

Resource Degradation and Egalitarianism in Hunter-Gatherer Societies

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Abstract

This project reimplements NeoCOOP, an agent-based model, in order to study egalitarianism in hunter-gatherer societies. NeoCOOP was initially developed to study the influence of environmental stress on cooperation in socially-stratified societies. The reimplementation uses the Rust programming language for greater performance, specifically via parallelization of many parts of the simulations. It also introduces the concept of resource degradation, where agents' accumulated resources diminish by a specific percentage each iteration. This allows for new emergent behavior to be studied. At lower degradation levels, findings aligned closely with the original version of NeoCOOP's results, which increases the validity of the new implementation as the previous implementation had no resource degradation. However, the greater result is that it is apparent that egalitarianism is critically dependent on resource degradation, as clearly displayed by simulations with higher levels of degradation. This new data offers insights into resource-sharing dynamics within simulated societies, which can then be applied to real-world scenarios with limited resources or high levels of resource degradation. Such results show how, as a species, decreasing levels of resource degradation could have led to increased egalitarianism in our societies.

Keywords: Agent-based Modelling, Neolithic Societies, Egalitarianism

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1. Introduction

Anthropologists, as illustrated by Alain Testart (1982), classically categorized hunter-gatherer societies into two distinct types: traditional, which are more common, and non-traditional, which are less common. Traditional societies are

nomadic, have a low population density, and have low levels of social inequality. In contrast, non-traditional societies are sedentary, have a higher population density, and most importantly, have much higher levels of social inequality and social stratification. This is known as the nomadic-egalitarian model as described in Singh and Glowacki (2022).

Academics have discussed hypotheses for this split and the egalitarianism typical of traditional-type societies for many years. As recorded in Widlok and Tadesse (2006), James Woodburn stated in 1981: "Greater equality of wealth and of prestige has been achieved in certain hunting societies than in any other human societies. These societies are assertively egalitarian. Equality is achieved through direct, individual access to resources; ... through procedures which prevent saving and accumulation and impose sharing; ... People are systematically disengaged from property and therefore from the potentiality in property for creating dependency."

However, the nomadic-egalitarian model has become a hotly-debated topic. Singh and Glowacki (2022) synthesises research challenging the model and outlines the more complex nature of these societies, arguing that while traditional and non-traditional societies are common, there are many societies that do not fit into either category and require more complex analysis. There is a growing level of research into how societal structures developed and under which conditions they arise or erode. Other examples include Kuijt (2009), and Soffer (1989).

This project aims to contribute to this discourse by analysing the impact of resource degradation on cooperation and egalitarianism. This is done by utilising a technique now common in the field: agent-based models. Gilbert (2019) defines the technique as "a computational method that enables a researcher to create,

analyse, and experiment with models composed of agents that interact within an environment.” Agent-based models are computational frameworks wherein autonomous agents follow a set of explicit rules to mimic complex systems. These agents interact with one another and their environment, allowing emergent phenomena to be observed, such as social stratification and cooperation patterns.

Essentially, by gathering and applying modelling techniques from many previous papers we have created a model that gives rise to and allows for the study of many emergent phenomena such as large-scale cooperation and egalitarian social structures. By improving this model we can better understand the area of study that we are modelling, but also models themselves and the techniques surrounding them which can then be applied to many diverse fields. Specifically, we contribute to the discourse surrounding the nomadic-egalitarian model by analysing whether the changing of resource degradation over the course of human history could have affected the levels of egalitarianism and cooperation present in the groups that we formed, and whether these groups would have likely conformed to one of the two categories or neither.

1.1. Problem Statement

While the nomadic-egalitarian model has traditionally been employed to explain the split between traditional and non-traditional hunter-gatherer societies, recent studies suggest that these societies and their social structures are more complex than originally anticipated. Particularly, the role of resource degradation in influencing cooperative behaviors and the emergence of egalitarian social structures has not yet been fully explored. Given the significance of understanding societal responses to resource scarcity and degradation, it is valuable to investigate how varying degrees of resource degradation affect cooperation and egalitarianism. Agent-based models have been used to explore the effect of resource degradation on cooperation, and cooperation in general, but this model builds on them to explore resource degradation’s effect on other variables.

We specifically aimed to answer the following questions:

1. Does varying storage efficiency lead to social stratification, or conversely, promote more egalitarian social arrangements?
2. How do agents adapt their sharing strategies in response to reduced storage efficiency, particularly in situations with high environmental stress?

1.2. Hypotheses

We hypothesised that low levels of resource degradation would allow for the same outcomes as previous iterations of the model, as those experiments were performed with no degradation. Differences would only become apparent when the degradation rises beyond a certain threshold, at which point we hypothesised that egalitarian social arrangements would be prioritised as sharing would be incentivized due to agents not being able to hoard resources, as described by Alain Testart (1982).

We also hypothesised that agents would generally become more cooperative in response to increased resource degradation, whether in situations with high environmental stress or not. We believed this because in situations with low storage efficiency, uncooperative agents gain nothing by hoarding their resources via low levels of cooperation, as their resources will simply decay. On the other hand, cooperative agents can effectively utilise social storage. This is when resources are stored in the society as a whole, as opposed to technological storage where resources are stored in some place or object, or biological storage where resources are stored in one’s physiology. As explained in methodology, resource degradation, however small, ensures that each agent has a limit on the amount of resources that they can store. The more agents that belong to a specific settlement, the more total resources that that settlement can acquire. They can only fully utilise this storage capacity, and the periods in which the resources available in the environment are plentiful, if resources flow where necessary through high levels of cooperation.

