Social Primitives: Exploring Spark of Life Collective Behavior in Agent-Based Models

Srikanth P. Mudigonda and Milton J. Friesen

Abstract This research is focused on finding the simplest possible agent-based model called SPECscape (Social Primitives Experimental Cohort) that can demonstrate the emergence of wealth inequality. Agents feature a simple North-South-East-West best sugar patch search function within a 2D grid style code environment that allows formation of a proto-institution (common pool resource capability) under certain conditions. A Nearly Orthogonal Latin Hypercube (NOLH) is used to explore the behavior space of the model's dynamics with four distinct sugarscape arrangements and introduction of exogenous shocks at specified stages of the model's evolution. Our results suggest that proto-institutions and moderate shocks, are beneficial for agent members, and play an important role in lowering wealth inequality when many institutions are present and increasing wealth inequality when only a few are allowed to form, thereby indicating the presence of such institutions have a significant effect on wealth inequality in a society of agents.

1 Introduction

This paper examines a simple agent-based model that can demonstrate the emergence of wealth inequality. Our interest is to clarify understanding about the primitive dynamics that may be implicated in human inequality. This work, however, is not an anthropological study and the term "primitive" is used in an artificial, computational sense. We are not attempting to demonstrate here the origins of inequality as an empirical, human cultural fact. Digital primitives are magnitudes of order different than even the most basic human exchanges, so that complex social issues such as social norms [1] are relegated to simple coded rules. We use an agent-based model to

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study the dynamics of inequality as an emergent property of agent interactions under certain primitive conditions as a means of bench testing social dynamics [2–5].

Our empirical orientation to the issue of inequality arises from a study of public records research in the City of Hamilton, Ontario during the years 1851–1860 [6]. Development of an agent-based exploration of this work suggested that there was potential for more extensive scrutiny of simplification approaches along with expanded data output analysis [7]. The key empirical dynamic was the existence of a small group of well-off people who remained in Hamilton over the decade of the 1850s, in contrast to a class of people (~80% of the population) who grew in numbers as a totality but among which there was a turnover rate of 2/3 during the same decade. The presence and participation in stabilizing institutions for the wealthy (and relative absence of such institutions for the lower 80%) was hypothesized by Katz as a primary driver of those contrasting dynamics. The transient nature of low-income populations has been observed in many contemporary settings leading to weaker social ties and fewer institutional investments [8]. Inequalities appear to be integral to many aspects of social structures [9].

Inequality is not a simple concept and the dynamic may exist across a range of social, cultural, and economic axes without clear consensus or understanding [10]. Rousseau discussed inequality at length in the mid-eighteenth century [11]. Changing one kind of inequality dynamic can lead to inverse changes in another [12] while attempts to make all people equal in all ways introduces impossible negotiations and dynamics [13]. The very terms and cultural environments involved in studies, interventions, and explanations of inequality may include a range of built-in biases and misconceptions [14, 15].

When Schelling and Sakoda, respectively, [16, 17] developed simplified models of one kind of inequality, neighborhood segregation, our understanding of the relationship between micro-motives and macro-behaviors was advanced in important ways even if such dynamics did not fully explain the complexities of actual segregation.

In a similar spirit, we are endeavoring to understand the structural aspects of inequality that arise when agents are not conscious, operate by very simple, deterministic rules, but have a certain probability of forming collective functions. We undertake this by comparing resource levels of agents who are not affiliated with a collective mechanism (a proto-institution in our model) and agents who are affiliated with a collective mechanism. Agents do not have an ability to choose to be part of a proto-institution and there are no dynamics related to agent features or characteristics that shape their choice such as may be found in employment, labor, or standards-driven models [18].

Our experimental foray is made with an awareness of the growing scope and scale of computational economics that begin at the bottom and grow their way up [19]. We want to examine as fully as possible the simplest form(s) of this differentiating dynamic. The example of Hamilton, ON in the 1850s provided the initial case study for the role that collective memberships may play in the structural dynamics of economic inequality [6] but we are not seeking to simulate that historical scenario in what follows.

2 Examples of Agent-Based Social Primitives

Agent-based models have been used in simple forms for a range of purposes. In what follows, we will examine Ring World and the Game of Life in the context of reflections on complex adaptive systems and a smoking cessation case study that tested the value of agent-based models for policy decision input.

2.1 Ring World

The value of artificial societies can be understood by using a framework that begins with simple elements and builds complexity on top of that [20]. Epstein and Axtell began with the assumption that if you could begin with agents and grow an artificial society that mirrored known, empirical dynamics, then you would have understood the dynamics involved. The most simplest model they proposed was Ring World.

In Ring World, the landscape is simplified as a connected ring with sugar levels of 4 assigned to each space at each step. During each time step, an agent in Ring World looks for the nearest unoccupied site with maximum sugar. If there are two agents in the ring and they get near to each other, then the logic of the coding says that an agent behind another agent won't take the occupied site but will take the site just ahead of the other agent—nearest with most sugar. Now the agent that got leap frogged will do the same. This creates a dynamic where they move together, apparently forming a group or clique. The agents "do stay together once they randomly encounter each other" [20]. They discovered a wide range of behaviors for this simple artificial set-up.

The relationship between individual agents and the larger modeling environment is complex so that the effect of agent action on larger social structures at different scales represents a significant challenge [21]. It is possible to link the endogenous agent dynamics with larger systems effects [22], but the intricacies of dynamics between and across social structures require careful interrogation of the source of those dynamics.

Our interest is in the nature of inequality and the role of a collective function among agents which, in the case of Ring World, is an artifact of the systems code—an agent-environment coupling. Agents are not able to cooperate in any way—they do not communicate, exchange information, or decide it is better to be in a group. The cliques that form result from interaction effects, important as examples of how emergence can occur, but not an example of cooperative behavior.[1] This is a significant primitive dynamic. There are clues in Growing Artificial Societies that point to even more

[1] Although outside the scope of this paper, it is important to note John Von Neumann's work on **one dimensional cellular automata**: "John Von Neumann in the late 1940s undertook analysis of machine reproduction under the suggestion of Stanislaw M. Ulam. It was later completed and documented by Arthur W. Burks in the 1960s. Other two-dimensional cellular automata, and particularly the game of "Life," were explored by John Conway in the 1970s. Many others have since researched CA's. In the late 1970s and 1980s Chris Langton, Tom Toffoli and Stephen Wolfram

primitive dynamics (e.g., Appendix A: Software Engineering Aspects of Artificial Societies, p15 on "agent-environment and agent-agent" interactions, p19 note 23 on formal descriptions of landscape and agent states, etc.) but the primary focus was on adding complexity (reproduction, trade, conflict) rather than interrogating simplicity even further.

