace combines results from many different individual disciplines including anthropology, archaeology, geology, and climatology. This provides an increased understanding of the fundamental elements of the behaviour of past hominins and offers a better insight into the subdisciplines, the data they create and how they are connected (Shaman *et al.* 2013). HomininSpace is implemented as an agent based model combining the representation of dynamic processes with geographical and real-world data allowing modelling of both processes (dynamic) and patterns (Mathur 2007).

2.2 Why model?

"Because we all do! But with simulation we can do it better!"[3] Even though people are taken aback by the assumed difficulty of implementing a computational model we are by all means a modelling species (Holland and Quinn 1987). The power of modelling is in part derived from the fact that one needs to explicitly specify all the details of the model that is to be used, and thus to engage the underlying assumptions. This forces the researcher to consider all needed elements, and to quantify them. Simulation, the execution of a model through time, and other process-based modelling techniques require an explicit description of the processes that are relevant to the system of interest. Such processes can be constrained by archaeological data that has timing information included to provide spatially explicit representations of patterns through time.

Modelling and simulating are inherent features of our cognition (Niazi and Temkin 2017). Abstraction may well be an indispensable element in any attempt to formalize real world systems. In this sense modelling is used more often than is realized. Some even go as far as to state that "*science in general is impossible without model[l]ing*" (Dershowitz and Gurevich 2008). To stress this point, it might be adequate to think of the following lines which belong to A.M. Turing, one of the founding fathers of computer algorithms: "*…if one wants to treat the problem seriously and systematically one has to replace the physical puzzle by its mathematical equivalent*" (Turing 1954, 11). In the context of this thesis, the puzzle is the complex way hunter-gatherers might find their way around the Palaeolithic landscapes and the mathematical equivalent is an abstraction in the agent-oriented modelling methodology.

Using computers, simulations become more feasible and allow more complex setups with the almost continual increase in personal computer power (Clarke 1973; Moore 1965; Brooks 2001). A model must be explicit in all details before a computer can work with it. A computer does what it is told, and does not do anything that is not explicitly requested[4]. Simply put, the model must be unambiguously explicit in all its details. Explicit models allow discussion with and replication by other researchers and thus reproduction of research. It is also possible to test the effect of large numbers of model parameters and wide ranges of parameter values over time on predefined starting scenarios (Bonabeau

[3] Private conversation with Iza Romanowska, 2017.
[4] Note that observed irregularities with computer usage always reflect errors by either user or software developer.

2002). With the general availability of powerful computers simulation has become possible and more fashionable in archaeological research (Lake 2014).

Students today are much more "computer fähig" then previous generations (Marc 2001; Kay and van Harmelen 2012). Computer hardware is more than sufficient where even cellular phones today have more built-in processing power than some desktop computers, especially since the introduction of the iPhone by Apple which reversed the traditional design of 'phone first, computer second' (Linge and Sutton 2015). Development tools become very sophisticated and some are dedicated towards simulation building (Nikolai and Madey 2009). It is possible to write meaningful simulations with less than one A4 of source code (Schmitz 2018).

Computer simulations have been used in archaeological research for almost 50 years (Lake 2014). Although initially hampered by insufficient hardware in the 1970s, the theoretical background in complex systems theory and significant improvement in computing power allowed many researchers to include more and more computational modelling in their research agenda (Kohler and Van der Leeuw 2007). Agent-based modelling especially offers the possibility of addressing individuality and emerging phenomena in social interactions in complex systems (Premo *et al.* 2005). Agent based models are now recognized as a powerful means to explore the relations between individual actions and larger social structures for any time scale (Rogers and Cegielski 2017). The capability to model change and emerging phenomena makes the method well suited to analyse certain categories of archaeological hypotheses (Cegielski and Rogers 2016).The method is quite appealing to archaeologists due to the analogy between agents producing simulation results and the humans in the past creating an archaeological record. And a significant number of archaeologists today has experience with writing, replicating and reviewing simulations as is illustrated by the five sessions (out of 42) at the Computer Application & Quantitative Methods in Archaeology (CAA) 2018 conference that were dedicated to some aspect of modelling and simulation[5].

