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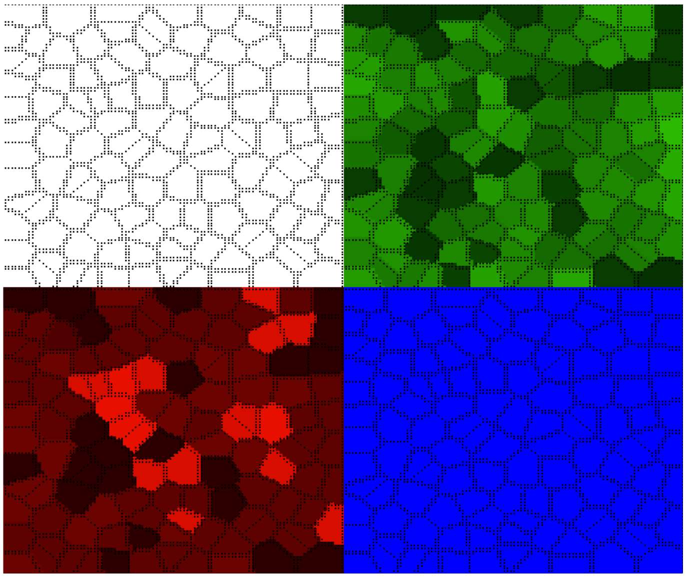

A Complex Systems Approach to Human Cultural Evolution

Master's Thesis in Complex Adaptive Systems

JAMES ALLEN

Division of Physical Resource Theory
Department of Energy & Environment
CHALMERS UNIVERSITY OF TECHNOLOGY
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Cover:
An example of the evolution of groups with various dietary strategies from the geographical model developed within this thesis.

Chalmers Reproservice
Göteborg, Sweden, 2013

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Abstract

This thesis will use two abstract computational models to investigate a number of outstanding questions related to human cultural evolution. Using simulations explanations for a number of phenomena within the archaeological record will be put forward. These will include the discontinuous cultural evolution patterns, the broadening of human diet and the extinction of the Neanderthals. The central theme throughout these findings is that it is the fidelity of transfer, and by extension the increase in complexity of early hominid culture, that constrains the subsistence strategies used within the Palaeolithic era, whilst the form of the resources dictates the form that these strategies will take. Key to these dynamics is the territorial competition between groups, with a more diverse strategy leading to more efficient groups that can encroach on the less efficient, reducing the carrying capacity and causing the population to move below the minimum group size allowed, thereby becoming extinct.

Key words: Palaeolithic culture, dietary evolution, fidelity, glass ceiling, punctuated equilibrium, Broad Spectrum Revolution.

Acknowledgements

Thanks must go to my supervisor Claes Andersson for suggesting such an interesting topic and putting up with my deficit of archaeological knowledge. His help and open door have been invaluable throughout. Helpful contributions have also been made by Petter Törnberg from Chalmers, and Mary Stiner and Steve Kuhn of the University of Arizona, and final thanks must go to my examiner Kristian Lindgren and all those involved on the CAS programme.

James Allen, Göteborg 3^{rd} June 2013

Contents

Chapter 1

Introduction

The Stone Age did not end because we ran out of stones
- Björn Lomborg, The Skeptical Environmentalist

The journey from the simple beginnings of human culture to the complex times that we currently live in has been a long one, taking in many different technologies and geographical regions. This began with basic stone flakes used within the Oldowan culture 2.6 Mya [1, 2], through to the first sightings of stone axes 1.8 Million years ago (Mya) and on to the change to agriculture and the beginnings of civilisation approximately 10 thousand years ago (kya). Along with advances in technology a change in diet is also observed [3, 4], within the Upper Palaeolithic around 45 kya with what appears to be a broadening in the types of resources that were consumed.

The questions that this thesis will address are questions of why human culture changed at all? Above all, why has human culture exploded in complexity, whereas animal complexity has remained at a very low level. And, as we know that human culture did become more complex, what were the mechanisms behind these changes?

In order to investigate these questions in more detail this thesis will study only a small part of human history, taken from the Middle to Upper Palaeolithic era (300 kya to 10 kya). Within this time a great many changes took place, moving from a hunter-gatherer lifestyle with the use of spears and big game hunting [5] all the way through to sedentary agriculture, over a time span of 200 kya to approximately 10 kya.

The first aspect of human culture to observe is that it exists at all. Humans are the only animals that are able to exhibit open-ended *cumulative culture*, e.g. the idea that the culture that you or I are part of today is built upon many previous generations of evolution within our culture. Whilst there are many examples of animals with the ability to use tools [6, 7], and even teach some methods to others there is no open-ended accumulation of technology and culture. The development of both more advanced tools and fire is a clear indication that early humans were able to move beyond their animal cousins. This mystery of the cumulative nature of human culture is one of the major themes of this thesis.

This thesis will also try to address the mechanisms behind these changes to the culture and diet of early humans. Rather than a gradual change it appears that there is a large leap between the Middle Palaeolithic (MP) and the Upper Palaeolithic (UP) at around 40 kya [1, 8], moving from a simple culture consuming mainly large game to a more developed culture supplemented with smaller, faster moving fauna.

Most explanations of these 'jumps' in culture use either environmental or population changes to explain the developments, and it can be seen that the increases in diet are accompanied by pulses of population increase [3, 9]. Within this thesis two abstract models will be built to test these ideas, and see how closely these models match the reality in the archaeological record.

1.1 Transfer of knowledge

In order to investigate the existence of cumulative culture, and the ways in which this may have affected the evolution of our diet a model of the transfer of information between generations will need to be built. The central theme in this case is the idea of *fidelity* e.g. how exactly information is able to pass between generations, or the probability of a piece of information making it across the 'jump' between generations [10].

Due to the lack of writing or any other permanent method of storing information within MP and UP societies transfer of knowledge through permanent artefacts is difficult. Although certain possibilities exist for knowledge to be kept in a permanent state (such as in the form of a finished tool) the only consistent way for information to be propagated between generations is through a Knower-To-Knower-Knowledge (KTKK) transfer system [8]. Although it may be difficult to assume that all knowledge would be passed on in this manner, it is difficult to see that all aspects of a culture would not have some KTKK component involved.

In order to model the transfer of knowledge between generations this thesis will therefore take a master/apprentice system of knowledge transfer. This means that the ability to make tools and to hunt certain prey are passed between the generations by one member of a generation teaching a member of the next. Within this thesis the information that is passed between the generations will be represented by units of culture. These will be the simplest units of the culture that can be known, and will have the ability to be combined to create more complex cultural parts.

The representation of how complex a culture is embodies a difficult conceptual challenge. There have been examples of anthropological studies using 'technological units' (TU's) in order to measure the advancement of different technologies [11], which can aid in providing a metaphor for stone age cultural complexity, and examples of various levels of technology can also be found in models of cumulative culture [12]. However, it can be noted that many of the constituents of culture can be represented as a set of instructions, and that these instructions can be broken down into their separate parts. In order to make this representation there are three assumptions about culture that need to be considered [10],

- Cultural representations can be decomposed into smaller units.

- These components are functionally linked.
- Each component is transferred separately, but in order for the final technology to be active all parts need to be transferred perfectly.

The first two of these assumptions lead on from the previous arguments. The third can be assumed, as if just one instruction is missing from a list of actions then this would most likely cause the failure of the entire process of cultural construction.

There have been a number of previous studies that have modelled fidelity [10]. These include Enquist [13] who has shown that higher fidelity is able to support longer traditions, and Lewis and Laland [1] who have shown that fidelity is a large factor in the creation of cumulative culture. However, in many of these studies of fidelity it is assumed that culture takes on an atomic form, and that each unit of culture passes on to the next generation whole, with little error involved [10], and so the discussion of culture then uses the paradigm of population genetics and simple ratios of the cultural units.

This is not the approach taken by Andersson [8, 10]. He argues that with KTKK methods of cultural transfer the errors of transfer would not be negligible, but instead would be large enough to have an effect on the transfer of the knowledge, and that rather than using the low error biological transmission model of genes in higher life forms a much more appropriate model for the transfer of information is that of the high error viruses, bacteria and RNA replicators. Taking inspiration from the work of Eigen and Schuster [14], here it can be shown that if cultural knowledge is taken to be a string of units that are each individually transmitted with fidelity then the total volume of knowledge that can be transmitted is exponentially proportional to this fidelity. This model leads to a number of very interesting phenomena that are able to give a number of insights into the mechanisms behind cultural evolution within the Palaeolithic era.

1.2 Punctuated equilbirum

One such phenomenon is that of the punctuated equilibrium found within the archaeological record. The standard view of the Palaeolithic era is that there are long periods of stasis followed by very short periods of intense technological and cultural advancement [8]. A good example of this is the jump in the complexity of technology between the MP and the UP. Somewhere between the time of 35-45 kya there was a large expansion in the complexity of tools [1]. These increases are found to bring increases in both population [3] and cultural and technological complexity, along with a change in diet within these human cultures. However, recent discoveries suggest that there were times within these periods of stasis when there have been isolated incidents of increased technology, both geographically and temporally.

The standard explanations of the step-like nature of increases in cultural complexity are two fold. The first is environmental, with a more suited environment leading to higher population, which then enables the ability to sustain more complex cultures [13]. The second explanation is physiological. As human brains get larger, or our bodies change to survive more easily within the environment this can lead to an increase in conceptualisation skills. This in turn will lead to the ability to make better tools, and then to higher populations [8].

The problem with both of these explanations is that the archaeological record only supports them loosely, if at all. The skeletal changes that may be found in the archaeological record are only weakly in sync with the times at which the large jumps in cognition are found, with a time lag of 100,000 years not uncommon. Allied to this is the fact that there are also sporadic appearances and then disappearances of more advanced technologies, which do not agree with a physiological explanation.

Along with these questions there are also many queries about why any change would be needed at all. If the environment was still conducive to these groups way of life then why would they change their strategy? Even if there was a physiological increase in cognition, this still does not provide a driving force for the changes found within the fossil record. As well as this, it does not appear to be the negative impacts of change that caused the increase in cultural complexity.

This is where the model by Andersson [8, 10] is able to shed some light. If each unit of cultural complexity is passed between generations with a certain fidelity then this introduces the concept of the glass ceiling (the maximum amount of knowledge that can be contained within the system). Information at a level higher than the glass ceiling will not be transferred to the next generation correctly, causing a loss of all knowledge in the model and destabilisation in more realistic settings. Therefore, if at any point there was a sudden increase in fidelity this would raise the glass ceiling, and allow more technologies to suddenly leap to a higher level.

This model is therefore able to explain two of the quandaries involved in these finds. The first is the lack of correlation between the skeletal developments and the jump in the cultural complexity. This can be explained by the fact that the leap in fidelity allows the glass ceiling to rise, but that culture takes a while before it reaches the maximum KTKK volume.

The second phenomena that the Andersson model can aid in explaining is the isolated expansions in culture and population. These can now be interpreted as the culture of a society gaining a complexity that is higher than the glass ceiling, and only being able to maintain this for a short time as the fidelity of transfer is too low, or that the complexity within the model was distributed in a more focussed way for a short amount of time.

Explaining the driving force behind these changes is more difficult. As was mentioned above, why the culture of a society should change at all if there are no external factors is difficult to understand. One suggestion that this thesis will attempt to expand on is the Broad Spectrum Revolution (BSR), which invokes population pressure to help explain the changes found.

1.3 The Broad Spectrum Revolution

The original suggestion for the BSR comes from Flannery [15], based on work by Binford [16]. Binford postulated that early groups were able to reach a cultural equilibrium point, at which they would remain before external factors pushed them away, whilst

Flannery observed changes in diet in the fertile crescent (in the region of Iran) towards groups eating a larger variety of plants around 20 kya. The broadening also led to the consumption of more grain and smaller fauna such as crabs and partridges. Before the change ungulates (hoofed animals) accounted for 99% of the food consumed by these groups by weight, but after the change the amount shifted downwards towards 90%.

The primary cause suggested by Flannery was that population pressure was behind the broadening of diet that he found at this time. However, many other causes have been suggested, such as environmental changes, and finding the true causes of this broadening of the diet has not been simple. It has been suggested that starvation is not a cause for the change, and BSR is found to occur in regions of high resource density [17]. In other words, it does not seem to be negative impacts that drive the changes in diet that are seen in the archaeological record.

Evidence for the diets of early humans and Neanderthals comes from isotopic measurements and bone remains. Here there is a lot of evidence that both Neanderthals and early humans were top level carnivores [18, 19] hunting deer, mammoth and bison. However, whilst the Neanderthal diet remained constant throughout this time it is seen that modern humans developed a much broader diet, supplementing the large game with hares, birds and fish [20]. There is also evidence that there may have been cultural diffusion between humans and Neanderthals [21].

Strong evidence for the broadening of Palaeolithic diet has also been found in work by Stiner *et al* [3], where they were able to show a broadening in human diet in two areas around the Mediterranean throughout the Palaeolithic era. Here it was found that sessile (slow moving) fauna were constantly present within the diets whereas it was the fast moving animals such as hares and small birds that begin to appear much later in the diet of these early humans.

Stiner was able to find these results by reclassifying the prey that were consumed by these groups. If a simple Linnaean classification system is used, grouping the animals into their taxonomic groups, then it is hard to see any kind of clear pattern within the fossilised remains. However, once the animals are grouped by the methods that they used to evade capture e.g. by moving fast or slow, using armour or residing in groups then the broadening of the diet becomes much clearer [22]. It could now be seen that the groups clearly change their strategy from that of capturing large and slow moving game to the smaller, faster and more difficult to catch animals. These results can be taken to be general as they are found within two geographically separate sites.

There were also suggestions that the BSR strategies spread through "the budding off of 'daughter' groups" [17] into regions where there was a smaller amount of resource density present. This involved more successful strategies building up large populations and then splitting, before pushing into outer regions. Due to these groups more successful strategies they would have been able to possibly drive less populated groups with simpler strategies to extinction. There is a suggestion that this was the cause of the extinction of the Neanderthals within mainland Europe [23].

In order to test the validity of these ideas in this thesis both computer and mathematical models will be created to simulate some of the key points addressed above.

1.4 Simulation in anthropology

The advantage of computer simulations in anthropology and archaeology cannot be overestimated. Many of the problems in palaeo-anthropology involve missing pieces of data, where important artefacts preserve poorly, or that there are so few sites to be discovered. Simulation (and to a lesser extent, mathematical modelling) can take any suggestions for the development of certain archaeological finds and test them. The ability to repeat experiments within the computer that cannot be repeated in the real world can also give valuable insights. Obviously, building a complete model that is able to account for all of the possible factors involved within any evolution of the early humans is impossible, and so what is needed instead are abstract models that investigate certain factors and give clues to what is and is not possible.

These abstract models include 'Stepping Out' [24], where the movement of peoples from Africa and out into Eurasia are modelled, that of Stiner *et al* [3] to model the behaviour of fast and slow moving prey under sustained predation, Andersson [8, 10] to investigate the role of fidelity on the glass ceiling and Laland and Lewis [1] who have simulated the effect of fidelity on cumulative culture.

Using the techniques found in these examples this thesis will create two models in an attempt to investigate the evolution of Palaeolithic humans. The first of these will extend the Andersson model using ideas from Lewis and Laland to observe if an RNA inspired fidelity model can replicate some of the latter's findings, and if a more complex method of culture can still give the glass ceiling phemoneon as found by Andersson.

Having then tested the phenomena found through the transmission of culture through the generations, and how the concepts surrounding the application of these units of culture can be applied to abstract models of cumulative culture, the evolution of the diet of the early humans will then be modelled. Here, a less abstract model consisting of caricatures of the resources consumed will be modelled on a geographical grid, with hopes of finding some of the key aspects of the BSR.

Chapter 2

Investigating Fidelity

In order to investigate the possibilities of combining the Lewis-Laland model [1] and the Andersson model [8, 10] and whether a fusion of these models can demonstrate the creation of cumulative culture, a computational model will be built. This model will look for aspects from the work from both Andersson and Lewis and Laland, including cumulative culture and the glass ceiling phenomenon.

Within the Andersson model complexity of knowledge is represented as a string of units, with the length of the string corresponding to the complexity and utility of the technology. This technology is then passed on between groups in a KTKK way i.e. one member of a stone age group teaching certain skills to another member of the same group. Within this model an error of transmission is built, the fidelity of transmission, which gives the probability of each technological unit being transferred correctly between generations. If an error is made then it is assumed that the technology becomes useless, and the knowledge will therefore be removed from the knowledge base of the society.

A mathematical form can be derived to show the maximum complexity that a technology can be expected to take within this society, given by,

$$N_c = -\frac{1}{\ln q} \tag{2.1}$$

where here q is the fidelity of transfer for each unit of complexity, and N_c is the critical length of the string representing the technology. The derivation of this result was inspired by the quasi-species model developed by Eigen and Schuster [14].