1.3. Motivation

As discussed by Ingold (1983), effective food storage is a cornerstone of human life that not only ensures survival but also shapes societal interactions and hierarchies. Food procurement has also been a driver of technological advancement for much of history, as described by ?. How communities store food, and how effective those methods are, can lead to cooperation, equality, and shared prosperity, or conversely, to competition, inequality, and social divisions.

While focusing on hunter-gatherer societies, the insights from this research contribute to explaining the relationship between material constraints and social organization with relevance to modern societies. The efficiency of resource storage techniques has changed monumentally throughout history as communities around the world have progressed technologically. By shedding light on how food storage practices can either foster or hinder egalitarianism, this project offers a perspective on the evolutionary dynamics of cooperation and egalitarianism within human societies in a time where questions of resource distribution, social equity, and community cooperation are more pertinent than ever.

2. Literature Review

Agent-based models are an increasingly common technique in anthropology, but this is a fairly recent development. Hanappi (2017) describes agent-based models as originally created and studied in the field of economics around 1970, in order to study the behaviour of different entities such as consumers and producers in hypothetical economic systems. The same techniques have been easily applied to the ecological and social sciences, and have been used to model organisms and how they interact with each other and their environment in order to study population or group dynamics. Recently, agent-based models have been used extensively in the health sciences and related fields to study the dynamics of epidemics and how different

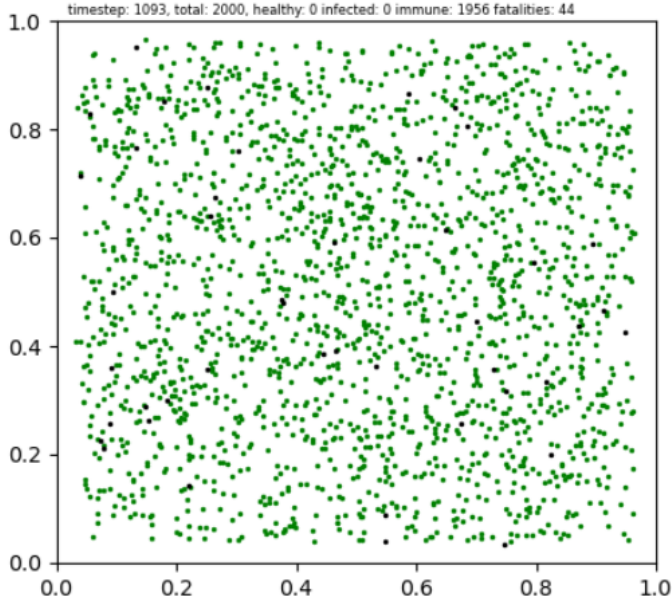


Figure 1: A frame from an agent-based model that simulates the spread of COVID-19 in a population. Source: van Gent (2021)

variables can affect the spread of diseases with certain characteristics, for example in Perez and Dragicevic (2009).

In Figure 1, the agents are people that live in proximity to each other and the environment is the area that they live and interact in. The pixels in the frame represent each agent and show the status of each agent with green pixels representing immune agents for example.

This project builds on Gower Winter and Nitschke (2022) and Nitschke and Gower Winter (2023). These both involve the use of a specially-created agent-based model called NeoCOOP. This model simulates Neolithic households, their environment and their capability for cooperation. In Gower Winter and Nitschke (2022), the effect of different stress scenarios on cooperation within these simulated societies is studied. Stress scenarios define periods in which less resources are generally available in the environment, both in their duration and frequency. Nitschke and Gower Winter (2023) is concerned with the emergence of social stratification as a result of differential access to resources. These provide the base model and many primary parameters of the simulation, as well as a high-level overview of the model, and an explanation for the scientific backing of many mechanics in the simulations. In short, NeoCOOP simulates hunter-gatherer societies with each agent representing a single Neolithic household, grouped into settlements. Agents can retrieve resources from the environment, can consume those resources, and have genes that control their tendency to share their resources with other households in times of need. They evolve through a genetic and a cultural algorithm. The genetic algorithm is the primary driver of evolution in this study and is described in detail below.

As described in Gower Winter and Nitschke (2022), the NeoCOOP model uses percentage-based cooperation, which means that each agent has a certain chance to cooperate or defect when

given an opportunity. To defect means to not cooperate, and non-cooperative agents are described as being defective, as opposed to altruistic. This is opposed to other systems where agents always cooperate or always defect, or can only cooperate with some subset of the other agents, those that are in their social network, for example.

This is a well-backed approach that also appears in Pereda et al. (2017), which studied the effect of resource pressure on cooperation. This work also utilises previous results from Chliaoutakis and Chalkiadakis (2020), which simulated inter-settlement trade and provides a system for creating hierarchies of agents based on some measure of social status, which is used to organise agents into superiors, peers and subordinates in NeoCOOP. The resources that an agent has stored and shared are used to determine their relative position in the hierarchy as described below.

