Societies prefer the Middle-ground between Selfishness and Cooperation

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Abstract

This study seeks to answer whether resource scarceness positively impacts resource sharing in socially stratified societies? We address this by developing an Agent-Based Model, called *NeoCOOP*, which utilizes reinforcement learning and artificial evolution as adaptive mechanisms to simulate the the emergence and evolution of cooperative behaviour in a Neolithic-inspired society. Experiments examine the resource trading preferences of the agents under varying degrees of environmental stress. Results indicate that neither extreme selfishness or extreme altruism is desirable with all agent-types opting for a "middle-ground" approach to cooperative behaviour. Also, results show that as the frequency of the environmental stress increases, agents will maintain a more diverse distribution of resource trading beliefs.

Introduction

At the core of cooperative behaviour lies the dichotomy of altruism and selfishness (Rachlin, 2002). Humans, unlike other social mammals, exhibit cooperative behaviour on a significantly larger scale and, in turn, exhibit a greater capacity for both altruistic and selfish acts (Boyd and Richerson, 2009). No time in ancient history demonstrates this more clearly than the transition from the Paleolithic to the Neolithic whereby egalitarian, hunter-gatherer, groups transitioned into sedentary agrarian societies with varying degrees of social stratification (Powers and Lehmann, 2014). The cause of this transitory period is likely multifaceted (Stiner, 2001) but, environmental stress is theorized to have played a significant role in the evolution of cooperative behaviour (Pereda et al., 2017).

Agent-Based Models (ABMs) are used to investigate the emergence of complex social phenomena and the impact of resource availability, as a function of environmental stress, on the emergence of cooperative-behaviour (Aktipis et al., 2016; Angourakis et al., 2015; Molin et al., 2021). These ABMs implement cooperative behaviour in one of three ways (although hybrid implementations do certainly exist):

Cooperative versus Defective Agents are categorized as either purely selfish (defective) or purely altruistic (cooperative) and the emergent phenomena that arise from both homogenized and mixed agent populations are compared. These models are typically older and more exploratory (Axelrod and Hamilton, 1981). Imitation or mimicking rules may also be added to these models to allow the agents to change their behaviour from cooperative to defective (or vice versa) over time (Power, 2009).

Network-Based Cooperation This refers to the modelling of agent-to-agent interaction and cooperation as a directed graph that acts as a form of social network (Chliaoutakis and Chalkiadakis, 2020; Molin et al., 2021). In order for two agents to interact directly, they must be connected within this network. ABMs implementing network-based cooperation are less common than the other ABM types with their existence heavily-reliant on the partitioning of agents along one or more metrics. Network-based solutions provide agents with the ability to specialize their behaviour more than other cooperation systems at the cost of removing an agent's ability to generalize.

Probability-Based Cooperation These Agents are an extension to the cooperative or defective models described above where the likelihood of agents exhibiting cooperative or defective behaviour is recorded as some probability p (Aktipis et al., 2016; Nhim et al., 2019). These ABMs typically include some form of learning allowing agents to adapt their p value in accordance with a predefined set or rules or fitness-based algorithms such as Evolutionary Algorithms (Revay and Cioffi-Revilla, 2018). Probability-based cooperation ABMs are a "middle-ground" of the highly generalized cooperate-defect systems and the highly specialized network-based systems.

In addition to studying emergent and evolving cooperative behaviour, ABMs are frequently used to study the emergence of social stratification in ancient societies (Chliaoutakis and Chalkiadakis, 2020; Powers and Lehmann, 2014). However, research marrying the two topics is scarce meaning the impact of environmental stress on cooperative-behaviour in socially stratified societies remains unknown. Given this, we seek to answer whether environmental stress (resource scarceness) positively impacts resource sharing (altruism) in socially stratified societies.

