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Does Low Spoilage Under Cold Conditions Foster Cultural Complexity During the Foraging Era?—Agent-Based Modeling and Reinforcement-Learning Approach

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Abstract: Human cultural complexity did not arise in a vacuum. This study employs agent-based modeling (ABM) and ecological modeling perspectives, combined with reinforcement-learning techniques, to investigate whether conditions that allowed for the lower spoilage of stored food, often associated with colder climates and abundant large fauna, might have indirectly fostered the emergence of cultural complexity. Specifically, we developed a mathematical framework to capture how spoilage rates, yield levels, resource management skills, and cultural activities interact within a multi-agent system. Under the restrictive constraints, we proved that lower spoilage and adequate yields reduced the frequency of hunting, freeing time for cultural pursuits. We then implemented a reinforcement-learning simulation to validate these predictions by training agents in different (Y, p) environments, where Y is the yield and p is the probability of daily spoilage. Our regression analysis and visualizations showed strong correlations between stable conditions with lower spoilage and higher levels of cultural investment. While we do not claim to replicate prehistoric social realities directly, our findings highlight the potential of ABM and ecological modeling to illuminate how environmental factors influence the allocation of time to complex cultural activities. This work offers a computationally grounded perspective that bridges humanistic inquiries into the origins of culture with formal agent-based methods.



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1. Introduction

The origin and early expansion of human cultural complexity have occupied a central place in debates among archaeologists, anthropologists, and historians of prehistory. Since the early twentieth century, scholars have recognized that certain ecological conditions might have created more opportunities for artistic, symbolic, and social innovation. Yet, these arguments often rely on speculative, albeit insightful, narratives rather than robust theoretical or computational foundations. With the advent of more nuanced analytical tools, recent scholarship began to rigorously test the links between environmental stability, resource availability, and cultural development. By leveraging computational modeling alongside ethnographic and archaeological data, contemporary research aims to understand not just the presence of symbolic artifacts or social institutions but also the underlying ecological and technological preconditions that may have nurtured these cultural forms.

In recent years, agent-based modeling (ABM) and ecological modeling have become central methodologies for examining how micro-level rules among heterogeneous agents lead to emergent social patterns. Classic works, such as Epstein and Axtell's Sugarscape model [1] and crowd behavior simulations under emergency conditions [2], demonstrated that bottom-up modeling approaches can provide rich insights into how environmental constraints and individual strategies shape collective outcomes. Inspired by these agent-based perspectives, this study integrated multi-agent simulations and reinforcement learning to investigate the interplay of spoilage rates, yields, and cultural behaviors.

Numerous interdisciplinary studies aimed to elucidate the relationships between the climate, subsistence strategies, and cultural development (see, for instance, [3–9]). Many of these works were derived from the long-standing hypothesis that colder climates, offering large mammals as stable, high-calorie resources, could reduce the frequency of hunting events needed to sustain a community. In turn, fewer hunting events might create windows of leisure time. This additional time, no longer spent merely ensuring survival, could be invested in the production of symbolic objects, the performance of rituals, the refinement of storage methods, and the reinforcement of social bonds. Scholars suggested that even subtle differences in the spoilage rates of stored food can shape the long-term evolutionary trajectory of societies, as lower spoilage reduces uncertainty and allows for the accumulation of surplus food (see also [10,11]).

However, existing narratives often treat technological and social management strategies as static or secondary. The complexity of social cooperation, the refinement of food preservation techniques, and the sophistication of storage containers and shelters are frequently acknowledged only as afterthoughts, rather than integral parts of the environmental–human nexus. Indeed, much earlier scholarship tended to regard “culture” as a byproduct of environmental abundance, rather than as an interactive and co-evolving component of the subsistence system itself. More recent discussions, influenced by theoretical and methodological advances in archaeology and cultural evolution studies, emphasized that “culture” and “environment” are mutually constitutive. In other words, as resource management skills (such as improved storage techniques, effective preservation methods, or knowledge of seasonal resource distribution) developed, they not only mitigated spoilage and improved yields but also reshaped the ecological constraints themselves (cf. [12–16]).

