Unraveling Ancient Mysteries: Reimagining the Past Using Evolutionary Computation in a Complex Gaming Environment

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***Abstract*—In this paper, we use principles from game theory, computer gaming, and evolutionary computation to produce a framework for investigating one of the great mysteries of the ancient Americas: why did the pre-Hispanic Pueblo (Anasazi) peoples leave large portions of their territories in the late A.D. 1200s? The gaming concept is overlaid on a large-scale agent-based simulation of the Anasazi. Agents in this game use a cultural algorithm framework to modify their finite-state automata (FSA) controllers following the work of Fogel (1966). In the game, there can be two kinds of active agents: scripted and unscripted. Unscripted agents attempt to maximize their survivability, whereas scripted agents can be used to test the impact that various pure and compound strategies for cooperation and defection have on the social structures produced by the overall system.**

The goal of our experiments here is to determine the extent to which cooperation and competition need to be present among the agent households in order to produce a population structure and spatial distribution similar to what has been observed archaeologically. We do this by embedding a "trust in networks" game within the simulation. In this game, agents can choose from three pure strategies: *defect, trust*, and *inspect*. This game does not have a pure Nash equilibrium but instead has a mixed strategy Nash equilibrium such that a certain proportion of the population uses each at every time step, where the proportion relates to the quality of the signal used by the inspectors to predict defection.

We use the cultural algorithm to help us determine what the mix of strategies might have been like in the prehistoric population. The simulation results indeed suggest a mixed strategy consisting of *defectors, inspectors*, and *trustors* was necessary to produce results compatible with the archaeological data. It is suggested that the presence of defectors derives from the unreliability of the signal which increases under drought conditions and produced increased stress on Anasazi communities and may have contributed to their departure.

***Index Terms*—Archaeological simulation, complex systems, computer gaming, cultural algorithms, defection, evolution of cooperation, evolutionary computation, intelligent agents, reciprocity.**

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I. Introduction

While computer gaming has been successful in transporting gamers to unique and exotic worlds, as well as immersing them in worlds of the reimagined past, our goal here is to investigate their use in discovering answers to ancient mysteries that have fascinated research scientists for decades. To do this requires combining knowledge from many sources to recreate an environment that is as close to the historical one as possible and to make the participating agents realistic using artificial intelligence technology. We can then embed an active agent in the environment and use it to systematically test various hypotheses concerning emergent system phenomena. Here, we demonstrate the potential of such an approach as we investigate one of the major mysteries in the prehistoric North American Southwest: what happened to the ancient Anasazi?

Sites and artifacts in what is today southwestern Colorado tell the story of agricultural peoples who endured for hundreds of years, discovering and using clay and stone resources, raising corn, beans, and squash, mastering hunting techniques, domesticating and raising turkeys, producing crafts, and building striking pueblos. Our 1816 sq. km. study area lies within the Mesa Verde region which, like all the northern Southwest, was depopulated in the late A.D. 1200s following 700 years of farming use, leaving behind thousands of pueblos on mesa tops and nestled in canyons. Their departure is one of the great mysteries of the ancient Americas; the problem is not so much where they went—although some perished in place, it is known that areas to the south and southeast gained in population at this time—but why did they leave?

Many reasons for their departure have been proposed. These include a cooler and dryer climate, disease, social conflict, and depleted regional resources. Recently, a multiagent simulation was designed to relive 400 years of prehistory with a degree of realism that includes a realistic terrain, maize productivity measures over that period developed using tree-ring proxies, and intelligent artifacts of highly sophisticated and cultural agents. The initial multiagent "Village" simulation written in the Swarm modeling system was developed to examine the settlement and farming practices of the Pueblo Indians of the Central Mesa Verde region of Southwest Colorado from A.D. 900 to A.D. 1300 by Kohler *et al.* [1]. The simulation uses detailed data from many sources, including archeological sites, soil maps, and tree-ring sequences [2].

In Kohler's initial simulation, the agent households did not interact socially. Each attempted to optimize its own productivity. One hypothesis guiding this work was that the drier con-

Fig. 1. Three-dimensional snapshot of the game concept illustrating a simulated terrain and realistic visualization.

ditions documented for the late A.D. 1200s [3] would be sufficient to force farmers out of the study area. The model did not generate the expected depopulation, however, suggesting to Kohler that other, perhaps social, factors had a role to play in the depopulation.

Since then, these simulations have been elaborated in three different directions. First, we have made numerous improvements in the realism and detail of the landscape, including new paleo-productivity reconstructions using additional tree-ring data to extend the simulation back in time to A.D. 600 and take into account the deleterious effects of cold temperatures on maize production. This work has also added the capacity to "grow" and harvest forests for fuel wood, and estimate animal productivity spatially and temporally [4].

Second, work by Reynolds and Kobti [5]–[9] has focused on introducing social networks based upon kinship and generalized reciprocal exchange into the model in order to update the simulation within a cultural algorithm framework [10], [11]. In the near future, these two regional modeling efforts will be joined. In this paper, we use the Reynolds and Kobti updates to the original simulation model as a framework in which to embed our game.

A third approach involves a "day in the life of an Anasazi" game concept being designed at the Artificial Intelligence Laboratory at Wayne State University. Fig. 1 illustrates the three-dimensional (3-D) terrain for the game showing the human-controlled player standing near his crop of maize. In this game, a player is the head of an active household. The objective is to optimize your acquisition of a resource during a period of several days by interacting with the environment and other agents through exchange, warfare (raiding), ritual, and religious activities. An agent needs to determine how best to allocate its resources among these various activities on a daily basis.

By interacting with others, the player can establish a network of dependencies and relationships to cause people to move with him out of the study area. The player can use whatever social techniques are beneficial in amplifying his power to persuade others to leave along with him. Such mechanisms are of particular theoretical interest in largely egalitarian societies where the "reverse dominance hierarchy" in which followers dominate leaders [12] is breaking down, as may have been the case under the political and population pressures experienced in this area in the A.D. 1200s [13].

In this paper, we focus on the second direction, the regional model of evolving social networks. These networks are composed of autonomous agents (households) that are intelligent and capable of individual and cultural learning. Each agent is controlled using a complex finite-state machine, the details of which will be described later. Both cultural and individual learning takes place in the context of this machine via the adjustment of its parameters, arcs, and nodes. Thus, evolution proceeds through the modification of finite state machines, one of the earliest methods for modeling evolutionary learning proposed by Fogel *et al.* [14].

The agent household is able to interact with other agents and influence both individual and cultural learning in many ways. In this paper, we focus on the exchange of resources between households. This is particularly important since the unpredictability and variability of the environment can make it likely that household's performance in a given year may fall below what it needs to survive. Thus, households must procure needed resources from elsewhere. Here, we focus only on the exchange of corn that provides the caloric intake for our agents.

Two basic models for exchange are used here: generalized reciprocal exchange between related individuals, and balanced reciprocal exchange between kin and nonkin. In the former, individuals can request resources from kin with no explicit requirement to pay them back. In the latter, there is a deferred exchange plus interest with either kin or nonkin.

In either case, an agent can request and receive goods from another household and in the future either cooperates or defects when the household asks for something in return. Much work has been done following Axelrod's early work [15] on evolution-based approaches to playing cooperative games such as the prisoner's dilemma, iterated prisoner's dilemma, and others [16]–[19].

Our goal is to examine the extent to which cooperation and competition needs to be present among the agent households to produce a population structure and distribution similar to what has been observed archaeologically. According to Gintis [34, p. xxviii], "game theory is a language and a set of analytical tools for modeling an aspect of social reality with perfect clarity." While many games can be embedded in the simulation to examine these issues, we use one simple game here, the "Trust in Networks" game. This is an example of a strategic interaction, evolutionary game. We view this game as a simplified version of our more realistic version. The analytical results known for this game can be used as a paradigm or prism within which to test and understand the behavior of our more complex version.

In the "Trust in Networks" game, there are three pure strategies, "Inspect," "Trust," and "Defect" [20]. A defector defects unconditionally against all partners. A *Truster* unconditionally trusts their partner and will always donate goods when asked if available. *Inspectors* monitor an imperfect signal that indicates whether a possible partner defects against cooperators.