Finally, another article of note is Angourakis et al. (2015). An agent-based model similar to NeoCOOP is used, within which agents can also contribute to and access a group storage along with a private storage, but they can only access the group storage if they contribute a certain percentage of their resources to it. The resource storage efficiencies of personal and shared caches were varied and the resultant levels of cooperation were explored. The effect of varying the amount of resources required to access the cooperative store was also explored. The "Food for all" model is different in that agents could adapt their strategies over time using a reinforcement-learning mechanism, as opposed to genetic and cultural algorithms. The results provided interesting insights into the evolution of cooperative social structures in order to support cooperative, and therefore more efficient, food storage.

2.1. Differentiation

"All models are wrong, but some are useful." is a well-known aphorism in scientific modelling coined by George Box in Box (1976). Previous iterations of NeoCOOP have explored the emergence of both cooperation and social stratification, but have assumed perfect resource storage. By refining certain parts of models, greater insights can be gleaned from them, and new emergent phenomena can be studied. The reimplementations of the model in the Rust programming language also allows for performance gains through Rust's powerful parallelization libraries.

This project differs from the "Food for all" model since resource storage inefficiency's effect on egalitarianism and social stratification is explored, as well as cooperation. Also, resource storage inefficiency is implemented differently. Agents can only access personal storages in the new iteration of NeoCOOP. However, the remaining similarities to prior work are advantageous because it means that the model can be validated by performing previous experiments and comparing previous results with the results that the new model produces.

3. Methodology

Firstly, the model is reimplemented in the Rust programming language. This is done in order to seek performance benefits

from Rust’s powerful parallelization libraries. Secondly, and primarily, the model is edited to bring about resource degradation. A percentage of an agent’s resources decay every iteration of the simulation. This parameter can then be varied and the effects on cooperation and egalitarianism in the simulation can be measured and analysed, as explained below.

What follows is a brief description of the mechanics of the model. The model simulates an $n \times n$ matrix in which each element is either a settlement or a resource patch. A settlement represents a group of hunter-gatherers and is made up of households, with each household being a distinct family unit. Each household attempts to claim a resource patch if it does not currently control one, and no more than one household can control each resource patch. Each household receives between 0 and 1 resources each iteration, depending on the environmental stress levels. 0.5 resources are consumed by each household each iteration, and excess resources are stored. Based on the amount of resources they could consume at the end of each iteration, households have a chance to reproduce, creating a similar household that shares some genetic information, or perish, being removed from the simulation. Sufficient resources mean that a household will be less likely to perish and more likely to reproduce, ensuring that effective agents that can provide for themselves are more likely to remain in and proliferate throughout any simulation. If a household has less resources than they require, they will request resources from a subordinate, peer, or superior. These are determined by a function of the social statuses of the two agents, with social status defined as the sum of the current resources and shared resources of a household. Agents will always provide resources to their superiors. If a peer or subordinate requests resources however, then the household has a chance of providing resources equal to their genes for peer transfer or subordinate transfer.

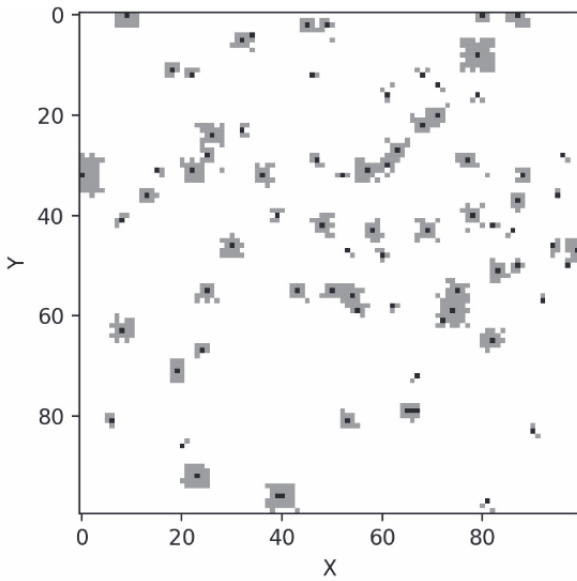


Figure 2: The original NeoCOOP at an arbitrary timestep. Source: Gower Winter and Nitschke (2022)

In figure 2, the matrix is visualised with the black pixels rep-

resenting settlements, the grey pixels representing claimed resource patches and the white pixels representing unclaimed resource patches. Gower Winter and Nitschke (2022) provides a more in-depth description of the technical details of the model.¹

Figure 5 shows the same visualisation for the new model. The repository that houses the new source code has an animated visualisation that shows the first 5000 iterations.²

3.1. Calculations

Resource degradation has been modelled in the following manner: each iteration a random percentage of the resources in a household’s storage are lost to spoilage. This chance is scaled by the decay rate, $\delta \in [0, 1]$. If r_i is a household’s resources at timestep i of the simulation,

$$r_{i+1} = (1 - \text{random}(0, 1) \times \delta) r_i$$

There is an approximate ceiling for the amount of resources that one agent can stockpile. On average, an agent will gain 0.5 resources per iteration, and lose 0.5δ times their resources. They will stop gaining resources when $0.5 = 0.5\delta \times r_i$. This is equivalent to $r_i = \delta^{-1}$. More generally, when resources are generated in some range $[a, b]$, the approximate limit for resource stockpiling becomes:

$$r_i = \frac{a + b}{\delta}$$

This limit is not generally reached as the households in the simulation are under intense stress scenarios, and the maximum amount of resources possibly available is only available for a short period of time, as shown by Figure 3. This figure also shows the seasonal effect of the stress scenario, in that the resources available range greatly depending on the iteration.