This study aimed to situate itself at the intersection of these debates by offering a refined mathematical model coupled with a computational simulation. The core question that guided this research was the following: Does environmental stability, characterized by a lower spoilage probability and higher yields, indirectly foster conditions more conducive to cultural complexity? Our hypothesis did not rely on simple deterministic claims. Rather, we posited that, under certain assumptions, a group operating in a stable environment is likely to experience fewer constraints in food acquisition and preservation, thus freeing up valuable time. This additional time can then be allocated to cultural pursuits, be they artistic, ritualistic, or technological in nature. Over repeated generations, even modest reductions in spoilage or slight increases in yield can be amplified through feedback loops, allowing cultural complexity to take root and flourish.

To explore this hypothesis, we propose a formal model that captures the essential variables: yield, spoilage, resource management skill, and cultural complexity. We introduced a factor G representing resource management ability (encompassing both technological and social know-how) and a factor C representing cultural complexity. The effective yield per hunting event is modeled as increasing with both G and C , capturing how cultural and technological sophistication can improve the subsistence returns. Meanwhile, daily spoilage p continuously reduces the stored food, making it a challenge. Agents (or “human

groups”) attempt to maximize C through a reinforcement-learning (RL) algorithm [17–19] that chooses whether to hunt, invest in resource management, or engage in cultural activities on a given day.

In this paper, we treat the cultural complexity C as an integer-valued state variable representing a cumulative index of culturally significant activities, artifacts, or knowledge. Each cultural activity performed by agents increases C by one unit, capturing a discrete (though simplified) measure of how many culturally relevant tasks have been performed. In practice, cultural complexity is not strictly one-dimensional, but here we use C as a coarse proxy to keep the model tractable. By “cultural activity”, we mean any ritual, artistic, or social task that is not strictly necessary for immediate survival. These tasks are discretized in our model to allow for daily increments of one unit, acknowledging that actual cultural evolution is more nuanced.

By running extensive simulations in which agents are exposed to various combinations of Y (yield) and p (spoilage), we could observe emergent patterns. While we cannot claim that these results constitute direct historical evidence, indeed, no simulation can replicate the full complexity of human prehistory, the patterns they revealed were suggestive. They indicate that stable, high-yield, and low-spoilage environments led the agents to allocate less time to subsistence and more to cultural pursuits. Over time, this trend correlated with higher final values of C .

Unlike previous works that might have been limited to hand-waving claims or lacked formal rigor, we provide a tractable mathematical proof of the core proposition: under restrictive but reasonable assumptions, a reduction in spoilage and an increase in yield reduced the hunting frequency, and thus, increased the available time for cultural elaboration. This theoretical result stands independent of any single simulation run. The simulations, in turn, served as a form of empirical validation within the model’s own constraints, showing that the theoretical relationship held even when multiple stochastic and dynamic factors were introduced.

This theoretical result should be understood as a limited demonstration of how, under restrictive assumptions, a reduction in spoilage and an increase in yield can free time for cultural pursuits in our simplified model. We acknowledge that the overall framework remains a hypothesis; it does not constitute proof in a universal sense since many real-world factors and alternative metrics (e.g., life expectancy instead of C) could also be used to represent cultural development. Nonetheless, our goal was to illustrate that within the constraints of this model, certain formal conditions can yield tractable results consistent with the broader hypothesis.

Additionally, it is important to emphasize that our approach does not claim that cold climates or stable conditions definitively caused cultural complexity. Rather, we argue that these environmental factors created a fertile ground, an enabling condition, within which cultural complexity could more easily emerge and intensify. Historical processes are always contingent, influenced by factors like social structures, cognitive capacities, migrations, and ecological disasters that we did not model here. Nonetheless, by showing a plausible causal chain, namely, lower spoilage leads to fewer hunts, which leads to more free time, which, in turn, can be allocated to cultural activities, we contribute to a growing body of literature that treats culture not as an isolated phenomenon but as dynamically linked to environmental parameters.

The remainder of this paper details our modeling framework and computational experiments. In the Methods Section, we outline the mathematical assumptions, the sets of actions, and the state variables. We then present theoretical propositions and a theorem that formalize the intuition behind our main claim. In the Experiments Section, we describe the reinforcement-learning setting and present the simulation results, supported

by Ordinary Least Squares (OLS) regression analysis and data visualization. Finally, we reflect on the meaning of these findings for our understanding of early cultural complexity, acknowledging the limitations of any model that attempts to bridge deep prehistory and computational abstraction.