TABLE I
PAYOFF GAME MATRIX

	Inspect	Trust	Defect
Inspect	p^2 p^2	p p	-2(1-p) 2(1-p)
Trust	p p	1 1	-2 2
Defect	2(1-p) -2(1-p)	2 -2	-1 -1

The signal that is produced is a probability $\mathrm{p} > 1/2$ that identifies a defector, and a nondefector with the same probability p. The *inspector* refuses to trade with a player who is signaled as a defector and otherwise will play a cooperative strategy. A nontrading player has a payoff of 0. The normal form for the payoff matrix of the game is given in Table I.

A mixed strategy for this network is a population with α *inspectors*, β *trusters*, and 1-α-β *defectors*. It can be shown there is no pure strategy Nash equilibria for this game, and that when the probability signal is greater than or equal to $3/4$, there can be no Nash equilibrium involving only two types of players. Thus, all three strategies must be present, with the number of *defector* types decreasing as p increases to 1.

The analytical behavior of this above model can be used to establish a benchmark against which to compare the behavior of our more detailed evolutionary model. For example, if we inject pure defectors into the model, individuals in the population should be able to learn who to trust completely and who to inspect. These strategies should emerge in the population and if the mixed strategy hypothesis is correct, coexist with the defectors in proportions that approximate what they might be in a mixed strategy Nash equilibrium for the more detailed version. In other words, there is no way to "punish" defectors explicitly in the game or our version, so they will not disappear since the signal used to detect them is not perfect.

In Section II, we describe the cultural algorithm framework within which the game is being embedded here. Section III describes the basic agent structure, knowledge, and their evolutionary learning. In Section IV, the basic social relations between agents used here are described.

In Section V, we inject defectors into the model and then observe the extent to which "Trust" and "Inspect" behaviors will emerge in the population. The extent to which the latter develop will be a function of how well the individuals can learn to identify and predict the signals of others using the cultural evolutionary framework. In Section VI, we describe a sequence of experiments that show how and why the mixed strategy needs to be present in the evolving population in order for the results to be compatible with predictions made by the archaeological data. The conclusions and suggestions for future work are given in Section VII.

II. MODELING CULTURAL EVOLUTION

A. Cultural Algorithms

Cultural algorithms consist of a social population and a belief space [9], as shown in Fig. 2. Selected individuals from the population space contribute to cultural knowledge by means of the acceptance function.

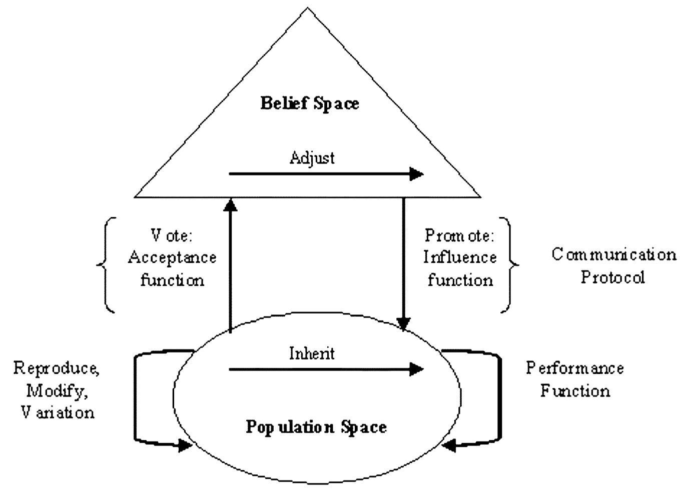


Fig. 2. Cultural algorithm framework.

The cultural knowledge resides in the belief space where it is stored and updated based on individual experiences and their successes or failures. In turn, the cultural knowledge controls the evolution of the population by means of an influence function. A cultural algorithm thereby provides a framework in which to accumulate and communicate knowledge to allow adaptation in both the population and the belief space [21]–[24]. The cultural algorithm framework easily lends itself to supporting various types of learning activities such as version space learning, decision tree induction, and ensemble learning.

B. Knowledge Types

There are at least five categories of cultural knowledge that are important in the belief space of any cultural evolution model: situational, normative, topographic, historical or temporal, and domain knowledge [6]. These knowledge sources are derived from work in cognitive science and semiotics that describe the basic knowledge used by human decision-makers. In our cultural model, all of these knowledge sources can be represented. For example, in our current model, we assume that agents can acquire knowledge about the distribution of agricultural land as well as wild plant and animal resources (topographic knowledge), the distribution of rainfall and water resources (historical or temporal knowledge), and agricultural planting and harvesting techniques (domain knowledge). Planting and harvesting techniques are held static at this time. Annual maize productivity varies according to the tree-ring data used to estimate the amount of rainfall, and therefore productivity, during each model year.

III. AGENT MODEL

A. Basic Agent Knowledge Structure

Each agent in the simulation represents a household consisting of several individuals living in the same dwelling. The prime objective of a household is to survive in its environment. Table II gives a short list of the model objects within the currently implemented 3-D gaming environment. An agent has to learn how to survive in its environment. The resources available to agents in the model include: caloric yields from agriculture,

TABLE II
3-D MODEL OBJECTS SHORT LIST

Class	Description
Agent	An embedded agent for modeling a human household
AIEngine	AI Engine for running cognitive structures
AtmosphereEngine	Handles day/night cycles and sky rendering
Camera	View point into the virtual world
Deer	Represents a deer animal / protein source
Dwelling	Represents a dwelling location and structure for one or more Agents
HumanBody	Body of an embodied agent representing a human
HumanBrain	Cognitive structure of an Agent
Inventory	Implements an inventory system
Logger	Data logger that writes to a console and a file
Message	A piece of communication from one Agent to any nearby Agent
NavMesh	A single zone of the navigation mesh (or navigation graph). These zones are seamlessly connected during a search (equivalent to model cells)
Plant	Represents trees, shrubs, small plants, etc…
Terrain	Physical landscape based on elevation, water and productivity data
Water	Handles simulation of water flow
WorldClock	Simulation clock
ZonePager	Paging system for zones

protein yields from hunting deer, hare, and rabbits, and burnable calories from firewood needed for cooking and heating. In the regional model under discussion here, we focus just on agriculture and the exchange of maize among the agents since the caloric yields from agriculture are the foundation for survival in the region. The other resources will be considered in future work.

With the fluctuating land productivity and, hence, water availability and agricultural yield, the agent has to search for the most productive plots in its vicinity to farm. This action may trigger the relocation of an agent's dwelling to a more productive location when resources become scarce.

Fig. 3 gives a finite-state machine (FSA) that describes the basic activities available to an agent in the model. The exact configuration and use of the FSA by the agent is controlled by an adaptive plan. The plan determines how they will allocate their resource procurement effort during the course of the year, and whom they will interact with if they need additional resources. Such interaction takes place within two evolving social networks, the kinship network, and the economic network. Learning at the agent level then relates to modifying how the agent moves through the FSA as it uses operators derived from Fogel *et al.* [25].

The two social networks in the model maintain the household's social relations independently. Each agent maintains links to its nearest relatives. It can use these links to request food when in need. Conversely, if the household is doing well and procures a surplus, it can opt to donate its excess to needy relatives close by. This is an example of generalized reciprocal exchange [26] in which agents donate needed food when they can upon request to kin and do not require any payment in return. This implies a type of family values where related households look after each other by satisfying each other's requests without requesting repayments. Although physical repayments are not required, a level of general beneficence is maintained by the households and in the cultural belief space.