Based on $\delta = 0.25, a = 0.4, b = 1.0$, a period of low stress, we see that the absolute maximum possible resources that an agent could be acquire would be 5.6. This value is never approached as the combination of the resource degradation and varying resource availability ensure that an agent can never stockpile resources perfectly for long enough.

The value that controls the stress scenario affects the simulation by changing the function that generates the resources present in each resource patch at the beginning of each iteration. The following functions defined in Gower Winter and Nitschke (2022) are used:

$$\begin{aligned} s(x) &= 0.5 + 0.5 \times \sin(2\pi \times x \times f) \\ \text{resources}(x) &= \text{random}(\text{lerp}(0.0, 0.6, s(x)), \text{lerp}(0.4, 1.0, s(x))) \end{aligned} \quad (1)$$

$\text{resources}(x)$ is the number of resources present at point x where x is a function of the timestep and the total number

¹The original NeoCOOP source code can be found here: <https://github.com/BrandonGower-Winter/NeoCOOP> and the new NeoCOOP source code can be found here: <https://github.com/TheSisyphian/neo>

²<https://github.com/TheSisyphian/neo/blob/main/visual.gif>

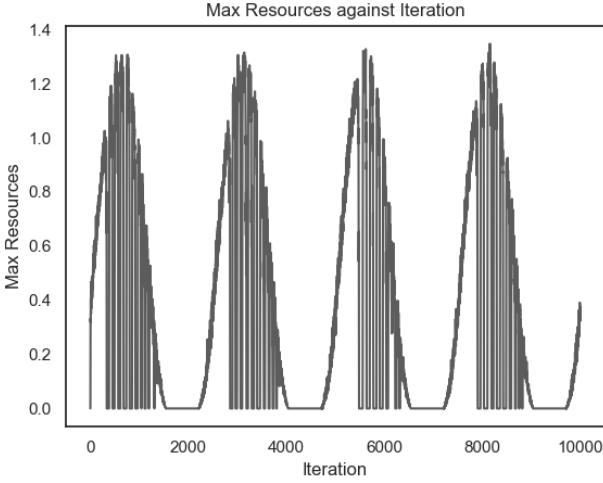


Figure 3: The average resources across a simulation with a stress scenario of 64 and a δ value of 25% over 10 000 iterations

of iterations in the simulation. In the experiments, the stress scenario is the value for f , which affects both the length and frequency of the periods with either low or high levels of resources. These are inversely proportional so longer periods of stress means a lower frequency and vice versa.

The level of cooperation at an iteration of the simulation can be measured by taking the average of the propensity of each agent to provide resources to their subordinates and peers. In the following formula, h_i refers to the i th household, and $h_{i\alpha}$ and $h_{i\beta}$ refer to that households propensity to share resources with their peers and subordinates respectively.

$$\sigma = \frac{1}{2n} \sum_{i=1}^n h_{i\alpha} + h_{i\beta}$$

This project uses a lack of inequality as a proxy for egalitarianism. The Gini coefficient is a statistical measure of the degree of inequality in sample, as described in Catalano et al. (2009), so social inequality can be measured by calculating the Gini coefficient of the social statuses of all agents in the simulation. Egalitarianism can then be taken as the inverse of this value, however the plots use the Gini coefficient since it will be more familiar to most.

Yitzhaki (2003) outlines how the Gini coefficient can be easily, if not efficiently, calculated by using the relative mean absolute difference, since it is exactly twice the Gini coefficient. The relative mean absolute difference is simply the mean absolute difference divided by the mean of the sample, and the mean absolute difference can be calculated as follows:

$$MAD = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n |\text{status}(h_i) - \text{status}(h_j)|$$

3.2. Genetic Algorithm

The primary method through which the population of agents changes is a genetic algorithm. Agents have a chance to reproduce at each timestep based on their hunger, so agents that

have enough food are more likely to reproduce than agents that do not. Over a long enough period of time, this means that more successful agents will spread more successfully, swaying the average levels of cooperation towards altruism or defection, whichever is more advantageous.

As with any genetic algorithm, considering the initial state is vital as it will affect the final state and the path that is taken to reach it. As stated in Diaz-Gomez and Hougen (2007), solutions or agents are initialised in such a way that as many parts of the search space as possible are considered, so that the globally optimal solution can be found. However, the hunter-gatherer societies that we are modelling tend to be homogeneous as far as cooperation is concerned. In order to take this into account, three different initialisation states are studied. The first state, A, is fully altruistic, so every agent is initialised with a peer transfer, and subordinate transfer, of 1.0. The second state, D, is fully defective, with both genes set to 0.0. The third state, S, has half the settlements initialised to altruistic and the other half initialised to defective.

If an agents is successfully selected to reproduce, another parent must be chosen from the population. This choice is weighted by the status of each agent in that the chance to pick a specific agent is approximately that agent's status divided by the total status of all agents in the simulation. Essentially, more successful agents are more likely to reproduce, ensuring that the next generation of agents is likely to be given effective genes.

