Do Harsher Environments cause Selfish or Altruistic Behavior?

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ABSTRACT

In this study we develop an *Agent-based Model* (ABM), called NeoCOOP, to investigate the emergence and evolution of altruistic and selfish behaviour in Neolithic-inspired household agents under varying degrees of environmental stress. We conduct scenario experimentation where we track the evolution of the agents' resource trading preferences in scenarios with varying frequencies of environmental stress and agent types initialized to exhibit differing altruistic or selfish tendencies. Our results suggest that neither extreme selfishness or extreme altruism is desirable but rather, some *middle-ground* value is. Additionally, we find that the frequency of the environmental stress plays a significant role in the emergence of selfish behaviour amongst the social elite with higher frequency environmental stress scenarios resulting in a greater disparity of resource transfer beliefs between agents with equal social status.

CCS CONCEPTS

• **Computing methodologies** → **Agent / discrete models**; *Artificial life*; • **Applied computing** → Anthropology.

KEYWORDS

Agent-Based Modelling, Evolutionary Algorithms, Altruism and Selfishness

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1 INTRODUCTION

At the core of cooperative behaviour lies the dichotomy of altruism and selfishness [11]. Humans, unlike other social mammals, exhibit cooperative behaviour on a significantly larger scale and, in turn, exhibit greater capacity for both altruistic and selfish acts [3]. No time in ancient history demonstrates this more clearly than transition from the Paleolithic to the Neolithic whereby egalitarian, hunter-gatherer, groups transitioned into sedentary agrarian societies that exhibited varying degrees of social stratification [10]. Environmental stress is theorized to have played a large part in this transition and is often mentioned when talking about the evolution of cooperative behaviour [7, 8]. *Agent-Based Models* (ABM) are commonly used to investigate the relationship resource availability, as a function of environmental stress, has on the emergence of cooperative-behaviour [1, 2, 6]. Additionally, ABM have also been used to study the emergence of social stratification [4, 9, 10]. However, research marrying the two topics is scarce leaving the underlying effects that environmental stress plays on cooperative-behaviour in socially stratified societies relatively unknown.

It is under this premise that this paper seeks to answer whether environmental stress (resource scarceness) positively impacts resource sharing (altruism) in socially stratified societies? We achieve this by developing an Agent-Based Model, called NeoCOOP, which utilizes Reinforcement Learning and Evolutionary Algorithms as adaptive mechanisms to simulate the the emergence and evolution of altruistic and selfish behaviour in Neolithic-inspired households.

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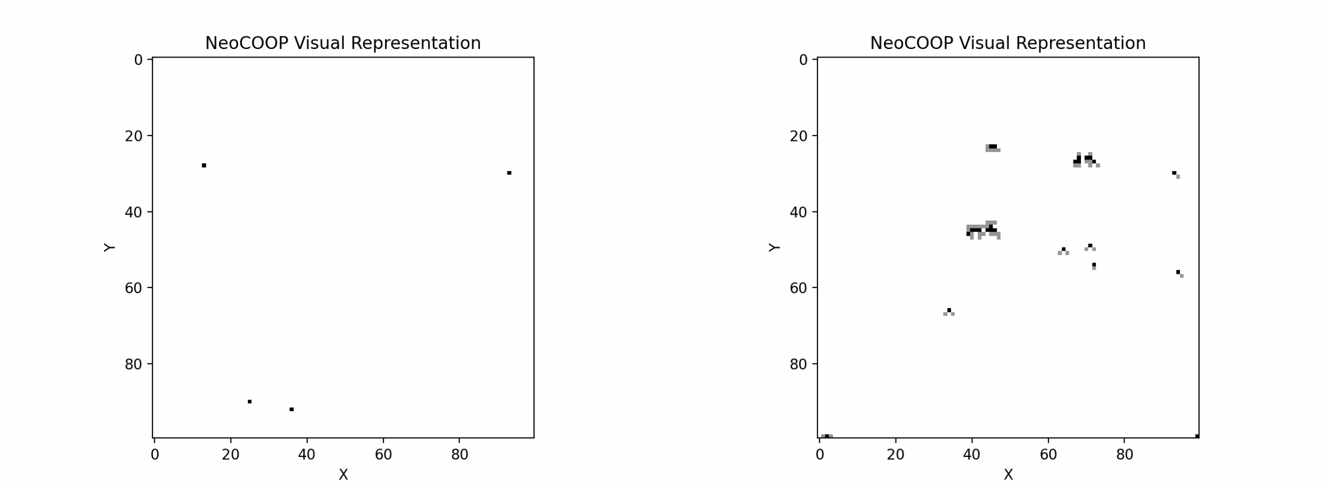
2 METHODOLOGY

NeoCOOP (Neolithic Agent Cooperation Model) is an iteration-based ABM developed using *Python 3* and the *ECAgent* framework that simulates the emergence and evolution of altruistic and selfish behaviour in Neolithic household agents on a *nxm* grid-world. The grid-world makes use of a simple Vegetation Model based on work done by Xu and Zhang [15] which grants the model the ability to simulate monthly global environment properties (rainfall and temperature) as well as vegetation growth and decay.