2.2 Conway—Game of Life

The famous "Game of Life" program developed by John Conway represents an early cellular automata model and a component of current agent-based models—typically the landscape or environment [20]. The discovery Conway made was that simple rules in a 2D grid where cells were affected by the state of their neighbors could lead to unexpected artifacts that would glide across the screen, blink, and undergo a range of other distinctive dynamics. Like the Ring World example above, the cells could evaluate the state of their neighbors but couldn't communicate in richer ways. These simple limits, however, gave rise to unexpected, complex behavior. Do those emergent patterns constitute cooperation? Do collections of cells in a common state ("alive") such as a glider represent a highly primitive form of inequality (vs. "dead" cells). Game of Life has been referenced in a wide range of disciplines as a source of insight about computational dynamics [23, 24] but more intensive interrogation about the "simplest possible states of inequality" may still be required.

2.3 Complexity Adaptive Systems—Page and Miller

Agent sophistication is a central consideration in developing social models [25]. In Ring World, the agents are very limited with only a simple set of instructions and very low dynamic range—move to nearest unoccupied space with most sugar. The problem is that model builders have not been as clear about the range of sophistication from the "hyperrational, hyperinformed, hyperable" agent to the "myopic simpleton" [25].

Moving from particle to fully functioning social system represents the introduction of many potentially confounding variables in virtual settings. The central goal of this paper is the identification of social primitives including critical analysis of the simplest possible model of institutions. There are not agreed to ways of establishing the exact nature of agent sophistication. That means, in turn, that we do not have an established means of differentiating levels of agent sophistication. Do we proceed by

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did some notable research. Wolfram classified all 256 one-dimensional two-state single-neighbor cellular automata. In his recent book, "A New Kind of Science," Wolfram presents many examples of cellular automata and argues for their fundamental importance in doing science." (Description from the "Info" section of the CA 1D NetLogo Model Library, accessed June 2, 2019).

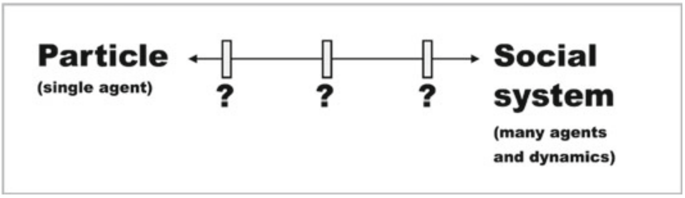

Fig. 1 Moving right increases sophistication and reflects emergence. Moving left reduces sophistication and reflects reduction. A taxonomy of critical transition points could be developed across this spectrum. We do not know if there are stopping points, if they are evenly spaced, or what effects may result from various interactions. It may be that emerging fields like chemoinformatics [28] that map massive possible chemical spaces could be instructive if applied to the design of new institutions, models, or feature sets [3]. Even simple physical systems like a sand pile make decomposition difficult—if you take sand away from a pile one grain at a time, at what point does it cease to be a sand pile [29]?

additive steps—absolute simplest and then add? Do we proceed by decomposition—take a suitable working model and then keep removing things until we are down to primitives, noting the effects along the way? Or are there other methods such as phase space/behavior space exploration but for sophistication rather than for known parameter variables in a model? (Fig. 1). Social primitives research requires that we interrogate the “myopic simpleton” side of the spectrum so that increases in sophistication are well understood [25]. Network science research discovered that a circle of nodes connected to first and second neighbors had a sudden decrease in average distance when nodes were randomly re-wired [26]. This dynamic was not owing to smarter or more capable nodes—they all remained homogenous. The sudden decrease in average distance between nodes was an artifact of the structural change in the network. Simple changes with significant dynamic impacts are an important feature of primitive systems [27].

2.4 Hammond—Tobacco and Policy—Low-Dimensional and High-Dimensional Models

A good example of a real-world problem being addressed by a very disciplined application of agent-based models is the tobacco use cessation study by Hammond that formally reviewed agent-based models in a highly disciplined way to answer an important public policy question about strategies to decrease tobacco use [30]. That discipline included identification of models that ranges from low-dimensional to high-dimensional approaches that are potentially useful and others that are potentially hazardous. Of particular interest was the effort to help individuals stop smoking. Aggregate data was useful descriptively but not in terms of understanding how smoking cessation actually worked for individuals. Agent-based models were identified as potentially relevant in understanding these dynamics.

The authors remark that the ability to run a given scenario over and over while changing variables can provide insight into either a strategic direction or introduce caution and more realistic expectations regarding various policy changes. For example, it is intuitive that increasing the legal age for smoking would prevent tobacco use but it may well drive up delinquent behavior as informal sources are pursued by underage smokers. Understanding the actual cessation causes would be necessary to determine which interventions would be most likely to yield desired results.

3 Taxonomy of Social Primitives

Examination of a relational dynamic requires elements that can interact. Agents, landscapes or environments, and some form of agent-level dynamic change are required. It can be challenging to fully specify the parameter space of a model even for simple dynamics. Implicit assumptions can also enter the model unwittingly through computing structures, coding approaches, language use and are of particular importance for the social primitives effort.

3.1 Agent Description

When we are interrogating the idea of social primitives, we must remain focused on systematic reviews of all features and elements. Agents are specific entities in an agent-based model. They are objects that are given characteristics, all of which are mathematically defined through the code. The idea of a relation using agents requires that there are at least two entities or objects that can be differentiated from each other and that they are able to interact in some way—either directly with each other or by means of something in the environment—such that the interaction changes something about a given agent (more or less of a resource, some characteristic of the agent, or a novel characteristic associated with the interaction such as becoming a member of a common group).

If we move beyond two agents, we must answer a range of questions: How many agents will populate a virtual landscape? How do they get there? What do they do when they arrive on the landscape? What cannot they do? How do they leave the simulation? What information do we collect on them? Agents can be in social networks without spatial definition, on landscapes that are constrained in two dimensions, others that operate in three dimensions, and they can possess an unlimited range of features that deeply impact the evolution and characteristics of the model.

3.2 Coding Agents and the Challenge of Implicit Assumptions

When a common term list of agent features is identified, translation of those terms into code suitable to run a model is another juncture where subtle influences may affect the effort to reduce unknown or unaccounted variables. Building agents from scratch is one way of minimizing this effect. Using code that is pre-built or models that are pre-built requires great watchfulness along this line. It would be useful to have a taxonomy of agents that range smoothly from the simplest possible agent up to the most sophisticated agent. Some earlier attempts to explore this can be glimpsed in Von Neumann's exploration of automata that are able to reproduce themselves [31] but computational sophistication has pushed us much more naturally to increasing agent, landscape, and social network features rather than making them more simple, fundamental and thoroughly understood.