Given two parents, each gene for the new agent is chosen from one of them with equal likelihood. Then, the gene has a chance to mutate a certain amount, according to two parameters, the mutation frequency and the mutation amplitude. The mutation frequency is the chance for each gene to mutate, and if the gene does, it follows this equation: $g_n = g_o + m_a * \text{random}(-1, 1)$, where g_n is the new gene, g_o is the original gene, and m_a is the mutation amplitude.

Parameter	Value
Mutation Frequency	0.33
Mutation Amplitude	0.25

These parameters were tuned by a simple mechanism built into the new model. Lower values tended to not produce enough of a change from the initialisation states, and higher values led to unrealistically unstable simulations.

Figure 4 shows how the average cooperation across the simulation changes over time due to the effects of the genetic algorithm. As seen in the previous iteration of the model, a middle ground is preferred with the cooperation spiking sharply in the positive or negative direction and then returning to around 0.5.

3.3. Pathfinding Algorithm

Another algorithm that is used in the simulation is a pathfinding algorithm. Specifically, the A* search algorithm which is an extension of Dijkstra's algorithm, as outlined in Yan (2023).

All agents that do not control a resource patch seek to control one. At the beginning of each iteration, every agent that does not begins a search from their settlement. A path to an unclaimed resource patch cannot proceed through resource

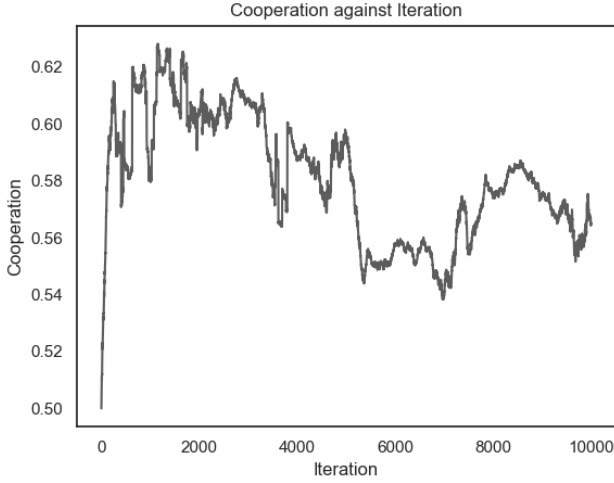


Figure 4: The average cooperation across a simulation with a stress scenario of 64 and a δ value of 25% over 10 000 iterations

patches that have been claimed by other settlements, or other agents' settlements. This means that specific settlements can be hemmed in by other settlements and have their population restricted even though there are other resource patches available in the environment.

3.4. Experiment

The following parameters are used to execute the simulations, and the peer transfer, sub transfer, Gini coefficient, and other values at each iteration are recorded. Each simulation has been executed 10 times, and averages across the different executions have been taken to ensure that the final results are not biased by any outliers.

Parameter	Initial Value
Iterations	10000 ^a
Households	100 ^a
Settlements	10 ^a
Environment Size	50
Hierarchy Split	0.6 ^b
Birth Rate	0.015 ^c
Death Rate	0.01 ^c
Stress Scenario	$2^1, 2^2, \dots, 2^{12a}$
Resource Degradation	0%, 5%, ..., 95%

^a Parameters from Gower Winter and Nitschke (2022).

^b Parameters from Chliaoutakis and Chalkiadakis (2020).

^c Parameters from Cardona et al. (2022).

3.5. Parameters

Agent-based models contain a large number of hyperparameters that must be tuned to ensure that the model successfully reflects reality or the intended environment. It is therefore important to justify the choices of all hyperparameters to avoid one of the choices unintentionally affecting the final results.

Different numbers of total iterations were explored and iterations higher than 10000 did not affect the final results. In fact, iterations as low as 5000 produced similar results but 10000 was a high enough value to ensure results.

The number of households originally in each settlement has been shown to not affect the final results, unless unreasonably low, since the agents reproduce quickly enough that they the carrying capacity of the environment early in the simulation and produce similar results from there. The number of settlements has also been shown to not affect the final results for the same reason. The agents can migrate often enough that whether a simulation starts with less or more settlements, within reason, the carrying capacity of the environment will be reached and a stable number will be sustained.

The hierarchy split, birth rate and death rate were all brought forward from previous papers which have extensively explored different values for them and justified their choices. The birth rate and death rate were also varied in our research and shown to simply speed up or slow down the simulation, as long as they were within a certain range of each other.

Resource degradation was ranged linearly and the stress scenarios were brought from Gower Winter and Nitschke (2022).

The size of the environment was partially reduced from previous iterations of the model. Through experimentation, the size of the environment was shown to not change the results meaningfully, but simply increase the rate at which the steady state of the simulation was reached. Decreasing the size of the environment meant that more simulations could be run with finer increments of the parameters, and so it was reduced from 100 to 50.



Figure 5: A visualisation of the new NeoCOOP at iteration 3250 of a simulation

4. Results

For egalitarianism, the Gini coefficient is plotted, and for cooperation the average of all agents' peer transfer and subordinate transfer is plotted.