Whilst this model gives a number of very useful insights into early human cultural evolution there exists an implicit relationship between complexity and utility, with the technologies within this model propagated with higher probability for longer string sequences. However, this is not necessarily how technologies are selected. There are some very simple technologies that are incredibly useful, and this model does not address this fact. There are also a number of other issues that need to be addressed within this model. The first is that this representation of technologies as one dimensional strings is simplistic and maybe a more interesting way of forming complex technologies will need to be investigated. Another factor is that this model is not able to demonstrate the creation of cumulative technology within these early human societies. The final aspect missing from this model that may affect the selection of technologies is how much time they take to teach, and how much time should be allocated to this. The volume of knowledge that is below the glass ceiling could be distributed in a number of different ways, in either few, very complex tools or many simple ones.

One model that has tried to address some of these issues is that developed by Lewis and Laland [1]. This model begins with a number of combinable seed technologies, representing the smallest units of technology or culture that can be found. For example, the idea of a sharpened point and the concept of attaching two objects together can lead to a spear. As time moves on larger and more complex technologies are built by combining these initial seed technologies. Each technology is also assigned a utility, dependent on the utility of the technologies combined to create it.

As well as being combined, technologies can also disappear, and will disappear at a rate that is inversely proportional to the utility of the technology. In this way the more useful technologies will be preferentially selected for within the population over time. The results that this model provides are claimed by the authors to demonstrate the importance of fidelity to the creation of cumulative culture. However, there are a number of flaws that the model developed within this thesis will try to address. The first is that the Lewis and Laland model still falls into the trap of absolute fidelity of transfer, something that was argued in the introduction to this thesis is a problematic assumption. The second problem is that this model is run for a set number iterations, and not to equilibrium. It is the opinion of this author that this may bias their results.

The model being described in this thesis will attempt to fuse the ideas represented within the Andersson and Lewis-Laland models to investigate the transfer of knowledge between different generations of pre-historic societies. In order to do this complex technologies will be built from smaller, less complex seed technologies that will then combine over time. These technologies will then transfer between generations using the mechanism based on fidelity e.g. the more complex a technology the more difficult it is to transmit between generations. Within this model it will be desired to remove the complexity/utility connection that is found within the Andersson model, whilst also including the ideas of fidelity of transfer and more explicit knower-to-knower technological transfer within the Lewis-Laland model.

The final aspect of the evolution of early human culture that this model will attempt to capture is the broadening of the diet as time progresses. Moving from the Oldowan, through the Middle to the Upper Palaeolithic it can be seen that the human diet broadened from one that was mainly based on scavenging to one that included the hunting of many large fauna supplemented with fish and other small game. Within this model the steady access of new resources with increasing complexity will be attempted. The following simulations were written and run in MATLAB.

2.1 Brief model description

2.1.1 The Technologies

In the model described here each tool will be represented as a collection of connected seed technologies. These seed technologies are the building blocks of all other technologies, and can be combined in a variety of ways. These seeds can be considered to be raw materials or very simple technologies, but they can also be thought of as simple techniques, representing ideas that cannot be broken down below this level, but which are needed in order to create the tools and cultures possessed by early human societies. Each final technology is then a combination of each of these simple raw materials and the instructions on how to assemble them.

Two identical sets of instructions and seed technologies may be combined in a different order to create two entirely different technologies. To represent the complex aggregation of these seed technologies as they may be combined the tools will be characterised as networks of seed technologies. An example of this is shown in Figure 2.1. Here each letter represents a seed technology and each of the connections are representations of the instructions used in order to create the final technology.

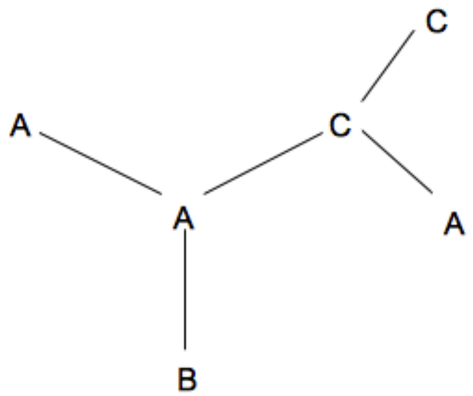

Figure 2.1: An example of a network of seed technologies, representing a single technology.

In order for the technologies to be recorded more easily than in the graphical form an adjacency matrix will be used to represent each technology. Here a link between one seed technology and another is represented by a 1. The adjacency matrix for the technology shown above is shown in Table 2.1.

If a technology has more seed technologies than another, then it will be defined as being more complex. But, if there are more connections between the seed technologies then this will also make the technology more complex, and more difficult to pass between generations. Therefore within this model the total complexity of a technology will be represented by the sum of the number of seed technologies plus the number of links between these seeds.

In order to combine technologies two tools will be selected at random. Random edges

Table 2.1: The adjacency matrix for the technology shown in Figure 2.1.

	A	A	B	C	C	A
A	0	1	0	0	0	0
A	1	0	1	1	0	0
B	0	1	0	0	0	0
C	0	1	0	0	1	1
C	0	0	0	1	0	0
A	0	0	0	1	0	0

will then be made between the seeds in each separate technology to create a new, more complex technology. An example of this is shown in Figure 2.2.

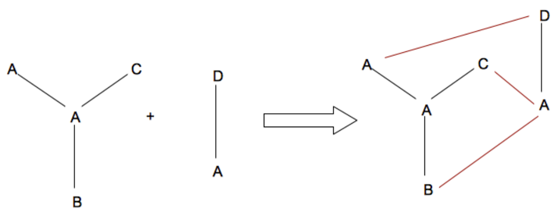

Figure 2.2: An example of the combination of two technologies.

Within this model technologies can also be broken apart in order to create new, smaller technologies. This will occur by taking a small sub-network within the larger network of the original technology and removing it. An example of this selection of a part of the network is shown in Figure 2.3.

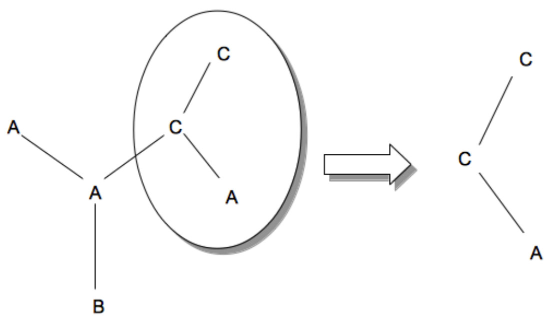

Figure 2.3: An example of the breaking apart of a technology.

The reason for including these two possibilities is that a new technology may be taken and combined with another in a more interesting way than just linear connection. In this methodology it is possible to take two technologies and intermingle the components and instructions so as to create something completely new. Whilst this may not be exactly how new technologies were created within early human societies, it does represent a useful caricature of the creation of new technologies and cultures, and is certainly in line with the methods used by Lewis and Laland.

Breaking apart technologies is also a useful technique to include as technological advancement is not just created by increasing the complexity and combining technologies, but by taking the seeds and then recombining them in interesting ways. When technologies are combined they may lead to sub-units that are themselves inherently useful in their own right, but which can only be found to be useful by breaking them away from their parent technologies. Also, by breaking apart the technologies a less complex technology that is able to perform the same function of the more complex parent may be found, which would create space under the glass ceiling for other tools.

2.1.2 The Resources

In order to develop the idea of tool utility within this model a number of resources will be included. These resources represent certain flora and fauna that were available to prehistoric human societies. For any set of resources there will be some that are harder to access and some that are more useful than others to the group. For example, in order to catch certain fish a net will be needed, and this technology needs to be developed before any fish can be acquired, whilst some fish will also be more nutritious than others.

Each of these resources will therefore have two parameters associated with them. The first is the minimum complexity that is needed to access the resource, and the second is the utility of the resource, with the latter indicating how useful the resource is to the group. By assigning the utility to the resource rather than the technology the link between complexity and utility can be severed. This is because the utility will not necessarily be correlated with the minimum complexity to access the resource. In this way, even if a tool has a particularly low complexity, if it is accessing a resource with a low minimum complexity but a high utility it will still be propagated into the next generation.

Each tool will then be randomly allocated a resource on which it is to work. The only resources that each tool will be able to be allocated to will be those with a lower minimum complexity than the complexity of the technology. Within this model there are an infinite number of resources, with the minimum complexity matching the complexity of the first technology assigned to it.

2.1.3 Propagation of Tools Between Generations

In order to propagate the tools between generations it will be assumed that there is a maximum amount of time that is available for the KTKK transfer. Each tool will be reproduced in the next generation by copying each unit of complexity, with fidelity q. Therefore, the probability of a successful transfer is given by q^C, where C is the complexity of the tool. If any part of the tool is not copied exactly then it is assumed that the transfer has failed and that technology will not be present in the next generation.

It is also presumed that the more useful a technology is the more a group will want to transfer it between generations. Therefore, the time that each individual tool will then be allocated will be proportional to it's utility. The time that each tool will be assigned is given by,

$$T = \frac{u_i}{\sum_{i=1}^{N} u_i} T_{max} \tag{2.2}$$

where here u_i is the utility of the resource level that the tool i has been allocated to, N is the total number of tools, and T_{max} is a constant within the model denoting the total amount of time for transmission of the tools from one generation to another.

The chance of failing to transfer a tool in the time allocated is given by $(1 - q^C)^T$, and so the final probability of a tool being transferred to the next generation is,

$$p = 1 - (1 - q^C)^T \tag{2.3}$$

This expression suggests that if a tool is not very complex, but is useful then it has a higher chance of being transmitted to the next generation, which is the behaviour that is desired. Also, if the fidelity is increased then the probability of a tool being propagated also increases.

The following section will now describe the algorithm used to run these dynamics.

2.2 Algorithm

2.2.1 Initialisation

Initially N_0 of single seed technologies will be selected at random (from a fixed, finite number of seeds) to form the first generation of technologies. The lowest complexity resource level will also be initialised, with a minimum complexity of 1, and a random utility (taking a value as described in Section 2.2.5).

2.2.2 Calculate Complexities

In order to calculate the complexities of each of the technologies the number of seed technologies and the number of edges between them are added together. In terms of the adjacency matrices this can written as the (size of the matrix -1) + (total number of 1's within the matrix divided by 2).

2.2.3 Combining Technologies

Each technology within the population will stochastically combine with another with probability p_c. If it is decided that a combination will occur then the second parent technology will be randomly selected from all members (including the initial technology) of the population. The adjacency matrices for each technology will then be placed into the top left and bottom right corners of the newly formed adjacency matrix. After this an edge will be placed in the remaining parts of the adjacency matrix with probability

$\frac{1}{2}$, so linking the two technologies as in Figure 2.2. The adjacency matrix then needs to be checked to ensure that it is diagonal as the edges within these networks are two way. Therefore any edge that is created in one direction needs to be replicated in the other.

If the resulting combined technology is small there is a chance that no new edges will be created. If this is the case then a seed from each parent technology needs to be randomly selected and an edge created between them. Once this process is complete both parent technologies and the newly combined tool are placed into the population of tools.

2.2.4 Breaking Apart Technologies

Each technology can also be broken apart with probability p_b. In order for this to occur a complete unit of the network of seed technologies is removed from the parent technology, with both parent and child then placed into the population.

In order to find a complete network within the parent technology firstly a random number of the seed technologies present will be selected (this can be anywhere up to $s-1$, where s is the number of seeds present in the tool), with these forming the seeds for the new tool. Then each link between the selected seeds is also taken and placed in the new adjacency matrix.

2.2.5 Allocating Resources

Each new technology found by either combination or splitting will be assigned to a resource level. This can be any of the resource levels present that have a minimum complexity lower than the complexity of the current tool.

However, if all of the resource levels present within the dynamics have complexities that are lower than the complexity of the new tool this means that a new resource level can be created. If a tool is randomly allocated to this 'new' higher level, then the minimum complexity of that resource level is set to the complexity of the tool that has just been allocated.

If a new resource level is created, then it will also be assigned a new utility. This value will be a random number selected from a normal distribution $N(0{,}0.5)$, with the absolute value then taken. The reason for this is to allow any value of utility to be possible, but to generally keep the values around 1.

2.2.6 Propagation of the Technologies

After finding the complexity and utility for each technology the tools can be stochastically reproduced in the next generation. For each technology the probability of transmission to the next generation is given by Equation 2.3. If a technology is selected to be transmitted then it is retained within the population, and if it is not then it is lost.

2.2.7 Final Algorithm

Taking Sections 2.2.1 to 2.2.6 into account the final algorithm will be given by the following.

1. Initialise population of technologies consisting of single seeds.
2. Initialise utility and complexity of first resource level.
3. Combine each tool with a randomly selected partner with probability p_c.
4. Break each tool apart with probability p_b.
5. Calculate complexities.
6. Find possible levels for each tool to be allocated to. If the complexity of the tool is higher than the largest minimum complexity then allow an extra level to also be selected.
7. Randomly allocate all new tools to possible resource levels.
8. If a new resource level is selected, assign it a random utility and a minimum complexity.
9. Repeat.

The results of running these simulations will now be shown.

2.3 Results

Within the following simulations each set of parameters were run until the dynamics have reached equilibrium. In this case equilibrium was taken to be reached when the change in the mean complexity over each window of size 500 time steps was smaller than 10^{-4}.

The initial parameters used in generating the following results were,

- $N_s = 5$
- $N_0 = 1000$
- $T_{max} = 10000$

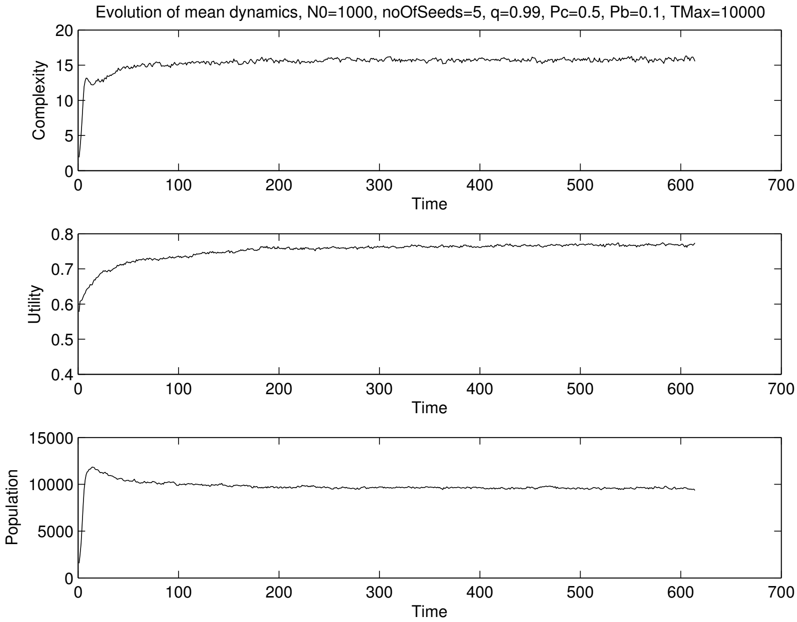

Figure 2.4: Evolution of the mean complexity, utility and number of tools.

2.3.1 Evolution of the Dynamics

Firstly taking $q = 0.99, P_c = 0.5$ and, $P_b = 0.1$ the dynamics were run to equilibrium. With these parameters it was desirable to observe how the tool number, mean tool complexity and utility evolved over time. The results of these measurements are shown in Figure 2.4.

From Figure 2.4 it can be seen that very quickly the mean complexity of the technologies increases before hitting a maximum of 15 complexity units. The number of tools, although starting high very quickly decreases to around 10,000. This equilibrium level then remains for the rest of the simulation. From these plots it can be seen that the dynamics of the simulations are very quick to find equilibrium, and are very stable once they have. Also in Figure 2.4 it can be seen that the mean utility, whilst it takes longer to reach equilibrium still does reach this point, with the fluctuations around this mean value also remaining small. In order to see what is happening within the simulations it is useful to plot the maximum and minimum complexity and utility, which is shown in Figure 2.5.

In Figure 2.5 it can be seen that the maximum and minimum utility are very quickly reached, as the complexity of the tools increases through combination. This is due to the maximum complexity also being reached within the first 20 time steps. After this point all of the resource levels that can be occupied are, and so there will be very little change in utility.

From the complexity graph it can be seen that although the mean complexity remains

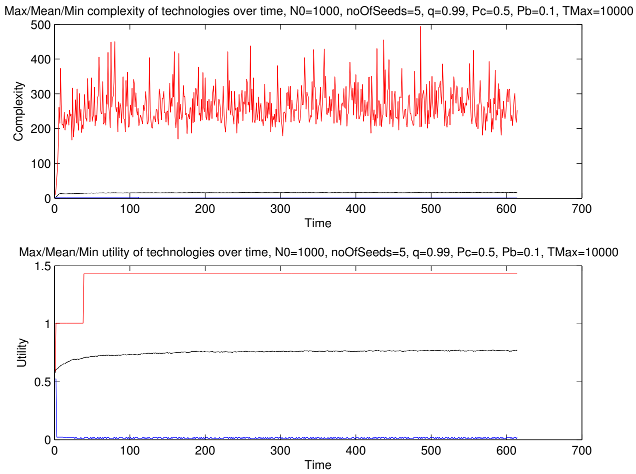

Figure 2.5: Evolution of maximum, minimum and mean complexity and utility.

at a stable value for the majority of the simulation the maximum complexity is able to jump by large amounts. The reason for this is that through combination the technologies will be able to form very complex tools. However, due to this high complexity they will not be able to transmit between generations for many time steps, and so we see the large oscillations within the maximum complexity. It is these large oscillations that lead to the fluctuations in the mean complexity that can be seen in Figure 2.4.