3.3 Environment Description

Spatial, social, and a wide range of other real-world features are often built into our modeling environments with a noble intent—creating a model that is similar to the real world in ways that are useful, generate insight, and that can communicate results to those who are trying to understand a given problem. As with agents, these environments have grown dramatically in scope and scale so that whole cities, even the full global compliment of +7B people can be housed in silico for our experimental purposes [32].

3.4 Coding the Environment and the Challenge of Implicit Assumptions

As with agents, characteristics of an environment (whether social, spatial or otherwise) must be translated into computer code by programmers. Evolving platforms for collaboration reflect how challenging it is to balance domain expertise and knowledge with code-writing capabilities. Conceptual and aspirational hopes from people who know a social or cultural setting—e.g., people interested in effective policy change around smoking cessation—are converted into Python (via the Mesa framework), R, Julia, NetLogo, GNU SWARM, Java (via MASON or Repast) or similar programming environments so that iterations can be run and data collected. Coding and domain complexity means that no one person can fully synthesize these differences—they are negotiated among teams and groups who work together.

Our most difficult challenge is giving due consideration to the role played by the meta-control of the coding environment. This also includes the way in which models are processed computationally, as serial systems, however quickly they are cycled. As noted above, the review of agent status and initiation of proto-institutions under certain conditions is the point at subtle details such as order, timing, and updating become much more important.

The gap is ripe for unwitting importation of assumptions; so, we need increased rigor to clearly understand the source of information coming out of models. It may be that fields such as swarm robotics hold promise for enacting more effective parallel agent interactions where each "agent" (individual swarm bot) operates without needing a procedure order from a controlling piece of code [33]. Robot swarms may be a way of operating truly parallel systems rather than the very fast but serial nature of many ABM computational model.

We are examining proto-institutions and their role in wealth inequality (resource distribution) without true agent cooperation. This is work contributes to the structural features of common pool resource dynamics but without the dynamics of cognition-driven agency. These simplifications are intentional, an experimental design approach focused on how proto-institutions change the evolution of a simple isomorphic system toward unequal distribution.

What is the operating framework doing, or, more specifically, how do we take stock of this functional framework as a contributor to the model's evolution? What order of operations do we follow when doing updates? Which agents go first? How are the patches in a 2D model seeded with resources—all at once or serially? In the notionally simple example of Ring World, the order of agent updates is noted as an important factor since in the execution of the operations, agents do move in a sequential set of turns but are updated randomly [20]. While Ring World may be robust to randomization of agent order, it suggests that this may not be a safe assumption in all cases and warrants more intensive examination.

Inequality and institutions research may also benefit from finding ways to encode both the agents and landscapes in ways that allow the institutional function to emerge out of agent interactions without prior specification. Would it be more logical to put agents into a landscape with no pre-coded "proto-institution" function and then see if a common pool dynamic would eventually emerge? In a fully constrained environment like a computational language with a given logic structure, novelty and mutation may be introduced through features such as genetic algorithms that can modify themselves [34–36]. These adaptive software structures can be applied to problems as diverse as detecting community structures in data or playing solos in a virtual jazz quartet. Our model uses exogenous shocks and various landscape sugar distributions to introduce external variations that allow us to see the effects of proto-institution absence or presence. In these experimental design decisions, we have held to the basic explanatory framework:

> In Analytical Sociology, the phenomena to be explained typically are important aggregate or macro outcomes such as network structures, segregation patterns, inequalities, cultural tastes and common ways of acting. The entities we refer to in the explanation typically are individuals, and the activities referred to are the behavior of these individuals [3].

These disruptions or nudges along the run of the model lead to insight about common pool resources [37, 38] that may provide important clues.

4 Coding a Social Primitives Model: The SPECscape Model

Just as a detailed party plan for 3-year olds may not survive contact with actual humans [39], a conceptual model may have difficulty with translation into a functional coding environment. We detail below work that we did to translate the social primitives concepts into a coded model capable of iterating dynamics suitable for graphing and comparison with our "as simple as possible" goal.

4.1 Agent to Agent Interaction

The 2D landscape version of our Social Primitives Experimental Cohort (SPEC) model features a range of agent, landscape, and meta-variables (the **SPECscape** model). Agents are very simple with basic landscape search and consume features and no means of communicating with each other directly. The ability (or inability) to communicate is a central dynamic for social modeling that needs to be clearly described given the impact of interaction (communication?) on model dynamics [25]. Efforts toward development of true primitives must show the kind of decomposition of capabilities so that communication is either clearly explained as pre-determined (coded into the model) or is one of the emergent properties that a model seeks to explain through changes in model variables that lead to communication.

Our SPECscape model agents possess an information exchange capability that is triggered under certain conditions. Agents cannot occupy a space that is already occupied by another agent.[2] If, however, an agent moves into a space adjacent to another agent in a North/South/East/West (NSEW) configuration (no diagonals to maintain all possible simplicity), then a sugar-level evaluation is made by the "supervising" code. If they both have enough sugar above a threshold, then a proto-institution is formed and each agent is considered to be a member of that new "virtual" entity.

An important distinction in the SPECscape model is the nature of the proto-institution. The primary function of this entity is to hold surplus sugar that is deposited by agents who then become its "members", manage a list of its member agents it, and dispense sugar when member agents require it. The proto-institution does not occupy a space on the landscape and does not interact with agents except as a secondary function. It may be useful to think about the proto-institution as a ledger of agents that have met the conditions required for membership (viz., surplus sugar

[2] Simultaneous occupation of a cell by more than one agent is often not specified or noted in any way. In NetLogo, for example, this can occur as matter of course given the unseen background coding.

and proximity to another agent that is, or can become a member of, an institution). As a ledger, it does not have the features or characteristics of an agent and does not occupy space on the 2D landscape. If sufficient sugar for a given agent to survive is not obtained by consuming 2D grid sugar and that agent is on the ledger, the proto-institution tops up the agent to enable it to continue to function. If the proto-institution runs out of sugar to dispense, the ledger is reset by releasing the agents. Subsequently, these free agents may happen upon more sugar or die, as the case may be. If they survive and thrive long enough, they can join another institution (new or existing) using the same mechanism as earlier.