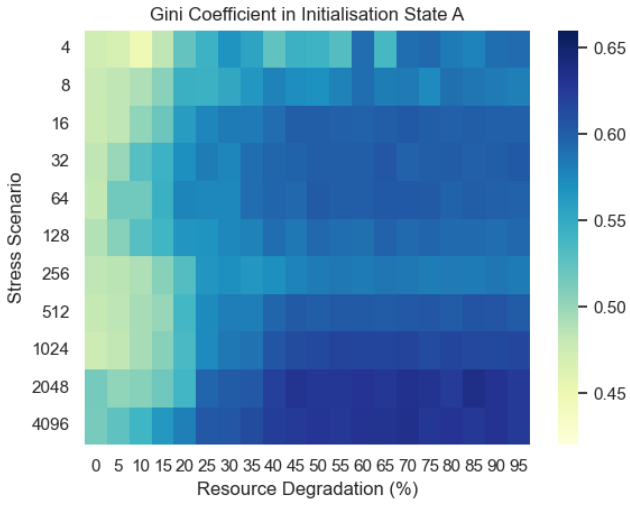


Figure 6: The Gini coefficient of the simulations with initialisation A

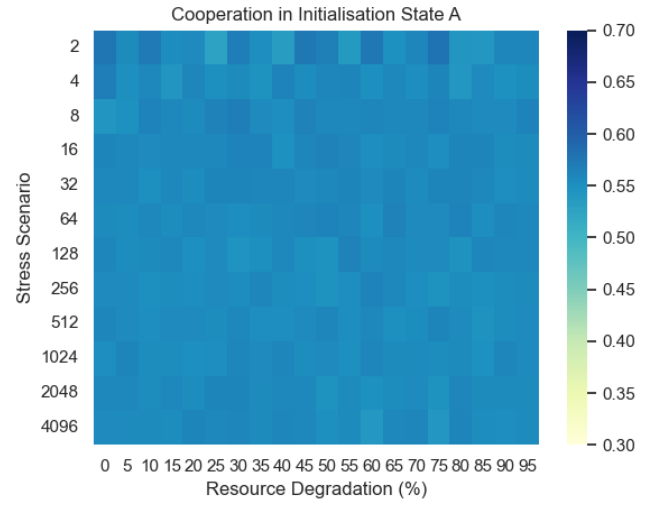


Figure 9: The cooperation of the simulations with initialisation A

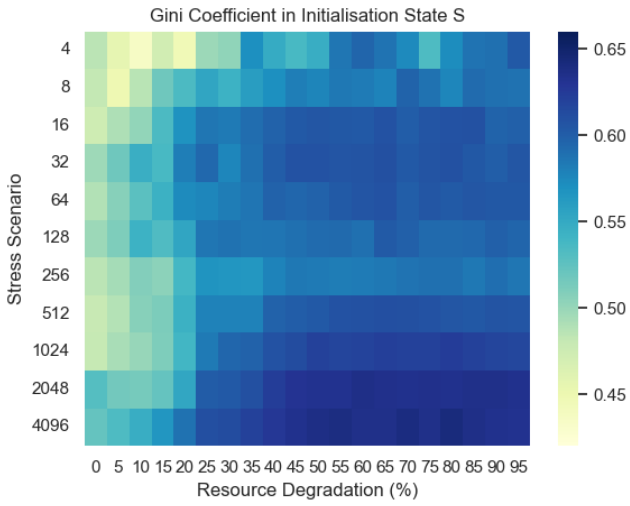


Figure 7: The Gini coefficient of the simulations with initialisation S

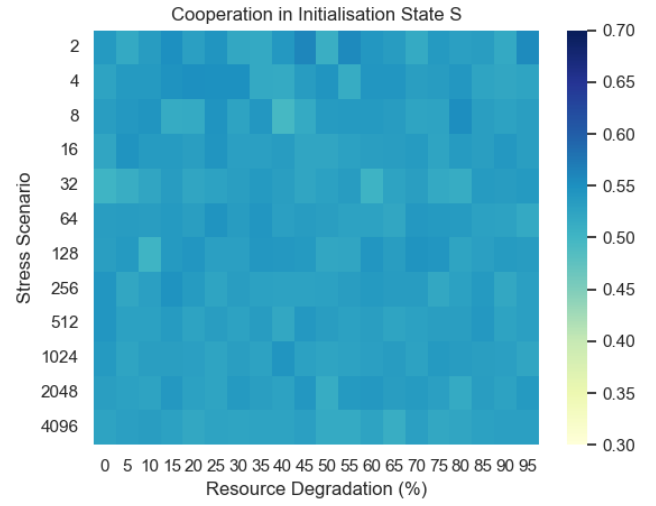


Figure 10: The cooperation of the simulations with initialisation S

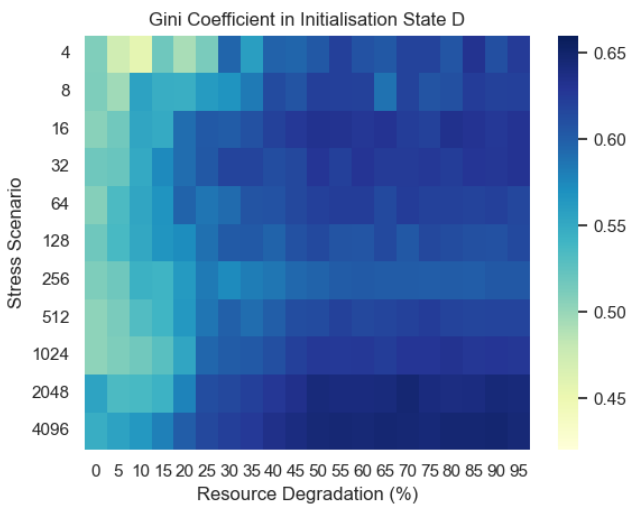


Figure 8: The Gini coefficient of the simulations with initialisation D

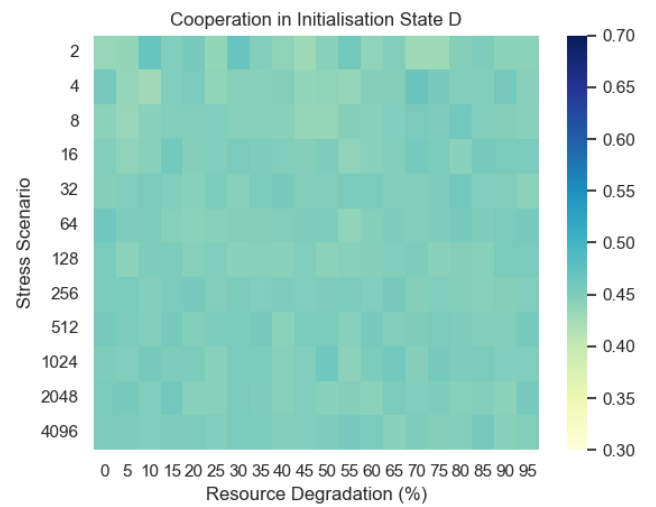


Figure 11: The cooperation of the simulations with initialisation D

5. Discussion and Conclusions

The model produced unexpected and interesting results. The opposite of many of our hypotheses were shown to be true, for example increased resource degradation led to increased levels of inequality and therefore decreased levels of egalitarianism. We discuss the results and the information therein regarding the research questions.

5.1. Cooperation

Unexpectedly, the level of resource degradation does not affect the cooperation present in the simulation. This means that the effects of other mechanisms in the simulation that keep the cooperation in the middle ground are greater than the effect of increased resource degradation. The different plots show greater or lesser levels of cooperation as the average across all iterations is taken and the simulations with initialisation state D will be weighted towards lower levels of cooperation and the simulations with initialisation state A will be weighted towards higher levels of cooperation. This is clear since in initialisation state D the initial iteration has full defection, and in initialisation state A the initial state has full altruism.

It is important to note that for the lesser stress scenarios, there are distinctly greater levels of cooperation, which is one of the phenomena that was explored in Gower Winter and Nitschke (2022). This improves the validity of the model as it has produced similar results to the previous model.

5.2. Egalitarianism

The results regarding egalitarianism allow for a much deeper analysis. Firstly, for low levels of resource degradation, we can see that levels of equality similar to that of the previous model are shown which again improves the validity of the new model. As resource degradation increases however, we see new phenomena arising. There is a threshold, based on the stress scenario, under which the inequality is low, and after which, the inequality increases steeply and stays high. The darkening of shades horizontally shows a strong positive correlation between resource degradation and inequality. Also, there is a slight increase in inequality in the D initialisation state, and a slight increase in equality in the A initialisation state. This is again likely because of the early states biasing the average very slightly. This is reasonable because with high levels of cooperation in the early states, resources will be easily shared and therefore reduce inequality quickly, and vice versa.