In NeoCOOP, the Household agents are utility-based. This means that every agent associates each action in the model with a utility value. Every iteration, the agents choose actions, based on experience, that return the greatest expected reward. Agents only have two actions: *FORAGE* and *FARM* which, when taken, result in an agent foraging or farming respectively. There is only one type of resource in NeoCOOP. The difference between *FORAGE* and *FARM* actions is their prerequisites and quantity of resources returned.

If the *FORAGE* action is chosen, the agent will look for a neighbouring cell with the greatest vegetation density and take resources directly from this cell equal to a predefined *(forage consumption rate*) amount based on the number of *able_workers* the agent has. If the selected action is a *FARM* action, the agent will choose one of it's owned farming cells and gather resources from it. If the agent does not own any farming cells, it will attempt to acquire some from the neighbouring cells. Farming is intended to be the better action as it returns 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 may be more beneficial.

To facilitate social interaction, NeoCOOP uses the self organization scheme described by Chliaoutakis and Chalkiadakis [4], whereby agents can categorize their relationship with another agent as either *subordinate*, *authority* or *peer* by comparing social statuses. This, unlike most other ABM, allows agents to accept or



(a) (b)

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.

reject resource transfer requests from other agents based on which relationship category the other agent falls into. Within the context of NeoCOOP, social status is defined as the amount of resources an agent currently possesses plus the amount of resources it has given to other agents over a parameterized period of time.

NeoCOOP makes use of two evolutionary algorithms: a Genetic Algorithm [14] (GA) for vertical generational adaptation and a Cultural algorithm [12] (CA) for horizontal generational adaptation. Both algorithms make use of a the agent's chromosome which contains six floating point values of which only two are important for this paper: *peer_transfer* and *sub_transfer* which describe the probability that an agent will accept a resource transfer request from a peer or subordinate agent respectively. Given that we are not trying to solve an optimization problem, our GA and CA implementations are not executed every iteration. The GA is executed whenever a household agent reaches carrying capacity and separates into two households. The two parent agents used in the crossover process are the original agent and another agent household with a similar social status. The offspring agent is produced using Uniform crossover with Random mutation used for the peer and sub transfer genes and a Gaussian mutation function used for the other four (Farm Utility, Forage Utility, Stubbornness and Conformity). For the CA, a belief space is generated per settlement and shares the exact same structure as the agent's chromosome. The settlement belief space is then influenced probabilistically by neighbouring settlements. The now altered settlement belief spaces then influence the agents within their settlements in accordance with the *influence_rate*. To avoid rapid homogenization of the agent chromosomes, the CA is only run every *influence_frequency* iterations. This ensures that beneficial, newly discovered, agent beliefs are given a fair amount of time to be evaluated. Lastly, to change its living conditions, an agent can move every *yrs_per_move* iterations. When this occurs, an agent will look at all neighbouring settlements and choose the settlement with the best living conditions (highest average available resources). If no settlement looks appealing, the agent will elect to make a new settlement at a cell within its relocation radius.

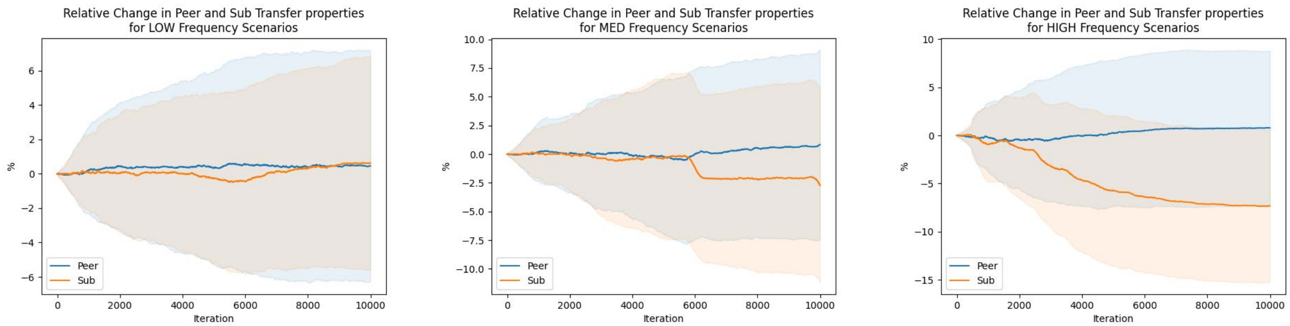
Our primary justification for the aforementioned design decisions is that our goal was to create a model that is complex enough to produce interesting resource trading and social stratification dynamics whilst maintaining explainability. This is why the vegetation model and household movement (aspects of the model we were not interested in investigating) are relatively simple when compared to the agent resource trading and adaptation processes.