Two agents meeting the above conditions lead to formation of a proto-institution. An unaffiliated agent may join an existing proto-institution if it is in proximity to an agent that is already a member of a proto-institution (and if that unaffiliated agent meets the excess sugar requirement). Once the joining agent becomes part of the proto-institution, it can draw on proto-institution resources as needed.

This description is a form of "communication as information exchange" but it does not take place independently in an agent-to-agent mode. The framework coding provides the exchange and enacting of a proto-institution with membership. As members, agents cannot look to see what other agents are doing or gain any information about those agents. The proto-institution manages its membership lists, sugar-reading, and allocating functions.

4.2 Agent-Environment Interaction

The environment is an essential part of the 2D SPECscape model. As such, the dynamics of agent with landscape must be carefully interrogated. As outlined above, at the beginning of a simulation run, agents are randomly placed on the 2D grid landscape where each cell can be occupied by just one agent at a time. Once on the grid, agents are capable of examining each (NSEW) cell adjacent (or further as a function of "vision"), identifying the cell with the most sugar (or, if more than one are highest, randomly choosing from among equal high sugar cells), and then moving there. The sugar is "consumed" (added to the agents existing sugar level) and the agent repeats the process. Agents who are members of a proto-institution can access the sugar as described earlier from any point in the 2D landscape.

4.3 Anthropomorphic Crossover

As noted previously, one of the considerable challenges in the design, coding, and execution of models is the language we use to describe what is happening. It is difficult *not* to describe agents, landscapes, and functions in anthropomorphic terms even when the functions are devoid of anything human (e.g., suggesting agents "consume sugar" is shorthand for a direct mathematical calculation within fully proscribed parameters).

4.3.1 Perception of Cooperation: Ring World, Game of Life, and Simulated Cooperation

When independent agents in a model begin to move together, it is natural to make a simple leap in language and call that motion "cooperative" or even a "behavior" even where the agents lack cooperative features. It may be that this is something like cooperative behavior. The explanatory power arises from the linkage between simple rules in behavioral entities like ants, birds and fish, where proximity, following, and adjusting path functions at an individual level produce swarms, flocks, and schools, respectively [40]. Ring World produced "cliques" of agents that moved around the ring together and even sped up so that a clique would overtake and incorporate solitary agents moving around the ring (up to the point where the clique size exceeded the "vision forward" parameter coded into the agents' search function).

The question for clarification is whether or not this qualifies as cooperation in the way that we usually understand that term. We would argue that it is not cooperation (whether in Ring World, Game of Life, or other simple models) but must instead be understood as an artifact of the coding because agents in Ring World have no awareness of themselves or other agents and no means of exchanging information with the other agents. The only signal an agent gets is the result of the rule that they cannot move to a space occupied by another agent. Again, the agent doesn't know the space is occupied by another agent, the code is designed such that the search parameters excluded consideration of a space if another agent is there. It is possible to reproduce the appearance of real-world phenomena via a model that cannot be equated with the empirical dynamic.

4.3.2 Actual Cooperation

A human understanding of cooperation is an evolved attribute that requires memory of past interactions and the potential to envision possible future outcomes. We learn that cooperation may lead to improved odds of individual-level survival or other kinds of benefits while non-cooperation leads to lower returns, loss of benefits, or even penalties [41]. In humans, this is a highly developed function, one that can be transferred across generations via culture (societal memory) and appears to be encoded as a potential in brain circuitry via genetic mechanisms leading to predispositions physically that can be amplified in practice [42, 43].

4.3.3 Coding Equivalents

We may need to be clearer when describing code functions in human language. For example, agents in models like Ring World or even our SPECscape arrangement do not cooperate as we usually think of cooperation—they simply reference conditions such as a space being occupied or not. Cooperation requires communication. Referencing is a more code aligned way to think about what is happening. When we write that an agent "looks to see if a space is occupied by another agent" there are many anthropomorphic assumptions we translate in reading that line which are not present in the agents themselves. When we code a 2D grid, we are not creating a landscape as that term is normally used. We are mathematically specifying potential X/Y coordinates that will form the basis for additional X/Y coordinate calculations.

When building automobiles, the effects of forces like surface tension are not a high priority even though the forces are present. In contrast, when designing nanodevices surface tension becomes a major concern because of the role that these "small" forces play at that scale [44, 45]. If we are pursuing rigorous understanding of social primitives, it will be vital to be much more aware of how much conceptual transference, attribution, and effect arises from language concepts rather than from the models' direct dynamics. These considerations apply directly to the visualization aspects of models as well where our propensity to stitch across gaps in information so that we can assemble meaningful patterns can get in the way of analytic clarity, shaping our perceptions about what is real and what is imagined [46].

5 Running the SPECscape Model

The SPECscape model was run with three operating modes to determine the dynamic characteristics of the model. We begin with general observations about the Gini index measures of the models, use four different landscape resource starting points, introduce exogenous shocks at various stages of model evolution to test resilience, and end by looking at the effect on models both with and without proto-institution capability.

5.1 SPECscape Model and Gini Index

Overall, it is evident that in sugarscape instances where agents have the possibility of forming proto-institutions in partnership with other geographically proximal agents, the inequality in sugar (wealth) reduces over time, as seen in the Gini index of sugar level distributions gradually decreasing and reaching an asymptotically stable value, when aggregated across all model parameter combinations. In contrast, the Gini in sugarscape instances where agents do not have the possibility of forming proto-institutions, a similarly computed Gini value is both higher and has a significantly higher level, with a greater amount of fluctuation over time, aggregated across all model parameter combinations (Fig. 2). Consequently, we infer that the availability of sugar reserves stored in proto-institutions are likely to serve as buffers that help agents that are unable to find sugar on the sugarscape in meeting their sugar-related needs and increasing their likelihood of longer-term survival.

5.2 Four Landscape Starting Points

We next investigated whether the overall pattern of wealth inequality's evolution across time, where sugarscape instances that have proto-institution formations perform better (i.e., have a lower Gini coefficient) than those sugarscape instances where such possibility is lacking, holds true when disaggregated across the four specific types of sugarscape instances:

- one where the sugar levels across cells in the sugarscape are randomly drawn from a uniform distribution;
- one where the sugar levels across cells are distributed in a more deterministic manner, with a central region having the highest concentration of sugar, and the concentration of sugar decreasing symmetrically in all directions, varying (reducing) inversely based on the cubed distance of each cell from the central region of highest sugar concentration;
- one where the sugar levels across cells are distributed in a more deterministic manner, with two regions of maximal sugar concentration that are located at the centers of the north-east and south-west quadrants of the sugarscape, and the concentration of sugar decreasing symmetrically in all directions, varying (reducing) inversely based on the cube of the combined distance of each cell from the two regions of highest sugar concentration;
- one where the sugar levels across cells are distributed in a more deterministic manner, with four regions of maximal sugar concentration that are located at the centers of each of the four quadrants of the sugarscape, and the concentration of sugar decreasing symmetrically in all directions, varying (reducing) inversely based on the cube of the combined distance of each cell from the two regions of highest sugar concentration.