2. Methods

2.1. Model Setup

We considered a simplified ecological model in which a human group inhabits an environment characterized by two key parameters: daily yield $Y > 0$ from hunted fauna and daily spoilage probability $p \in [0, 1]$ that reduces the stored food each day. The group requires a fixed annual amount of food $F > 0$ and must allocate its time to hunting, investing in resource management skills, or engaging in cultural activities. Time is discretized into daily units on a fixed horizon of T days. Throughout our analysis, we assumed that $Y \in [1000, 3000]$ and $p \in [0, 1]$. In our experiments, we further constrained p to $[0.2, 0.5]$ to represent plausible daily spoilage rates in cold or moderate climates.

Assumption 1 (Basic requirements). *The group must secure a total amount of food F over T days. Each day, a fixed daily consumption $c > 0$ is subtracted from the stored food. If the stored food becomes negative, the group suffers a starvation penalty.*

Assumption 2 (Actions). *On each day, the group selects one of the following actions:*

1. **Hunt:** Costs $d_h > 0$ days (e.g., $d_h = 2$). The group consumes daily rations during these days. After completing the hunt, they obtain an effective yield proportional to Y , adjusted by the group's management skill G and cultural complexity C . The effective yield is

$$\text{eff}(Y, G, C) = Y(1 + 0.1G)(1 + 0.01C).$$

2. **Invest (resource management):** Costs $d_i = 1$ day. Improves G by a fixed increment $\Delta G > 0$.
3. **Culture:** Costs $d_c = 1$ day. Increases C by a unit and grants a small immediate reward.

These coefficients (0.1 for G and 0.01 for C) were selected for demonstration purposes to ensure that moderate increases in G or C yield tangible but not extreme effects on the effective yield. Preliminary experiments indicated that larger coefficients could cause overly rapid growth in the stored food, diminishing the impact of scarcity, while smaller values made skill and cultural activities almost inconsequential. We adopted a balanced choice to highlight the relationship between spoilage, yield, and cultural investment.

Assumption 3 (Daily spoilage). *At the end of each day, the stored food is reduced by a spoilage factor $p \in [0, 1]$. If f_{current} denotes the current food, then*

$$f_{\text{next}} = (f_{\text{current}} - c)(1 - p).$$

If $f_{\text{next}} < 0$, the group incurs a large penalty and the process ends prematurely.

Assumption 4 (Initial conditions and ending). *Initially, the group starts with a small positive amount of food (e.g., enough for several days). After T days, the episode ends. We considered that no final additional reward is given, except that the final cultural complexity C itself is recorded as a measure of success. Thus, the objective is to maximize C without starving.*

2.2. Propositions and Theorem

The following propositions formalize how lower spoilage (p) and higher yield (Y) affect the time allocation and cultural complexity C . A lower p implies that each hunted food unit remains available for longer. Similarly, a larger Y per hunt reduces the required hunting frequency.

Assumption 5 (Comparative conditions). *Consider two environments A and B . In A , we have a higher yield $Y_A > Y_B$ and lower spoilage $p_A < p_B$. Both groups require F units of food annually and have access to the same actions.*

Proposition 1. *Under the given assumptions, environment A requires fewer hunts to achieve the annual requirement F due to $Y_A > Y_B$ and a lower effective daily spoilage.*

Proof. If the hunt yield is higher and the spoilage is lower, the effective retained food per hunt in A is strictly greater than in B . Hence, to obtain F , fewer hunts are necessary in A . Thus, $H_A < H_B$, where H_i is the number of hunts in environment i . $\square$

Proposition 2. *Because fewer hunts are required in A , the group in A allocates fewer total days to hunting, resulting in more spare days available for either cultural activities or resource management.*

Proof. If $H_A < H_B$ and each hunt costs at least d_h days, then the total hunting time $T_{\text{hunt},A} < T_{\text{hunt},B}$. Since T is fixed, $T_{\text{free},A} = T - T_{\text{hunt},A} > T - T_{\text{hunt},B} = T_{\text{free},B}$. $\square$

Theorem 1 (Cultural complexity advantage). *Let C_i denote the cultural complexity achieved in environment i . If $H_A < H_B$ and environment A invests the extra free time in cultural actions, then $C_A > C_B$. Furthermore, since a higher C increases the future hunting efficiency through $(1 + 0.01C)$, environment A experiences a strengthening cycle that further elevates the cultural complexity.*

Proof. By Proposition 2, environment A has strictly more free days to allocate. The culture action increases C by one unit per day and provides immediate rewards. Given that A can afford more cultural actions (due to less frequent hunting), $C_A > C_B$. This increment in C loops back to improve the effective yield in future hunts, reinforcing the cycle and maintaining or increasing the gap. $\square$

The theorem shows that under lower spoilage and higher yield conditions, groups can minimize the hunting frequency, thereby freeing up time for cultural activities. This leads to an emergent advantage in cultural complexity.