Simulation as a technique is used for a wide range of purposes that include prediction, performance, training, entertainment, education, proof and discovery (Axelrod 1997). As a methodology it adds a novel way of doing science: like deduction it starts with explicit assumptions but then generates new data that can be analysed inductively. But unlike

[5] http://2018.caaconference.org/sessions/, accessed 11 December 2017. Sessions include S3, S9, S10, S17, S19, and S22.

standard induction, this data is not derived from measurements in the real world, but extracted from explicitly stated model environments (Axelrod 1997, 25).

2.2.1 In or out: what to include in a model

Archaeological models necessarily (over)simplify the past. A model is thus inherently incomplete[6]. And if any factor is not included in the model, it will not influence the results and might not be included in the discussion (nor in the reconstruction of that past). This realization has resulted in more complex modelling with positive feedbacks (Kohler 2012). Elements of a model can be parameterized, where different values for a parameter create different models. The addition of model elements or parameters can result in over fitting, where the exclusion of details can lead to under-fitting.

The selection of parameters is ultimately guided by the principle of parsimony (Forster 2000). Adding more parameters will capture noise in the data, and it is therefore essential to keep the number of parameters low, or to prune the model when possible. By adding parameters it is possible to fit all data (it takes about 30 parameters to fit an elephant according to Burnham and Anderson (2003, 30)). Under-fitted models will capture little structural information and are equally ill fitted for inferences about novel data sets (Wagenmakers 2003). A model is constructed by people, and therefore implements the biases of the author(s). It is very difficult to avoid such biases and effort must be invested in mitigating the steering effects. Minimally, the biases must be stated as explicit as possible. Ultimately it is the creator of a model who can and must rationalize what is included and what is not.

2.2.2 Model credibility

Modelling and simulating past hominins in a reconstructed environment using demographic parameters that are documented ethnographically (like birth rates, mortality figures, procreation, and consumption) allows representation of human behaviours in a reproducible manner. Actors who interact according to individual level behaviours create a system that is characterized by aggregate patterns which are quite comparable in scale to those observed in the archaeological record (White 2013, 124). Reality is modelled to some degree with the hominins behaving according to the rules as put forward by the model.

[6] Cliff Notes version: All models are wrong, cited by John Hawks: http://johnhawks.net/weblog/reviews/neandertals/neandertal_dna/neandertal-ancestry-iced-2012.html, verified 8 okt 2013.

The validity of such a model, that is 'how well the model represents hominin behaviour' can be addressed by comparing the simulation results of the model with the known material remains that are the results of hominin behaviour in the past (Gilbert 2008). A prerequisite for a valid comparison is that the reflected behaviours are not directly programmed into the model, and that these behaviours are not the emerging phenomena that are being investigated. As such, comparison must be made with elements of the archaeological record and the corresponding aspects of the model that are the result of the dynamics of the simulated system. The elements of the archaeological record may not have been used to construct the model. These comparisons allow assessment of the degree to which the internal dynamics of the model match those of the system it represents (White 2013, 137-138).

Since a model is always by definition a simplification of reality, the results from simulating that model reflect some elements (but not all!) of the real world. Statements based upon modelling results thus have an inherent believability problem. Within archaeology, a model should be able to explain past observations, predict future findings, should be refutable, should enable an estimation of the level of confidence in the model and should be simple (Marwick 2017). One of the most important gains is that one unrepeatable process (the behaviour of hominins in the past) can be imitated by another process (the simulation), one that can be replicated and parameterized at will (Hartmann 1996). Sometimes simulated experimental data is even preferential to compare theories against, since for this data input values are known (Konigsberg and Frankenberg 2013, 295).

The evaluation of simulation results can be quantified using a utility function, the design of which is a key element in the modelling effort. Simulating models does not duplicate reality and correctness of a model cannot be formally proven. It is up to the designer of a model to ensure that the model contains the key elements of the modelled process, and that therefore simulation results actually represent what could have happened in the real world.

An important issue with models when used as an explorative tool in archaeological reconstructions or interpretations is the stochastic nature of the input and the results (Peeters and Romeijn 2016). Generally, only after a multitude of simulation runs certain patterns are certified to occur and not due to chance events, and thus by definition have a statistical likelihood and comparative reality value. This diminishes the credibility of the model and the simulation results. Thus, a sound theoretical basis is required beforehand and a statistical significant validation of the results afterwards.