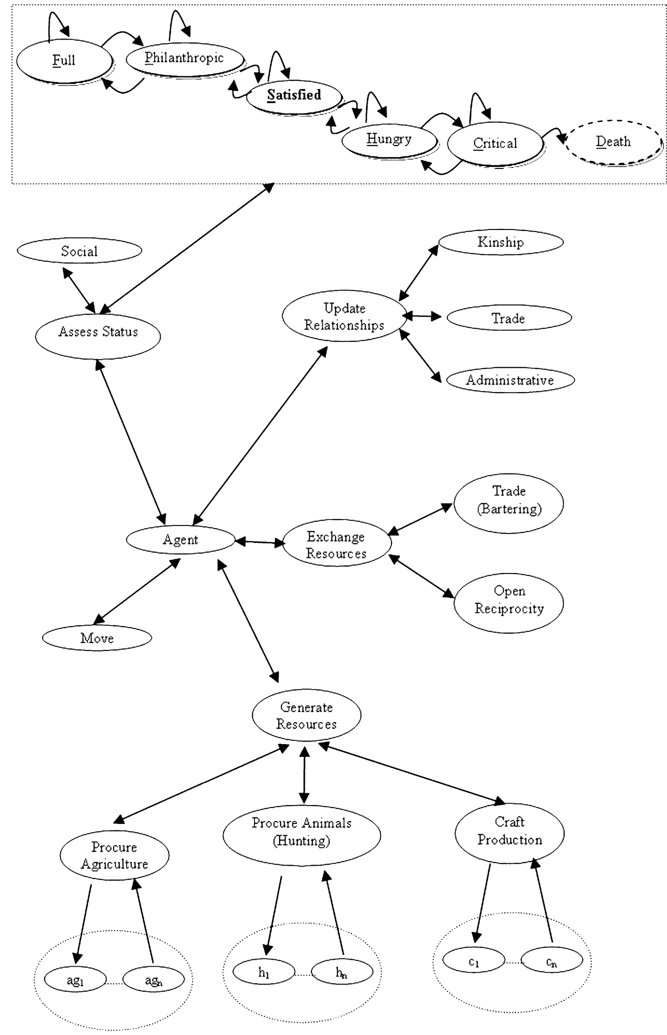


Fig. 3. Agent finite-state diagram.

The second base network illustrates the balanced reciprocal network (BRN), where a household may exchange resources with neighboring agents who are not necessarily related to it [26]. In this model, the household maintains a set of trading partners to exchange resources. Unlike the generalized reciprocal network, this model enables the agent to keep tabs or balances on trades. It measures the trustworthiness of trading partners by means of debt repayment. An agent that repays its debt on time earns more trust than one who does not.

The highlighted portion of the FSA in Fig. 3 describes the agent's state in terms of food needs. Figs. 4 and 5 describe the state model and the transitions between the states in more detail.

The states are as follows: Satisfied—an agent is in a "satisfied" state when it has sufficient food in storage to feed the entire household. Philanthropic—an agent becomes a philanthropist when it has a surplus of food in storage, defined in terms of stored maize in excess of a given threshold. For instance, an agent that has filled 90% or more of its storage capacity would be able to donate its surplus food. Hungry—a buffer state is implemented at the level just above critical need so that the agent

Fig. 4. Agent state transition diagram. Note that additional state transitions are possible directly between full, philanthropic, satisfied, hungry, and critical states, but the ones shown are the most frequent.

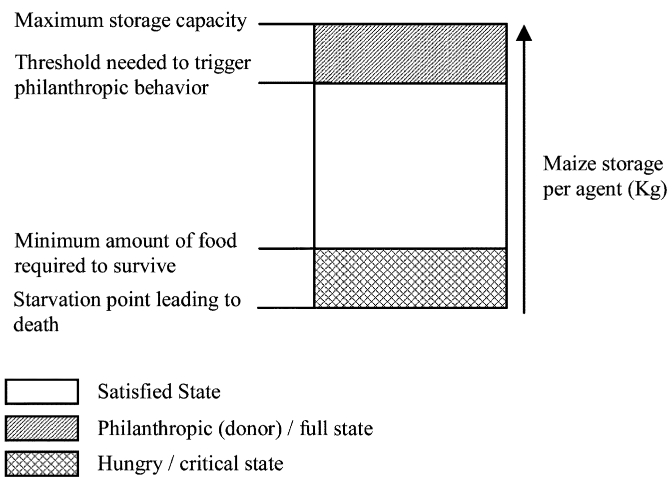


Fig. 5. Actual maize amount in storage determines the state of an agent.

TABLE III
DESCRIPTION OF THE DIFFERENT COOPERATION METHODS AT THE KINSHIP LEVEL

Cooperation Method	*Description*
0	No cooperation. No exchange of food between households.
1	When an agent requires food, it is allowed to select and request food from within its kinship network in order to survive.
2	When an agent has an excess of food, above a determined threshold amount, it is allowed to select an individual(s) from its kinship network and donate some of its excess.
3	Both methods 1 and 2 are enabled simultaneously.
4	Full cooperation across the kinship and economic network (generalized and reciprocal exchange simultaneously)

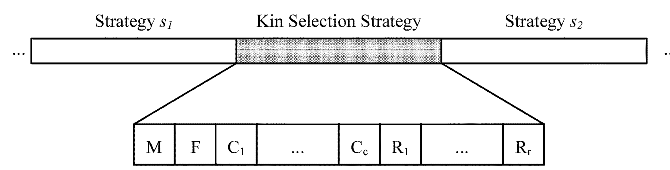


Fig. 6. Individual strategy composition for kin selection.

can try to prevent the starvation associated with critical need. When the agent is left with its last food ration, it then enters a "hungry" state that triggers precautionary requests for food to avoid starvation. Critical—an agent that has insufficient or no food to eat has no choice but to ask for food or face starvation and imminent death. If the household does not receive its ration to feed the entire family it will die. Death—an agent is marked for immediate removal from the system.

Table III describes the details of the cooperation or exchange methods that an agent can perform. The cooperation method is a parameter that can be controlled in the model for the autonomous agents.

B. Agent Learning

In the cultural algorithm framework, agents learn to adjust their exchange plans at the individual level based on their experiences and at the cultural level in the belief space. Belief space knowledge is used to condition the changes that individuals make to their plans as the result of failures to procure needed resources either directly via agriculture, hunting, etc., or indirectly through exchange. The individual's network knowledge and learning is implemented similarly in both the generalized reciprocal exchange and balanced reciprocal exchange processes. The main difference is that agents for the generalized reciprocal network (GRN) are kin, while those for the BRN can be both kin and nonkin within a given distance from the agent on the landscape. So, we will discuss only the generalized reciprocal exchange here [27].

Each agent's strategy is comprised of a vector of probabilities for selecting each of its kin as a possible donor (Fig. 6). These probabilities can be viewed to constitute the "signal" associated with possible exchange partners. Initially, each of its kin has an equal chance to be selected, so a uniform random selection starts the process. The vector contains the likelihood for selecting the mother's household (M), then the Father's (F), then any of its children $(C_1 \dots C_c)$, and any of its relatives $(R_1 \dots R_r)$.

Each individual selects a kin member with which to interact using a random process based on roulette wheel selection. Each possible kin is assigned an area under the wheel that reflects their relative likelihood of selection based upon past performance. The wheel is spun and the selected agent is asked for a donation. If that request is fulfilled successfully by the selected agent then the odds for selecting that kin again will increase. If the request is unfulfilled, then that kin's odds are penalized and the likelihood of its future selection decreases (Fig. 7). Over time, each individual agent will learn to adjust its values to reflect its past experiences.

Agents learn these signals through their individual experience and are also guided by cultural knowledge. We use the cultural algorithm belief space as the repository for collecting and using cultural knowledge to guide agent change. In particular, two types of knowledge are adjusted dynamically here: situational and normative (Fig. 8). In terms of situational knowledge, exemplars are maintained in the global space to represent individual agents who have been most successful at requesting donations when in need. Every time an agent completes a request, it updates its local strategy and is evaluated for its maize productivity based on the results of that strategy. In terms of the acceptance function of the cultural algorithm, the local strategy fitness is then compared with the exemplars currently in the belief space. If the individual's strategy is found to outperform any of the exemplars then it is inserted into the exemplar list. If the maximum number of exemplars in the list is exceeded, the one with the lowest performance score is dropped.

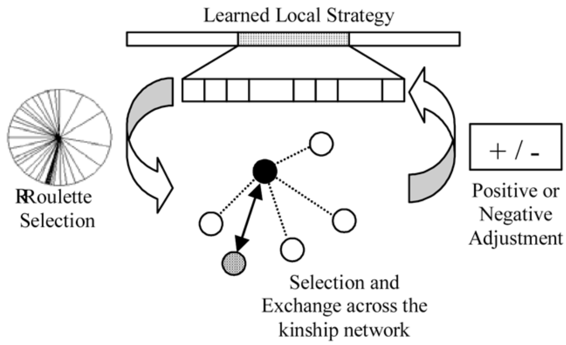


Fig. 7. Selection mechanism for an individual agent.