From the subplots, we infer that

- the overall pattern of sugarscape instances with proto-institutions having lower sugar level inequality, when compared to sugarscape instances without proto-institutions, holds true across the four types of sugarscape;
- the variation in the Gini coefficients, aggregated across all model combinations within each specific type of sugarscape is the least in the case of the 4-quadrant sugarscape instances, followed by the 2-quadrant sugarscape instances, and single area of concentration sugarscape instances, followed by the randomly-distribution sugarscape instances; the most stable, lowest inequality sugarscape instances

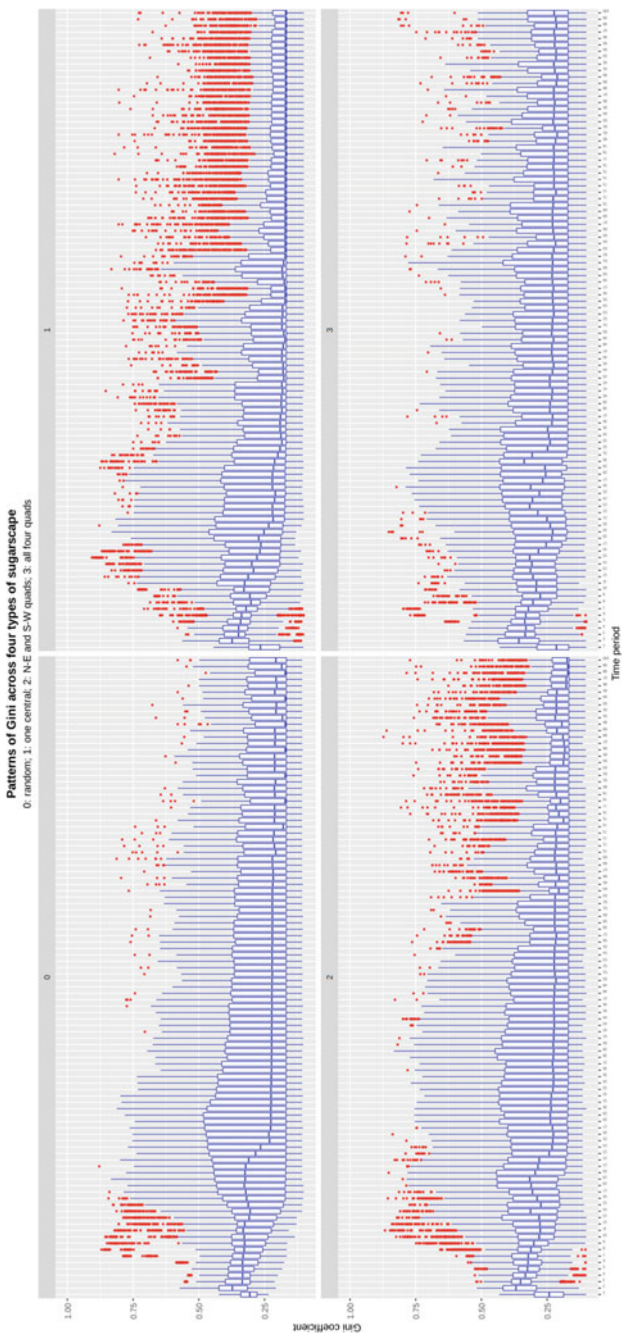

Fig. 2 Agent Ginis when landscape sugar value patterns are changed without proto-institutions

are to be found in the four-quadrant models where proto-institutions are present (Fig. 3).

5.3 The Effect of Exogenous Shocks at Various Stages of Model Evolution

Next, we analyzed the effect of environmental shock, represented in the form of a sudden decrease in the sugar level of every single cell in the sugarscape, affected the evolution of sugar (wealth) inequality in the sugarscape instances aggregated across all combinations of model parameters, but separated into three groups, one for each type of shock.

In the first group, no shock was present. In the second group, a single shock was delivered after roughly 1/3 of time periods have elapsed (so out of 100, at the end of time period 33) and in the third, a single shock was delivered after roughly 2/3 of time periods have elapsed (so out of 100, at the end of time period 66). We found that condition (a), wherein no shock was delivered, produced the most stable and lowest inequality in sugarscape agents' sugar levels followed by (b), and then by (c) (Fig. 4).

It appears that while having no shock produces the best outcome, having a shock earlier in their lifetime appears to allow sugarscape agents to recover and reach the same state as those in condition (a) during the last ~20 time periods. By contrast, when there are agents in sugarscape instances in condition (c), where a shock was delivered at the beginning of the last 1/3rd of the sugarscape instances' lifetime, the sugarscape instances' agents, as a whole, continued to experience fluctuations in both aggregate inequality, and in the asymptotic behavior prior to the end of the sugarscape instances' lifetime (of 100 periods). This provides further evidence that sugarscape instances require a long time to recover from the time when they experience shock, to settle down into a more stable distribution of sugar levels among their agents.

5.4 Models with and without Proto-institutions

We next sought to determine whether the patterns of perturbation and return to stability in the sugarscape instances agents' sugar levels' inequalities would differ between the conditions of proto-institutions could not be formed versus those where proto-institutions could be formed. We found that across all three shock types, sugarscape instances where proto-institutions could not be formed performed worse than those where proto-institutions could be formed. Additionally, these differences among the three shock types are not strongly distinguishable from each other, in sugarscape instances where proto-institutions could be formed (Fig. 5).