Thus, we developed an ABM called *NeoCOOP*, using reinforcement learning and artificial evolution as adaptive mechanisms to simulate emergent evolution of altruistic and selfish behaviour in Neolithic-inspired households. Our experiments examine agent resource trading preferences under varying degrees of environmental stress. We hypothesize the duration of environmental stress impacts agent resource trading preferences with longer periods of stress resulting in more altruistic behaviour in comparison to shorter, more frequent, periods of stress. Also, we hypothesize that more frequent periods of stress will result in the emergence of a more diverse range of resource trading preferences.

Methods

NeoCOOP (*Neolithic Agent Cooperation Model*) is an iteration-based ABM[1] implemented in *Python 3* that simulates evolving altruistic and selfish behaviour in a Neolithic inspired artificial society.

Agent Definition

Each agent represents a Neolithic *household* consisting of one or more *occupants*. The motivation for this is that typical Neolithic households were ruled by a single patriarchal figure who was responsible for making all of the family's decisions as well as managing their resources (Lehner, 2000). *NeoCOOP* (Figure 1) uses *settlements* to keep track of one or more *households*. A settlements primary purpose is to store the coordinates of all the agents contained within that settlement.

Unlike most cooperation-based ABMs, *NeoCOOP* allows agents to make decisions based on their social status and the social status of the agents they are interacting with. We define social status as the sum of an agent's available resources and its *load*, where *load* is the amount of resources the agent has donated to other households over a period of time. To facilitate social stratification, we use the self-organization scheme described by Chliaoutakis and Chalkiadakis (2020) whereby a relationship type can be determined for every agent pair by comparing their social statuses. We define each of the relationship types as follows:

$$is\_peer(h_1, h_2) = \frac{|h_2.ss - h_1.ss|}{max(h_1.ss, h_2.ss)} < L \qquad (1)$$

$$is\_auth(h_1, h_2) = \frac{(h_2.ss - h_1.ss)}{max(h_1.ss, h_2.ss)} > L \qquad (2)$$

$$is\_sub(h_1, h_2) = is\_auth(h_2, h_1) \qquad (3)$$

Where is_peer, is_auth and is_sub describe whether household h_2 has a, peer, authority or subordinate relationship with household h_1 respectively. $h_n.ss$ is a household's social status. L is the *load_difference* $\in [0, 1]$ input parameter defines how much more social status an agent requires to be considered an authority over another agent. In order for a peer, authority or subordinate relationship to be formed, the two households must be from the same settlement.

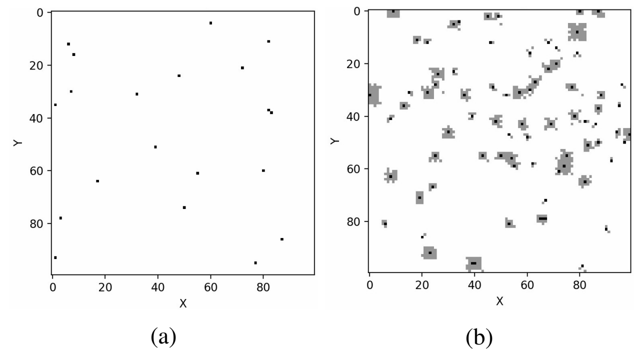


Figure 1: Visualization of *NeoCOOP* ABM at initialization (a), and at an arbitrary point in the simulation (b). Black pixels indicate settlements, white pixels indicate uninhabited land (foragable land) and grey pixels indicate farmland.

Environment & Vegetation Model

NeoCOOP places agents on a nxm grid-world and uses a simple *vegetation model* based on Xu and Zhang (2021), simulating monthly global environment properties (rainfall, temperature and solar radiation) and vegetation growth. The environment comprises two layers, each containing a nxm matrix storing the grid-world's soil moisture (mm) and vegetation (kg). Every iteration, the global environment system generates 12 randomly sampled rainfall and temperature values. The soil moisture system transforms the temperature values into potential evaporation (PET) values using the *Thornthwaite* equation. For each of the 12 rainfall and PET pairs, the soil moisture values of each cell are updated as described by Xu and Zhang (2021). The vegetation growth system then uses the soil moisture values to calculate vegetation growth for all uninhabited cells.