3 EXPERIMENT DESIGN

We conducted scenario experimentation whereby we altered the environmental stress of the model over time. We achieved this by modifying the amount of rainfall available at each iteration in accordance with sine waves of varying frequencies.

We also experimented with the initial distribution of the peer and sub transfer agent properties. This allowed us to study various agent archetypes with more altruistic agents exhibiting higher *peer_transfer* and *sub_transfer* properties and, conversely, more selfish agents exhibiting lower *peer_transfer* and *sub_transfer* properties. These four distributions are: random (R) where the *peer_transfer* and *sub_transfer* properties are random values $\in [0, 1]$. The 50/50% distribution (F) splits the distribution of the agent *peer_transfer* and *sub_transfer* properties such that half of all agents exhibit altruistic behaviour and the other half exhibit selfish behaviour. The last two distributions split the initial population 75/25% in favour of either altruistic or selfish behaviour (A and S respectively).

By combining the environmental stress categories with the initial *peer_transfer* and *sub_transfer* distributions, 12 scenarios were explored. The grid-world's dimensions were set to $100x100$.



(a) (b) (c)

Figure 2: Relative difference in peer and subordinate agent properties averaged over all simulation runs and agent types for environments with LOW (a), MED (b) and HIGH (c) frequency (of environmental stress increase). Shaded regions indicate average standard deviation of means for all agent types.

Each simulation was initialized with 100 agents and 4 settlements which were randomly placed on the grid-world. The model was run for 10000 iterations per simulation run and each scenario was simulated 50 times. Figure 1 presents a visual representation of NeoCOOP and Appendix A lists all of the model's input parameters.

4 RESULTS AND DISCUSSION

As presented in Figure 2, results indicate the *sub_transfer* decreases as the frequency of environmental stress increases. This can clearly be seen in Figure 2b where, at approximately iteration 6000, the *sub_transfer* property decreases as a new wave of environmental stress is introduced. Such increases in selfish behaviour have been similarly noted by Ember et al. [5], as groups tend to behave more selfishly when environmental stress is frequent. The choice to become more selfish towards subordinates is also indicative of this specific agent-environment interaction, since within the context of the simulations, subordinates are by definition the individuals who require resources be given to them and by lowering the *sub_transfer* property. A wealthier agent can thus maintain their wealth by increasing the likelihood of them rejecting a subordinate resource transfer request. This is in keeping with our understanding of several Neolithic civilizations which developed a high degree of social stratification [10].

Our results also suggest that extreme altruism and extreme selfishness are both undesirable for lower frequency environmental stress scenarios (*LOW* and *MED*) with both the *A* and *S* agent-types evolving more selfish and altruistic behaviour respectively (See Figure 3a). This suggests that there is an ideal range of values under which fitness maximizing cooperation can take place. This range of values is likely affected by environmental stress and future work will expand upon these findings in search of this "ideal range". This theory is also further supported in Figure 3a by the fact that despite the abrupt decrease in the *A* and *S* *sub_transfer* properties at approximately iteration 6000 (due to an environmental stress wave in the *MED* scenario), both properties maintain their previous trends once the stress wave has passed.