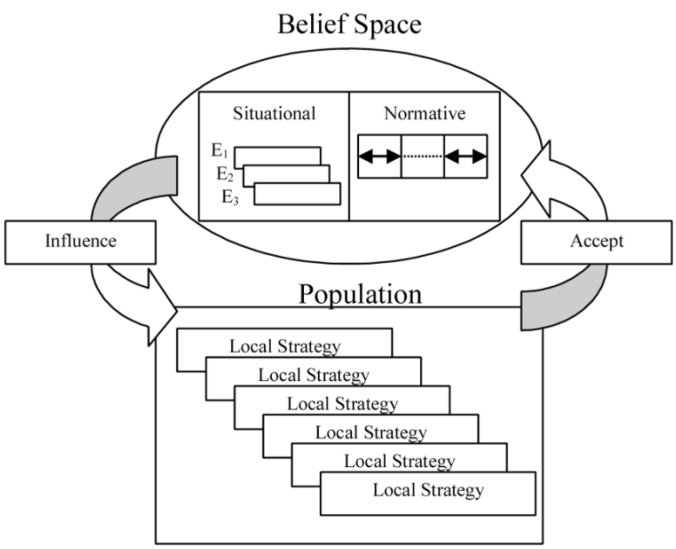


Fig. 8. Situational and normative knowledge.

In the belief space, normative knowledge is also used to accumulate information on the frequency (the signal in terms of the trust in networks game) with which various kinship types have been selected successfully by exemplars in the population. The ranges reflect the probabilities maintained by the currently selected exemplars. Thus, both normative and situational knowledge can be used to influence the choice of donors by the population. Specifically, if an individual in the population has not been successful in attempting to secure a donor, the knowledge in the belief space can be used to bias its next selection. Using normative knowledge causes the individual to shift its own probability values closer to the range specified.

Knowledge in the belief space can also be used to influence individual memories as described in Fig. 9. Each agent, in addition to its local set of probabilities, maintains a local memory that stores the last successful exchange with a cooperating kin. This list can expand to store additional positive experiences. Currently, it is set to one. The method used is to allow the agent to keep the last positive experience in memory so as to be able to use it as the first choice next time it needs to request food. If that agent fails to deliver in subsequent attempts then it is removed from the memory. The individual then selects a new kin to cooperate with from its local strategy conditioned by the culture's normative knowledge.

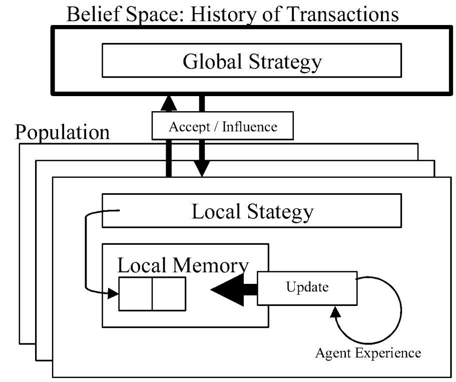


Fig. 9. Cooperation learning with memory of last positive cooperating kin.

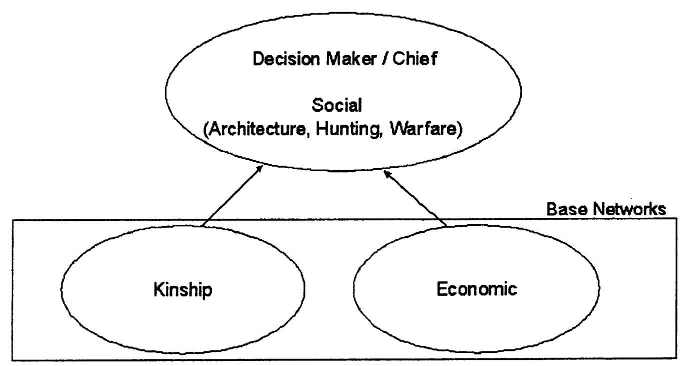


Fig. 10. Overall social network including the two base models and the evolving social network.

On a regional scale, positive experiences are tracked as exemplars and accumulated in a generalized strategy expressed as normative knowledge. This regional strategy can be used to influence the local ones and act as a tracking technique to identify the kin with the ability to provide a positive response when requested for food.

IV. Social Networks

A. Base Social Networks

The variability and unpredictability of the climate in this region from year to year [3] necessitates interactions between households. See Appendix A, Fig. 18, for the reconstructed precipitation curve for the region. Some farmers, even in close proximity, may accumulate a surplus during a given year, while others draw theirs down. The current model allows these networks to evolve as they are needed by the social group.

The overall social network framework takes a hierarchical form derived from the combination of two base networks (Fig. 10). The introduction of social concepts into the model focuses on two basic forms of exchange taken from the economic and anthropological literature: the generalized reciprocal network (GRN), and the balanced reciprocal network (BRN). The first network is the kinship network in the model, while the second one is the economic network. Both networks are essential components in the social evolution process here. Each agent is able to maintain its own set of exchange partners independently within each network. Furthermore, agent learning may occur independently within each network. For instance, an

TABLE IV
CONNECTED NODES IDENTIFIED BY THE KINSHIP SOCIAL NETWORK

ParentHouseholdTagA	a link to the parent from the mother's side
ParentHouseholdTagB	a link to the parent from the father's side
ChildHouseholdTag	one link to each child that moves away from this household and from its own household
RelativeHouseholdTag	one link to each extended family member

agent can learn which kin is best to call in for help while being able to learn which neighbor is best to trade with.

B. Generalized Reciprocal Network (GRN)

The GRN was introduced in previous work [5]–[9] using a kinship network. The GRN links agents with one another based on their kinship relations. The GRN serves to guide the flow of resources between relatives based upon the states of a giver and a receiver. One agent can request goods from a related agent without the donor expecting payback explicitly.

Each agent is a household composed of a husband, a wife, and their children. Household members live together in the same location, share their agricultural production, and are affected by the same environmental conditions. Children can grow up, marry, and move out to form their own households. Their connections to their parent households and siblings are maintained in our model. Similarly, the parents maintain ties to their children. When one of the parents in a household dies, the other can form a new household with an available single agent. They are given a limited number of attempts to do this each time period until successful. The initial structure of the social network here supports the notions of parents, siblings, and grandparents on both sides of the family.

The layout of the GRN social network from the perspective of a household is described in Table IV.

The household (agent) rules for marriage and kinship dynamics were described in earlier work [5]–[9]. The social network is defined as the set of all kinship links.

C. Balanced Reciprocal Network (BRN)

The BRN is an economic network that supports the exchange of goods between neighboring agents. In a balanced reciprocal transaction, the giver expects a deferred payback plus interest on demand. Here, we set the interest rate to 0. The localization of the exchange between agents in the model recognizes physical constraints on travel in these societies. This constraint is consistent with what was implemented in the generalized reciprocal network.

Each agent maintains a set of trading partners who are not necessarily associated with the kinship network. A trading partner can be any agent within a given radius from the agent.

The overall agent strategy for exchange using both the GRN and the BRN is given below. The key idea is that exchange in the current model occurs when an agent needs resources. After updating their networks they first try to satisfy their resource need by calling in debts from their neighbors using the BRN. If they are not successful, then they request aid from their relatives through the GRN. If they still are deficient in terms of resources, then they go back to the economic network to acquire more. Fig. 11 illustrates the agent connectivity in the BRN.

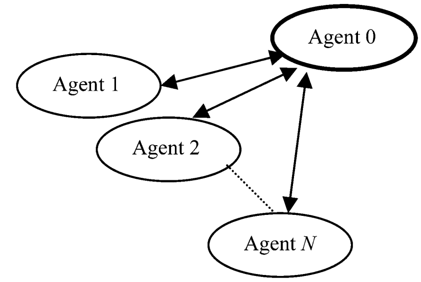


Fig. 11. Agent connectivity in the BRN. Agent 0 maintains its links with its exchange partners Agents 1 to N.

Every year, modeled as one step in the simulation, the agent performs the following actions specific to exchange.

1) Update GRN.
2) Update BRN.
    a) Remove expired, inactive, and out of region partners.
    b) Search each neighboring cell within a trade radius and get its settlers list and add new ones to the trade list up to a MAX_TRADE_LIST.
3) Request payback of debt from BRN partners.
4) if HUNGRY/CRITICAL:
    a) Request food from GRN (no payback).
5) if HUNGRY/CRITICAL:
    a) Request food from BRN (with payback promise).
6) if CRITICAL:
    a) Agent is DEAD and removed.
7) if PHILANTHROPIC/FULL :
    a) [Donate surplus into GRN].
    b) [Pay back debt owing into BRN].