While Theorem 1 is stated as a mathematical proposition, it applies only under the narrow assumptions outlined in this section (e.g., fixed p and Y , discrete daily actions, and linear yield scaling). We do not claim that it proves a general or universal property of human societies. Rather, it demonstrates that if one accepts these simplifying constraints, then a lower spoilage rate and higher yield can, in principle, free time for cultural activities and reinforce cultural complexity within our specific model. Thus, the theorem supports a hypothesis rather than an all-encompassing law.

2.3. Additional Clarifications of Key Assumptions

Our model assumes a constant daily spoilage rate p and a uniform agent decision-making process. We acknowledge that real-world hunter-gatherer societies may experience more variable spoilage rates due to environmental fluctuations, seasonal changes, or cultural knowledge about preservation methods. Moreover, individual or sub-group differences in resource allocation, risk aversion, and social norms can lead to more diverse

behavioral strategies than our model currently captures. These simplifications allow us to focus on the core question of whether reduced overall spoilage correlates with increased cultural investment, but we recognize that they only approximate the complexity of real-world dynamics. Future models may integrate stochastic or seasonally varying spoilage factors, as well as the heterogeneity between agents in terms of skill-learning rates or resource preferences.

3. Experiments

3.1. Simulation Procedure

We conducted a computational experiment using an RL framework. Each agent represented a hypothetical human group that operated within a given environmental condition. The agent selected actions from a discrete set (hunt, invest, culture) each day to maximize the cultural complexity C while avoiding starvation. We simulated N agents, each assigned a unique environment defined by a pair (Y, p) . The yield Y and spoilage p values differed between the agents, which allowed us to capture a wide range of environmental conditions. We ran multiple training episodes for each agent and evaluated their learned policies after the training.

3.2. Parameter Settings

All agents shared the same initial baseline conditions, including an initial food stock, a daily consumption rate, and a total number of days T . We varied Y and p between the agents to cover a broad range of ecological conditions. After the training was complete, we recorded the final cultural complexity C achieved by each agent.

3.3. Data Collection and Analysis

We gathered the final cultural complexity C values from all agents and their respective (Y, p) parameters. We applied an OLS regression to relate C to Y and p . We also generated plots to illustrate how C correlated with Y and p . Regression and visualization allowed us to assess the agreement between the computational outcomes and theoretical predictions.

3.4. Reinforcement-Learning Setting

We formalized the theoretical model as a Markov decision process (MDP). We modeled each agent's daily choices as an MDP because the system evolved in discrete time steps, and the decision at each step depended on the current state (stored food, skill G , culture C , etc.) without explicit memory of the earlier states. This memoryless property and day-by-day transition naturally mapped onto an MDP framework, which facilitated the use of reinforcement-learning algorithms that updated policies based on the observed rewards and state transitions.

The state on day t included the following:

- Stored food level normalized by the annual requirement f_t/F .
- Resource management skill level G .
- Cultural complexity C .
- The fraction of remaining time $(T - t)/T$.
- Normalized yield $Y/3000$ and spoilage probability p . Here, 3000 served as a convenient normalization factor that corresponded to our maximum yield in the experimental range ($Y \in [1000, 3000]$). Normalizing the yield helped stabilize the agent's input scale for learning.

The agent chose one action per day:

1. **Hunt:** Occupied $d_h = 2$ days, with each incurring daily consumption and spoilage. After completing the hunt, the agent obtained $\text{eff}(Y, G, C) = Y(1 + 0.1G)(1 + 0.01C)$ units of food.
2. **Invest:** Took 1 day. Improved G by a fixed increment $\Delta G > 0$. Daily consumption and spoilage was applied.
3. **Culture:** Took 1 day. Increased C by 1 and gave a small immediate reward. Daily consumption and spoilage was applied.

The reward structure penalized starvation. If f_t fell below zero at the end of the day, the agent received a -100 penalty and the episode ended. The culture action gave a $+5$ immediate reward. No other action granted direct positive rewards. On the last day T , we recorded C for analysis. Although C was not added as a terminal reward, it represented the primary outcome. Since C was incremented once per cultural activity, it was measured in integer “activity units”. Although lacking a direct historical unit, it served as a notional count of how many cultural tasks had been performed. We applied a starvation penalty of -100 to strongly discourage agents from running out of food, thus emphasizing the survival imperative. Meanwhile, a small positive reward of $+5$ for each cultural activity was sufficient to incentivize non-subsistence actions without overshadowing the importance of preventing starvation. These values were chosen to make survival a priority and cultural pursuits a secondary but worthwhile goal.