Resource Acquisition, Transfer and Consumption

Household agents in *NeoCOOP* are utility-based, meaning that every agent associates each action in the model with a utility value $U_{h,t}(a)$. Every iteration, agents choose actions that, based on experience, return the greatest expected reward. *NeoCOOP* has only two actions: *FORAGE* and *FARM*. Both actions return the same resource type, so the only difference between the two actions is their prerequisites and quantity of resources returned. If the *FORAGE* action is chosen, the agent will look for neighbouring cells with the greatest vegetation density and take vegetation directly from these cells equal to a predefined (*forage_consumption_rate)* amount based on the number of *occupants* the agent has. If the selected action is a *FARM* action, the agent will choose

[1] Source Code and ODD+D Description available at: `https://github.com/BrandonGower-Winter/NeoCOOP`

its owned farming cells and gather resources from it directly. If the agent does not own any farming cells, it will attempt to acquire some from unoccupied neighbouring cells.

Farming is intended to return a greater surplus of resources. However, it is an action that rewards a sedentary lifestyle and, in times of stress, having access to the diverse set of vegetation cells that are available when foraging can be more beneficial. After the agents have completed their resource acquisition actions, they update the utility values in accordance with the following RL-based equation:

$$U_{h,t+1}(a) = U_{h,t}(a) + \eta_h(R_{h,t}(a) - U_{h,t}(a)) \quad (4)$$

Where, h is the agent, a is the action, η_h is the *stubbornness* of the agent, t is the iteration, and U and R are the utility and reward functions respectively.

Once acquisition is complete, agents determine if they have enough resources to satisfy their needs for the iteration. If not, the agent asks its authority agents if they would be willing to give some of their excess resources to the agent as a donation. For each authority asked, a random value $\in [0, 1]$ is generated and compared to the authority agent's *subordinate_transfer* property. If the generated value is less than the *subordinate_transfer* property, the authority agent is willing to grant donations for that iteration. Whenever a donation is granted, the authority agent has its *load* property increased by the resources donated. If an agent has asked all of its authority agents for resources and it will still go hungry, it then repeats this process for its peer relationships with the donating agent using its *peer_transfer* property to determine if the donation succeeds.

If that is still not sufficient, the agent will then ask all of its subordinates for resources. Given that we are modelling Neolithic households, if a subordinate is asked to give any of its excess resources to an authority agent, it does so with 100% certainty. The *peer_transfer* and *subordinate_transfer* properties allow us to simulate different agent types that exhibit varying degrees of altruistic and selfish behaviour. When resource transfer is complete, agents consume their food and determine their *hunger* using equation 5.

$$hunger(x) = min(\frac{x.resources}{x.required\_resources}, 1.0) \quad (5)$$

Population Growth, Loss and Migration

Every iteration, households may birth additional occupants in accordance with the *birth_rate* and their *hunger*. If a household reaches *carrying_capacity*, the *split_household* function is called and the household is divided into two separate households. Occupants and resources are split amongst the two new households but load is not. That is, the new household signifies the arrival of a new patriarchal figure within the community and someone who must work to gain the same social status as their parent household.

Households may lose one or more occupants in accordance with the *death_rate* and their *hunger*. If a household reaches zero able occupants, it is removed from the simulation. Agents can migrate to another settlement or form a settlement of their own every *yrs_per_move* iterations. This decision is based on the agent's *satisfaction* which is the average *hunger* of the agent over the past *yrs_per_move* iterations. If the *satisfaction* of the agent is low, it has a higher likelihood of moving. When an agent moves, it chooses between all settlements in its vicinity or an unclaimed cell. Typically, an agent will move to the settlement with the most resources. However, if none of the neighbouring settlements have enough resources, the agent will choose to make its own settlement at a new location.