V. EXPERIMENTAL METHODS

In this paper, we focus on experiments that relate our model to the "trust in networks" game described earlier. Since our model networks and the interactions within them are similar to the base version given earlier, we expect that if we seed the population with "defector" households and allow successful defector households to spawn new defector households when they reach maximum size, the number of defectors will increase to a number that reflects their frequency within a mixed strategy equilibrium associated with our model. At the same time, nondefectors can learn via their local memories and shared experiences in the belief space whose signals to trust and whose to distrust. If the cultural learning is successful, we expect to see all three pure strategies emerging within the population.

Theoretically, as the quality of the signal is reduced, the number of defectors should increase. In the game, the signal is viewed as a fixed probability, but in the simulation it is a vector of probabilities defined over the current set of active agents. Each agent will keep a set of probabilities relating to the observed response of the individuals. The belief space can keep a generalized probability over a class of agents, such as uncle, etc. A negative response to a request and, therefore, a reduced probability of cooperation, can be due to either a lack of resources as a result of environmental scarcity, or it can be a result of an explicit decision not to cooperate. As the

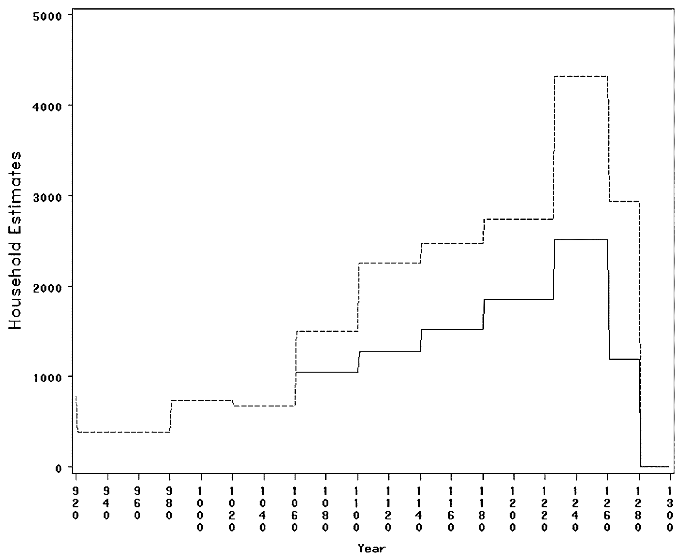


Fig. 12. Empirical estimates for the total momentary number of households in this study area from A.D. 900–1300.

environment becomes harsher, it will be harder to distinguish the reason for the decline, and it will be harder to detect defectors in terms of probabilities alone. This may make it easier for defectors to exist without detection. Since the exchange networks are key to the redistribution of resources to those in need, the net effect of this potential increase in defectors is to reduce network effectiveness. This adds competition explicitly into the system and can be used to test several hypotheses.

First, we can use just one pure strategy, "trust," so that everyone always cooperates when possible. We will examine the system with the GRN only, and then the GRN and BRN combined when there are no defectors present. Next, we will add defection into the system with the GRN only, and then to the GRN and BRN combined. The social systems produced with and without defection will be examined and compared with the archaeological data. The addition of defection allows us the opportunity to have "defectors" and also "inspectors." However, we know that there is no pure strategy Nash equilibrium for this type of game so adding in "defectors" and "inspectors" will cause a shift toward a mix of the three strategies and a different Nash equilibrium. We should observe similar shifts when we compare the systems with and without defection. The actual equilibrium achieved will be a function of how well individuals can learn the signals for defectors, their individual probability vectors. The results of these experiments will suggest that such competitive influences had to be present in the system in order to produce the observed archaeological data.

Fig. 12 gives empirical estimates for the number of households in the study area. Where there is just one line, it represents out best estimate of the momentary number of households in the study area, based on decades of archaeological survey and excavation, as analyzed by the Crow Canyon Archaeological Center. Where there are two lines, the upper represents an approximate upper bound on that estimate, and the lower line, an approximate lower bound. We will compare our emergent model populations, under different sets of network and agent strategies, to this reconstructed demographic history, as a preliminary validation technique.

VI. Results

A. No Cooperation

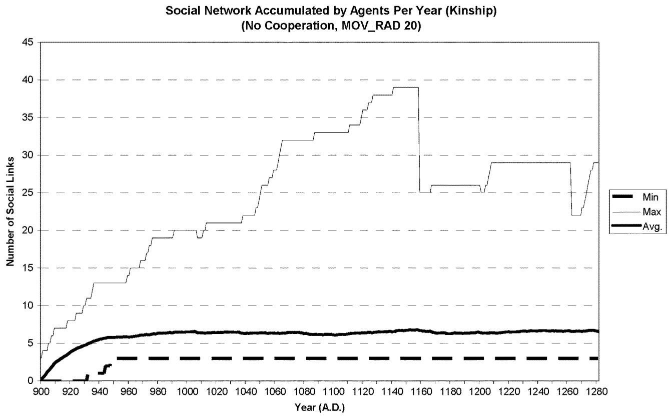
Fig. 13(a) gives the results of the simulation when there is no cooperation between the agents in the model. It also shows the minimum, maximum, and average social links over time for agents (upper graph in the figure). Fig. 13(b) gives the social network volume, the product of the out-degree over the total number of the nodes in the kinship network (lower graph in the figure) for this situation. The results are produced between A.D. 900 and 1281 (the horizontal axis in both graphs). The average number of links for an agent is around six, and is constant over the simulation as is the network volume. Network volume is the product of the links over all agents, an index of network complexity. Also, there are some nodes with a much higher number of links. We call these hub nodes. These statistics characterize what is often called "a small world network," where most nodes have a small number of local links and a few nodes, the hub nodes, have many more general links. These hub nodes serve as the glue that holds the network together by allowing connectivity throughout. Small world networks based upon kinship have been observed in real-world populations [28].

Thus, with no cooperation, the population starts small and remains small. In Fig. 13(c), the estimated population (households) for this configuration is given. This is below the lower bound for population size throughout nearly all the sequence (Fig. 12). This suggests that this model version lacks a good fit with the archaeological indicators.

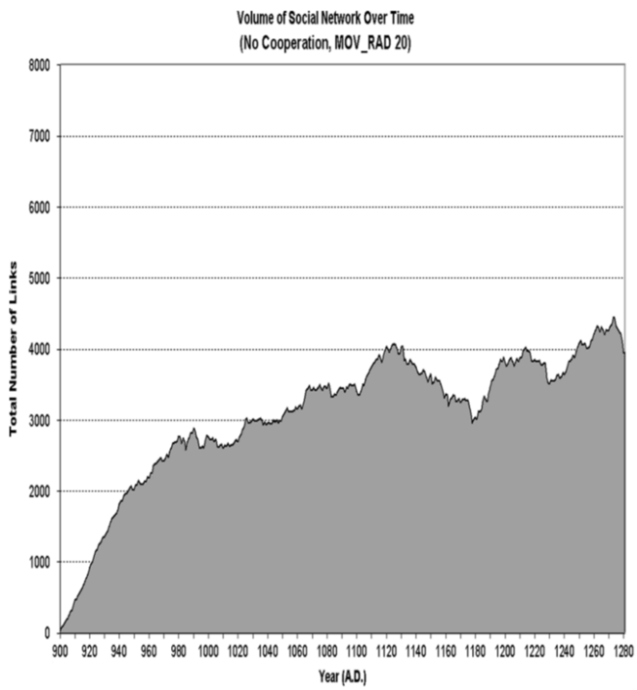
B. Cooperation Via Generalized Reciprocity

Fig. 14(a)–(c) illustrates the results when generalized reciprocal exchange with kin is allowed and there are no defector agents. Individuals can request food if in need and those with excess can offer donations to needy relatives. In Fig. 14(a), the small world properties still emerge here with most households having a small number of strong links and a few nodes have a larger number of weak ones. A strong link is characterized by a connection to another household that is highly productive and likely to cooperate, whereas a weak link is a connection to a less productive or more distant household. The social network complexity as given in Fig. 14(b) is 2000, greater than observed previously in the absence of cooperation and the population size is now almost double that reported above. It is compatible with lower bound estimates until about halfway through the run. At that point, it falls below the minimum number. Thus, the addition of cooperation into the model produces a better fit than before and suggests that it is a necessary social process here. However, as drought conditions persist over several decades around 1140 A.D., see Fig. 18, there is a corresponding drop in network complexity.