To verify the results intuited via the graphs, we performed a pooled panel regression analysis on the dataset consisting of agents' Gini coefficients across time as

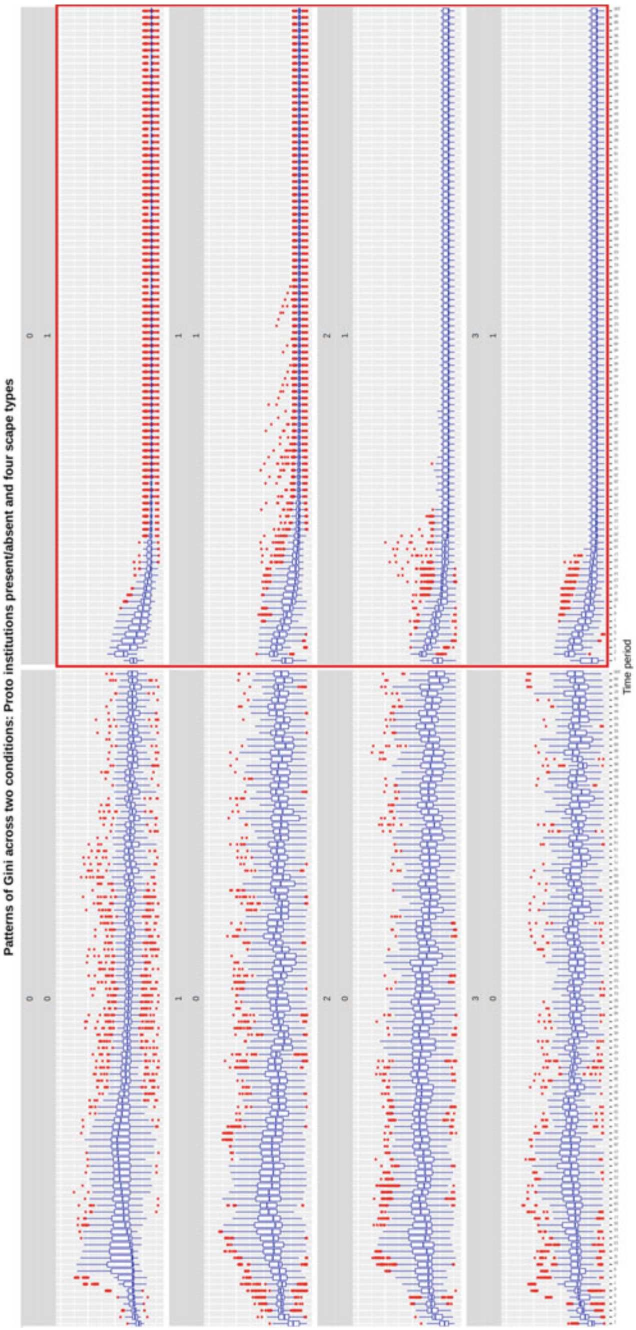

Fig. 3 Agent Ginis when landscape sugar patterns are changed and proto-institutions present (red box)

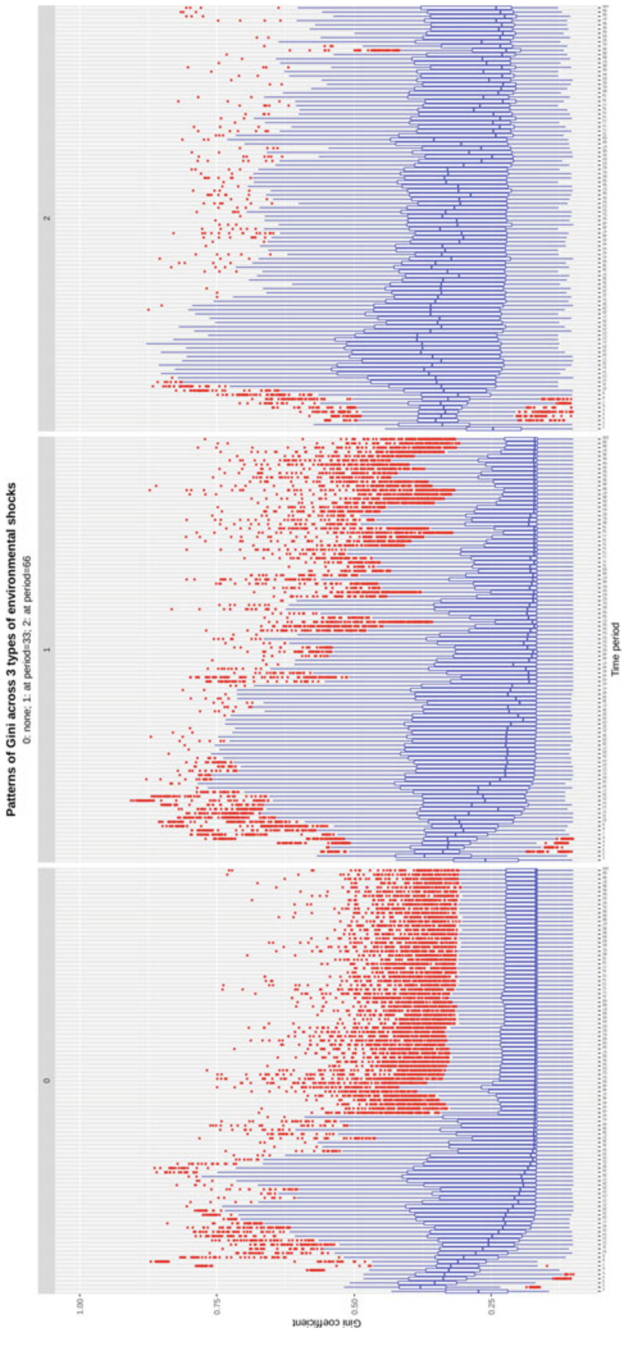

Fig. 4 Agent Ginis with exogenous shock (shortage) at beginning, time step 33, and time step 66 (of 100)