Agent Adaptation

Generational agent adaptation uses two evolutionary algorithms: a *Genetic Algorithm* (GA) (Whitley (1994)) for vertical generational adaptation and a *Cultural Algorithm* (CA) (Reynolds (1994)) for horizontal generational adaptation. Both use an agent's genotype containing six gene values: *Forage Utility* and *Farm Utility* (Utility value of the FORAGE / FARM action respectively), *Stubbornness* and *Conformity* (Individual and Generational adaptation learning rates respectively), *Peer Transfer* and *Subordinate Transfer* (The probability an agent will accept a resource transfer request from a peer / subordinate agent respectively). Both the GA and CA make use of *influence* when determining best performing settlements. *Influence* describes the probability that two settlements will interact with each other. This is done using the XTENT formula (Equation 6):

$$I(s_1, s_2) = W(s_2)^\beta - mD(s_1, s_2) \quad (6)$$

Where, s_1 and s_2 are settlements, $I(s_1, s_2)$ is the influence of s_2 on s_1, $W(s_2)$ is the social status of s_2, $D(s_1, s_1)$ is distance from s_1 to s_2. β and m are coefficients describing required social status of one settlement to influence another. Calculating *influence* of every settlement on a given settlement, gives a probability distribution (equation 7).

$$P(s_1, s_2) = \frac{I(s_1, s_2)}{\sum_{k \in K} I(s_1, s_k)} \quad (7)$$

Where, $P(s_1, s_2)$ is the probability of settlement s_2 influencing settlement s_1 and K is the set of neighbouring settlements that have a positive *influence* value $I(s_1, s_k)$ on s_1.

The GA executes whenever the *split_household* function is called. The child agent produced is a combination of two parents with the first parent being the household that reached capacity and the second parent gotten via *roulette wheel* selection (Eiben and Smith, 2015). This selection uses the social status of other agents within the same settlement of the first parent and from other settlements that have enough influence. The offspring agent is produced using *Uniform crossover* with *Gaussian mutation* for genes 1-4 and random mutation for genes 5 and 6. The CA uses Knowledge

Sources (Reynolds and Peng, 2004) to diversify how agents are influenced. They are: *Normative* (Influence on an agent's beliefs from its settlement), *Spatial* (Influence on an agent's beliefs from another settlement) and *Domain* (Equivalent to GA mutation function, where domain influence mutates one of the agent's beliefs).

Every *influence_frequency* iterations, agents are influenced in accordance with the *influence_rate*. If an agent is selected for influencing, a roulette wheel is spun to determine from which knowledge source influence will come from. Influence from the Domain knowledge source occurs at a rate defined by the *mutation_rate* parameter. Influence from the Normative and Spatial knowledge sources occur with varying probability defined by equations 8 and 9.

$$N(s_h, s_i) = max(\frac{s_h.ss}{s_i.ss}, 1.0) \tag{8}$$

$$S(s_h, s_i) = 1 - N(s_h, s_i) \tag{9}$$

Where, N and S are the probability of choosing the *normative* and *spatial* knowledge sources respectively, s_h is the settlement of the agent being influenced, s_i is the settlement that would influence agent h if the spatial knowledge source is selected. s_i is determined by performing roulette wheel selection on all neighbouring settlements with a positive *influence* on settlement s_h. Roulette wheel weights are determined by the values returned by Equation 7.

Each settlement's beliefs are represented by *Belief Spaces* B_s. Belief Spaces have the same structure as the agent genotype with each property calculated using a weighted average of the corresponding property of all agents within that settlement. The weight an agent contributes to the belief space is determined using its social status relative to the social status of the other agents in the same settlement. If an agent is influenced by the *normative* knowledge source, the belief space that influences it is the belief space of the settlement the agent belongs to B_{s_h}. If the agent is influenced by the *spatial* knowledge source, the belief space that will influence the agent is the belief space of the settlement selected during roulette wheel selection (B_{s_i}). Agent properties are influenced as follows (equation 10):

$$G_{h,t+1}(p) = G_{h,t}(p) + \sigma_h(B_{s,t}(p) - G_{h,t}(p)) \tag{10}$$

Where, p is the agent property (genes 1-6), t is the timestep, G is the agent's genotype, σ_h is the *conformity* of the agent and B is the selected belief space (B_{s_h} or B_{s_i}).