3.4.1. RL Model and Optimization

We implemented an actor–critic RL model. The policy (actor) and value function (critic) were parameterized by neural networks with two hidden layers of 64 units each, using rectified linear unit (ReLU) activations. We orthogonally initialized all weight matrices to improve the stability. The policy network output logits over the three possible actions, and the critic network output a scalar value estimate.

We employed an advantage-based policy gradient approach similar to A2C. Let $\pi_\theta(a|s)$ be the policy and $V_\phi(s)$ the value function. For a batch of collected episodes, we computed the advantages $A_t = R_t + \gamma V_\phi(s_{t+1}) - V_\phi(s_t)$, where R_t was the immediate reward at time t and γ was the discount factor. We then updated θ by ascending the gradient of the objective $J(\theta) = \mathbb{E}[\log \pi_\theta(a_t|s_t) A_t]$, and we updated ϕ by minimizing the mean squared error between $V_\phi(s_t)$ and $R_t + \gamma V_\phi(s_{t+1})$. We used the Adam optimizer with a fixed learning rate and applied gradient clipping to maintain stable updates.

3.4.2. Training Details

Each agent was trained for 50 episodes, each with $T = 365$ days. In each episode, the agent attempted to secure enough food while allocating days to resource management or cultural activities. After training, we conducted 100 evaluation tests without learning updates and measured the mean C .

3.4.3. Parameter Variations

We generated $N = 1000$ agents, each assigned a random (Y, p) from predefined ranges ($Y \in [1000, 3000]$, $p \in [0.2, 0.5]$). This large sample size provided sufficient variability to statistically analyze how the changes in Y and p affected the results.

3.4.4. Pseudocode for Agent Decision Algorithm

We illustrate the daily decision rules for each agent with the pseudocode in Algorithm 1. This procedure mirrors the logic used in our code implementation, capturing how the agents updated resource levels, applied spoilage, and chose their actions via reinforcement learning.

Algorithm 1 Daily Agent Decision Pseudocode

```

1: Initialize: food  $\leftarrow$  initial_food, skill  $G \leftarrow 0$ , culture  $C \leftarrow 0$ 
2: Initialize: time_used  $\leftarrow 0$ , done  $\leftarrow$  false
3: while (not done) and (time_used < T_total) do
4:   food  $\leftarrow$  food - daily_consumption
5:   food  $\leftarrow$  food  $\times$  (1 -  $p$ ) ▷ Apply spoilage
6:   if food < 0 then
7:     apply starvation penalty
8:     done  $\leftarrow$  true
9:     break
10:  end if
11:  action  $\leftarrow$  RL_Policy(food, G, C, time_used)
12:  if action = Hunt then
13:    if time_used + T_hunt  $\leq$  T_total then
14:      for  $d = 1$  to T_hunt do
15:        same daily consumption and spoilage steps as above
16:        if food < 0 then
17:          apply starvation penalty
18:          done  $\leftarrow$  true
19:          break
20:        end if
21:        time_used  $\leftarrow$  time_used + 1
22:      end for
23:      yield  $\leftarrow Y \times (1 + 0.1G) \times (1 + 0.01C)$ 
24:      food  $\leftarrow$  food + yield
25:    else
26:      advance any remaining days, then end episode
27:      done  $\leftarrow$  true
28:    end if
29:  else if action = Invest then
30:    if time_used + 1  $\leq$  T_total then
31:      apply daily consumption and spoilage (1 day)
32:       $G \leftarrow G + \Delta G$ 
33:      time_used  $\leftarrow$  time_used + 1
34:    else
35:      advance any remaining days, then end episode
36:      done  $\leftarrow$  true
37:    end if
38:  else if action = Culture then
39:    if time_used + 1  $\leq$  T_total then
40:      apply daily consumption and spoilage (1 day)
41:       $C \leftarrow C + 1$ 
42:      grant small reward (e.g., +5)
43:      time_used  $\leftarrow$  time_used + 1
44:    else
45:      advance any remaining days, then end episode
46:      done  $\leftarrow$  true
47:    end if
48:  end if
49: end while
50: Output final cultural complexity: C