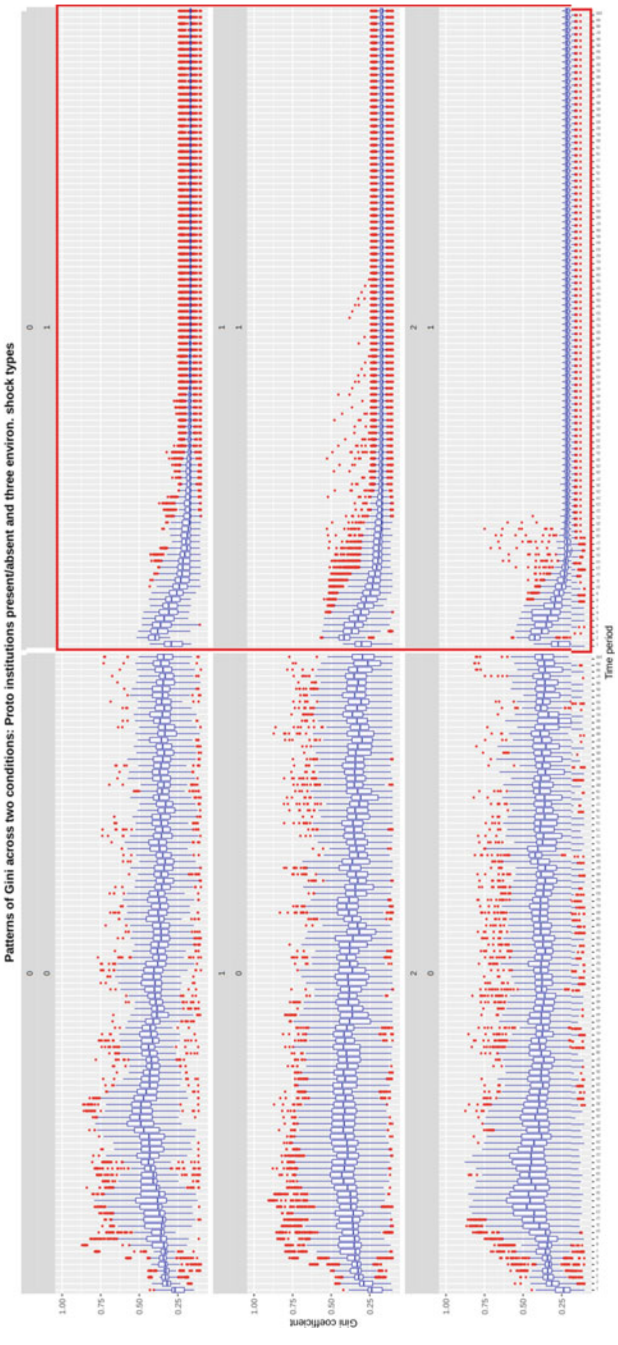

Fig. 5 Agent Ginis with exogenous shock (shortage) at beginning, time step 33, and time step 66 (of 100) but proto-institutions are present (red box)

the outcome variable, and all of the agent-based model's parameters as the predictor variables. Since we have different sugarscape instances, with different configurations and agent populations, for each combination of our simulation parameters, we analyzed the data using a pooled panel regression approach.

The following is the output of the pooled panel regression model. From the results, it is evident that (Fig. 6):

- the patterns of evolution agents' sugar levels' Ginis in each of the three non-random-distribution-of-sugar sugarscape configurations are significantly different from the patterns observed in the random sugarscape;
- the patterns of evolution agents' sugar levels' Ginis in both types of environmental shock situations are significantly different from the evolution of Ginis in the baseline category;

```
Unbalanced Panel: n = 129, T = 376-2600, N = 281295

Residuals:
    Min.   1st Qu.   Median   3rd Qu.     Max.
-0.394748 -0.070325 0.003037 0.066521 0.563736

Coefficients:
                                                Estimate  Std. Error
(Intercept)                                    0.39474762 0.00115417
as.factor(ScapeType)1                         -0.04544488 0.00112339
as.factor(ScapeType)2                         -0.00980199 0.00118004
as.factor(ScapeType)3                         -0.03129348 0.00125977
as.factor(ProtoPresent)1                      -0.21676892 0.00142485
as.factor(ShockType)1                         -0.04136747 0.00109462
as.factor(ShockType)2                         -0.01321831 0.00112347
as.factor(ProtoPresent)1:as.factor(ShockType)1     0.02489080 0.00131853
as.factor(ProtoPresent)1:as.factor(ShockType)2    -0.01020485 0.00146094
as.factor(ScapeType)1:as.factor(ProtoPresent)1     0.05204196 0.00147594
as.factor(ScapeType)2:as.factor(ProtoPresent)1    -0.00030962 0.00150192
as.factor(ScapeType)3:as.factor(ProtoPresent)1     0.00172500 0.00164786

                                                t-value  Pr(>|t|)
(Intercept)                                    342.0194 < 2.2e-16 ***
as.factor(ScapeType)1                          -40.4532 < 2.2e-16 ***
as.factor(ScapeType)2                           -8.3065 < 2.2e-16 ***
as.factor(ScapeType)3                          -24.8406 < 2.2e-16 ***
as.factor(ProtoPresent)1                      -152.1349 < 2.2e-16 ***
as.factor(ShockType)1                          -37.7917 < 2.2e-16 ***
as.factor(ShockType)2                          -11.7656 < 2.2e-16 ***
as.factor(ProtoPresent)1:as.factor(ShockType)1  18.8777 < 2.2e-16 ***
as.factor(ProtoPresent)1:as.factor(ShockType)2  -6.9851 2.852e-12 ***
as.factor(ScapeType)1:as.factor(ProtoPresent)1  35.2602 < 2.2e-16 ***
as.factor(ScapeType)2:as.factor(ProtoPresent)1  -0.2061   0.8367
as.factor(ScapeType)3:as.factor(ProtoPresent)1   1.0468   0.2952
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares:    6982.6
Residual Sum of Squares: 4510.7
R-Squared:      0.35401
Adj. R-Squared: 0.35399
F-statistic: 14013.3 on 11 and 281283 DF, p-value: < 2.22e-16
```

Fig. 6 Summary statistics of data generated by model

- these patterns are significantly different across sugarscape instances where proto-institution formation was present when compared to those sugarscape instances where proto-institution formation was absent. The other interactions included in our model were not significant.

6 Conclusion

These are early results that are exploring important dynamics present in the germinal evolution of cooperative behavior among agents that produces primitive institutions. While a great deal more work remains to be done, salient observations at this point in time can guide future work.

6.1 Elements of Collective Function

There is still a lot of research to be done in developing the SPECscape version of social primitives. One of the most persistent challenges in looking at non-primitive models is that model builders and domain experts are eager to apply their tools to actual human and social problems. This interest in direct equivalence means that more fundamental research about dynamics that are not immediately transferable are precluded [25]. While primitive elements may not apply directly to any real-world problem, they may turn out to be vital ingredients for more powerful, explanatory models that we would do well to understand:

> The origin of life question has played a central role in the biological sciences. Alas, the origin of social life has had much less attention. Such questions lie at the heart of understanding our world. How do we recognize social life? What are the minimum requirements for it to arise? What are the deep, common elements in a social system that transcend time and agents? Is social life inevitable? (Op. cit.)

Collective functions, whether as potential outcomes of other interactions or coded directly into a model, are root issues for analytical sociology, anthropology, political science, and other broad fields of human interaction. Paring down our agents and landscapes with a “how simple can we get” motive could promote new insights that are valuable beyond single domain settings.