Experiment Design

Before running our experiments, we parameter tuned our model using values derived from other works (See Table 1) and, where no parameters could be be found, we performed multi-objective optimization using *Optuna*[2]. The optimization process ran for 119 simulation runs and final input parameters for our model can be seen in Table 1. A report of the optimization process is included with the source code[1]. Experiments apply environmental stress over time, via varying rainfall each iteration according to *sine* waves of varying frequencies. This approach is similar to Molin et al. (2021) where environmental stress is induced periodically. Using f for each scenario, we linearly interpolate (Equation 12) every iteration i between two predefined ranges called *max_rainfall* and *min_rainfall* using the the output of the sine waves (Equation 11) at iteration i/M as the mixing parameter x.

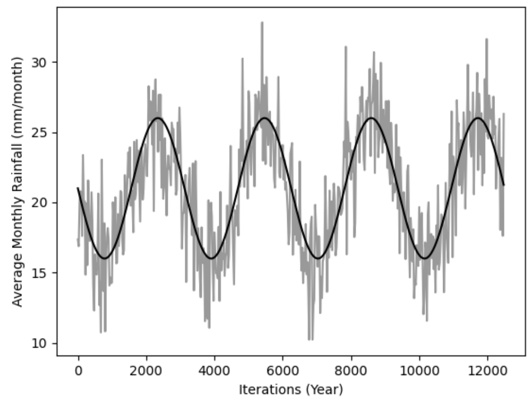


Figure 2: Example of the generated rainfall data for a single simulation run using Equations 11 and 12

$$s(x) = 0.5sin(2\pi x.f) + 0.5 \tag{11}$$

$$lerp(r_{min}, r_{max}, x) = r_{min} + s(x) * (r_{max} - r_{min}) \tag{12}$$

An example of what the result of this process looks like can be seen in Figure 2. The *stress scenarios* investigated are as follows: $f \in [1, 2, 4, 8, 16, 32]$. We also explore two scenarios in which environmental stress is non-existent and perpetual (N and P) respectively.

Each simulation was initialized with 100 agents and 10 settlements. At initialization, each agent in the model has their *peer_transfer* and *sub_transfer* agent properties randomly assigned $\in [0, 1]$. The settlements were randomly placed on the grid-world and the model was run for $M = 10000$ iterations. All stochastic processes utilized a pseudo-random number generator to ensure reproducibility. Each scenario was simulated 50 times for a total of 400 simulation runs across the 8 *stress scenarios*.

[2] *Optuna* available at: `https://optuna.org/`.

Property	Value
Iterations (M)	10 000
Initial Households	100
Initial Settlements	10
L	0.6[1]
Carrying Capacity	10[1]
Years Per Move	5[1]
Birth Rate	0.15%[2]
Death Rate	0.1%[2]
β	1.5[1]
m	0.005[1]
Mutation Rate	0.1
Influence Rate	0.1
Influence Frequency	15
Stubbornness Range	$\in [0.2, 0.7]$
Conformity Range	$\in [0.2, 0.7]$

Table 1: NeoCOOP Initialization Parameters. Some model properties are from Chliaoutakis and Chalkiadakis (2020)[1] and Cardona et al. (2022)[2]. Properties without reference were determined by multi-objective optimization (*Optuna*).

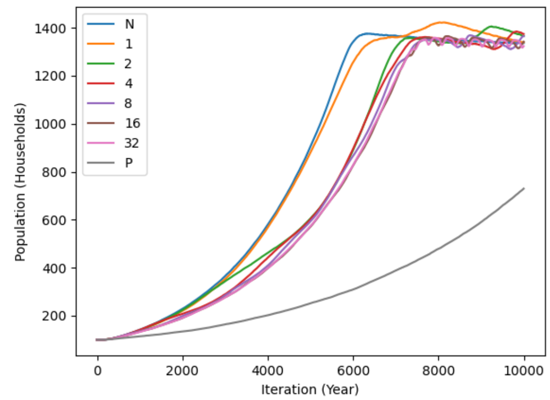


Figure 3: Mean population level for each *stress scenario*.