```

4. Results

4.1. Overall Patterns

The results indicate a strong negative association between the probability of spoilage p and the cultural complexity C . The agents in environments with a lower p generally achieved a higher C . While a higher yield Y also correlated with an increased C , its effect was weaker than that of p . Figure 1 illustrates the steep decline in C as p increased. For Figure 1, we chose a linear fit as the simplest option to approximate the relationship between C and p . Although the scatterplot might seem to suggest a non-linear trend, such as a logarithmic relationship, we do not currently possess theoretical proof or strong empirical evidence to justify that form of regression. Consequently, we adopted the most common and direct approach: the linear fit. If future studies provide a robust mathematical or empirical basis for a non-linear model, we will revisit our regression choice. Figure 2 shows a gentle upward trend in C as Y grew.

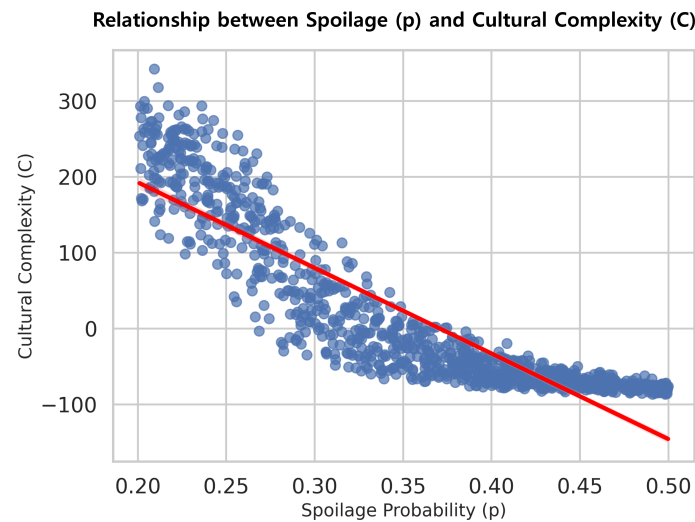


Figure 1. Cultural complexity C as a function of the spoilage probability p . Each point represents one agent. The red line is a linear fit. As p increased, C declined.

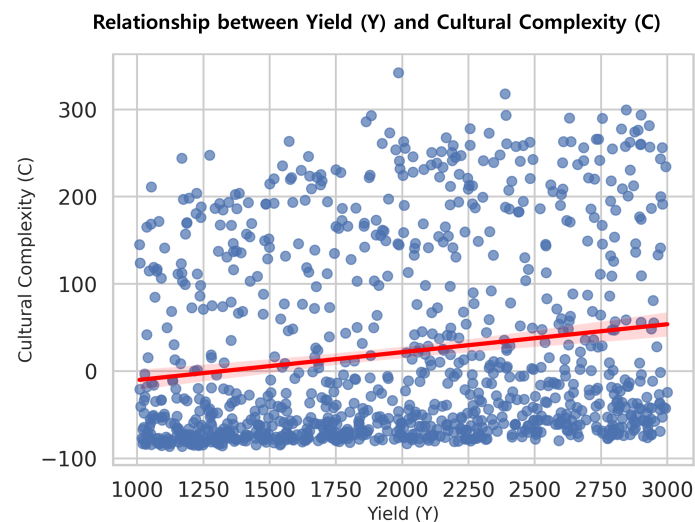


Figure 2. Cultural complexity C as a function of the yield Y . Each point represents one agent. The red line is a linear fit. As Y increased, C tended to rise modestly.

4.2. Statistical Relationships

We fit an OLS regression model with C as the dependent variable and (Y, p) as independent variables.

The regression (Table 1) confirmed that p exerted a dominant negative influence on C . A small increase in p led to a large decrease in C . The effect of Y was positive but less pronounced. These findings were consistent with the theoretical framework, where stable low-spoilage conditions reduced the hunting frequency and allowed for more cultural activities.

Table 1. OLS regression results. Both Y and p were highly significant. The negative coefficient for p was large in magnitude, indicating that spoilage strongly reduced C .

Parameter	Coefficient	p -Value	StdErr
const	347.45	<0.000001	7.50
Y (x1)	0.0370	<0.000001	0.0024
p (x2)	−1134.83	<0.000001	16.23

Figure 3 shows that many agents failed to achieve a high C , reflecting frequent hunting and occasional starvation. However, some agents in stable environments reached a substantially higher C . Figure 4 highlights how a low p combined with a moderately high Y fostered conditions conducive to cultural elaboration.