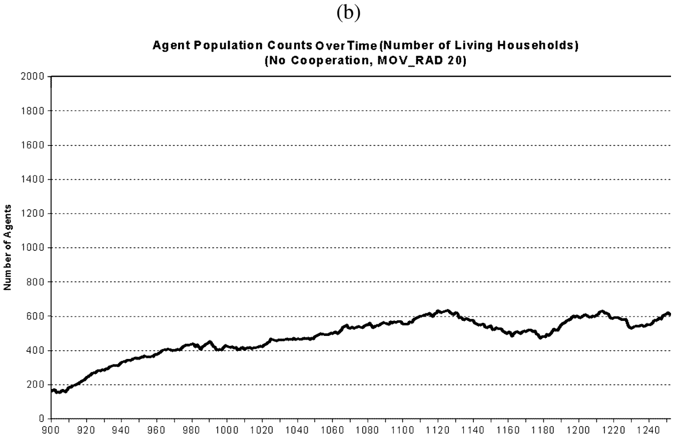
Fig. 15(a)–(c) gives the results when defector agents are added into the system. Notice that all three of the structural statistics have dropped from the previous runs. Here, the average linkage per individual is down to 5 from 6 and the minimum



(a)



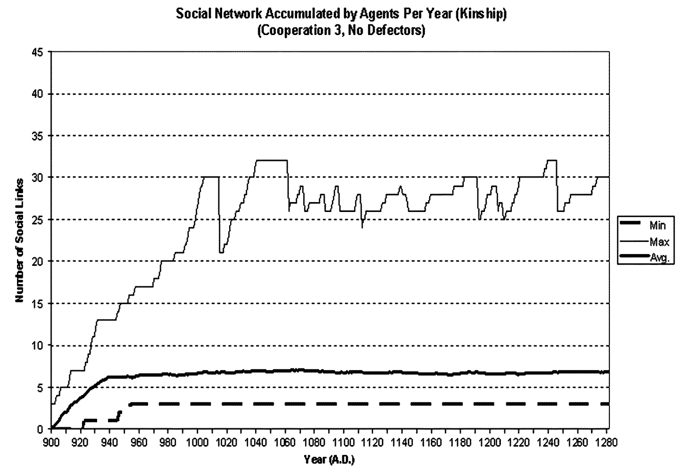
(b)



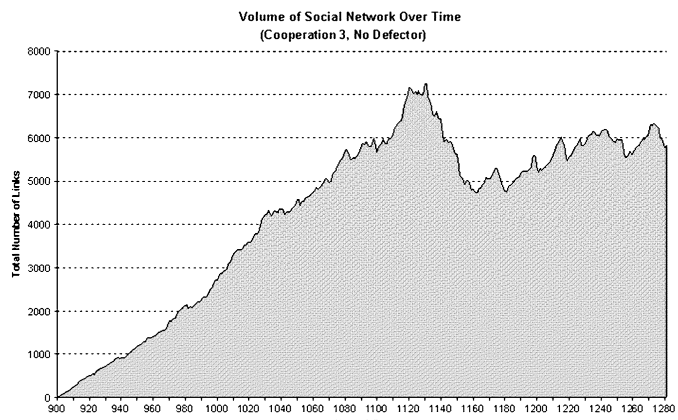
(c)

Fig. 13. (a) Min, max, and average node sizes over time without the presence of cooperation. (b) Network volume over time without the presence of cooperation. (c) Agent population (number of households) over time without the presence of cooperation.

linkage is down to 1 from 2. The maximum number of links has dropped almost by half and varies between 15 and 20.



(a)



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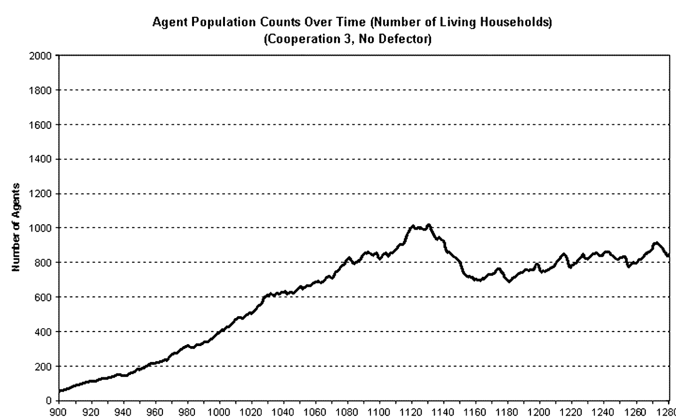
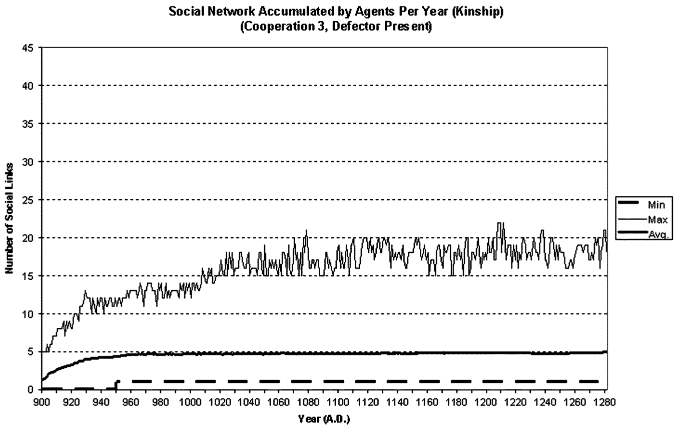


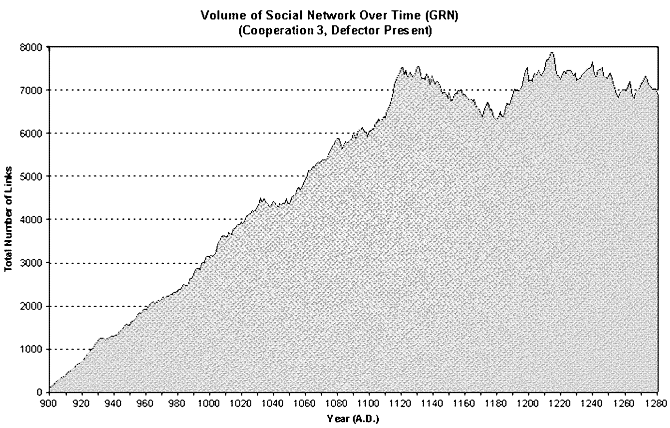
(c)

Fig. 14. (a) Min, max, and average node sizes over time with the presence of cooperation over the kin network (GRN) without defectors. (b) Network volume over time with the presence of cooperation over the kin network (GRN) without defectors. (c) Agent population (number of households) over time with the presence of cooperation over the kin network (GRN) without defectors.

What is interesting is that network volume and population counts again increase relative to the previous scenarios. In Fig. 15(c), we see that the total number of agents has increased by about 500 over that for the GRN network without defectors. Notice that the total number of defectors increases to about 1/2 of the total population and stabilizes there. This plateau may represent an approximation of the number of defector



(a)



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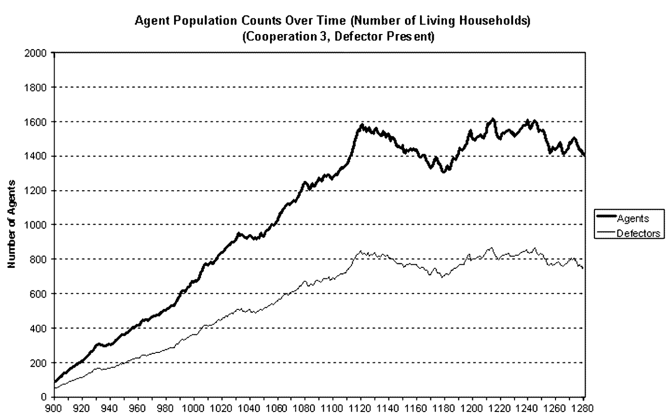

(c)

Fig. 15. (a) Min, max, and average node sizes over time with the presence of cooperation over the kin network (GRN) with defectors. (b) Network volume with the presence of cooperation over the kin network (GRN) with defectors. (c) Agent population (number of households) over time with the presence of cooperation over the kin network (GRN) without defectors.

strategies active for the mixed strategy Nash equilibrium. This increase may result from the fact that drought years occur periodically over the 400-year period, which makes it harder to tell a defector from one who cannot produce enough that year. The total population is now more than it had been without defectors. This makes sense given that we know for the simpler model that a mixed strategy approach will outperform a pure strategy in this situation.