A fundamental aspect of the scientific method in general is that experiments can be reproduced and replicated by other researchers, who can sub sequentially build upon these results to advance the field of research (Wilson *et al.* 2014). Credibility, that is the acceptance of model and results as correct, increases with the quality of the development process (Law and McComas 1991). Computational reproduction of simulation results and replication by different researchers will strengthen the model as a true approximation of past behaviour and will increase the credibility of the research (Marwick 2017). To allow proper reproduction, certain basic requirements must be met. At the very least these include making publicly available the raw input data, source code and output data (Peng 2011, Sandve *et al.* 2013).

2.3 Techniques for modelling dispersal in landscapes

Neanderthals no longer exist and thus cannot be observed nor can they be subjected to experiments to test hypotheses. Ethnographic data has limited applicability, allows little experimentation as well, is generally difficult to reproduce, has limited control group facilities and has limited time depth. Computational modelling and complex systems theory can offer remedies to all of these issues (Gilbert 2008; Kohler and Van der Leeuw 2007; Miller and Page 2007b; White 2013, 131). For exploring dispersal hypotheses in a constructed landscape there are basically three different techniques available: Mathematical Modelling (MM), Cellular Automation (CA) and implementing an Agent Based Model (ABM). Each of these methods has its specific advantages and disadvantages.

A well-known example in MM is the "wave of advance" model for population expansion (Ammerman and Cavalli-Sforza 1984; Fisher 1937). Fisher (1937) defined the constant rate of advance (r) in his model of the spread of an advantageous gene as follows: $r = \sqrt{(2 * g * m)}$, with g the growth rate and m the migration rate per unit of time and space. This has been applied to many other diffusions, for instance to the spread of agriculture in Europe by Ammerman and Cavalli-Sforza (1984) and Davison *et al.* (2006), or Paleoindian dispersals in North America using environmental carrying capacity and estimated diffusion coefficients by Steele *et al.* (1998). A disadvantage of the very abstract mathematical models is that often restrictive or unrealistic assumptions are imposed that limit their applicability. Examples are linearity, homogeneity (identical individuals) and normality (Bankes 2002, 7199).

A CA is a dynamic system in which space and time is discrete and where the system is specified through a regular matrix of cells, their boundary conditions and their relations with other cells, a finite set of states for each cell, and rules that determine the dynamics of the cells (Wolfram 1983, 602). In CA the basic unit is the cell, and each cell is updated by a state transition function synchronously in discrete time steps (see for instance Pfeifer *et al.* (2008)). Good examples are by Surovell (2003), who studied the colonization of the Americas with a grid based simulation using the carrying capacity of the coastal areas, or SteppingOut implementing Out-of-Africa dispersal by Steven Mithen and Melissa Reed (Mithen and Reed 2002). One of the more restrictive elements of grid-based modelling is the memory requirements when modelling large areas using small grid sizes. Using large or equally-sized grid cells gives the simulation an abstract character and limits free movement through space. Modelling individual entities is cumbersome in CA models. ABM addresses some of the limitations of both MM and CA.

2.3.1 Agent Based Modelling

Agent-based Modelling (ABM) [7] focuses on the behaviour of individual entities who act according to certain rules (Abar *et al.* 2017). It enables in a bottom-up approach the study of how aggregate system-level and individual-level patterns emerge without a central controller (Bonabeau 2002; Bankes 2002, 7200; Young 2002, 138). This means that individual activities (interactions, processes) produce system level dynamics (like cultural norms or institutions) which are not visible (or even known to be present) at the individual level. This is contrary to more traditional models where the characteristics of a population are averaged and changes in these characteristics are simulated for the whole population. In ABM the characteristics and actions of each autonomous individual are tracked through time and systematically the aggregated consequences are established. Due to these properties heterogeneous agents in such a system form a natural specification of the concepts in many social problems (Bankes 2002, 7199; Macal and North 2009) for which empirical methods of analysis are often the only available alternative (Edmonds and Bryson 2004).

[7] Referred to as Individual-based Modelling (IBM) in ecology, and conceptually the same as in Multi-agent Systems (MAS) where the agents are complete systems like the computers in a network.

Detecting the emergence of such phenomena often relies on graphical output in which the operator is needed for identification of (newly emerged) features. Micro motives can result in macro behaviours (Schelling 1978, with an illustrative example in the analysis of non-malicious segregation in black and white neighbourhoods resulting from only minor preference differences). Defining measurable macroscopic behaviour across multiple simulations can give rigor to the analysis. Non-linearity of interactions between individuals and the unpredictability of the effects of individual behaviour on social dynamics and structures complicates understanding of macro scale implications (Miller and Page 2007a).