The relationship between the tools and the resources will now need to be investigated. The first question is, how are the complexities and the utilities between the technologies related? Are the more complex tools based on the resource levels with a higher utility, or is there no correlation between them? A scatter plot of the complexity and utility of each of the tools is shown in Figure 2.6.

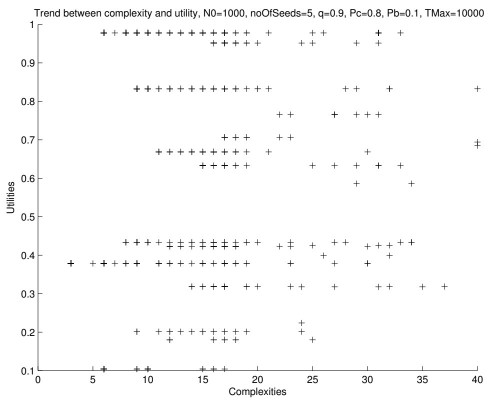

Figure 2.6: Distribution of complexities and utilities.

This scatter plot (Figure 2.6) shows that there is no relation between the complexity and the utility of a tool, which is what was originally desired.

The next question is how are the tools distributed across the resource levels? Are all of the tools present on the resource with the highest utility, or are they evenly spread? The following figure (Figure 2.7) shows the final distribution of the tools within the resource levels for the utility and minimum complexity.

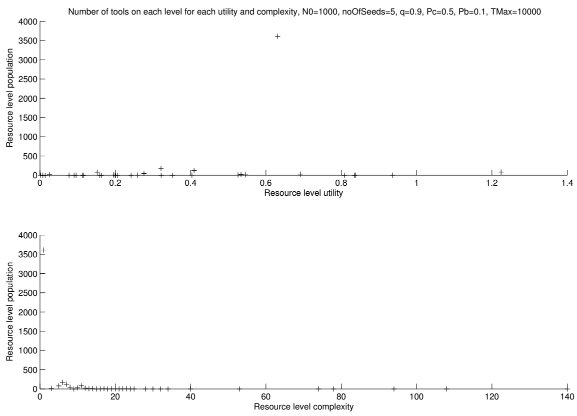

Figure 2.7: Population of the resource levels for both complexity and utility

In Figure 2.7 it can be seen that nearly all of the technologies are present on a few levels, with the majority based on just one. The most occupied level is the level that has the lowest minimum complexity. The reason for this may be that when a tool of high complexity is created it can randomly be assigned to any level with lower minimum complexity. This means that just by straight chance the lowest level will become the most occupied.

From the scatter diagram of resource population against utility it can be seen that there is no real distribution between them, and that the population in each resource level of a certain utility is random.

2.3.2 Investigation of the Glass Ceiling

Now that the dynamics of the system have been explored the next question that this model is intended to answer is whether the glass ceiling, as demonstrated within the Andersson model [8, 10], also exists here. In other words, are there periods when the mean complexity of the technology is at a steady (but fluctuating) level, before rising with an increase in fidelity? The next plot shows the dynamics run with increasing fidelity levels at each intervals of 100 time steps, shown in Figure 2.8 for the complexity and Figure 2.9 for the utility.

The results here show that when the fidelity is increased to a larger value the mean complexity also rises (as shown in Figure 2.8). This is because there is now a larger probability of a tool of a certain complexity being transmitted to the next generation.

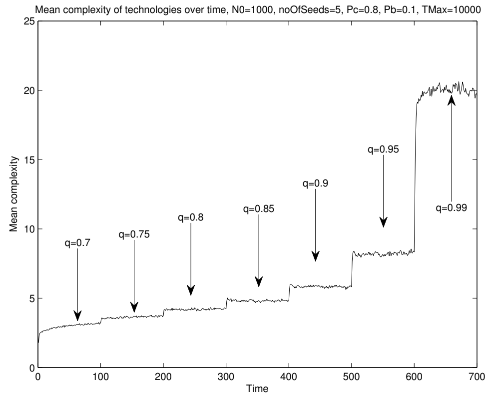

Figure 2.8: Increased fidelity at intervals throughout the dynamics and the mean complexity.

Also, it can be seen that the jumps between each equilibrium mean complexity get larger as the fidelity increases. The reason for this is the fact that (as will be shown in Section 2.3.4) the fidelity is exponentially proportional to the mean complexity.

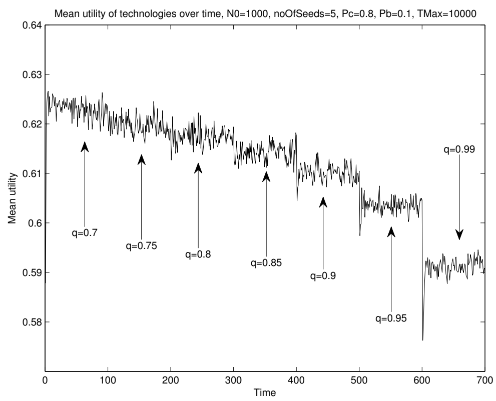

Figure 2.9: Increased fidelity at intervals throughout the dynamics and the mean utility.

From Figure 2.9 it can be seen that the mean utility actually decreases with an increase in fidelity. However, the steps are not as clear as those of Figure 2.8, and the range of decrease is very small. The reason for this is that the utility values for each resource level are assigned randomly. So, as the complexity increases, and new levels are accessed by the larger technologies, there is little change to the mean utility. However, as the mean complexity increases with increased fidelity the number of levels that the tools can be assigned to grows, causing a small reduction in the mean utility.

These two figures are able to show that the characteristics that were found in Andersson's model have also been reproduced within this one. The complexity of the tools that occur within these populations are shown to increase as the fidelity of transfer increases. Also, there are fluctuations within the mean complexity and utility which show that although there are occasional large increases the dynamics quickly return to the equilibrium point. In the next section the behaviour of this model under the varying of the different parameters will now be investigated.

2.3.3 Varying Parameters

In order to investigate how the parameters affect the final results of the model the dynamics will be run with various values of fidelity, probability of combination and probability of break down. At the end of each simulation measurements will be made on the final tool population, and then these will be averaged over five iterations.

The first parameter to be varied will be that of T_{max}. This is the amount of time that is available to each of the groups to transmit the tools to the next generation. The results of increasing this value are shown in the Figure 2.10.

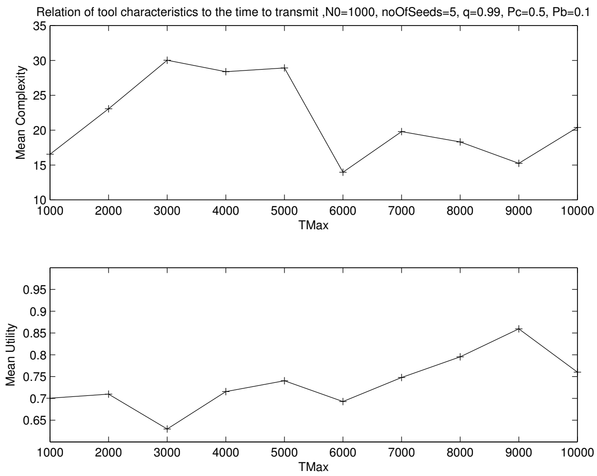

Figure 2.10: Effect of increasing T_{max} on the mean complexity and utility.

As can be seen from Figure 2.10 the increase in the amount of time that can be allocated to each of the tools makes very little difference to the mean complexity of the system. However, there does appear to be a trend in the increase of the mean utility as time moves on, suggesting that the more useful technologies may be selected if there is more time.

When varying the parameters a number of graphs will be produced in order to demonstrate the behaviour of the dynamics. The first is a surface plot of the mean complexity or utility for each parameter, with the two graphs below showing the maximum and the minimum of the respective measurement. Then, in order to see the behaviour for a single varied parameter the final two plots will show the maximum, mean and minimum for just one variable.

The first two parameters that are to be varied are the fidelity and the probability of combination. The fidelity was increased between 0.09 and 0.99 and the probability of combination was increased between 0 and 1, with measurements taken at intervals 0.1. Figure 2.11 shows how the complexity varied within as these two parameters increased.

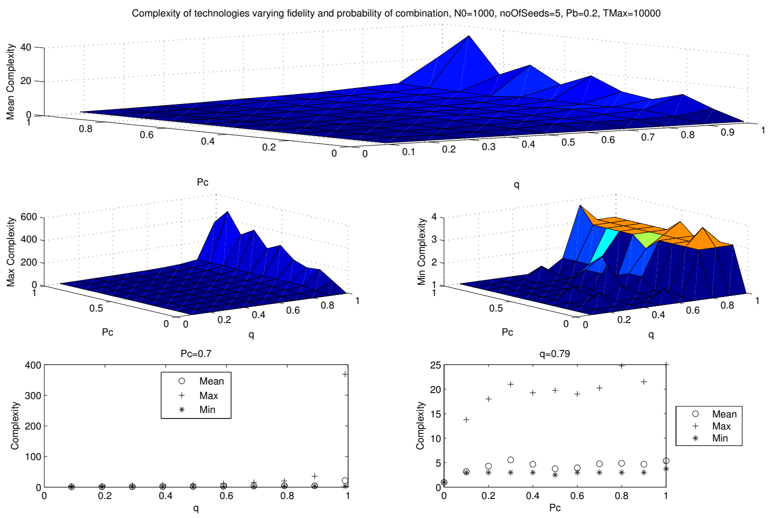

Figure 2.11: Surface plots of complexity (varying fidelity and probability of combination).

In Figure 2.11 the first thing to notice is that it is only at very high values of fidelity that any change begins to become noticeable. The mean and maximum complexity remain at low levels until high values of fidelity are reached. It can be seen that the minimum complexity makes a jump once the fidelity increases above a certain level, due to the fact that with a higher fidelity it is easier to support higher complexities. These minimum complexities are also interesting because at low values of fidelity the minimum complexity is 1. Therefore, at these low values there are still some seed technologies present within the population, and they only disappear at higher levels of fidelity.

Finally, from the graphs of increasing fidelity and probability of combination with constant variables increasing either parameter makes a very small amount of difference to the final complexity. These same findings can also be seen in Figure 2.12, where the effect of varying the probability of breaking down the tool is varied.

In Figure 2.12 it can be seen that the same effects as were found with varying the probability of combination are found with the probability of breaking a technology down. Once again, only when the fidelity becomes large enough is the minimum complexity able to rise above those of the single seed technologies.

The reasons behind the lack of impact on the mean complexity that the combination and break down probabilities have is that these are rates at which combinations and splitting of technologies occur. However, if larger tools are being produced by combination this will not affect the complexity distribution of the population of technologies because the chances of these tools being passed onto the next generation are minimal.

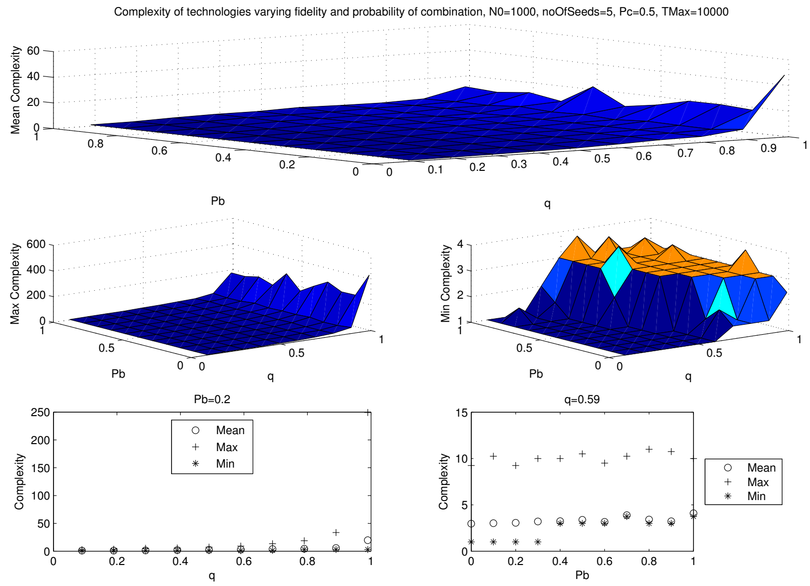

Figure 2.12: Surface plots of complexity (varying fidelity and the probability of break down).

The next figure (Figure 2.13) shows how variation in the combination probability and fidelity effect the value of the utilities within the simulation.

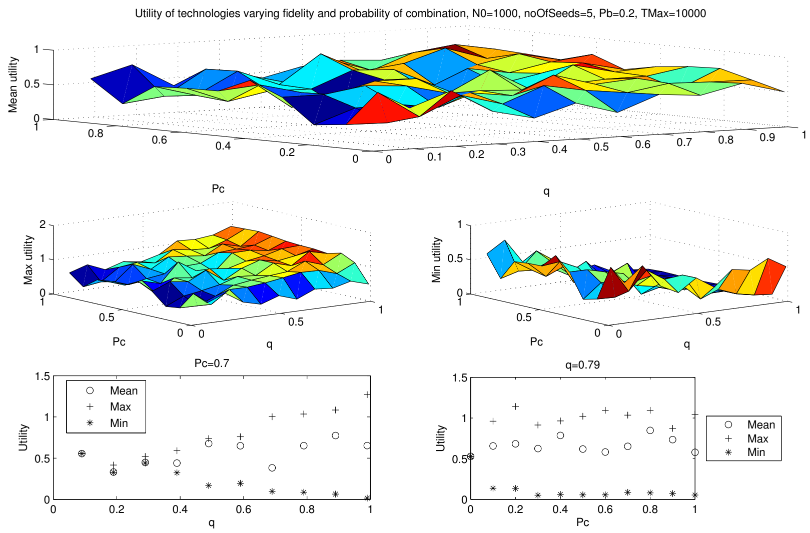

Figure 2.13: Surface plots of utility (varying fidelity and probability of combination).

There are a number of features that can be seen in the graphs of Figure 2.13. The first is that it is quite difficult to see any trend at all in the mean utility. This is to be expected, as due to the stochastic nature of the assignment of utilities to each of the resource levels a trend is unlikely to be found. The place where a trend can be found is in the increase of the fidelity. Within this plot it can be seen that the minimum utility decreases and the maximum utility increases. The mechanism behind this is that due to the random nature of the utility values, as the fidelity increases more resource levels are able to be created. This will therefore increase the range of the utility values within the system. The effect of the probability of a tool breaking down on the utility was also measured and is shown in Figure 2.14.

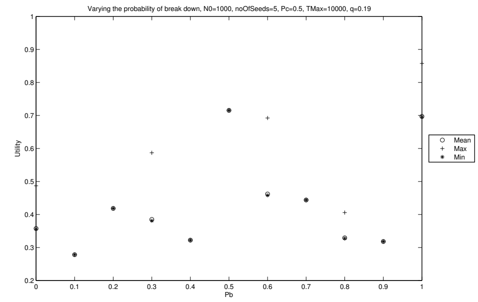

Figure 2.14: Effect of probability of tools breaking down on the utility.

From this Figure it can be seen that there is no effect on the minimum, maximum or mean utility from the probability of breaking down the utility. The reason for this is that although a higher probability of combination will lead to a larger number of resource levels, and therefore a higher variation in utility, the splitting of a tool does not have this effect. Therefore, only the stochastic nature of the allocation of utility to resource levels is shown in this figure. To finally show how the number of resource levels increases with an increase in fidelity and combination probability the number of resource levels present at the end of each simulation are plotted in Figure 2.15.

Within Figure 2.15 it can be seen that the number of resource levels grows once again with both an increase in fidelity and combination probability. The reasons for the increase in the number of levels as fidelity increases have been previously outlined, and are due to the increase in tool complexity that accompanies the increase in fidelity.

The mechanism behind the increase in the number of resource levels following an increase in the probability of two tools combining is a little more subtle. There is an effect where the increase in combination probability causes a slight increase in mean complexity, but this would not necessarily explain the large rise in the number of resource levels. The main reason for the increase is that a new resource level is accessed if the complexity of a newly combined technology is larger than all previous resource levels minimum complexity. The tool that is then assigned to this high level does not have to be transmitted to the next generation after the creation of the level, and so the reason for the large number of resource levels for high p_c is that complex technologies are created,

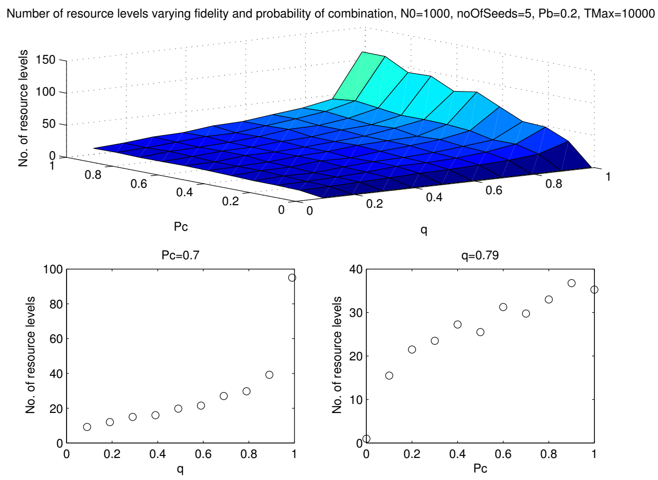

Figure 2.15: Number of resources as fidelity and probability of combination vary.

which then create a high minimum complexity resource level before immediately (or in a very small number of iterations) failing to be transferred to the next generation.