While the "Trust in Networks" model suggests that the mixed strategy should be superior strategically, the question is why it is happening in terms of our more specific real-world model. This can be answered by looking more carefully at the more detailed model. By adding competition via defection, some agents kept additional reserves around that allowed them to be more productive when the drought years occurred. In fact, the runs with both cooperators and defectors produced a better fit with the archaeological data in the second half of the runs than it did with just cooperators alone.

Apparently, when everyone is constantly redistributing resources, the population becomes more vulnerable to drought than when some defectors are present. This is a practical reason why the "mixed strategy Nash equilibrium" is more competitive here than just a pure strategy. It also demonstrates that the pure strategy approach to cooperation was probably not operative in the real-world system.

C. Adding in Balanced Reciprocal Exchange

While generalized reciprocity can achieve some increase in population size, the results here show the power of the economic network in the improvement of performance. Fig. 16(a) and (b) gives the network statistics for the GRN and the BRN, respectively. The minimum number of connections for the BRN is 0, while the minimum for GRN is 2. This means that for the BRN, not everyone is participating in the economic network since the minimum value is 0. The average value for the GRN is up to 7, while that for the BRN increases as population density increases. Thus, the presence of the BRN enhances the structural complexity of the GRN. While everyone uses the GRN, not everyone participates in the BRN.

Fig. 16(c) compares the volumes of the evolved BRN and GRN networks, while 16(d) gives the resultant population curve. Notice that the synergy of the two networks combined results in an increase in GRN volume above what the GRN produced on its own. Also, around halfway through the simulation, the economic network volume becomes larger than the social network.

The population size shows a similar increase, reaching almost 18 000 households at the end of the model run. This is about ten times greater than achieved through generalized reciprocal exchange by itself. This suggests that both networks working together with no defection produces results that are not compatible with the archaeological bounds toward the end of the simulation time period. This makes theoretical sense because we know that there is no pure strategy Nash equilibrium for this type of game. Thus, in the real-world, this solution is inherently unstable and will not exist if there are "inspector" and "defector" strategies available.

In Fig. 17(a)–(d), we observe the effects of adding in defector strategies for agents in the combined network. The network statistics are similar to the previous scenario. In Fig. 17(d), we observe that the agent population has now dropped from around 17 000 to around 15 000, a figure closer to the archeological expectations (especially using the preliminary estimates from [4]). Also, in the figure, we notice that the trait for potential defection that is initially given to everyone has begun to be replaced

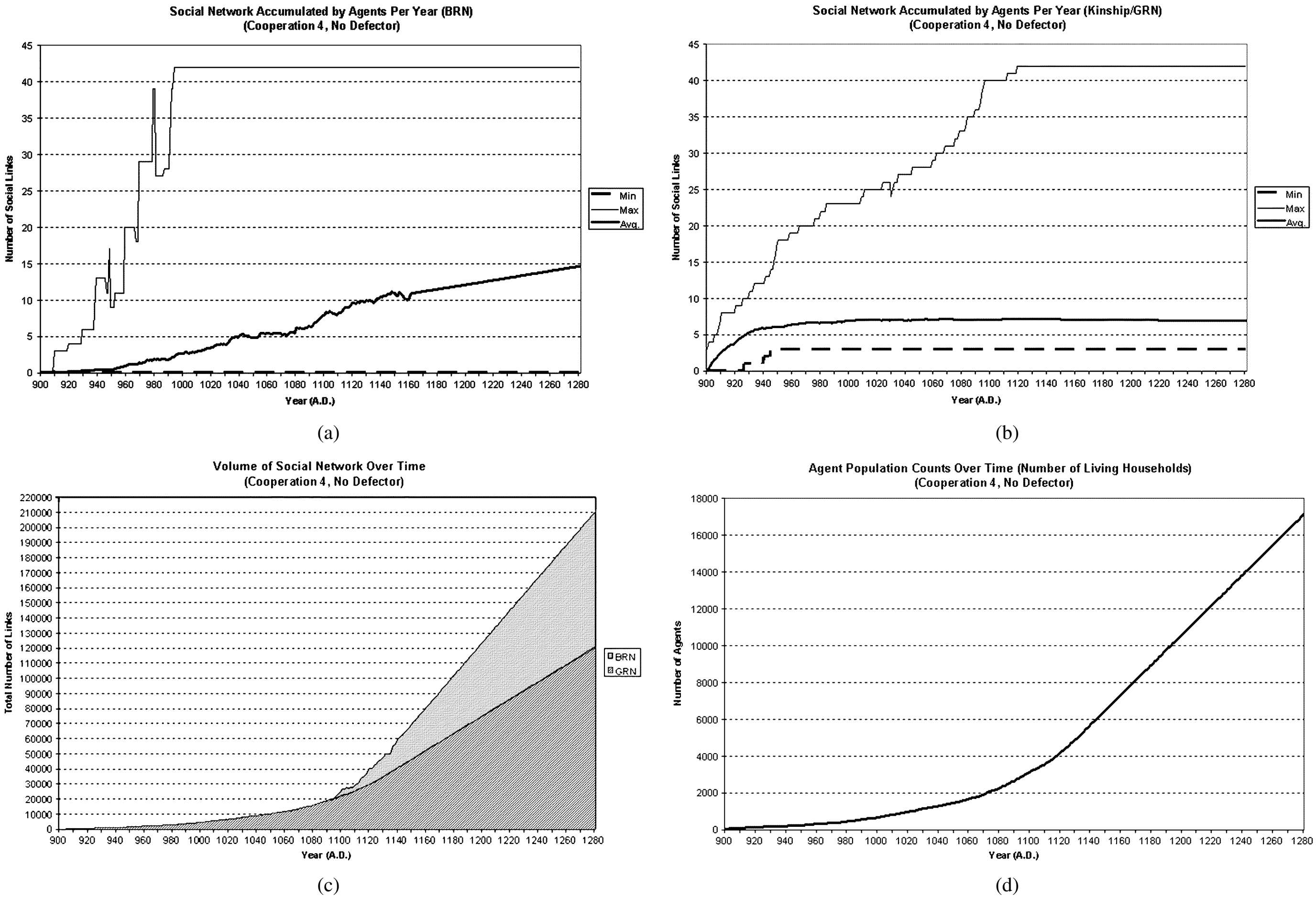

Fig. 16. (a) Min, max, and average node sizes over time with the presence of cooperation over the BRN without defectors. (b) Min, max, and average node sizes over time with the presence of cooperation over the GRN without defectors. (c) Network volume of the BRN and GRN over time without the presence of defectors. (d) Averaged agent population (number of households) over time with the presence of cooperation over both GRN and BRN without defectors.

by the trait for no defection near the end of the run. This is very interesting since with increased environmental variability and stress toward the end of the simulation period the "signal" with which to distinguish cooperators from defectors has likely gotten weaker as mentioned earlier. The system's response to this is to produce a group of individuals (trustors) who will never defect, thus reducing the need to use the "signal." In terms of the "Trust in Networks" game, this implies a shift in the equilibrium mix toward one with more "Trustors" as a result of the environmental deterioration.

Another interesting observation is that the population estimates for the system without exchange, and with the GRN only (with and without defectors), all fall below the minimum population predicted archeologically. Only the system that uses both the GRN and the BRN generates population estimates within the expected range. The system in which there are defectors in the GRN and BRN produces estimates that are closest to the averaged expectations archaeologically. What this suggests is that in the real-world system both generalized and balanced reciprocal exchange had to be operative and that there was the potential for individuals to defect within those networks. From the point of view of game theory, we also note that the equilibrium distribution of "Trustors," "Inspectors," and "Defectors" may shift as the environment becomes more stressful.

VII. Conclusion

A. Discussion

In this paper, we have introduced strategic gaming concepts as a vehicle in which to investigate the disappearance of an ancient prehistoric North American Indian population, one that has left behind numerous impressive cultural artifacts. Within the gaming environment, agents can learn different strategies for interacting within the GRN and BRN networks. The interaction modeled here corresponds to a simpler "Trust in Networks" game. Theoretical studies of that game suggest that our more complex version will have certain properties, e.g., no pure strategy Nash equilibrium. This means that if defectors are allowed then they will spread through the population, achieving a frequency that reflects its presence in the mixed strategy for the population.