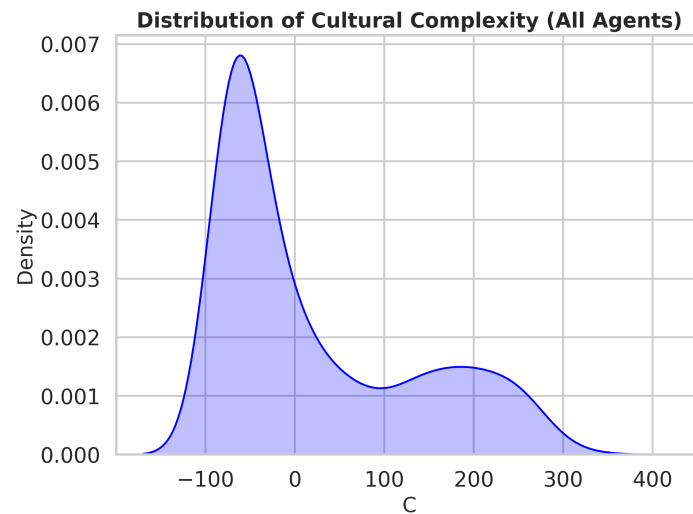


Figure 3. Distribution of cultural complexity C across all agents. Most agents clustered near low or slightly negative C values, but some achieved a higher complexity.

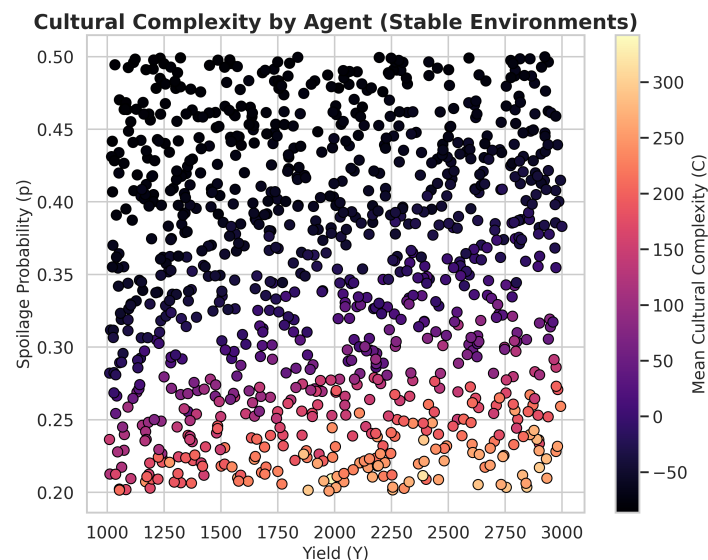


Figure 4. A two-dimensional map showing C as a function of Y (horizontal axis) and p (vertical axis). Colors indicate the mean C achieved. Lower- p -and-higher- Y environments produced a higher C .

5. Discussion

Our findings align with theoretical arguments stating that environmental stability, represented by lower spoilage rates and adequate yields, can indirectly foster the conditions necessary for cultural complexity. This idea resonates with several strands of research in archaeology, anthropology, and cultural evolution.

Numerous studies addressed the relationship between stable resource bases and cultural elaboration. For example, Gamble [20] discussed how consistent resource availability in Pleistocene Europe could have facilitated symbolic behavior, while Mithen [21] explored how cognitive fluidity and symbolic thought might have emerged when subsistence pressures diminished. Similarly, Richerson and Boyd [13] emphasized how cultural capacities

can expand when ecological constraints are relaxed, and Shennan [22] linked variation in subsistence strategies to the complexity of material culture.

In our model, the lower p reduced the need for constant hunting, mirroring the arguments that stable conditions free humans from perpetual resource pursuit, allowing them to invest in activities unrelated to immediate survival. Authors such as Klein [23] and d'Errico and Henshilwood [24] noted that symbolic artifacts, ritual practices, and social cooperation intensified when groups faced fewer environmental risks. Our computational results lend quantitative support to these claims. While these simulations do not replicate actual human prehistory, they suggest a plausible mechanism by which environmental parameters shape the space of possible cultural outcomes.