Results and Discussion

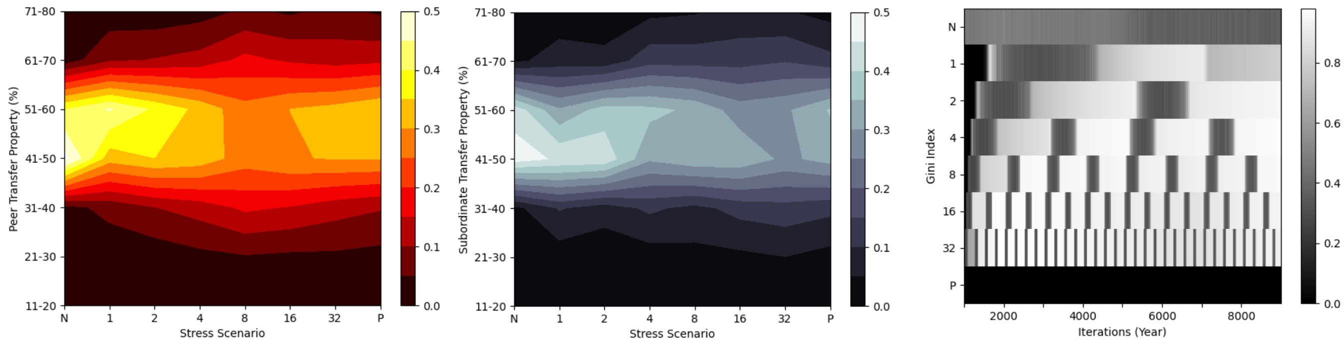
Figure 3 showcases the mean populations levels over the course of the simulations. A Kruskal-Wallis H-test for independent samples and Dunn's post test with Bonferroni correction ($p = 0.05$) reveal that scenarios 1 and P had significantly higher population levels than all of the other scenarios investigated. Scenario 2 had a higher population level than scenarios 4, 8, 16 and 32 with the aforementioned scenarios maintaining similar population levels. Expectedly, the Perpetual drought scenario P had the lowest population levels.

The Wilcoxon rank-sum test ($p = 0.05$) was used to determine statistical differences between two resource transfer beliefs. The tests reveal that only scenario 1 had significantly distinct final peer / subordinate transfer beliefs with the peer transfer being significantly greater than subordinate transfer. In fact, the mean peer and subordinate transfer properties maintain a value of 0.5 for all *stress scenarios*. Figure 4 showcases the various distributions of the final resource transfer beliefs. In all scenarios, agents avoided extreme cooperation and selfish values (resource transfer beliefs close to 1.0 and 0.0 respectively).

We hypothesized that as the frequency of the environmental stress increased, the agents would become more selective. Initial results seem to disprove that with neither the peer or subordinate transfer properties seeming to have undergone much evolution and maintaining a mean value of 0.5. However, the mean is not an appropriate measurement for two reasons: One is a limitation of this study where initial agent resource transfer beliefs are taken from a uniform distribution which naturally biases the mean towards 0.5 (Future work will explore varying the initial resource transfer distributions). The other reason is that only looking at the mean does not reveal the underlying distribution of the agents beliefs. Figure 5 demonstrates the importance of this whereby we can see that agent beliefs are more homogenized the lower the stress frequency (with N and P representing the two extremes). Diversity maintenance in high frequency stress situations is a phenomena documented in other organisms such as multi-trophic rockpool communities (Romanuk et al., 2010). Our model suggests that this is also the case for 'human-like' resource trading agents. These findings don't disprove our initial hypothesis, but rather add nuance to our overall understanding.