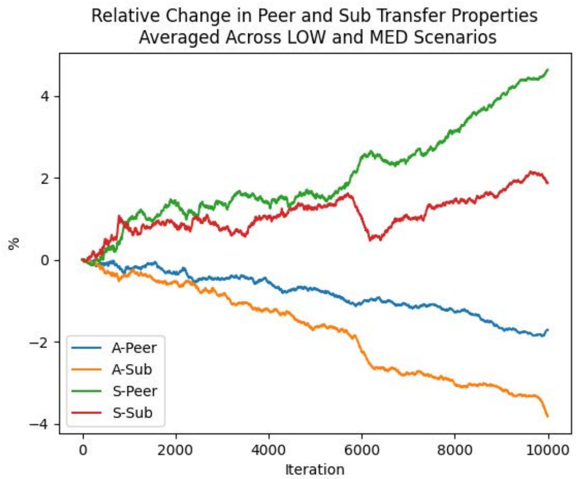
Unexpectedly, the *peer_transfer* property underwent less evolution than expected across all scenarios. Further examination of the results indicate that this is due to the lack of peer resource transfer requests when compared to subordinate resource transfer requests. This can be seen in Figure 3b where the number of subordinate transfer requests skyrockets during an environmental stress wave while the number of peer transfer requests remained relatively low. This meant that an agent's *peer_transfer* belief was less important than its *sub_transfer* belief in determining its fitness. This suggests that peer resource transfer beliefs may only be affected by population capacity-based stress as opposed to the environmental stress investigated in this work. Interestingly, the uptick in peer transfer requests is the result of an emergent behaviour whereby authority agents who have donated their excess resources to subordinate agents now require resources themselves. Given their social status, they ask their peers (other authority agents) for such resources. This creates a cyclical process whereby authority agents donate excess resources to their subordinates and other authority agents then donate their excess resources to their peers in need.

Despite the preliminary nature of these results, the next steps in this research endeavour are clear. The two most interesting results we obtained were the emergence of selfish behaviour as the frequency of environmental stress increased and the tendency for agents to avoid extreme altruism or extreme selfishness. Future work will focus on searching for the *ideal range* of values under which fitness maximizing cooperation can take place and its relation to environmental stress. We also plan to increase the ABM's scope via initializing more agents and settlements as well as running artificial evolution simulations for longer. The goal of this is to encourage peer to peer resource transfer and to better explore the conditions under which the *peer_transfer* property evolves.

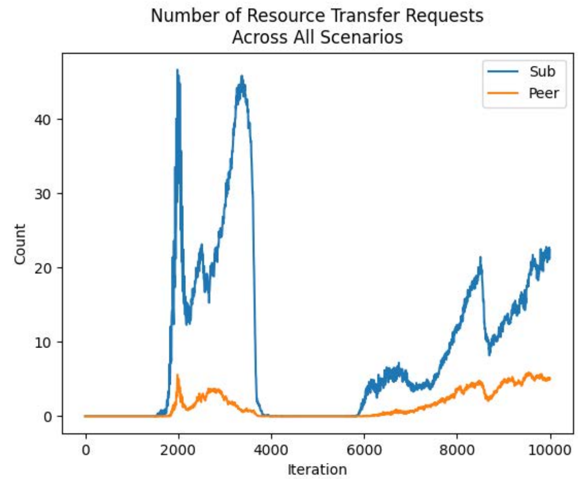
Finally, we will also expand our CA implementation to include knowledge sources [13] to help maintain a more diverse belief space thus producing results with increasing relevance to historical and archaeological data related to Neolithic societies.

5 CONCLUSIONS

In this paper, we investigated the evolution of altruistic and selfish behaviour in Neolithic-inspired households under varying degrees of environmental stress. We found that as the frequency of the



(a)



(b)

Figure 3: Figure (a): Change in Peer and Sub-transfer properties for agent types: A, S. Percentage is average relative change across *LOW* and *MED* environmental stress scenarios. (b): Number of resource transfer actions summed across all scenarios.

environmental stress increased, so did selfish behaviour towards subordinate agents. Additionally, our results suggest that extreme selfishness and extreme altruism are both undesirable and that there may be an ideal range of values under which cooperative behaviour can occur while maximizing agent fitness. Future work will search for an *ideal range* of cooperativeness as well as the conditions under which peer resource transfer beliefs adapt most.

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A MODEL INPUT PARAMETERS

Property	Value
Iterations	10 000
Initial Households	100
Initial Settlements	4
L	0.6
Carrying Capacity	12
Birth Rate	0.135%
Death Rate	0.1%
Years Per Move	5
Stubbornness Range	$\in [0.05, 0.2]$
Conformity Range	$\in [0.05, 0.2]$
β	0.75
m	1.5
Mutation Rate	0.05
Influence Rate	0.05
Influence Frequency	10
Selfish Range	$\in [0.05, 0.45]$
Altruism Range	$\in [0.55, 0.95]$
LOW Frequency	8
MED Frequency	16
HIGH Frequency	64

Table 1: NeoCOOP Experiment Parameters

B SOURCE CODE

Source code for NeoCOOP can be found at the following link: https://github.com/BrandonGower-Winter/ABM-gecco2022.

Source code for the ECAgent framework can be found at the following link: https://github.com/BrandonGower-Winter/ABMECS