Another line of research, represented by works like Boyd and Richerson [25] and Henrich [14], highlights that cumulative cultural evolution thrives under conditions where knowledge transmission is reliable and long-term planning is possible. Our simulation shows that when daily spoilage is less severe, agents can plan beyond mere survival. This shift enables them to develop resource management (G) and engage in cultural activities (C) that would be impossible under harsher conditions. The model indicates that as the groups improved their resource management skills, the returns on hunting days improved, which reinforced the cycle of cultural investment. This insight echoes Laland [26] and Maryanski [27], who argued that material and social factors co-evolve, each facilitating the complexity of the other.

Furthermore, our results link environmental constraints to the trajectories of cultural complexity in a manner consistent with Powell et al. [28], who proposed that demographic and ecological factors together shape the rates of cultural innovation. In stable, low-spoilage environments, agents engage in fewer hunts, have more time to learn and transmit skills, and have greater opportunities to invest in non-survival activities. Although we did not model demographic factors directly, the pattern of improved cultural complexity in stable environments suggests that demographic expansions could further enhance these effects, as larger group sizes may sustain more complex cultural repertoires.

While our approach is abstract, the implications resonate with arguments about environmental influences on cultural emergence. Historical societies that managed to store and preserve food, such as those discussed by Wrangham [29] and Prentice [30], often saw increases in social complexity and specialization. The emphasis of our model on daily spoilage captured a simplified version of these preservation challenges. When preservation was easier, as represented by lower p , agents could afford to experiment with cultural activities.

It is important to note that we do not claim that cold climates or stable ecosystems directly caused cultural complexity. Rather, we suggest that such conditions reduce the time spent on basic subsistence, and thus, create opportunities for cultural elaboration. The notion that the environment sets the stage, rather than determines the script, is aligned with the work of Clarke [31] and Bettinger et al. [32], who stressed that the environment provides constraints and opportunities that societies navigate through cultural and technological strategies.

While our analysis emphasizes the effects of yield and spoilage on cultural complexity, we acknowledge that many other ecological and social variables remain outside our current framework. Factors such as the population density, social hierarchy, trade, intergroup competition, and linguistic diversity could substantially influence how cultural complexity emerges and evolves. Additionally, demographic structures and cooperative networks often co-evolve with ecological constraints, potentially shaping both subsistence activities and cultural practices. Future research could extend our model to include these dimensions, perhaps by incorporating dynamic population sizes, more nuanced forms of social organi-

zation, or cooperative behaviors. By capturing these additional factors, we may arrive at a more holistic understanding of how environmental stability and social structures jointly shaped the cultural trajectories in early human societies.

6. Conclusions

The emergence of cultural complexity in prehistoric foraging societies remains a central question in the humanities, prompting inquiries that span archaeology, anthropology, and beyond. These investigations often highlighted the potential significance of environmental stability, including factors such as resource predictability and reduced spoilage, as enabling conditions that opened the temporal and cognitive space for symbolic, ritualistic, and technological innovation.

Our study contributes to these discussions by providing a formal and computationally supported model that captures the interplay between yield, spoilage, subsistence labor, and cultural investment. By demonstrating a quantitative link between ecological parameters and cultural outcomes, this work does not assert a deterministic cause-and-effect scenario. Instead, it proposes that certain ecological settings created more favorable grounds for cultural elaboration. These settings, characterized by relatively stable conditions, allowed human groups to invest fewer days in securing immediate sustenance and more days in pursuits that, over time, contributed to cultural complexity.

This approach resonates with long-standing debates in the humanities, where scholars argued that cultural forms emerge not merely as epiphenomena of abundance, but as adaptive and co-evolving strategies shaped by environmental constraints. Our findings offer a structured, testable hypothesis: that lower spoilage probabilities and moderately increased yields are not just background variables but essential components that shape the tempo and mode of cultural evolution. Through computational simulations and theoretical proofs, we illustrated how groups that inhabited environments with certain ecological parameters could, in principle, shift their time budgets away from relentless foraging toward activities that nurtured symbolic behavior, technological refinement, and social cooperation.

In acknowledging these patterns, we do not discount other vital factors, such as social hierarchy, cognitive development, language complexity, demographic processes, or the role of migration and intergroup exchange. Rather, we present one segment of a larger tapestry in which environmental stability stands out as a significant, if indirect, determinant of cultural flourishing. Future research can extend this model to incorporate dynamic ecological cycles, fluctuating resource patterns, and culturally transmitted practices. Such integration would further align computational modeling with the rich empirical record of the humanities, potentially revealing deeper insights into how and why human culture assumed its remarkable diversity and complexity over the long arc of prehistory.

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