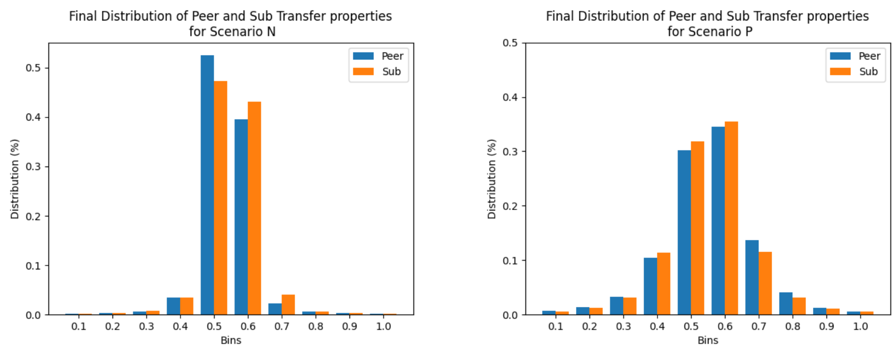
The reason why diversity maintenance occurs is due to cyclic population aggregation and dispersal. Figure 6 shows that average settlement household density decreases during times of environmental stress. This includes scenario N when the environment starts to reach its carrying capacity. Results indicate that mean settlement density goes through periods of increasing settlement size at the start of the environmental stress and decreasing settlement size towards the end of the stress period. Agents dispersed into groups of between one and four households. Population dispersal due to environmental stress is a well-known phenomena (Kennett et al., 2007). The result of this dispersal, within context of the model, is that households have fewer households to be interact with / be influenced by. This results is diversity maintenance which explains the results our simulations produced. Furthermore, we found that monitoring the fluctuations in the degree of social stratification (Figure 4c) could be used to predict cultural diversity in our model with more frequent fluctuations maintaining a higher degree of cultural diversity. Ascertaining whether this finding is true in all cases is the topic of future work.

The majority of agents across all scenarios maintained their mean resource transfer (peer and sub) properties within the range: [0.4, 0.6] for all scenarios. This is distinct from



(a) (b) (c)

Figure 4: Final distribution of the *peer* (a) and *subordinate* (b) transfer agent properties and *agent social status inequality* (c) for all *stress scenarios* investigated.



(a) (b)

Figure 5: Final distribution of the transfer agent properties (peer and sub) for the N (a) and (P) (b) *stress scenarios*.

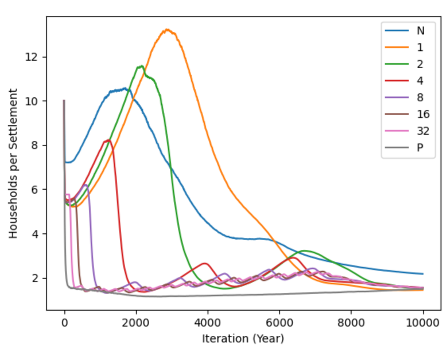


Figure 6: Mean Number of Households per Settlement.

the mean resulting from the initialization process because if $[0.4, 0.6]$ was not the optimal range for probabilistic resource transfer beliefs, the agents would've simply evolved to the optimal range. This "middle-ground" phenomena has been documented previously (Angourakis et al., 2015) in scenarios where cooperative food storage is low and household storage efficiency is high. Both of which are applicable in *NeoCOOP*. How this optimal range of cooperativeness relates to diversity maintenance is interesting. It is not entirely clear that the same trends would persist as the optimal range of resource transfer beliefs change both positively and negatively. This provides a clear opportunity for future research.

Conclusions and Future Work

This study investigated if environmental stress positively impacted resource sharing in socially stratified societies. Our results indicate that neither extreme selfishness or altruism is desirable with agents opting for a *middle-ground* approach to their cooperative behaviour. Results also indicated that as the frequency of environmental stress increases, agents maintain a more diverse set of resource transfer beliefs.

Future work will extend *NeoCOOP* to support different forms of resource storage that accurately reflect resource storage strategies of Neolithic societies. We will also investigate different initial resource transfer belief distributions and non-uniform terrains to further understand the role the environment has on emergent altruistic and selfish behaviour.

References

Aktipis, A., De Aguiar, R., Flaherty, A., Iyer, P., Sonkoi, D., and Cronk, L. (2016). Cooperation in an uncertain world: For the maasai of east africa, need-based transfers outperform account-keeping in volatile environments. *Human Ecology*, 44(3):353–364.