Figure 2.16 now compares two separate parameters, fidelity and probability of combination, along with two different values for these variables.

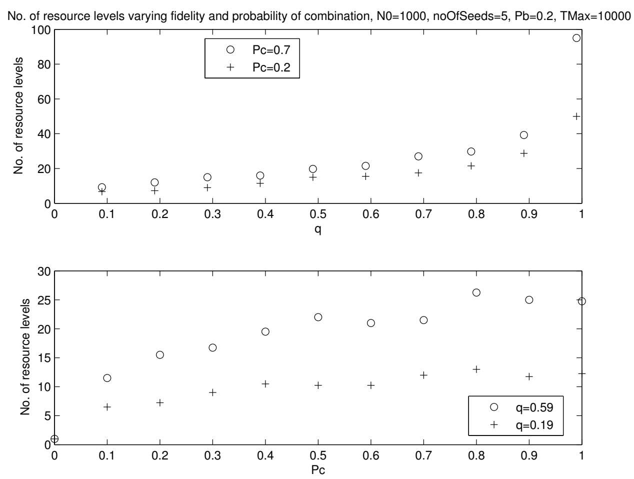

Figure 2.16: Number of resources compared for different values of fidelity and combination.

In Figure 2.16 we see that for larger fidelity and combination probability the number of resource levels are more, which is consistent with the ideas of larger complexity technologies within the population.

2.3.4 Analytical Solution to Maximum Complexity

The derivation of the mean complexity found for increasing probability of combination or breakdown is derived using the methods given by Eigen and Schuster [14], and also Andersson [8] in his derivation of the level of the glass ceiling.

The number of tools at each time step is given by,

$$N(t+1) = (1+P_c)(1+P_b)(1-(1-q^{\bar{C}})^{\tau})N(t) \tag{2.4}$$

where $N(t)$ is the number of tools at time t, $(1+P_c)$ is the increase in the number of tools due to combination, and $(1+P_b)$ is the increase due to the break down. The expression $1-(1-q^{\bar{C}})^{\tau}$ is the probability that these tools will be transferred to the next generation as given in Equation 2.3. However, here the complexity is replaced by the mean maximum complexity $\bar{C}$ for the entire population of tools, and the allocated time is replaced by the parameter τ. The reason for this is that the utility of each tool is unknown prior to the simulation as they are randomly assigned for each resource level, and therefore this differs between tools of the same complexity. Therefore τ is a parameter that varies depending on the particular simulation.

When the system has reached equilibrium the number of tools at each time step will be equal, and so $N(t) = N(t+1)$. Therefore,

$$1 = (1+P_c)(1+P_b)(1-(1-q^{\bar{C}})^{\tau}) \tag{2.5}$$

This can be rearranged to give the mean complexity of the tools in terms of the parameter τ, shown in the following expression.

$$\bar{C} = \frac{\ln\left(1-\left(1-\frac{1}{(1+P_c)(1+P_b)}\right)^{\frac{1}{\tau}}\right)}{\ln q} \tag{2.6}$$

These theory lines were now tested on simulations varying both the fidelity and the probability of combination with the results shown in Figure 2.17. The values for the fitted parameter τ are included within the plots and were found using the MATLAB curve fitting toolbox.

As can be seen from Figure 2.17 this theory curve seems to match the simulation results well, and so is able to demonstrate how the glass ceiling depends on both the fidelity and the probability of combination and breakdown. These results also show that it is the fidelity that is the main factor behind large increases in mean complexity rather than the combination or breakdown probabilities.

2.3.5 Maximum Number of Levels

The final simulations that were run using these dynamics introduced a maximum number of resource levels. The reason for this is that in nature it is unlikely that there would be an infinite number of resources that could be accessed by pre-agriculture humans, and only allowing a certain number of resource levels may alter the final complexity. In order

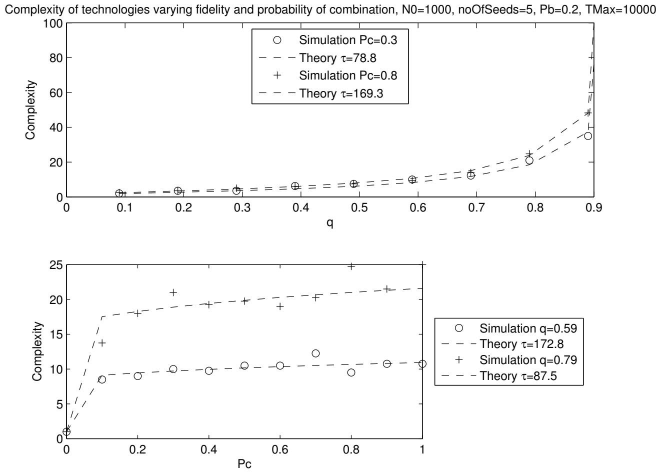

Figure 2.17: Simulation results and fitted theory lines. τ parameters for each line are included in the plot.

to test if the number of levels has any influence on the results a finite number of possible levels were introduced. To implement this the dynamics were run in exactly the same way as in previous simulations, but a count was kept on the number of resource levels. Once the maximum number had been reached then no more levels could be created, and the only levels that it was possible for each tool to be assigned to were those already in existence. This was run, with the results shown in Figure 2.18.

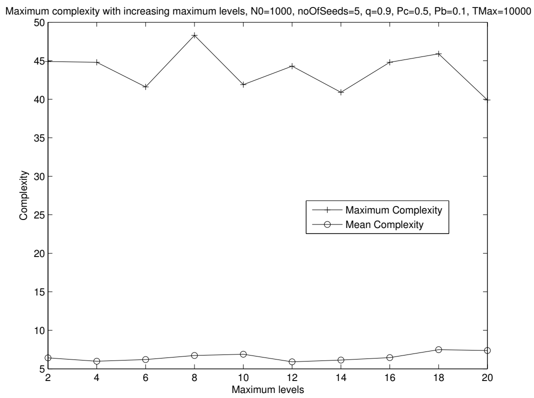

Figure 2.18: Complexity values for increasing maximum resource levels.

The results in Figure 2.18 show that there is no effect from the introduction of the maximum levels, to either the maximum or the mean complexity of the population of tools. This suggests that the previous results that have been found can also be applied to a finite number of levels, and that it is the fidelity that is the core parameter that defines the behaviour of the system.

2.4 Discussion

The main aim of this work was to develop a model that combined the central ideas from work by both Andersson [8, 10] and Lewis and Laland [1]. Taking the themes of fidelity of information transfer of culture and tools between generations, and also the more complex formation of technologies, and a lack of correlation between the utility of a tool and it's technological complexity, this has been achieved. The separate results from both Andersson and Lewis-Laland were also able to be replicated, and the question of which were the more important features of the model was then able to be investigated.

The central result from this work was that the decisive parameter in the outcome of the dynamics is the fidelity of transfer. Each of these results suggests that no matter how complicated the dynamics between the set up of the technologies, how they are combined and then broken up, and the number of seed technologies that can be selected the glass ceiling effect will still be found within any system with a fidelity of transfer, and it is this fidelity that decides how complex the final population of tools is found to be.

It can be seen that the probability of combining or breaking up the technologies does slightly effect the final mean complexity of the tool population. However, the increase in tool complexity is small, and overshadowed by the increase that can be found through an increase in fidelity. The other parameter's main influence is on the rate at which the dynamics occur.

Within this model it has been possible to show that the Andersson model can be extended to include a decoupling of the complexity and the utility from each tool, and also to make the formation of new technologies more interesting and realistic, with the introduction of cumulative culture. It has also been possible to show that the position of the glass ceiling of technological complexity can be found analytically, and is exponentially proportional to the probabilities of forming a new technology and the fidelity of transfer, with the same proportionality as was found by Andersson.

What has been found with these simulations is that even though extensions were made to the Andersson model, the central results still stand. This suggests that within the increase in tool complexity found in the archaeological record it is the fidelity of transfer between generations, and not the utility or the complexity of a tool or the methods used to create them that defines how complex a society will be.

Despite the success of the model, there are a number of issues that will need to be worked on. The first is that these dynamics only focus on one population of tools, and therefore do not represent the changes between different groups of pre-historic individuals. Linked to this is the idea that there is no pressure for resources from other groups connected to these dynamics. There are also no human population dynamics associated with these tools, and each of the tools are only able to access one resource. Within the results in this model the dynamics over the resources has been shown to be particularly static, and so does not address any of the questions raised by the BSR. Finally, there is no large change in the utility of the resources that the tools are able to access as time increases.

Resource pressure, either through the environment or through population pressures (both internal and external) may create very different dynamics within these constraints. In order to include these factors a new model has been built. Using the concept that there are a maximum mean number of complexity units these units will now be distributed among various resources for geographically located groups. This extended model will then be able to take the central themes found within these simulations e.g. that the fidelity of transfer of the total complexity of the tool population is the central cause of advancement for the culture and diet of early human groups, and extend them to investigate some of the causes behind the BSR.

Chapter 3

Modelling the BSR

After the investigations of the effects of innovation and fidelity on tool complexity a model will now be built to test some of the predictions of the BSR and to take some of the ideas from the previous chapter into a less abstract environment.

This model will be designed to show a plausible explanation for two of the unsolved aspects of the changes in human diet leading to the Upper Palaeolithic. The first is the evolution from a purely scavenging strategy to a more diverse strategy where humans would hunt large game whilst supplementing this with small game. The second aspect is the surprisingly rapid spread of these strategies across the landscape inhabited by these early humans. It can be seen in the fossil record that as new tools and hunting strategies are invented they are able to spread at (relatively) fast speeds through the population, leading to pulses of population increases [3, 9]. This model will therefore attempt to model an evolutionary change in strategy from a simple to a more complex (and diverse) hunting method, and show how any more diverse strategies are able spread quickly throughout the population.

The creation of this model will draw heavily on work performed by Stiner [3] in modelling the effects of heavy predation on fauna of different types. Here she suggests that a number of factors may be linked to each of the prey hunted by Palaeolithic humans that help determine how they perform under increased predation. These include the *resilience* of the prey, or how resilient the prey is to being hunted over a long period of time, and *work of capture*, which includes the technological and human cost of capturing the prey.

Combining the concepts of the work in the previous chapter of units of culture and the ideas of assigning differing attributes to various types of prey a model will be designed where technology and resources interact to find the best strategies for surviving in various landscapes.

3.1 The Basic Model

The basic form of this model will be to create a landscape containing a number of groups of hunter-gatherers. This landscape will contain a variety of resources of differing densities at various locations, and populated by a number of groups, each with a set area. The groups will then consume the resources present on the landscape, move position, split or die out, depending on their circumstances. An example of a tribal landscape is shown in the Figure 3.1.

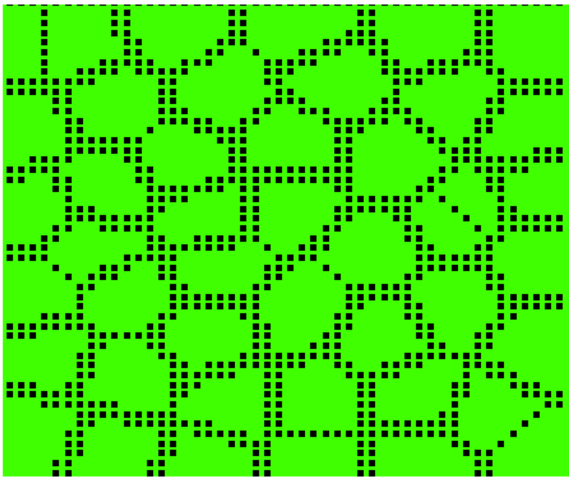

Figure 3.1: An example of the layout of the groups. Black dots signify the boundaries between groups.

The groups will interact with their landscape by acquiring the resources present at that point. The amount of a resource that is able to be consumed is decided by two factors. The first is the complexity of the tool being used. The more complex the tool, the better it will be at harvesting a resource (e.g) a bow and arrow is better for hunting game than a spear. The second is the number of group members that are able to acquire the resource.

Each group will be populated by a certain number of humans, and will have a maximum number of 'complexity units' associated with it. The way that the population and the tool complexities are distributed between the resources will be termed the 'strategy' of the group. This strategy, along with the area that the group is able to access, and the density of the resources that are present, will then be used to calculate the harvest extracted by each group from the landscape. From this information the increase or decrease of the population of the group is then calculated. A low harvest leads to a decrease in the population, whilst a good harvest leads to an increase.

As complexity or effort is increased this should lead to an increase of the harvest, as a larger number of workers or better tool use should lead to more of a resource being acquired. However, as more of a resource is used it will eventually be over harvested, leading to a diminishing and ultimately a negative return from this resource. In order to calculate how much of a resource a group is able to harvest an extraction function will be developed which will model the characteristics of the different resources.

As time moves on the strategy of each group is able to mutate. This involves either an increase in the complexity of the technology used for each resource, or a shift in either complexity or effort (the number of group members assigned to a specific resource) between resources. When a group mutates, it will first generate a number of possible strategies. It will then shift to the mutation that gives the best harvest, or remain with it's present strategy if there is no improvement. The reason for this implementation is that the timescales involved in this model are of the order of tens of thousands of years. Therefore you would be unlikely to detect sub-optimal mutations appearing for a very short amount of time within the archaeological record. The following sections will now describe the dynamics of the model in more detail.

3.2 The Resources

The resource function will take a form that gives realistic behaviour to certain dietary niches that have been found to have been consumed during the Palaeolithic era. The amount of harvest extracted from the resource will be related to the number of groups members acquiring the resource (the effort), and the complexity of the technology used for accumulation. The amount of harvest, or the resource extraction will be given by,

$$X(e,c) = I(e,c) - \chi(e,c) \tag{3.1}$$

where e is the effort, c is the technological complexity required to harvest the resource, I is the amount of income from the resource and χ is the cost of supporting the effort and tool complexity used in the harvesting.

3.2.1 The Income Function

The amount of income energy that can be taken from a resource is calculated using,

$$I(e,c) = r_{energy} W(e,c) \tag{3.2}$$

where r_{energy} is the amount of energy present in each unit of the resource and $W(e,c)$ are the work units amassed from the resource.

Within each resource there will be a minimum complexity and effort that will need to be attained in order to access the resource. In order to gain access to certain food stuffs (e.g) hunting horses or fishing for certain species, a minimum number of group members or tool complexity needs to be reached before they can even begin to be collected. In the following definitions of the resource functions the minimum complexity needed to begin to gain any income from a resource will be represented by Z_c and the minimum effort by Z_e. Therefore,

$$I(e,c) \begin{cases} > 0 \text{ if } c > Z_c \text{ and } e > Z_e \\ = 0 \text{ if } c < Z_c \text{ or } e < Z_e \end{cases} \tag{3.3}$$

The gross amount of the resource that can be amassed will be labelled the work units, $W(e,c)$. As the effort or complexity that is used to acquire and process a resource is increased the amount of the resource that can be consumed also increases. This will be proportional to the effort and the net complexity used in gathering the resource. Therefore,

$$W(e,c) \propto e(c - Z_c + 1) \tag{3.4}$$

For each different resource the return for each additional unit of effort or complexity will not be the same. Therefore the final expression for the units of work gained from the resource is given by,

$$W(e,c) = \frac{e(c - Z_c + 1)r_{lpc}}{r_{eb}} \tag{3.5}$$

where here r_{lpc} is the amount of leverage gained per each additional unit of complexity. So, a higher value of this parameter will mean that as each unit of complexity is added to the technology relatively more of the resource is able to be harvested. The parameter r_{eb} is the base effort, which relates the difficulty to extract each unit of the resource. A higher value of this parameter means that more effort is needed to harvest the same amount from two different resources.

3.2.2 The Access Function

The amount of the resource within a set area may not be accessed all at once. For example, a small complexity may mean that the current tool is not advanced enough to access all of the resource within the tribal area. In order to calculate what proportion of the resource can be obtained an access function, represented by $\alpha(e,c)$ is shown in Equation 3.6.

$$\alpha(c) = \frac{1}{2} + \frac{1}{2}\frac{c - Z_c + 1}{r_{max} - Z_c + 1} \tag{3.6}$$

Here r_{max} is the value of the complexity at which point the total resource present can be harvested. The value of this function can range from 0.5 when $c = Z_c - 1$, to 1 when $c = r_{max}$.

3.2.3 Resource Density

The amount of each resource present at different points on the landscape will vary, and will be described by the parameter r_d, or the resource density. Therefore, the amount of any resource found within any region of area A of the landscape will be given by $\bar{r_d}^j A$, where $\bar{r_d}^j$ is the mean amount of resource density within this area, and j identifies the resource that this density is referring to.

Therefore, the maximum amount of income that can be obtained for any one group from each resource (for a given effort and complexity) is given by,

$$I_{max}(e,c) = \bar{r_d}^j A \ r_{energy}\alpha(c) \tag{3.7}$$

An example of a contour plot for the income function for various values of effort and complexity is shown in Figure 3.2.