There are also two areas of stress scenarios for which egalitarianism is maximised relative to their surroundings. The first area is that of low stress scenario values, where we see the lowest levels of inequality, even for high levels of resource degradation. The second area is that around the stress scenario value of 256, where we again see a distinctly higher level of equality across all resource degradation values. There is clearly a more complex relationship at play that could be the focus of future work.

5.3. Conclusions

The first research question was "Does varying storage efficiency lead to social stratification, or conversely, promote more egalitarian social arrangements?", and our results clearly show that beyond a certain threshold, increased resource degradation leads to increased levels of inequality and therefore does not promote egalitarian social arrangements. One factor that likely contributes to this is that of so-called "free riders". These are agents in the simulation that cannot control a resource patch, either because all resource patches are already controlled, or their settlement has been hemmed in by larger settlements. These agents rely purely on the resources of other agents that do control resource patches to sustain themselves. This means that they rely on a certain level of cooperation in order to receive the resources they require. However, high levels of resource degradation and high levels of environmental stress would mean that agents with resource patches would be too low on resources to provide extra to free riders, depriving them of resources and increasing the levels of inequality in the simulation as the free riders can never access them.

The second research question was "How do agents adapt their sharing strategies in response to reduced storage efficiency, particularly in situations with high environmental stress?". Our results show that agents do not adapt their sharing strategies in response to reduced storage efficiency as the other factors that affect cooperation dominate the results, and a middle group is still the optimal sharing strategy in these new environments.

This research specifically intended to contribute to the discourse around the nomadic-egalitarian model. Our results show that in the specific case that we were simulating, societies with high levels of nomadism and low technological development, which would be correlated with high levels of resource degradation, can also have relatively low levels of egalitarianism. This clearly indicates that there are many more factors affecting the usual case of high levels of nomadism and low population density correlated with high levels of egalitarianism.