6.2 Determining Anthropomorphic Leaps

Our language is a challenge in this endeavor. We describe “cliques” when agents have no means of interacting. Dynamic patterns appear to us like purposeful direction even when it is not possible for agents to exercise foresight. We take an empirical example, build a model, and then use the language of the empirical setting to bridge to our model. In the process, we smuggle more meaning into our models than we should. These anthropomorphic leaps represent a habit, witnessed in many modeling papers and presentations, which is clearly useful but may amplify unintentionally the meaning of a model beyond what is responsible.

6.3 Determining a Parameter-Based Measure of Model Complexity

Another challenge is careful delineation of model parameters. This builds on the noted differentiation between parameters that operate the modeling framework and parameters that alter the behavioural capabilities of agents. Parameter accounting needs a similar clarification (see Appendix for full description of SPECscape model parameters).

Our hope is that these types of clarifications would put the work of exploring social primitives more squarely in the path of error rather than confusion. From that clarity, better approaches have a greater chance of being developed.

6.4 Possibilities for Increasing the Complexity of SPECscape Model

6.4.1 Expanding on SPECscape with SPECnet Approaches

One of the ways by which to make the SPECscape model more complex would be the addition of stronger agent-to-agent ties. Using a network model, another group of researchers has adopted the SPECscape objectives and parameters as much as possible but without the 2D grid. Instead, a network model is used where there are no spatial considerations, only relational ties. This approach raises many of the same concerns and possibilities that were discovered in earlier attempts to determine formal means of comparing two models—what the authors called “docking” [2]. This is an evolving project; equivalence and alignment were pursued through the development of common agent and proto-institution capabilities in all respects except where it was necessary to deviate on the “relational vs. spatial” designs of the model structure.

6.4.2 SPEC [Other]

There are other ways to develop aligned or equivalent models with modalities that may be different than either SPECscape or SPECnet. Some of these possibilities include hybrids of these two early types, the addition of agent characteristics, proto-institution interactions both with agents and each other. These different approaches could arise from empirically informed modifications such as repetitive transactions that lead to cooperative behavior that is formally "institutionalized" via proto-institution membership akin to the "community lending societies" like credit unions/chit funds/etc. This approach would be in contrast to the purely network-based approach that is being explored in a sibling project—SPECnet. Future work could include development of a set of primitives that could lead to more realistic cooperative behavior. These may be sets of rules based on game theory, network dynamics, interactive genetic algorithms, or other dynamic modeling approaches.

Appendix

SPECscape model parameters, ranges of values, and description. Given the significant number of possible combinations, the Nearly Orthogonal Latin Hypercube is used to sample the behavior space of the model.

Parameter	Min value	Max value	Description
Side	5	100	Side of the sugarscape. Total cells = side * side—e.g., 10 side = 100 cells
Capacity	1	12	Carrying capacity within each cell. Assigned individually for each cell, drawn from a range [1, maxval]. Max. value is determined for each combination via the NOLH design
RegRate	1	5	Regrowth rate for each cell. Assigned using the same approach as capacity
Adensity	0.1	0.4	Agent population's density: no. of agents at the start of a simulation run for a given parameter combination = area of sugarscape * agent density, rounded to nearest integer
MtblRate	1	3	Metabolic rate: Number of units of sugar an agent needs to consume to stay "active" (i.e., not starve) during each time step. Assigned from a uniform distribution [1, maxval], where maxval is determined for each combination via the NOLH design
VsnRng	1	7	Vision Range: Number of cells in the NESW directions (von-Neumann) an agent can see on the sugarscape (cannot see beyond the boundary). Assigned from a uniform distribution [1, maxval], where maxval is determined for each combination via the NOLH design
InitSgLvl	1	12	Initial sugar level with which an agent enters the sugarscape. Assigned from a uniform distribution [1, maxval], where maxval is determined for each combination via the NOLH design

(continued)

(continued)

Parameter	Min value	Max value	Description
Birthrate	0	0.3	Number of agents added during each time step, in proportion to the number of agents alive at the beginning of the time step. Assigned from a uniform distribution [1, maxval], where maxval is determined for each combination via the NOLH design
InbndRt	0	0.45	In-bound Rate: Number of agents migrating inwards (currently indistinguishable from birth; in future birth rate can be used to determine agents produced via "interaction" between a "couple" of agents). Assigned from a uniform distribution [1, maxval], where maxval is determined for each combination via the NOLH design
OtbndRt	0	0.2	Out-bound Rate: Probability value determining the likelihood of an agent that is currently in a starvation state migrates out of the sugarscape. Assigned from a uniform distribution [1, maxval], where maxval is determined for each combination via the NOLH design
Threshold	1	2	Amount of excess sugar needed (constant for all agents in a given sugarscape) to form/join a proto-institution by forming an alliance with a geographically proximal agent, who also has excess sugar available to contribute
ResilienceTime	1	25	Number of time steps an agent can remain in starvation mode, prior to departing the sugarscape via death. Assigned individually for each agent, drawn from a range [1, maxval]. Max. value is determined for each combination via the NOLH design
ScapeType	0	3	One of four sugarscape types constant across all cells. Each cell's initial sugar level is initialized to: (0) a random value, (1) a central region with maximal sugar value, and sugar level falling off uniformly as an inverse power of 0.3 with distance (2) two regions of maximal sugar value, located in the north-east and south- west quadrants (3) four regions of maximal sugar value, located roughly in the middle of each of the four quadrants

(continued)

(continued)

Parameter	Min value	Max value	Description
StrvFeedPcnt	0	0.2	Starvation Mode Feed Percent: Value by which a starving agent's metabolic rate (amount of sugar needed to be consumed in each time step) reduces when the agent is in starvation mode. This represents a continual reduction in the metabolic rate, as time progresses—eventually leading to death if the agent does not migrate out, or find a sugar-rich cell to come out of starvation. Assigned individually for each agent, drawn from a range [1, maxval]. Max. value is determined for each combination via the NOLH design
ProtoPresent	0	1	Identifier for whether proto-institutions can form or not in a given sugarscape—does not change over time. Determined at the beginning of a simulation via NOLH design
VisRedPcnt	0.01	0.6	Vision Reduction Percentage: Value by which a starving agent's vision rate reduces when the agent is in starvation mode. This represents a continual reduction in the agent's ability to look around its neighborhood for sugar rate, as time progresses. So the longer an agent exists in starvation mode, the narrower is the space it can investigate for sugar, thereby creating a vicious cycle of sugar poverty. An agent's vision is restored to its original value when it finds a sugar-rich cell and exits starvation mode. Assigned individually for each agent, drawn from a range [1, maxval]. Max. value is determined for each combination via the NOLH design

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