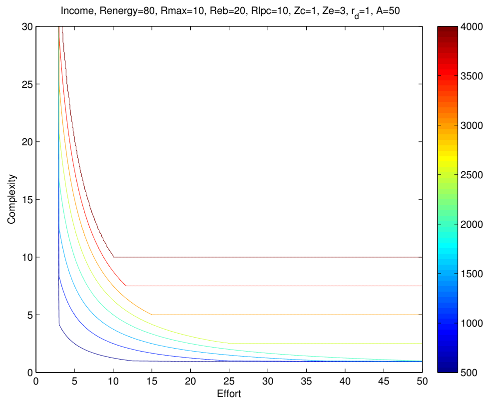

Figure 3.2: An example of the income function. Parameters used are shown in the title.

As can be seen from this figure, the income function only takes a non-zero value when the complexity is larger than the minimum complexity ($c > Z_c$) and the effort is larger than the minimum effort ($e > Z_e$). Also, as both the effort and the complexity increase after this point the income rises until it reaches the maximum allowed value (given by Equation 3.7), which matched the desired characteristics of the income function for a dietary niche.

3.2.4 The Cost Function

The second part of the extraction calculation (Eq. 3.1) is the cost function, $\chi(e,c)$. This is the cost of supporting a certain effort, and also building tools of a certain complexity. This should increase with both the complexity and the effort, and so the form of the cost function is given by,

$$\chi(e,c) = cC + eE \tag{3.8}$$

where C is the cost per unit complexity, and E is the cost of one unit of effort.

3.2.5 The Extraction Function

The final extraction function is given by Equation 3.1 and is the sum of the income and the cost functions for each value of effort and complexity. An example of an extraction function is shown in Figure 3.3.

As can be seen from Figure 3.3 this function gives the desired form for the harvest of the resources. For very small values of the complexity and effort the groups are not able to harvest any of the resource at all. As the complexity and the effort increases they are then able to harvest increasing amounts, until the maximum is reached. At this

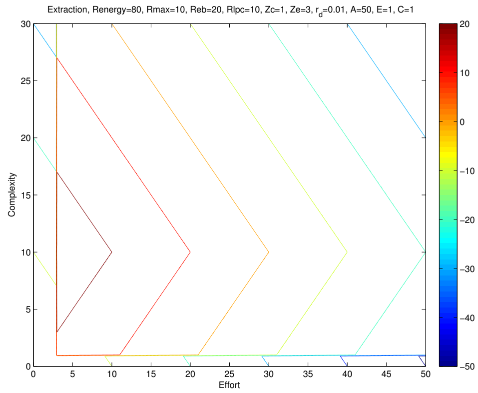

Figure 3.3: An example of the extraction function. Parameters used are shown in the title.

point the harvest decreases as too much of the resource is acquired, reaching the point at which the resource is unable to sustain either the large amount of technology or the large number of groups people that are harvesting the resource.

3.2.6 The Selected Resources

During these simulations the landscape will be populated by four different resources. These four resources have been chosen as they broadly describe the different dietary niches that are found within the Palaeolithic era. They will be labelled as,

- Opportunistic
- Scavenging
- Large Game
- Small Game

The characteristics of these resources are as follows.

Opportunistic

This is a resource represented by the kinds of material found without any effort on the landscape, flora such as berries and mushrooms for example. All of the members of the group will be searching for this resource at all times, but it does not give a large amount of energy for each unit of resource that is consumed. This resource has a very low minimum effort and complexity in order to access it, and there is not a large increase in return for a higher effort or complexity.

Scavenging

The scavenging resource is the act of finding animals previously hunted and killed by large carnivores, and then taking and processing the meat, bone marrow etc. from them. This does not need a large strategic complexity, though some is needed in order to break open bones to access marrow and remove flesh. There is also a need for a fair number of individuals to be present to be able to scavenge from large animals as often other predators and scavengers will need to be scared away, and parts of the animal may need to be carried back to a dedicated activity area.

Large Game

Large game will be those animals such as deer and horses that are easy to find and will often be hunted using spears or bows and arrows. The hunting techniques will require more complex tools than those needed for scavenging, and also more effort from the group. The reason for this is that large game are often hunted using multiple members of the tribe chasing a group of the large game into a corner, making them easier to kill. Large game are particularly good prey as they are easily located, and give a large amount of energy per unit of work. However, due to the fact that multiple members of the group are already needed to hunt the prey, adding additional effort will not increase the return by as much as adding group members to scavenging, but increasing the complexity of the technology will increase the harvest considerably.

Small Game

The final type of resource will be small game. These are fauna such as rabbits and small birds, which need smaller numbers of group members to capture them, but also need much more complex technology to be acquired. The energy that is gained from hunting the small game is not as large as that of the large game (from either scavenging or hunting), but, at least for higher levels of resource use, does increase in harvest faster than with an increase in effort compared to the large game.

3.2.7 Selected Parameters

With the discussion from Section 3.2.6 in mind, the following parameters were chosen for each of the resources (as shown in Table 3.1). A number of characteristics found in different diet niches within the early human culture will need to be filled. Firstly, for a given area the maximum harvest that can be extracted from each resource should be smallest for the opportunistic, followed by scavenging and small game, with large game being the most energetically worthwhile resource. Also, as the complexity and effort are increased the harvest should firstly increase to a maximum, before then decreasing as the effort and complexity become too large.

The parameters have been chosen to be in the correct relative size to each other, and to give realistic relative values for the harvest for different combinations of effort and tool complexity. Although the choices of parameter values are arbitrary, each of them is tied to the other in terms of both observed characteristics and also the relative values for each resource.

Table 3.1: Resource Parameters

Resource	r_{energy}	r_{max}	r_{eb}	Z_c	Z_e	r_{lpc}	r_d	E	C
Opportunistic	0.75	0	0.1	0	0	0.05	0.2500	1	1
Scavenging	80	5	20	1	3	10	0.0050	1	1
Large Game	400	15	40	5	10	10	0.0035	1	1
Small Game	70	25	5	12	5	12.5	0.0175	1	1

These four resources will now be shown as a contour plot in the Figure 3.4 with the area that the resources are harvested from set to $A = 75$.

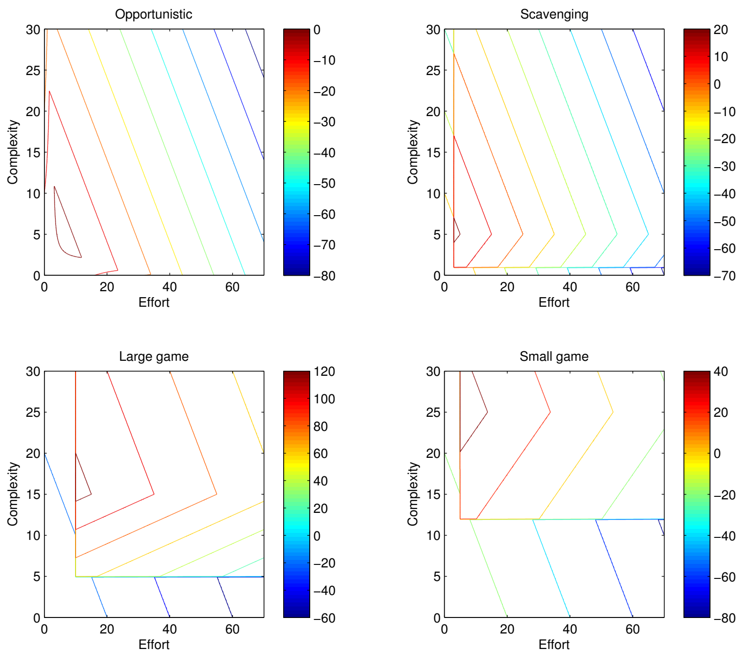

Figure 3.4: A contour plot of each of the resources. $A = 75$

From Figure 3.4 it can be seen that the resources do indeed behave in the desired way, with the minimum effort and complexity taking the correct relative values, and with the large game resource being the one that contains the highest density in terms of energy content.

If the area or the resource density that the group is able to access decreases, this should decrease the amount of the resource that can be extracted. As can be seen in

Figures 3.5 (reducing the area) and 3.6 (halving the resource density), as the area of the group or the density of the resource is reduced the amount of harvest that it is possible for the group to extract with a certain strategy is reduced. This is the desired behaviour from the resources, as a group with a decreased area or smaller amount of resource within that area will be able to find less of each resource and therefore generate a lower harvest.

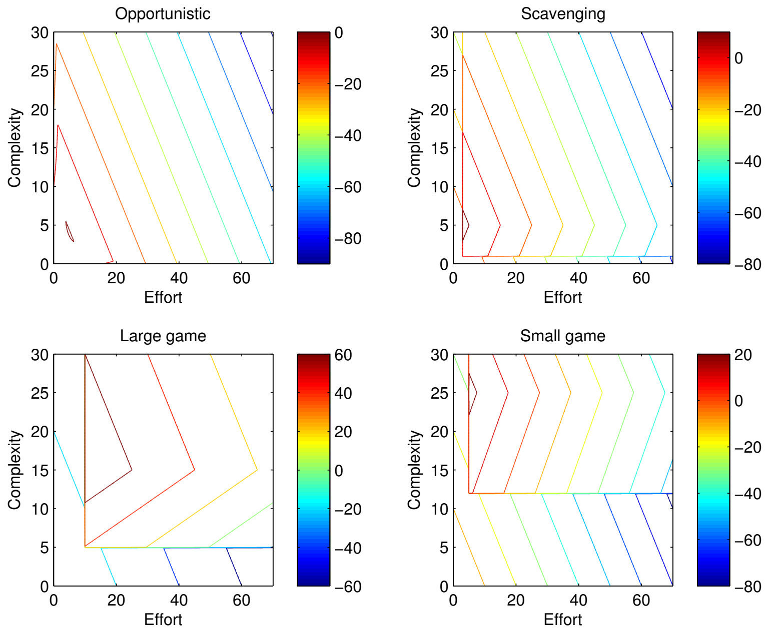

Figure 3.5: A contour plot of each of the resources. $A = 50$

The final algorithm used with these resources is now described in Section 3.3.

3.3 Algorithm

This section will describe in more detail the model used to investigate the evolution of human diets.

3.3.1 Initialisation of Tribes

In order to begin the dynamics the group's centres must first be placed randomly on a lattice. Each group will be assigned an initial random population (between 20 and 30), and an initial strategy (see Section 3.3.3). The landscape on which the groups reside will be square (with size given by L), with a boundary on each side. The groups will not be able to cross this boundary, and each groups influence will not extend beyond it. The area of each group will then be calculated (see Section 3.3.2).

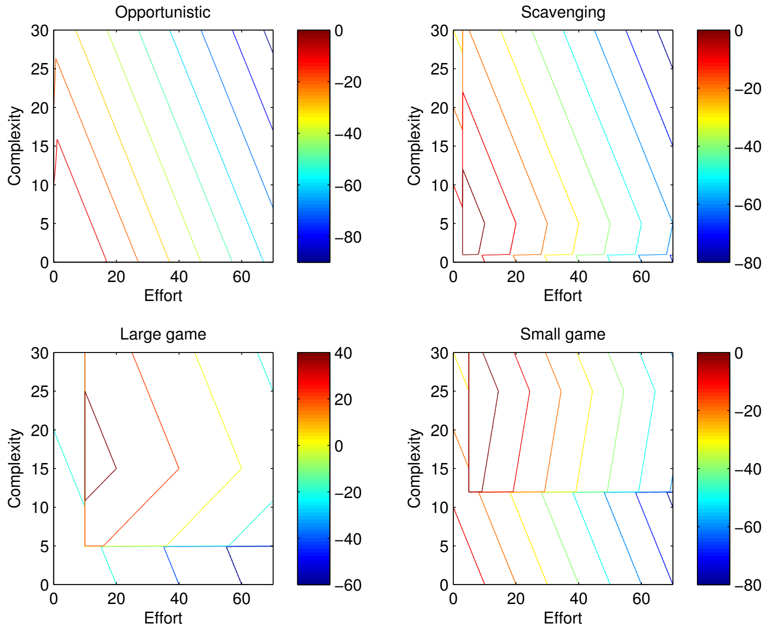

Figure 3.6: A contour plot of all of the resources. $A = 75$, r_d for each resource halved.

3.3.2 Group Areas

Each group area will consist of all of the points on the landscape that are closest to itself in comparison to all other groups. To calculate the group's areas the distance from each group's position to each point on the landscape is calculated. For each group the point that is closest to itself compared to each of the other groups is then allocated to this group. The points that are equidistant between two groups are then recorded and represented using a dot. This therefore builds up the tribal landscape as shown in Figure 3.1. The area that is now associated with each group is therefore the sum of all the points on the landscape that are closest to itself. Once the group's area has been calculated, the position of the group is moved to the centre of this area.

3.3.3 Group Strategies

Each group will be assigned a strategy which gives the tool complexity and the fraction of the group's population that is then used to harvest each resource. An example of a strategy is given in Figure 3.7.

The first four numbers are the complexities of the strategies in the opportunistic, scavenging, small game and large game resources, and the final four numbers are the fraction of individuals within the group that are assigned to each of the resources. As all of the members of the group are always harvesting any opportunistic food then this number is always 1, and because the total fraction of the group sums to 1 the fraction

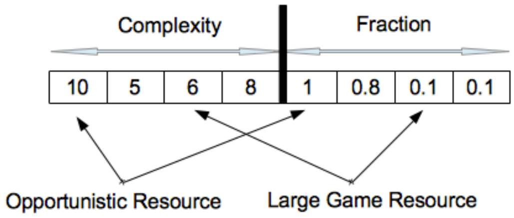

Figure 3.7: An example of a groups strategy.

must therefore always sum to two.

The minimum amount of total complexity that can be allocated to any resource is Z_c. This is because any smaller amount will not enable the group to harvest any income from that particular resource.

The initial strategy for each group will be one unit of complexity in the opportunistic and scavenging resources, with zero units in the final two resources. Therefore every member of the group will initially be both opportunists and scavengers.

3.3.4 Calculation of Extraction

In order to find the change in population the harvest from each resource will need to be calculated. The total extraction for each group will be found by summing the extraction from each of the resources.

For each group, in order to calculate the size of the extraction, four pieces of information will be needed. The first is the complexity of tool used for the resource, and the second is the effort that the group uses in harvesting the resource. This is calculated using,

$$e^j = PS^j \tag{3.9}$$

where here e^j is the effort assigned to the resource j, P is the total population of the group and S^j is the fraction of the group assigned to that resource (as shown in Figure 3.7).

The final two pieces of information are the group's area, and the mean density for the resource in question, $\bar{r_d}^j$. This mean density is the average of the resource density at each point within the group's area. The extraction for each resource can then be calculated using the resource functions and parameters described in Section 3.2, and summed for each resource for the total extraction.

3.3.5 Moving Tribes

If the calculated extraction is negative for a particular group then this suggests that it has a poor strategy. There are therefore a number of options that it can take to improve this situation and attempt to move to a more favourable scenario. The first of these is to simply move position. In this model the groups are allowed to move one space in any direction, unless they reside on the boundary of the landscape.

3.3.6 Updating the Population

Once the total extraction for each group has been calculated the new population can then be evaluated. This will be calculated using the function given in Equation 3.10, which will use the amount of energy extracted to give a change in the population. It would be desirable to have a maximum population increase or decrease within the function, as very large changes in population would be unrealistic with the dietary niches modelled here.

Using these assumptions it was decided to model the change in population by,

$$\Delta P(X) = \Delta P_{max} \tanh\left(\frac{X}{X_c}\right) \tag{3.10}$$

where here ΔP_{max} is the largest change in population and X_c is the critical value of the extraction (a scaling parameter).

The desired form of this function will take the standard values of extraction expected from the model (of the order of ≈ 200) and translate this into an acceptable increase in population. Because the populations of hunter-gatherer groups were of the order of $20 - 60$ [25, 26], very large increases or decreases would be unrealistic. As well as this, with the relatively short update times within this model increases or decreases larger than a few percent would be unlikely. Therefore, in the calculations of the change in population the parameters used were $\Delta P_{max} = 5$ and $X_c = 100$. A graph of this function is shown in Figure 3.8.

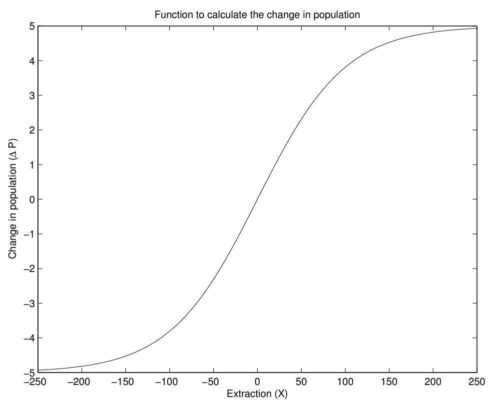

Figure 3.8: An example of the change in population function with varying extraction values.

3.3.7 Removal of Tribes

If the population of the groups moves below a certain level (given by P_{min}) then the groups will be removed from the simulation. The area that was previously occupied by that group will then be available for distribution among each of the remaining groups.

3.3.8 Splitting of Tribes

Within anthropology it is found that groups split for many reasons. These could be because the group has become too large to support the society on which the group is based, but it could also be for more unpredictable reasons such as conflict within the group or environmental reasons. A number of examples of human groups being kept to a certain size are discussed in Dunbar [26], for example.