Simulations in ABM progress through time in discrete time steps, where all actions for one time step are completed before the next time step is started. Agents in ABM interact in rule-based and goal-oriented ways. An agent perceives (senses) and interacts with its environment and with other agents. Its behaviour depends at least partially on its own state and experience. The agent decides what actions are needed to satisfy its objectives. Table 1 describes the general characteristics of agents in ABM (Macal and North 2005). ABM has been extensively used in ecology, biology, and the social sciences (Abar *et al.* 2017).

Table 1: Common characteristics of agents in Agent Based Modelling.

Characteristic	*Description*
Individuality	Each agent is uniquely identifiable, with individual characteristics in the form of a distinct set of attributes. The social organization is decentralized.
Environment	There may or may not be influence from the agent on the environment, but there is always influence from the environment on the agent.
Autonomous	Each agent is goal directed and independently decides what action to take to achieve its goals, according to certain rules.
Flexibility	An agent has the ability to learn and adapt its behaviour over time based on its experience.
Local view	The individual agents can only access that part of the environment which they can perceive. Not one has a global view of the complete system.

An important concept of ABM is the environment in which the agents operate. Often the agents have some influence on the (local) environment, but they are always influenced by that environment. Adding data from a Geographical Information System (GIS) to an ABM system maps the characteristics of the real world onto the space of the agents and greatly enhances the representation possibilities to visualize patterns (Mathur 2007). Information in a GIS tends to be static, whereas the dynamic environment in an ABM generally tends to be schematic (instead of real-world data). A combination yields the benefits of both approaches. A small change in the simulated environment of an ABM can change the nature, and even the occurrence, of high-level behaviours (Polack *et al.* 2010). As a result, simulated environments are as important as agents in order to reach the purpose of the simulation study.

The ABM methodology shares with all other modelling approaches the difficult and creative process of deciding what to include (more realistic) and what to exclude (more abstract) from the model (cf. Janssen 2009). Ultimately it is the modeller that decides, but via peer-review processes and other techniques it can and must be ensured that the model actually represents those parts of the real world that the modeller intended to model. Agent based models are calibrated using data on individual behaviours, which can include archaeological data.

Validation of modelling results is one of the most important methodological challenges in ABM (Gilbert 2008). This can be approached in two ways: first one can look at the process and quantify the way the model represents elements of the real process, or one can compare the modelling results (aggregated patterns) against real, empirical data (and implicitly assume or explicitly define that a good match means that the model represents the causal process well). The independence of the calibration process with the validation step provides ABM its explanatory power (but as noted by Angus and Hassani-Mahmooei (2015) this is surprisingly often lacking in publication efforts). It is essential to address such critical elements of the method documenting the modelling process (Marwick 2017).

Humans and human groups are highly individual, have territories and live in diverse dynamic social structures. Analytical models are less suited to model these characteristics (Pitt *et al.* 2003, 110). In archaeology ABM has been used to investigate a number of research questions. Good examples are the MAGICAL project with agents harvesting resources (Lake 2000), ENKIMDU simulating Mesopotamian settlement systems (Christiansen and Altaweel 2005) and the Prehistoric Patagonia model where initial hunter-gatherers become farmers (Barceló *et al.* 2008). For a good overview of the use of ABM in archaeology, see Barceló *et al.* (2008) and Lake 2014. ABM has been chosen as the modelling technique to implement HomininSpace.

2.4 HomininSpace – a model of the past world of hunter-gatherers

The core of my research and the main topic in this thesis is the HomininSpace modelling and simulation system. HomininSpace builds upon the experience gained when implementing SteppingIn, a simulation tool I implemented in order to compare alternative scenarios about how Europe was populated by modern humans (Scherjon 2011). The current thesis draws further upon the development of an early version of HomininSpace (version 1.0, Scherjon 2015a). Underlying research question in that study was the identification and qualification of key hominin characteristics (parameters) needed to model dispersal in the landscape and to assign values to these key parameters from biological, archaeological, paleoanthropological and ethnographic data and literature. Simulated presence of modelled hominins is then compared against archaeological data from specific sites to assess the quality of the model, where more matches means a better model. A case study of different mobility types for Neanderthals in western Europe served to assess the usability of the tool and explored whether distributions of Neanderthals in the landscape through time were caused by continuously tracking preferred habitats (Hublin 2009, Roebroeks *et al.* 2011).