The autonomous agents in the model exhibited evolutionary learning at both the individual and cultural levels. These agents were given the opportunity to cooperate first via generalized reciprocity through a kinship network, and then through an economic network. The generalized reciprocal network increased regional population somewhat but when combined with the balanced reciprocal exchange generated a substantial population increase. The synergy between the two was surprising. This synergy may be explained by the fact that an individual agent can

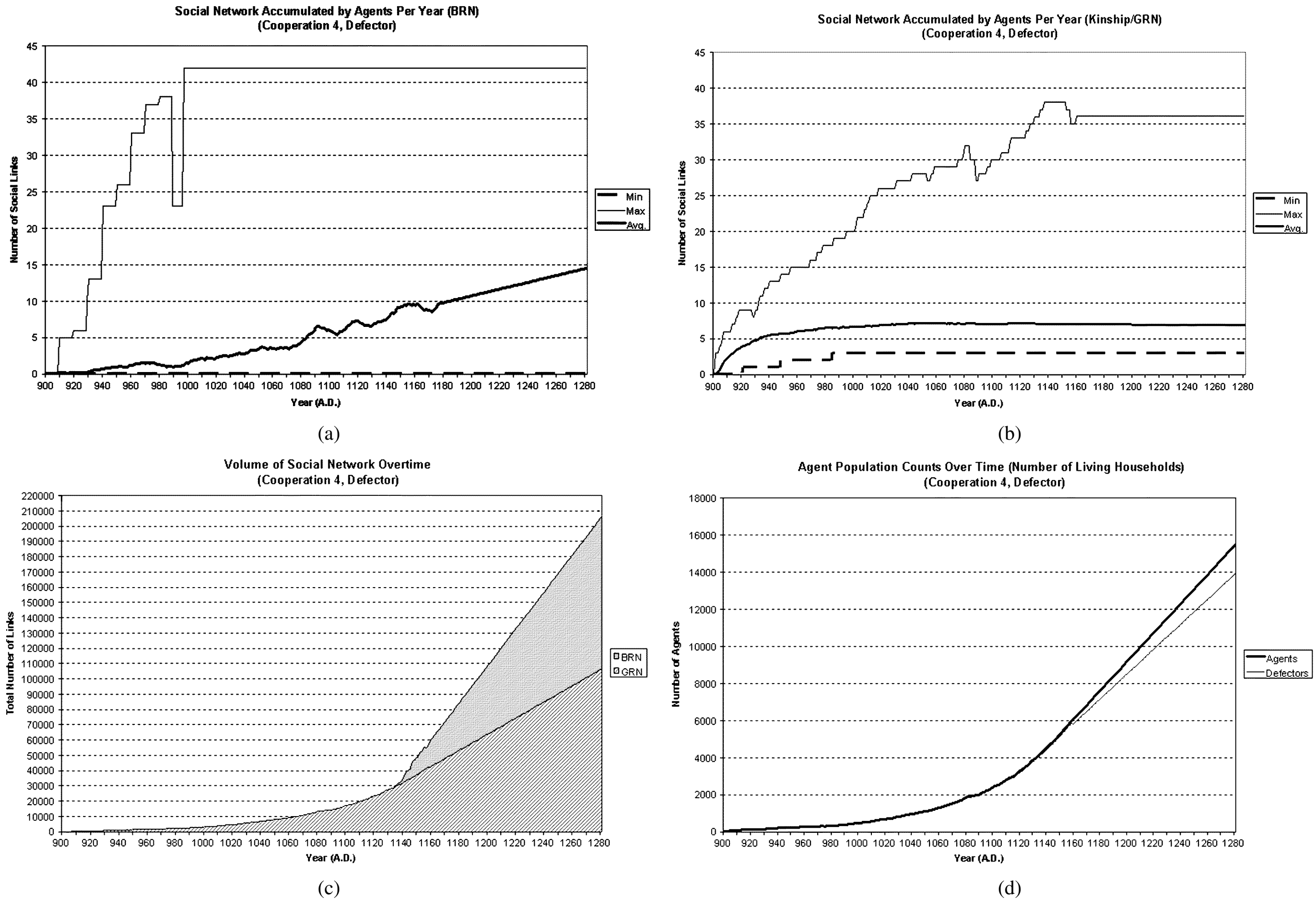

Fig. 17. (a) Min, max, and average node sizes over time with the presence of cooperation over the BRN with the presence of defectors. (b) Min, max, and average node sizes over time with the presence of cooperation over the BRN and GRN with defectors. (c) Network volumes over time with the presence of cooperation over the BRN and GRN with defectors. (d) Averaged total agent population (number of households) over time along with the number of "potential defectors" in the agent population.

"reach" beyond its kin network to improve its own well being using the BRN. But, if successful the result is to make the agent a more reliable presence in the GRN than it would be otherwise.

The system configuration that used the combined GRN and BRN networks along with defection produced results that fit broadly with the archaeologically based population estimates. We suggest that this occurs for the same reasons that Hegmon discovered in her simulation of Hopi agriculture and exchange [31]: populations that share too much and too broadly (pooling, in her terms) are less successful than are more restricted sharers.

In addition, the analogy with the "Truth in Networks" game allowed us some leverage in the interpretation of the results. The fact that the number of traits for "potential defection" declined at the end of the simulation seemed at first very counterintuitive. However, in terms of the "Trust in Networks" game, it just signals a change in the equilibrium distribution of "Trusters," "Inspectors," and "Defectors" as a result of environmental change that reduces the quality of the signal that the "Inspectors" will see. The response of the system is to move more individuals into the "Trustor" class, which makes the system more predictable. It is premature to use these results to comment on the causes of the depopulation of our study area in the late A.D. 1200s, since this appears to have been a multidimensional phenomena responding to several factors not yet included in these simulations, including scarcity of wood and protein resources [4], [32], and immigration into our area from harder hit regions in the A.D. 1200s, possibly pushing it beyond its sustainable use level [33]. These results do suggest that successful exchange practices may accelerate population growth, exacerbating climatically and human-induced resource scarcity. Clearly, computer gaming and game theory can be mutually beneficial in exploring problems of considerable complexity, as demonstrated by the nonintuitive character of some of these results.

B. Future Work

Environmental constraints such as erosion, depletion of firewood, and reduction in plant and animal density due to increased human populations have yet to be added to the current model and will certainly serve to reduce population levels more than observed here. It will be of interest to observe how the agents adapt their networks and cooperation strategies in response to these density- and time-dependent factors.

We can also add complexities to our agent behaviors within the network. For example, agents could defect in just one network or the other. Offspring households could also be made defectors for certain networks (GRN, BRN, or both) with a certain probability. Likewise, community-related approaches to "punishing" defectors are not included in either the "Trust in Networks" model or our extension. Other work in game theory suggests that allowing the population to evolve "punishment" for defectors, as well as related approaches will also be useful in understanding our real-world situation more clearly [34]–[36].

APPENDIX A

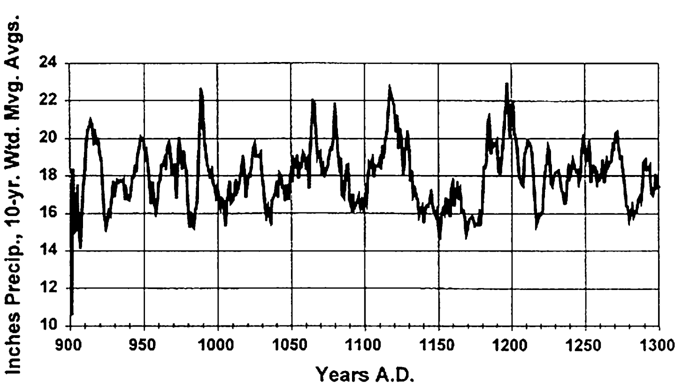

Fig. 18. Reconstructed total annual precipitation (inches) estimated from the Mesa Verde Douglas-fir chronology after [3].

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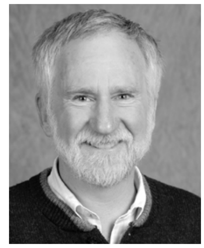

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