Taking the central reason for splitting of a group to be the fact that population has become too large the groups will split when they have a population above a certain critical value (labelled P_c). However, due to the unpredictable nature of group division this will not be a deterministic value, but instead will give a stochastic probability of splitting given by,

$$p_s = \frac{1}{2}\left(\tanh\left(\frac{P - P_c}{2}\right) + 1\right) \tag{3.11}$$

where P is the current population of the group. This function gives a probability of splitting $p_s = \frac{1}{2}$ at the critical population. An example of this function is shown in Figure 3.9.

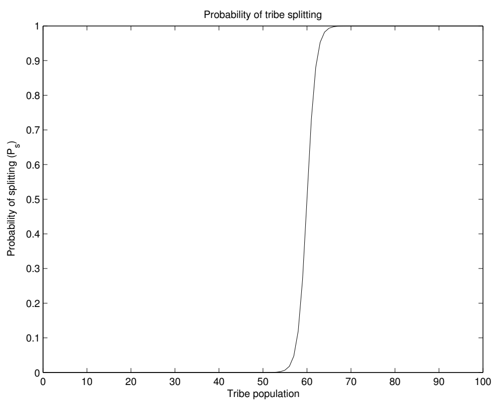

Figure 3.9: An example of the probability of a group splitting depending on its population. $P_c = 60$.

If at a certain time step the groups do split then the centre of the new group moves one space (in a random direction) away from the previous group location. The population is split in half between the two new groups, and they each take the same strategy.

Although the splitting of the population into exactly half for the two new groups may not seem realistic, an unequal split would introduce a complication that would not give any change in the dynamics of the system. The exact copying of the strategy from the parent group to the two new groups (rather than two new mutations) was chosen because the simulations are modelling change over large time scales indicating that the current strategy would be the standard for this group.

3.3.9 Mutation of Strategies

Internal Mutation

As suggested in Section 3.1 a number of mutations (in this case 10) will be generated by each group, and the extraction for each of these possible mutations calculated. The new strategy (including the initial un-mutated strategy) that gives the highest extraction is then selected. As well as the time scales mentioned in Section 3.1 it would be unrealistic to have a large number of maladapted strategies within the landscape, and would also hide many of the important results found within these dynamics.

Within these dynamics there will be two possible ways of mutating the strategies. Either,

- Increase the tool complexity of one resource by one unit (with probability p_+)
- Alter the strategy (with probability μ)

These two mutations are independent of each other and can occur together or separately.

Increase in Complexity

To increase the complexity of a group one unit of complexity is randomly added to any resource that already contains units of complexity. For example, if the complexity of the opportunistic and scavenging resources are 2 and 3 respectively, and the complexities of the small and large game are zero, then one of the opportunistic or scavenging resource tool complexities will be randomly selected to increase by 1.

Altering the strategy

To alter the strategy either a unit of complexity or a fraction of the group assigned to a resource can shift from one resource to another. The choice between these options is stochastic, and will occur with equal probability.

When shifting a unit of complexity between two resources an important factor is that the amount of complexity present in a resource must be either zero of greater than Z_c. Therefore, before shifting complexity between two different resources the first calculation that needs to be made is how much *excess* complexity there is within the strategy. This is the sum of the total number of units above Z_c present for each resource.

The next step is to choose a resource from which to move a unit of complexity and a resource that this unit will be moved to. Selecting the resource to move a unit of complexity from is simple, where any resource that contains units of complexity can be selected.

Choosing the target resource is more difficult. It is possible for any resource that has a unit of complexity to be a target for the shifted unit of complexity. However, an 'empty' resource (e.g one which contains no units of complexity) can only be filled if there is enough excess complexity present in the system to fill the resource up to Z_c. If this is the case then this resource can then also be selected.

The final step is then to move the unit of complexity from the source to the target. If the removal of a unit of complexity takes the amount of complexity within this resource below Z_c, then the remaining units of complexity are dispersed throughout the other resources already containing units of complexity.

If the target resource initially has no units of complexity associated with it's strategy, then the excess present in the strategy can be randomly assigned to the new resource, filling it up to Z_c. If a resource is newly occupied by some units of complexity then 25% of effort will be moved equally from the other occupied resources, in order that some effort is allocated to the resource.

In summary, a unit of complexity is moved from one resource to another, but the only moves allowed are those that keep the complexity in each resource above Z_c.

The second mutation is the shift of effort. Here once again a source and a target resource are selected, with the condition being that each must have a complexity larger than Z_c. Then 10% of the effort from the source to the target resource will be reallocated. If the fraction is less than 10%, then as much effort as can be spared whilst leaving one unit of effort harvesting the resource will be shifted.

3.3.10 Summary

In conclusion, the dynamics of the system are run with the following algorithm.

1. Randomly place groups across the landscape, and initialise their strategies.
2. Calculate the area of each group by finding all of the points on the landscape that are closest to that group.
3. Calculate the extraction for each resource for each group.
4. Update the populations.
5. If the population is smaller than P_{min} remove the group from the landscape.
6. If the extraction is negative, move the group one step in a random direction.
7. Stochastically split the groups.
8. Generate 10 possible strategy mutations.

- Stochastically add a unit of complexity with probability p_+.
- Stochastically alter the strategy with probability μ.

9. Select the highest extraction strategy from the present strategy and the 10 mutations.

10. Repeat.

3.4 Results

The simulations were run in order to investigate the behaviour of these dynamics, with the results represented in this section. The simulations were run on a landscape of size $L = 100$, with the initial number of groups being set to 100, and the probability of each kind of mutation having a probability of $p_+ = \mu = 0.05$. The minimum population is set to $P_{min} = 20$, with a critical population (for the splitting of the groups) of $P_C = 60$. The parameters that describe the resources will be those that are shown in Table 3.1. Initially the distribution of the resources will be homogenous, with the resource densities as given in Table 3.1. In the following simulations a *time step* will describe the process of each group moving through points (2)-(9) in the algorithm described in Section 3.3.10.

The code for the simulations was written using C++, and the graphical displays using the OpenGL and GLUT frameworks. The reason for this is that there are parts of these simulations that are computationally intensive. Specifically, the calculation of the tribal areas scales with the landscape area multiplied by the number of groups. With the large landscape sizes and subsequent large numbers of groups a computationally efficient language such as C++ is needed for simulated time steps of the order of a few seconds. The OpenGL is then used in order to be able to observe these simulations in real time.

3.4.1 Introduction of a Mutation

The first simulation to be run is that of the introduction of a more diverse strategy, and to observe if this mutation is able to spread throughout the landscape. Initially within this simulation a strategy of three units of complexity are allocated to the opportunistic resource, and five units of complexity to the scavenging, with this strategy being assigned to every group. After 100 time steps a more diverse strategy is introduced at a random point on the graph. This strategy increases the number of complexity units allocated to the large game resource to 10 and the number of units allocated to the small game to 18. The fraction of effort between scavenging and small game is 0.25, with the remaining half allocated to the large game. Four snapshots of the evolution of this simulation are shown in Figure 3.10.

Figure 3.10 is an example of four screen shots of the dynamics at four different time steps throughout the evolution. Each time step shows four pieces of information. The top left (white) is the location of each of the groups on the landscape. The top right (green) is the population density (the lighter the colour, the denser the population), and

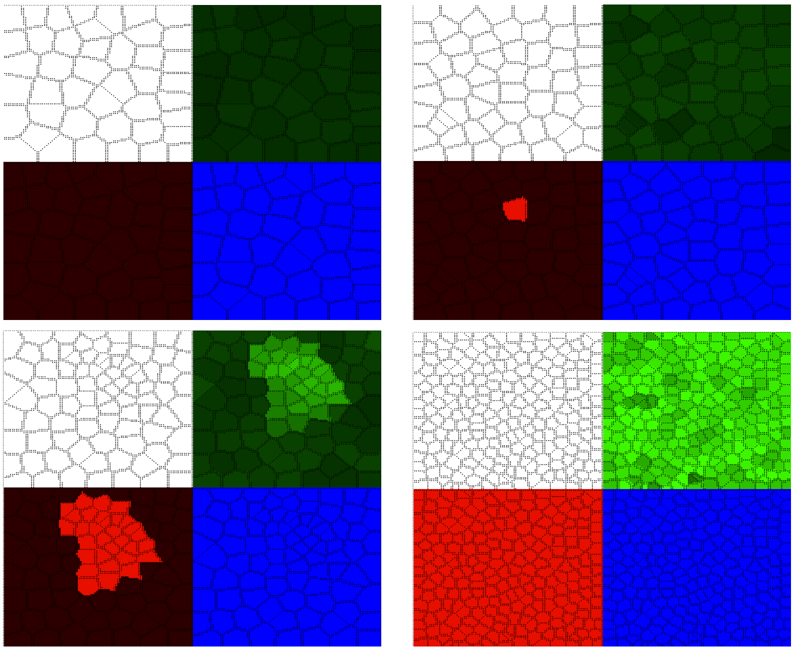

Figure 3.10: Introduction of a more diverse strategy after 100 time steps.

the bottom right is the total resource density ($\sum_{j=1}^{4} \bar{r_d}^j$) at each point (the lighter the shade the more resources that are present).

The final panel (red, bottom left) is the strategy. As there are four resources the strategy for each group will be represented by a binary number (depending on which resources are being accessed by the group). As there are four resources this number will therefore range between 0 and 15. The higher the number, the more resources that are begin accessed, and the lighter the colour in this panel. A table with the occupied strategies and the strategy number that this relates to is shown in Appendix A. The chronological order of each of the snapshots will move from left to right, and then from top to bottom.

In Figure 3.10 the initial position of the groups is shown in the top left. Here it can be seen that the resources are homogeneously spread across the whole landscape (as they will remain) and the strategy is the same for each group. It can also be noted that the area of each group is approximately equal. This is due to the homogenous strategy, and so therefore there is an equal optimal area for all groups. The population density between each group is also approximately the same, as with the same area and strategy they will also support approximately the same tribal population.

The top right snapshot then shows the introduction of the more diverse strategy at a random point. The next two panels then show this strategy splitting and spreading throughout the landscape, before it comes to completely dominate. One characteristic that can be seen with the more diverse diet is that the area is much smaller than that of the less diverse strategy (and therefore the population density is higher).

The question is, is it just the introduction of a new strategy that is able to spread, or is it only certain kinds of strategies? The next simulation (shown in Figure 3.11) has taken a landscape populated with the same diverse strategy as in the previous simulation. It has then introduced a less diverse strategy at 100 time steps, in order to see if this less diverse strategy is able to spread in the same way.

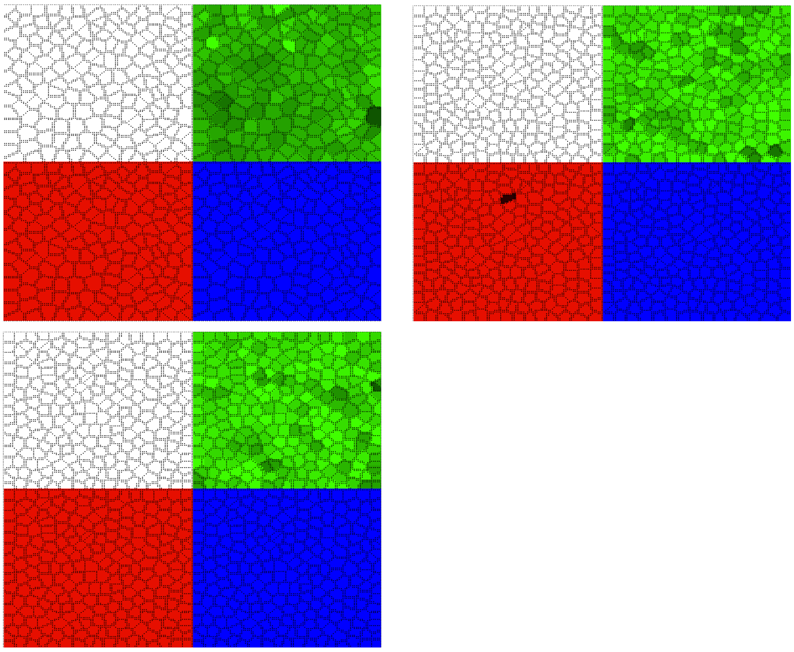

Figure 3.11: Introduction of an less diverse strategy after 100 time steps.

As can be seen from Figure 3.11 the newly introduced less diverse strategy disappears almost immediately, and does not split or spread.

Why does this spread of the more diverse strategy occur? The more diverse strategy will push the population of the group above the critical value, which will then dramatically increase the probability of the group splitting. Once this occurs, due to the diverse strategy the group will be able to survive in a smaller area, and may push against those groups with a less diverse strategy. These groups will not have the ability to survive with their current populations too high to be sustained by a smaller area, and so their populations will shrink. Eventually, the pressure of the other groups will cause the population to become too small, and so the less diverse group will disappear. This process will then repeat until the entire landscape is populated by the more diverse groups.

Having now observed what happens when a single group is deterministically mutated, the next simulations will allow each group to mutate at each time step.

3.4.2 Evolutionary Dynamics

The dynamics will now be run from a simple strategy, with mutations allowed for all groups at each time step. The initial strategy for each of the groups will be that described in Section 3.3.3. In this simulation the landscape has the same resource density for each of the resources at every point. The results of allowing the dynamics to run over 2000 time steps are now shown in Figure 3.12.

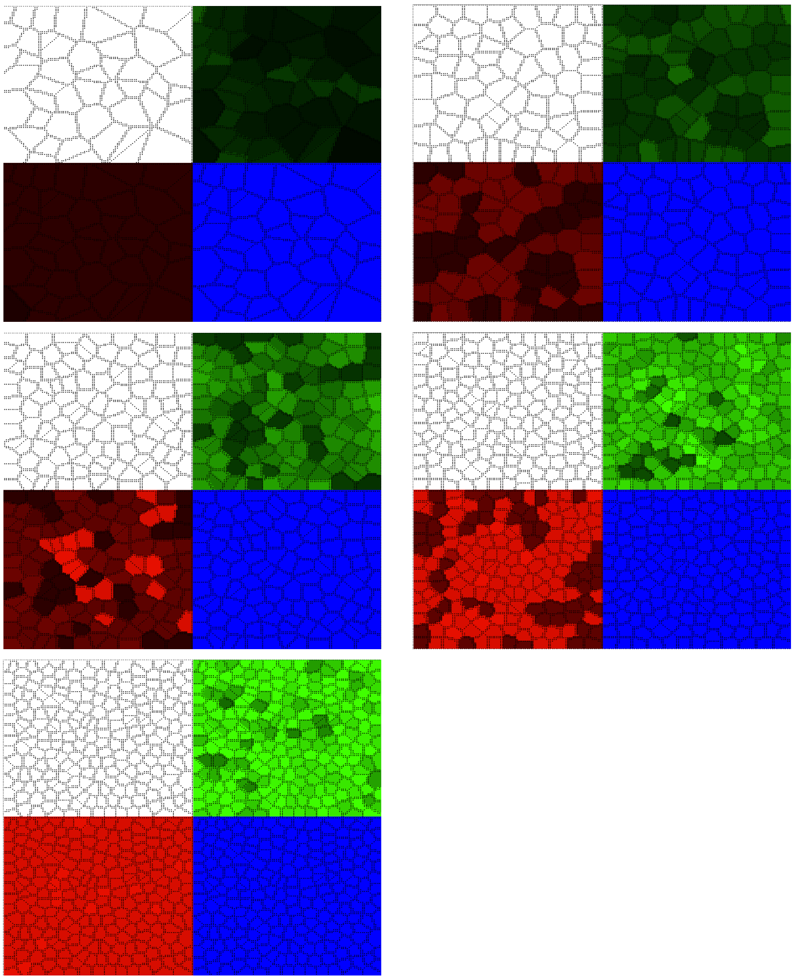

Figure 3.12: Evolution of the groups on a full homogenous landscape.

As can be seen from Figure 3.12 the groups all start out with low population density, large areas and the same strategy. However, as time moves on the population density has increased and some of the groups move into the large game resource as well as opportunism and scavenging. As time increases the more dominant strategy of the large game hunting spreads, and causes the population density to increase, with a few groups beginning to supplement their diets with small game. Finally, in the last two panels is can be seen that the population density increases, along with the number of groups, and the most diverse strategy comes to dominate the entire landscape. In order to observe how the groups mean population density and strategy change over time these were averaged over all of the groups, with the results plotted in Figure 3.13.

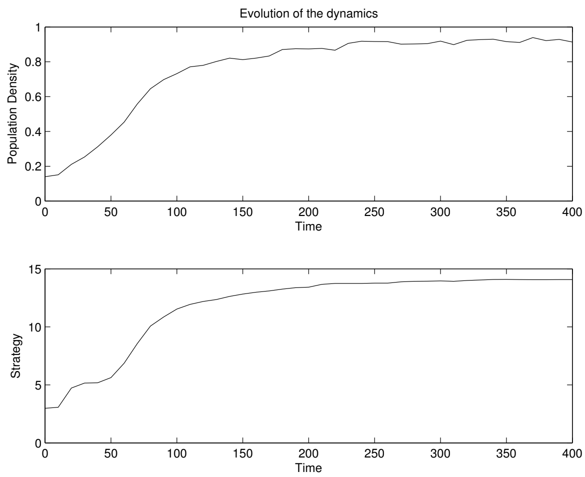

Figure 3.13: Evolution of the population density and strategy of the full, homogenous landscape (first 400 time steps).