Angourakis, A., Santos, J., Galán, J., and Balbo, A. (2015). Food for all: An agent-based model to explore the emergence and implications of cooperation for food storage. *Environmental Archaeology*, 20(4):349–363.

Axelrod, R. and Hamilton, W. (1981). The evolution of cooperation. *science*, 211(4489):1390–1396.

Boyd, R. and Richerson, P. (2009). Culture and the evolution of human cooperation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1533):3281–3288.

Cardona, P.-J., Català, M., and Prats, C. (2022). The origin and maintenance of tuberculosis is explained by the induction of smear-negative disease in the paleolithic. *Pathogens*, 11(3):366.

Chliaoutakis, A. and Chalkiadakis, G. (2020). An agent-based model for simulating inter-settlement trade in past societies. *Journal of Artificial Societies and Social Simulation*, 23(3).

Eiben, A. and Smith, J. (2015). *Evolutionary Computing*. Springer, Berlin, Heidelberg, 2nd edition.

Kennett, D., Culleton, B., Kennett, J., Erlandson, J., and Cannariato, K. (2007). Middle holocene climate change and human population dispersal in western north america. In *Climate Change and Cultural Dynamics*, pages 531–557. Elsevier.

Lehner, M. (2000). Fractal house of pharaoh: Ancient egypt as a complex adaptive system, a trial formulation. *Dynamics in Human and Primate Societies. Agent-based Modeling of Social and Spatial Processes, New York/Oxford*, pages 275–353.

Molin, L., Kanwal, J., and Stone, C. (2021). Resource availability and the evolution of cooperation in a 3d agent-based simulation. In *Proceedings of the Genetic and Evolutionary Computation Conference*, pages 93–101.

Nhim, T., Richter, A., and Zhu, X. (2019). The resilience of social norms of cooperation under resource scarcity and inequality—an agent-based model on sharing water over two harvesting seasons. *Ecological Complexity*, 40:100709.

Pereda, M., Zurro, D., Santos, J., Godino, I., Álvarez, M., Caro, J., and Galán, J. (2017). Emergence and evolution of cooperation under resource pressure. *Scientific reports*, 7(1):1–10.

Power, C. (2009). A spatial agent-based model of n-person prisoner's dilemma cooperation in a socio-geographic community. *Journal of Artificial Societies and Social Simulation*, 12(1):8.

Powers, S. and Lehmann, L. (2014). An evolutionary model explaining the neolithic transition from egalitarianism to leadership and despotism. *Proceedings of the Royal Society B: Biological Sciences*, 281(1791):20141349.

Rachlin, H. (2002). Altruism and selfishness. *Behavioral and brain sciences*, 25(2):239–250.

Revay, P. and Cioffi-Revilla, C. (2018). Survey of evolutionary computation methods in social agent-based modeling studies. *Journal of Computational Social Science*, 1(1):115–146.

Reynolds, R. (1994). An introduction to cultural algorithms. In *Proceedings of the third annual conference on evolutionary programming*, volume 24, pages 131–139. World Scientific.

Reynolds, R. and Peng, B. (2004). Cultural algorithms: modeling of how cultures learn to solve problems. In *16th IEEE International Conference on Tools with Artificial Intelligence*, pages 166–172. IEEE.

Romanuk, T. N., Vogt, R. J., Young, A., Tuck, C., and Carscallen, M. W. (2010). Maintenance of positive diversity-stability relations along a gradient of environmental stress. *PloS one*, 5(4):e10378.

Stiner, M. (2001). Thirty years on the "broad spectrum revolution" and paleolithic demography. *Proceedings of the National Academy of Sciences*, 98(13):6993–6996.

Whitley, D. (1994). A genetic algorithm tutorial. *Statistics and computing*, 4(2):65–85.

Xu, D. and Zhang, X. (2021). Multi-scenario simulation of desertification in north china for 2030. *Land Degradation & Development*, 32(2):1060–1074.