5.4. Application

While the resources in the model generally refer to food, they can also include all manner of different items such as tools and equipment, clothing, buildings, and more. Any object that has a lifetime and eventually needs to be either repaired or replaced can be considered a resource.

There are many societies present in modern times that align with the societies that we are simulating, and to which the data we have gained can be applied. One useful example is understanding how climate change might affect these societies. As outlined by Warner et al. (2010), climate change exacerbates resource degradation due to increased temperatures which affect the storage of food, more frequent and more violent weather patterns, and decreasing agricultural yields. It is therefore reasonable to expect an increase in the levels of inequality in such societies. By developing technologies that help counteract the effect of climate change in regards to resource degradation we can not only protect humanity's resources as a whole but also

ensure that the small subset of societies remain as egalitarian as possible.

Similarly, environmental conservation efforts that aim to protect natural resources that such societies rely upon should focus their efforts on areas that produce resources that degrade the least, in order to maximise the levels of equality in such societies.

Finally, this data supports the use of sustainable practices in various sectors. Many effective but unsustainable practices in various industries, for example mining in rural southern Africa, have the capacity to damage the environment and increase levels of resource degradation in surrounding areas. This could give rise to increased levels of inequality in local communities if their access to resources is impacted and should therefore be analysed and regulated.

5.5. Future Work

One of the most valuable avenues that future work could take could be the exploration of the effect of resource storage degradation in a model that utilises a different mechanism for cooperation. For example one that uses a social network, or a more complicated mechanism, to determine how agents can communicate with each other.

Another possible avenue could be the improvement of resource degradation in the model, as the current implementation is an extreme simplification. This would provide more realistic data and could lead to new emergent phenomena arising.

Finally, another interesting avenue could be the removal of free riders from the model and the exploration of egalitarianism against resource degradation in this new model.

References

- Alain Testart, e.a., 1982. The significance of food storage among hunter-gatherers: Residence patterns, population densities, and social inequalities .
- Angourakis, A., Santos, J., Galán, J.M., Balbo, A., 2015. Food for all: An agent-based model to explore the emergence and implications of co-operation for food storage. *Environmental Archaeology* 20, 349–363. doi:10.1179/1749631414Y.0000000041.
- Box, G., 1976. Science and statistics. *Journal of the American Statistical Association* .
- Cardona, P., Catala, M., Prats, C., 2022. The origin and maintenance of tuberculosis is explained by the induction of smear-negative disease in the paleolithic. *Pathogens* .
- Catalano, M., Leise, T., Pfaff, T., 2009. Measuring resource inequality: The gini coefficient. *Numeracy* 2. doi:10.5038/1936-4660.2.2.4.
- Chliaoutakis, A., Chalkiadakis, G., 2020. An agent-based model for simulating inter-settlement trade in past societies. *Journal of Artificial Societies and Social Simulation* .
- Diaz-Gomez, P., Hougen, D., 2007. Initial population for genetic algorithms: A metric approach., pp. 43–49.
- van Gent, P., 2021. Python covid-19 simulation.
- Gilbert, N., 2019. *Agent-Based Models*. SAGE Publication Inc.
- Gower Winter, B., Nitschke, G., 2022. Extreme environments perpetuate cooperation , 1243–1250doi:10.1109/SSCI51031.2022.10022236.
- Hanappi, H., 2017. Agent-based modelling. history, essence, future. *PSL Quarterly Review* .
- Ingold, T., 1983. The significance of storage in hunting societies. *Man* 18, 553. doi:10.2307/2801597.
- Kuijt, I., 2009. What do we really know about food storage, surplus, and feasting in preagricultural communities? *Current anthropology* 50, 641–4. doi:10.1086/605082.
- Nitschke, G., Gower Winter, B., 2023. Inequality and the emergence of social stratification , 159–162doi:10.1145/3583133.3590529.
- Pereda, M., Zurro, D., Santos, J.I., Briz Godino, I., Alvarez, M., Caro Saiz, J., Galán, J.M., 2017. Emergence and evolution of cooperation under resource pressure. *Scientific Reports* 7, 45574. doi:10.1038/srep45574.
- Perez, L., Dragicevic, S., 2009. An agent-based approach for modeling dynamics of contagious disease spread. URL: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2729742/>.
- Singh, M., Glowacki, L., 2022. Human social organization during the late pleistocene: Beyond the nomadic-egalitarian model. *Evolution and Human Behavior* doi:10.1016/j.evolhumbehav.2022.07.003.
- Soffer, O., 1989. Storage, sedentism and the eurasian palaeolithic record. *Antiquity* 63, 719–732. doi:10.1017/S0003598X00076857.
- Warner, K., Hamza, M., Oliver-Smith, A., Renaud, F., Julca, A., 2010. Climate change environmental degradation and migration. *Natural Hazards* 55, 689–715. doi:10.1007/s11069-009-9419-7.
- Widlok, T., Tadesse, W.G., 2006. *Property and Equality Volume II: Encapsulation, Commercialization, Discrimination*. Berghahn.
- Yan, Y., 2023. Research on the a star algorithm for finding shortest path. *Highlights in Science, Engineering and Technology* 46, 154–161. doi:10.54097/hset.v46i.7697.
- Yitzhaki, S., 2003. Gini's mean difference: A superior measure of variability for non-normal distributions. *Metron - International Journal of Statistics* LXI, 285–316.