From Figure 3.13 it can be seen that the change from one strategy to the next is very rapid, and it does not take long for a more diverse strategy to spread throughout the landscape. Once the most diverse strategy has been found, a period of equilibrium follows from which the groups cannot improve. It can also be seen from the mean strategy that there are three distinct phases within the simulations. The first is the scavenging phase, the second is the large game, and the third is the small game phase.

The question is, under what conditions is this diverse strategy a good one? Is it always a good idea for the groups to diversify, or is it only if there is enough of each resource to justify this. In order to test this the density of small game was now reduced to $r_d^{\text{small game}} = 0.0100$ across the whole landscape. The dynamics were then run once again from the same initial conditions as in the previous simulations. This gave the evolutionary dynamics shown in Figure 3.14.

From Figure 3.14 it can be seen that the groups start off scavenging before the large game dominated strategy begins to evolve and spread. However, at no point do any of the groups evolve into a more diverse strategy where they are able to supplement their diet with small game. This is also shown in Figure 3.15, where the mean population density and strategy remain at much smaller levels than in Figure 3.13. From these simulations it can be seen that diversification of strategy is of benefit to the groups, but will only occur if there is enough of a resource in existence to justify the switch.

These simulations have all been performed on homogenous landscapes, which whilst useful are not particularly realistic. A more realistic landscape would be one where

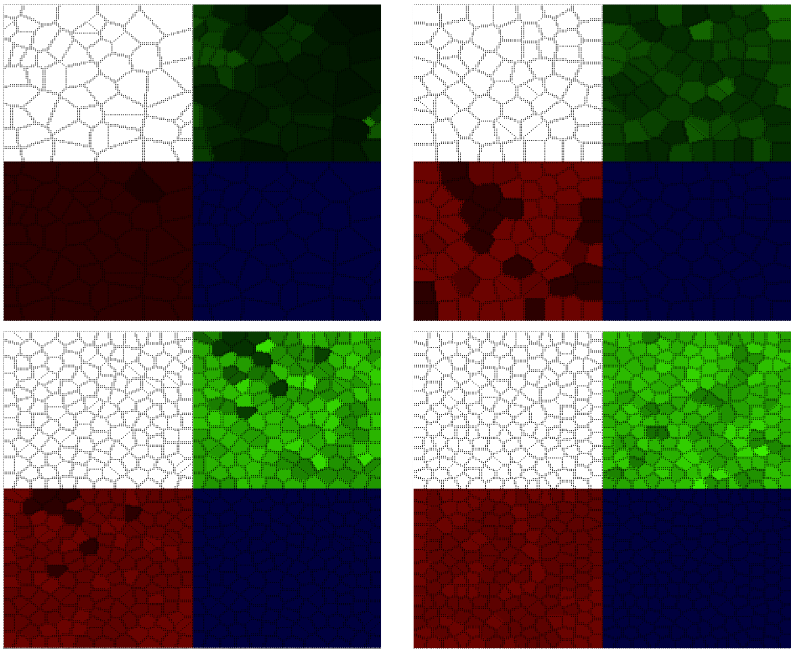

Figure 3.14: Evolution of groups on a reduced small game resource density homogenous landscape.

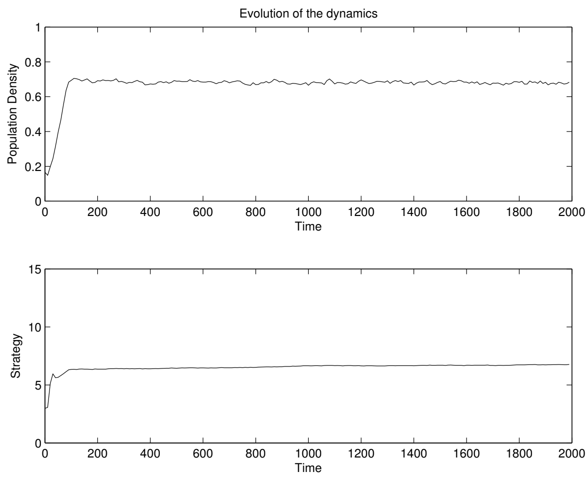

Figure 3.15: Evolution of the population density and strategy of the reduced small game, homogenous landscape.

there is more of one resource in a particular location than at another. These ideas will be explored in the next two sections.

3.4.3 Split Landscape

The first heterogenous landscape to be investigated will be that of the split landscape. Here there will be a plentiful southern hemisphere compared to a more barren north. More specifically, the southern half of the landscape will contain $r_d^{\text{small game}} = 0.0175$, whilst the northern half will have a smaller amount of small game, or $r_d^{\text{small game}} = 0.0100$. Once again the initial conditions will be those of one unit of complexity in the opportunistic and scavenging resources. The dynamics were now run with snapshots of the landscape shown in Figure 3.16.

From Figure 3.16 it can be seen that some very interesting behaviour emerges. During the first moments the landscape takes on the standard homogenous scavenging to large game diversification as has been previously observed. However, after this the evolution of the strategies begins to separate between the two hemispheres of the map. In the northern hemisphere the landscape continues to look homogenous in the large game, but the south begins to fill with a more diverse small game supplemented strategy. So far in these dynamics the behaviour is exactly that from Figures 3.12 and 3.14, where it is as if the two landscapes have been stuck together, as would be expected.

However, as can be seen from panels 5-7 in Figure 3.16 after this the groups with the more diverse strategy then begin to move up into the northern hemisphere, and eventually push the groups with the less diverse strategy towards extinction. This behaviour shows that even though there is not enough small game in the northern hemisphere to cause a diversification of the strategy of the groups already present there is enough to support a group that has been able to develop this strategy elsewhere. The evolution of the strategy shown in Figure 3.17 is able to show how the more diverse strategy slowly spreads into the north and steadily increases the mean strategy across the landscape.

It should be noted here that the only differences between the groups within this simulation is location. The groups in the northern half of the map are perfectly capable of developing a more diverse strategy. However, due to the lack of certain resources it does not pay for them to do so. The reason for their extinction is that the strategy that they have developed is not able to compete with a more diverse strategy, not because these groups are less capable.

3.4.4 Graded Landscape

To find if the results found in Section 3.4.3 are an artefact of the binomial form of the landscape or if this is a more general result a continuous change in the resource density will be implemented. In this section the resource density will be varied in a gradual way, from a maximum value in the bottom left hand corner of the landscape to a minimum value in the top right. In this case the resources were varied using the following formula,

$$r_d = \frac{r_d^{min} - r_d^{max}}{L\sqrt{2}} D + r_d^{max} \tag{3.12}$$

where r_d^{max} and r_d^{min} are the largest and smallest values that the resource density will take and D is the Euclidean distance from the point of resource density maximum.

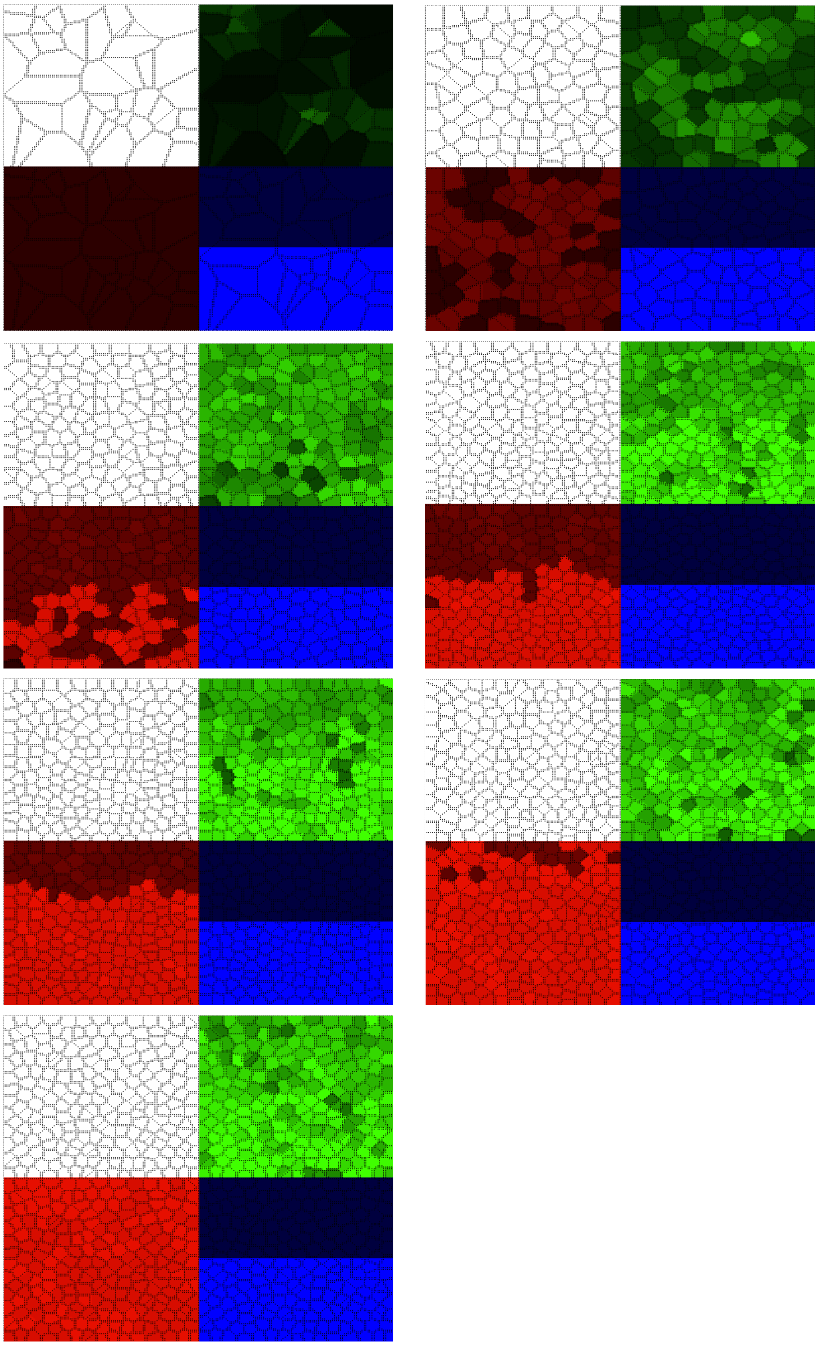

Figure 3.16: Evolution of the groups on a split landscape.

In these simulations $r_d^{min} = 0.0100$ and $r_d^{max} = 0.0175$ Running these dynamics gives the snapshots shown in Figure 3.18.

In Figure 3.18 it can be seen that the dynamics start off as in the previous examples,

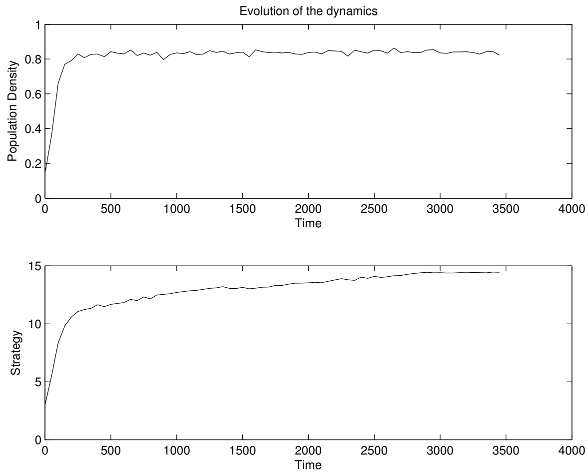

Figure 3.17: Evolution of the population density and strategy of the split landscape.

with the initial strategy being supplemented with large game across the whole landscape. As the dynamics move on it is found that in a region of high density small game the strategy of two groups become more diverse. This strategy then spreads quickly into the areas of higher density, and much more slowly into the areas of low density, before once again spreading across the whole landscape. The speed at which this spread occurs is shown in Figure 3.19.

3.4.5 Variable Resource Parameters

In the previous simulations it has been shown that the density of the resources is a large factor in the evolution of the diets and strategies used by these groups. This section will now begin to investigate how sensitive the system is to the form of the resources. And specifically, does it matter how high the minimum complexity is to access the resource. If this is changed how will this change the dynamics?

To find out how the resource parameters affect the dietary evolution of the groups the dynamics will be run on a homogenous landscape with the full resource density. For each run a different value of the parameter Z_c in the large game resource will be used, with the final mean strategy measured to see what the final state of the system is. Running this gave the results shown in Figure 3.20.

What the results in Figure 3.20 show is that at low values of Z_c the final dominant strategy is a diverse one spread between all of the resources. However, at a critical value of Z_c the final strategy drops to one that is much less diverse. Interestingly, this final strategy does not involve the large game, but is instead wholly opportunistic and scavenging.

What is the reason for this? When the strategies are mutating, in order to access a resource there needs to be enough excess within the complexity units allocated to other

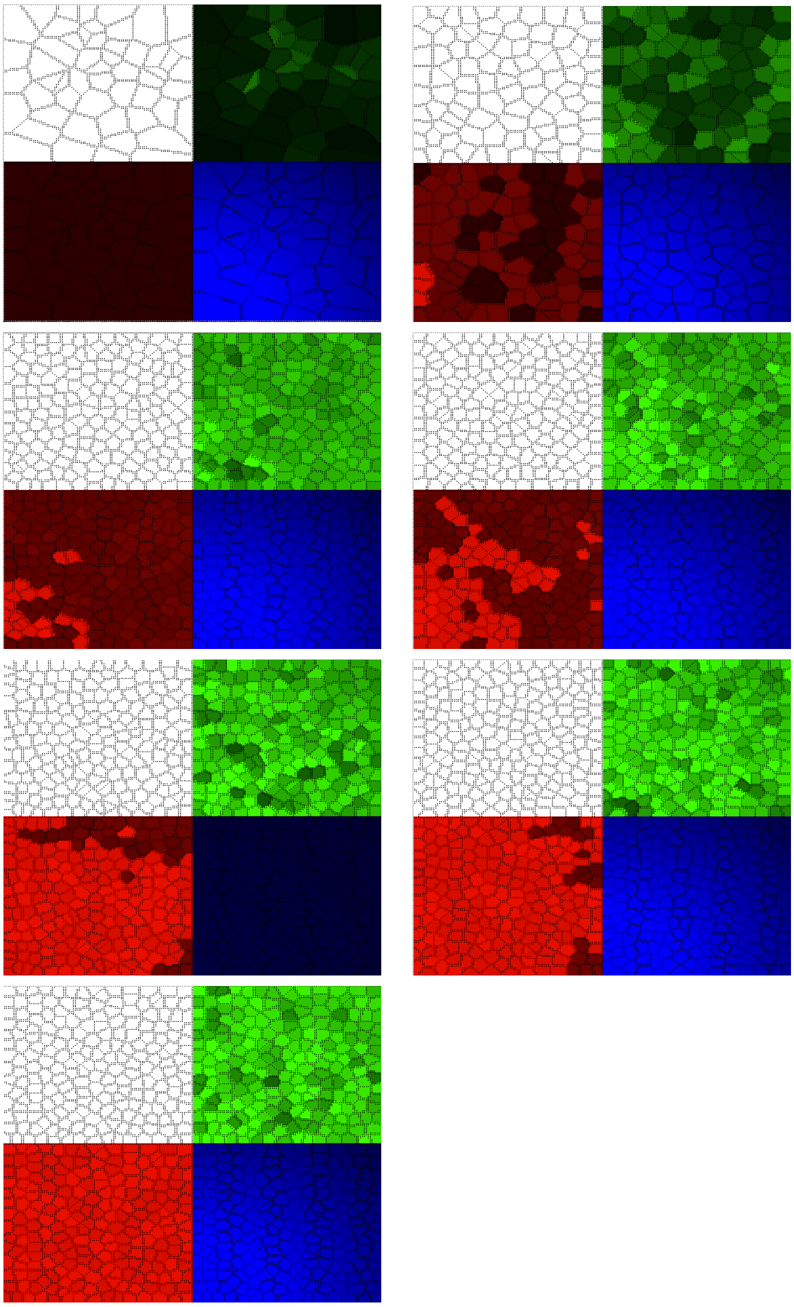

Figure 3.18: Evolution of the groups on a graded landscape. The maximum resource density is found in the bottom left corner.

resources in order to diversify. When Z_c is low for the large game, there is more than enough excess in the opportunistic and scavenging resources with which they are able to make this leap. Once the strategy is diversified to the large game, then the dynamics can

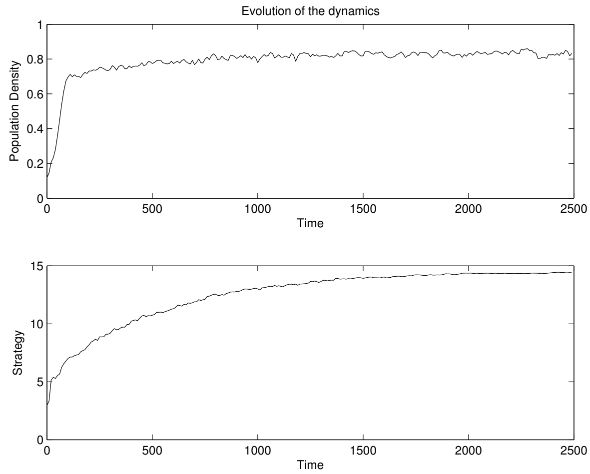

Figure 3.19: Evolution of population density and strategy for a graded landscape.