The tracking of favourable habitats has also been described as the “ebb and flow” of populations (e.g. Hublin and Roebroeks 2009), and involves individuals or groups of individuals moving to areas where the most favourable circumstances are found. When conditions worsen, populations would retreat into refugia with more benign environments (Stewart and Lister 2001). The dynamic “ebb and flow” of constantly moving populations has often been opposed to a more static “sources and sinks” model where local populations must adapt behaviourally and/or genetically to cope with the changing climate or become (locally) extinct when conditions become less favourable (Pulliam 1988; Pulliam 1996). They are replenished from more productive areas when the situation improves (Dennell *et al.* 2011; MacDonald *et al.* 2012). Obvious examples of this “sources and sinks” model are most species of flora. Since individuals cannot move by themselves they invariable die when the climate deteriorates sufficiently. For species to live there again when conditions improve the area must be re-colonized from other source areas.

Analysis of the simulations in HomininSpace 1.0 implementing a static versus a dynamic mobility suggested that the archaeology of Late Pleistocene Neanderthals best matches hominin groups following a static strategy where they occupy an area and stay there even if the environment becomes less favourable. Note that static here does not mean sedentary. Static hominins in HomininSpace still move around collecting resources but they do this in a confined local area from which they cannot leave. It was concluded that Neanderthals would have followed at least partly this more static strategy and were thus maybe less mobile staying in more confined areas than previously thought.

Results and details from the HomininSpace 1.0 program were presented at international conferences including the Computer Applications and Quantitative Methods in Archaeology (CAA) and the European Society for the study of Human Evolution (ESHE) meetings (Scherjon 2015b, 2015c). The enthusiasm that was expressed by peer researchers illustrated the interest in this topic. Due to the importance of peer review and replication in modelling studies a replication of some of the core elements of HomininSpace was implemented in 2016 by Iza Romanowska, a researcher trained in Palaeolithic Archaeology and computer modelling.

This replication in the NetLogo simulation environment failed to reproduce the patterns observed in the simulation results. In the original model a 'source and sink' mobility pattern consistently outperformed the 'ebb and flow' hominins for those simulations that have a good match with the archaeology. Doubts imprinted by the replication efforts inspired more simulations in HomininSpace, and then the identification of a pattern of peak simulation results. Many parameter value combinations lead to good matches with the archaeology and indeed, the 'source and sink' implementation scored higher on these than the 'ebb and flow' mobility type for the same parameter values. But next to many low scoring simulations there were occasionally some parameter value combinations that produced high scores in which the reverse was observed: 'ebb and flow' scored higher than 'source and sink' for the same parameter values (Figure 1).