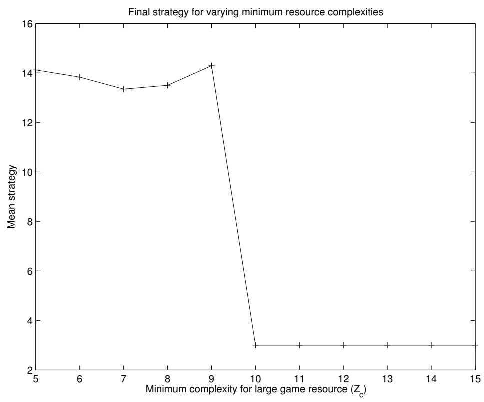

Figure 3.20: Final mean strategy with increasing large game minimum complexity.

continue to the final strategy spread across all resources. However, if there is not enough excess present in the first two resources to diversify into large game, as happens when $Z_c > 9$, then the jump cannot be made and the system is locked in to the opportunistic and scavenging strategy.

What these results are therefore telling us is that the large game resource is acting as a bridge across to the small game resource. Although there is a lot of small game present within the landscape, the groups are unable to become complex enough (even though in theory they could) due to a lack of access to the large game, and therefore support enough complexity to move through the intermediate technologies.

3.4.6 Complexity Ceiling

It has been shown that the form of the resources are a central factor in establishing the optimal strategy and how diverse that final strategy is. What has not been established here is the driving force behind the change in strategy. Is the driving force an increase in population, or is it that a chance improvement in technology can lead to a whole new, improved strategy? Also, what are the effects of the results found in Chapter 2? If a glass ceiling is imposed onto the maximum number of complexity units in this model, how does this effect the evolution of the dynamics?

In order to test this an artificial complexity ceiling will be placed within the simulations. This ceiling will limit the total number of complexity units available to each group, and will be raised every 50 time steps. This ceiling will initially start at $C_T = 2$, and then be raised by 2 units each time. Running these dynamics on a full homogenous landscape gave the results shown in Figure 3.21.

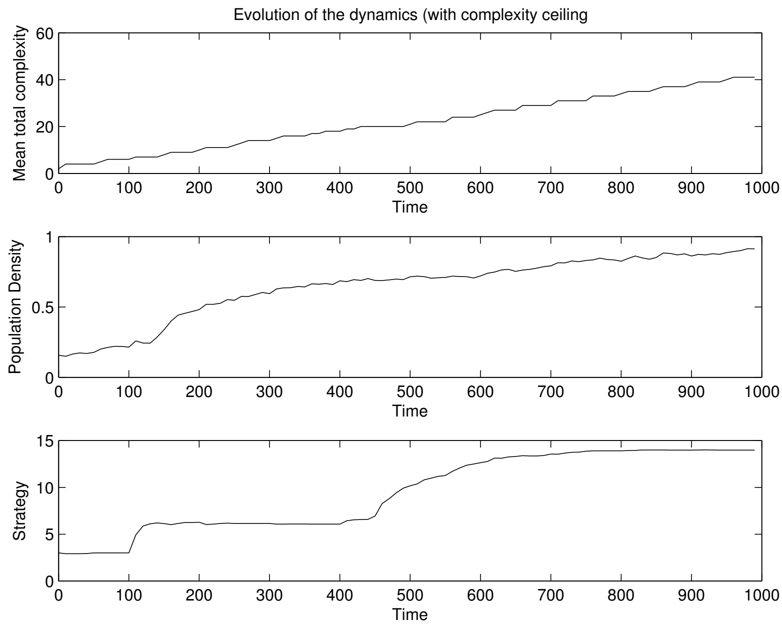

Figure 3.21: Mean complexity, population density and strategy for the artificial increase in the complexity ceiling.

If Figure 3.21 is compared to Figure 3.12 then this shows that including an artificial complexity ceiling does indeed slow the evolution to a fully diversified strategy across all resources. This suggests that it is the total complexity that is the driving force behind the diversification of strategy. In order to test this idea further each simulation was now run for 1000 time steps with an artificial complexity ceiling included. The final strategy was then measured in order to demonstrate the final state of the groups. The results for this are shown in Figure 3.22.

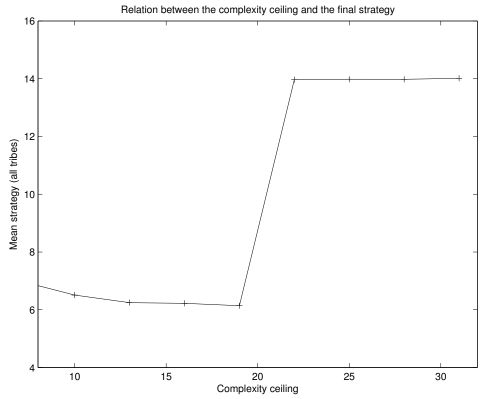

Figure 3.22: Final mean strategy on a landscape for various complexity ceilings.

As can be seen in Figure 3.22 for low complexity ceilings the mean final strategy suggests diversification only up to large game. However, once the complexity ceiling rises above a certain value (in this case $C_T \approx 20$) the final strategy is then found to have diversified to small game. This suggests that it is the total complexity for a group that will determine the final strategy, and that this increase in total complexity is the driving force behind the diversification.

3.5 Discussion

A number of interesting results can be gleaned from the simulations that have been performed in Section 3.4. The first of these is that on a landscape that is populated by many different resources the most dominant strategy is one that is spread among many of them. Whilst it is possible for groups that have a less diverse strategy to survive, as soon as a more diverse strategy arrives it is able to flourish within this landscape, and push less diverse strategies towards extinction. It was also seen that the spread of these new, more diverse strategies happens very quickly.

From the simulations performed in Section 3.4.6 it can be seen that the increase in population density is a product of the shift to diversification, and not the cause. Instead, the driving force behind the change to a more diverse strategy appears to be the increase in complexity units. It is this steady increase that seems to push the optimal strategy towards large and small game. However, as can be seen in Figure 3.20 this will only occur if the technology needed to access a particular resource is low enough that the strategy is able to shift across. If this value is too high, this also precludes strategies diversifying further, showing that some resources can be seen as a bridge to those that are more complex.

This last point has implications for the final shift at the end of the Upper Palaeolithic to agriculture. This shift is generally considered to have happened within the fertile crescent, where there were many resources available. One possibility is that it would be too difficult to go from a low complexity technology straight to a high complexity one, and that what is needed in between are other bridging resources. This could explain why agriculture was first found in a region with many varied dietary niches.

Following from this, it was found that the density of the resources was a major determining factor in the evolution of the groups strategies. If some of a resource is present, then it will not necessarily be of use to a group unless it is there in a large enough amount. Therefore, the strategy may only diversify if there is enough of the resource present to justify this. This does not mean that this resource is not useful, and if another strategy moves into existence which does use this resource, then it will then have an advantage over the groups with the simpler strategy, and may push them towards extinction.

This could point towards a reason for the extinction of the Neanderthals. It has been suggested that one reason for the disappearance of this species is that modern humans moved towards their territory, and there was a competition for resources. It was the inability of the Neanderthals to supplement their diet with more varied (but harder to extract) resources that meant that they were therefore unable to compete with the modern humans.

In conclusion this work has demonstrated that in the evolution of human diet the form of the resources present at any point on the landscape were key. These resources were able to act as a bridge to a more varied and complex diet, and this in turn led to more successful dietary strategies.

Chapter 4

Conclusions

From the results in Chapters 2 and 3 it can be seen that many aspects of Palaeolithic culture and diet have been successfully modelled within this thesis. Beginning with novel models of cumulative culture and moving on to investigating the particular situations in which the evolution to a broader diet is possible, these abstract models have given valuable insights into the possible mechanisms for change in pre-agriculture societies.

4.1 Summary of results

This work began by investigating the mystery of cumulative culture within Palaeolithic humans. In Section 2.3.1 a cumulative culture model was built that could reach equilibrium, and therefore generate results that were independent of the rate at which the base units of culture were combined. These models were able to show that within the dynamics of maximum time and fidelity of transfer cumulative culture does exist, and that the complexity of the culture increases with time up to a maximum level. This evidence of cumulative culture continues with the simulations in Section 2.3.3. These simulations agreed with the findings of Lewis and Laland [1] that the rate at which technologies survive is the most important factor, followed by the rate at which technologies combine.

The results of cumulative culture were also present within the simulations run on the geographical model. Within the results in Section 3.4.5 it can be seen that as the maximum complexity increases, the culture of the humans became more complex, and passed on more complex cultures between generations. Within all of the examples of cumulative culture it can be seen that you cannot make large leaps between very simple and very complex technologies, and so this work suggests that any very complex technology or diet must be built on simpler ones of similar complexity.

As well as cumulative culture the models within this thesis were consistently able to replicate the glass ceiling phenomenon. The central results demonstrating the glass ceiling were found in the fidelity model in Section 2.3.2. Here it can be seen that exactly the same results as found by Andersson [8, 10] were produced, but with an algorithm that was closer to that of the model by Lewis and Laland [1]. Even though the link between utility and complexity was severed the glass ceiling effects were found for the complexity of the technology, although none were found for the utility of the resources accessed.

In Section 2.3.4 it was also seen that an analytical solution for the glass ceiling can be reproduced, with the same proportionality as that found by Andersson. However, this result has also been extended by including the rates of combination and break down of technologies, showing that the glass ceiling can be applied in a much wider way than was previously thought. The effect of applying a glass ceiling can also be seen in the geographical model in Section 3.4.6. Here it was shown that even though the glass ceiling is artificially placed onto the dynamics the simulations still lead to the results that you would then expect in the archaeological record.

One large failing of the fidelity model shown here is that it did not show a broadening of the tools across each of the resources over time, but instead shows an allocation to the lowest complexity resource that would be expected by chance. It is only when the more advanced model of Chapter 3 is built, and specifically when this model is allowed to evolve from simple beginnings in Section 3.4.2, that the desired evidence of the broadening of the diet is then found.

When the model is able to reproduce the broadening of the diet it is also able to produce many of the facets found in the BSR. These include the observation that the broadening of the diet tends to occur in regions of plenty, rather than those regions where there is a scarcity of resources. This result was also demonstrated in Sections 3.4.3 and 3.4.4 where the leap to a broader diet occurred within the regions on the landscape with higher resource density. Finally, it was found that the broadening of the diet could be restricted by imposing a ceiling on the amount of complexity allowed per group, as shown in Section 3.4.6.

Along with the broadening of the diet this model was also able to show the 'budding off' of the more successful groups as suggested by Flannery [15]. The first time this phenomenon is found is in Section 3.4.1 when, with the introduction of a more diverse strategy, the population of this group increases. After this point the group splits, and then continues to do so until the more diverse strategy has enveloped the whole landscape. This can also be seen in the results of Section 3.4.2 where on the initial evolution of a more diverse strategy daughter groups are created that move away from the initial point of inception. This budding off of daughter groups into the regions of less dense resources can be seen more explicitly in the results of Sections 3.4.3 and 3.4.4, where on the evolution of a more broad strategy these groups then bud off and push into regions of less dense resources, as predicted by the BSR.

From these results a possible mechanism for the elimination of the Neanderthals and other early humans can now be posited. If the Neanderthals were mainly based in Eurasia with a diet that was almost exclusively large game, a group with a diet that was broader than this may be able to out compete these large game dependent societies. This is what can be seen to be happening in Section 3.4.3. The groups in the northern hemisphere are unable to create a more diverse diet, and so when the groups in the southern hemisphere do so they are able to squeeze the less diverse groups into smaller areas, until eventually they are eliminated.

This could point towards the reasons behind the extinction of the Neanderthals. As suggested by Fa *et al* [23] it was the inability of the Neanderthals to catch small game that could have led to their demise through extra competition for other resources, as shown in Section 3.4.3 and 3.4.4. An important point to note here is that the groups in the regions of lower density resources have a less broad diet not because they are less able, but because it is not in their best interests to move to a more broad diet. It is only because of a broader diet group arriving in this region that this strategy does not prove optimal. This work is therefore able to show that the Neanderthals may not have needed to have lower intelligence in order for their terminal fate to befall them.

Finally, these simulations were designed to investigate the phenomenon of punctuated equilibrium found within the archaeological record. Both of the models developed within this thesis were able to show this phenomenon in a number of different scenarios. The first representation of punctuated equilibrium was seen in Section 2.3.1. Here in Figure 2.5 it can be seen that although the mean tool complexity is stable the maximum value oscillates between a wide set of values. This aspect of the model produced in Chapter 2 can explain the isolated cases of increased complexity in the archaeological record.

Another example of the punctuated equilibrium is found with the rising mean complexity with rising fidelity, as shown in Section 2.3.2. It can be seen in the results here that as time moves on there are periods of stasis where the mean complexity changes by a small amount, followed by very large leaps in the mean complexity as the fidelity is increased.

However, it is not just the fidelity model that is able to demonstrate punctuated equilibrium. In Section 3.4.2 it can be seen that there are periods when there are plateaus followed by increases in both the population density and the strategy of all of the groups involved within the simulation. This is particularly noticeable within the strategy plots, results which would certainly show up in the fossil record as punctuated equilibrium. It was also found within this model that the punctuated equilibrium could be introduced artificially in Section 3.4.6, as only when the total complexity has risen above a certain level would the next stage in the broadening of the diet be found. In each of these examples it can also be seen that the change between each period of stasis is rapid.

The results from Section 3.4.4 tell a slightly different story. Here the punctuated equilibrium is not evident, and so the increase is gradual. Therefore, in order for this phenomenon to be observed within these models the resources need to be distinct in their densities across the landscape.

4.2 General findings

In Section 4.1 a number of interesting phenomena were noted from the two models built within this thesis. The question is, what are the general mechanisms behind these results?

The first important mechanism that can be seen from these results is the spread of a superior strategy within the geographic model. More specifically, the kinds of strategies that have been found to be superior vary with both the density and the parameter values selected for the resource, but in each case when a broader strategy exists it is able to spread throughout the landscape. From the results it is seen that a broader strategy is able to survive in a smaller area, as the prey lost in a reduced area is supplemented by the extra prey that can be consumed. Consequently, as the groups ‘bud off’ from the parent group they can push the less broadly dieted groups to the edge of the landscape, and reduce their area. This causes a reduction in the amount of prey that can be harvested, until the group is eliminated. In other words, the replacement by superior strategies of less superior ones is caused by encroachment into their tribal area. It can also be seen that the resources are used as a bridge to the higher complexity resources, and taking this bridge away will lead to groups being stuck in a particular niche.

The second mechanism that is found across this whole thesis is the relationship between the increase in fidelity and increased complexity, leading to more complex tools and broader strategies. In raising the fidelity of transfer between generations many more complex, and useful, tools are able to transfer to the next generation, and once the complexity ceiling has been raised above a certain level this can lead to a broadening of the diet.

From all of the results that have been found it can be seen from these simulations that it is the fidelity of transfer, and by extension the number of complexity units available to the groups that is the real driving mechanism. The broadening of diet and increase in population density come after this increase in complexity, and not before. After the fidelity the second most important factor is then the form of the resources, or the rate of technology creation, but if a culture is stuck underneath the glass ceiling then these factors will not move the cultures above it for long.

The central theme running through this thesis has been, why did human culture change at all? If the hunter-gatherer societies were able to support themselves through their hunting strategies for hundreds of thousands of years, why did they then change to supplementing their diet with small game? And why ultimately did they then move to agriculture?

From this work it appears that the answer to this is raised fidelity of transfer, and from this improved technology. As technology improves this pushes the Palaeolithic societies away from a position of equilibrium, and causes them to over harvest certain species, and increase their population. The only way to get away from this was to then supplement their diets with extra resources, before the process started all over again.

4.3 Future work

This author feels that the geographical model developed in the second half of this thesis shows great promise in its use as an abstract model for the evolution of pre-agriculture humans. Future work could certainly include parts of the studies on fidelity, and transfer of knowledge between generations. However, external factors could also be introduced. Barriers within the landscape could give a more realistic topology of the geography that these groups existed in, and variable resources could model climate change to observe how this may have affected the broadening of the diet.

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Appendix A

Strategy Values

This table shows the resources allocated to a strategy and the strategy value that this corresponds to.

Table A.1: The strategies and their values.

Opportunistic	Scavenging	Large game	Small game	Strategy Value
Yes	No	No	No	1
No	No	No	No	2
Yes	Yes	No	No	3
No	Yes	Yes	No	4
Yes	No	Yes	No	5
No	No	Yes	No	6
Yes	Yes	Yes	No	7
No	Yes	No	Yes	8
Yes	No	No	Yes	9
No	No	No	Yes	10
Yes	Yes	No	Yes	11
No	Yes	Yes	Yes	12
Yes	No	Yes	Yes	13
No	Yes	Yes	Yes	14
Yes	Yes	Yes	Yes	15