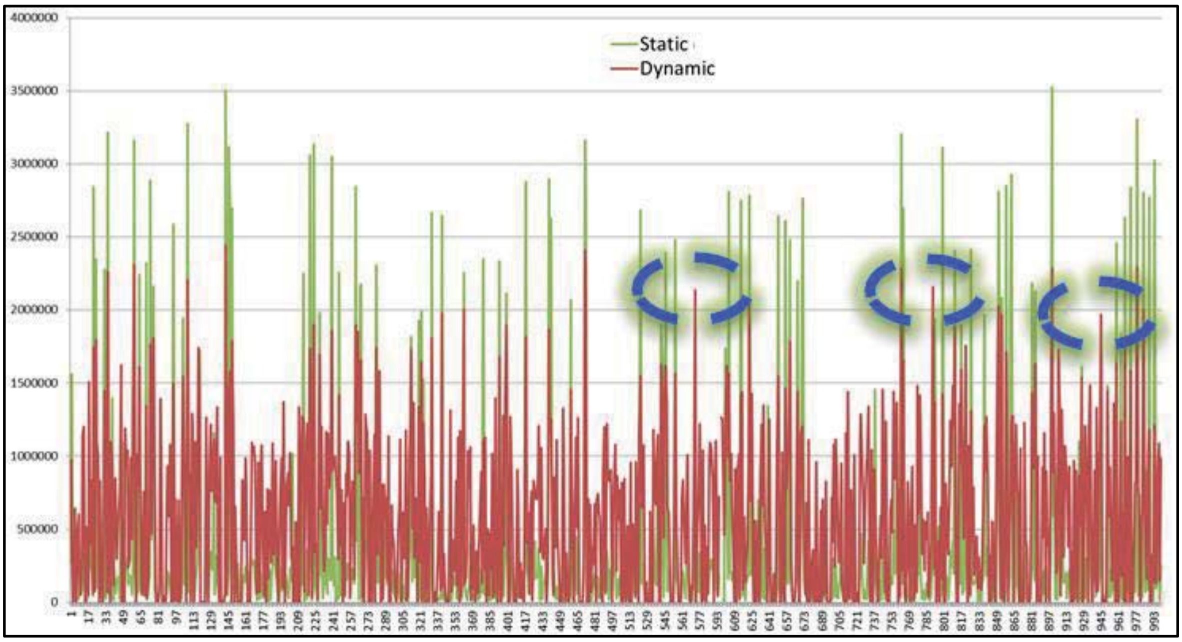

Figure 1: Simulation scores in HomininSpace 1.0. Blue circles indicate some local maxima where the dynamic or 'ebb and flow' hominin implementation (in red) score higher than the static or 'source and sinks' hominins (in green).

This important find made clear that the bias in value selection from a researcher should not be used when creating hominin parameter values in this model. Instead in an exhaustive search many different simulations must be executed to find the best simulation results. The new system, HomininSpace 2.0, is able to vary autonomously all parameter values, run simulations, collect and analyse results. The system then identifies promising parameter value combinations and creates new ones in an attempt to improve the match with the archaeology. This is an intelligent and autonomous implementation that can operate without intervention and more important without guidance by a human researcher. Therefore a dedicated implementation of a Genetic Algorithm model (cf. Calvez and Hutzler 2006) is developed that optimizes parameter values while matching archaeology (Scherjon 2016). This automated exploration also allows more hypotheses to be explored simultaneously. Analysis finally identifies those parameters that are relevant for answering the different questions, and the parameter values that give for each question the best match with the archaeological data.

Computer based simulations in archaeological research are mostly related to the testing of hypotheses, to theory building, or to the development of new methodologies (Lake 2014, 260). HomininSpace was developed as a tool to be used to explore the effect of implemented model elements on the behaviour of hominins in a reconstructed environment, with matching archaeological data as the main indicator of success. It is specifically designed to allow easy introduction of new functionality that can be combined with already implemented model elements to analyse more complex (and maybe more realistic) scenario's. The functionality in the model that is associated with certain questions can be activated at will and is used to project the consequences of the alternatives for the behaviour of the system (Nichols 2001).

The model is constructed following a bottom-up, pattern-oriented strategy (Grimm 1994; Grimm *et al.* 1996). In this approach, a pattern in the real world is observed and within the model variables and processes are included to enable (but not force) a pattern to emerge in simulations (Grimm *et al.* 2005, 987). Today one can see hunter-gatherers move through their environment according to certain preferences, and in the archaeology archaeologists find (in)direct traces of past mobility through time in a changing environment. HomininSpace implements a changing environment and a parameterized behavioural repertoire for modelled hominins. This technique is bottom-up in the sense that at the individual level the hominins (agents) are given certain characteristics and are then allowed to interact amongst each other and with the environment. The emerging system level patterns in the simulation output are analysed and compared against the archaeological data. It then becomes possible to systematically explore how changes at the lower level affect the patterns that emerge at the system level.

The environment in which the hominins in HomininSpace live uses modern day topographical data for land and sea masses, augmented for reconstructed sea levels. Climate parameters that are most influential on the environmental circumstances (temperature and precipitation) are reconstructed for the whole simulation period. The hominins are modelled with parameters inspired by ethnographic data. The use of ethnographic analogies for modelling the hominins in HomininSpace may seem an obvious choice, but the Neanderthals from the Late Pleistocene are not modern humans and they lived in an environment that is largely non-existent today. If they are used such analogies should be well motivated (Wylie 2002, 147-153).

Within the model underlying HomininSpace ethnographic data is used to (1) identify the physiological variables and cultural behaviours that influence dispersal, and (2) illustrate the regularities and the range of variability of these behaviours and constraints thereof. Within the ethnographic record there is not one single culture that forms a direct analogy to the Neanderthal way of life. Instead this record is used to identify the parameters and possible value ranges thereof to be used in the design and implementation of the hominins in the model. HomininSpace is a spatially explicit model that attempts to quantify relevant variables that are involved in hominin dispersal.