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Research, part of a Special Feature on Long-term Vulnerability and Transformation

Population Aggregation in Ancient Arid Environments

Marco A. Janssen [1]

ABSTRACT. Human societies have adapted to spatial and temporal variability, such as that found in the prehistoric American Southwest. A question remains as to what the implications are of different social adaptations to long-term vulnerability of small-scale human societies. A stylized agent-based model is presented that captures small-group decision making on movements and resource use in ancient arid environments. The impact of various assumptions concerning storage, exchange, sharing, and migration on indicators of aggregation and sustainability are explored. Climate variability is found to increase the resilience of population levels at the system level. Variability reduces the time a population stays in one location and can degrade the soils. In addition to climate variability, the long-term population dynamics is mainly driven by the level of storage and the decision rules governing when to migrate and with whom to exchange.

Key Words: *agent-based model; archaeology; arid landscapes; climate variability*

INTRODUCTION

A high degree of environmental variability and uncertainty is the norm in arid and semiarid regions such as the American Southwest. Much of this variation is climatic, but these arid and semiarid systems link not only biophysical processes, but also social and cultural processes. Plants, animals, and people have different mechanisms to adapt to spatial and temporal variability (McAllister et al. 2009, Janssen et al. 2007). Larger organisms can persist locally in time if they invest in extensive resource harvesting structures (such as the root structure of trees), or have large home ranges (such as dingos) (McAllister et al. 2009). Humans can adapt to spatial variability by combining various mechanisms, such as a nomadic lifestyle, storage of resources, and trade and exchange of resources (Janssen et al. 2007). The city of Phoenix in the modern American Southwest extracts resources from all over the globe. Even for its basic water supply, it must depend on water resources from hundreds of miles away (Luck et al. 2001). Such an adaptation is only possible with relatively cheap nuclear and fossil energy supplies and sophisticated technology.

Although we observe mobility here to deal with spatial variability in arid landscapes, the frequency of mobility is lower than in tropical regions (Kelly 1983). The reason for this is the unpredictability of successfully finding alternative locations with sufficient resources in arid environments. When one can store resources in livestock to buffer the resource uncertainty, a nomadic lifestyle can be adopted (Niamir-Fuller 1999). We are interested in how prehistoric societies adapted to the prehistoric American Southwest landscape. People in the prehistoric American Southwest were handicapped by a lack of domesticated large mammals, such as horses or camels, which could facilitate transport of resources or could serve as mobile storage units for meat, fat, and milk. They were restricted by limited transport capabilities, which affected their abilities to adapt to the arid landscape.

Another adaptation to temporal and spatial variability is storage of resources (Janssen et al. 2007). In prehistoric societies, the ability to store food resources was limited, but was used for maize, grain, etc. Stored resources could only last for a few years, and there was a significant loss of the resources due to rodents and decay. In a region like

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the American Southwest, a mixture of storage and exchange of resources between settlements was used to buffer environmental variability. An analysis of exchange between settlements (based on ceramics data) and spatial climate patterns in ancient New Mexico suggests that distance alone is not a good indicator of social interactions (Rautman 1993). Because nearby settlements may have similar rainfall patterns, it is often more beneficial to exchange with settlements that are further away and experience different climatic patterns. On the other hand, kinship relations can facilitate the strength of exchange networks (Kobti et al. 2006). Thus, both social and environmental conditions affect the pattern of exchange of resources.

In this paper, we contribute to the understanding of vulnerability of prehistoric societies in arid environments by developing a stylized agent-based model. We developed a model that captures in a stylized way important environmental and social processes of prehistoric societies. Although the paper is inspired by case studies discussed in other papers of this special issue, such as the Mimbres, Hohokam, Zuni, and La Quimada societies, the model does not aim to represent a specific case. With the model, we try to derive a more general understanding of the possible mechanisms underlying the periods of aggregation and disaggregation in arid environments. Especially, we are interested in the role of climatic variability as well as different social processes of exchange, storage, and migration.

The model allows us to explore the resilience of settlements and the population at the system level to climate variability and resource degradation. Settlements can be depopulated as a result of climate-induced migration (Kohler et al. 2008). However, we will show that climate variability enhances the resilience and reduces the appearance of system-level collapse and reorganization (Gunderson and Holling 2002). Furthermore, we will show the long-term consequences of assumptions about storage, decisions to migrate, and exchange.

Model-based archaeology is increasingly used to test alternative hypotheses of mechanisms that can explain observations (Kohler and van der Leeuw 2007). We use agent-based modeling to formulate our model of households that cope with spatial and temporal variability. In contrast to some existing agent-based models of the Southwest archaeology literature, such as Axtell et al. (2002), Kohler et al. (2000), and Reynolds et al. (2003), our model focuses on dynamics occurring on a large spatial scale. In their models, the focus is on population movements within a specific region. In our models, agents also move and maintain an exchange network between regions. These regions do not represent a specific case as we are not interested in driving our model results by the input data, but aim to understand the consequences of different social mechanisms for a variety of Southwest-like landscapes. As Janssen (2009) demonstrated, the insights of modeling studies of specific cases can be completely driven by input data. Instead of looking at one particular landscape, we generate many different possible landscapes, which may lead to insights that are less dependent on specific landscape characteristics. There are some existing regional models of migration (Young 2002), but they do not include dynamics of social complexity such as we include. By social complexity, we refer here to the inclusion of various response mechanisms such as storage, sharing, learning, economy of scale, and exchange. Careful representation of social complexity and exchange networks is important if we wish to explore the reasons why households and communities migrated large distances in the ancient Southwest.

The model presented here is a preliminary attempt to develop a model of agents, representing small groups, making decisions about resource use and movement. In this paper, we explore the consequences of different types of adaptations, ranging from movement, storage, sharing, and exchange. Introducing more institutional complexity will be challenging because of the lack of written records; thus, it will be based on interpretations of the ethnographic record of contemporary communities in similar situations. In future versions, we may include cultural tags, reciprocity, and kinship networks, but we keep the model in this paper to the bare bones of a few simple mechanisms.

With our initial model, we focus on the mechanisms that stimulate aggregation of populations in landscapes with low productivity and high uncertainty. Why do the people not distribute themselves according to an ideal free distribution (Fretwell 1972), which assumes that individual resource users will aggregate in various patches proportionately to the amount of resources available in each patch? First, we present the model and explore the results of some typical runs. Then, we carry out a sensitivity analysis of the main parameters of the model. Finally, we present the results of agents adapting their strategies over time and explore what kind of strategies agents evolve in different types of landscapes.

MODEL DESCRIPTION

The model described is a stylized representation of agents farming the landscape, aggregating in settlements, sharing resources with other agents and settlements, and moving to new locations. The model is based on basic equations frequently used in social–ecological systems and adjusted to represent social and ecological processes as understood in archaeology. The model is not, however, intended to retrodict specific observations of the US Southwest, but is used to systematically explore the consequences of different plausible assumptions about population dynamics in a spatially explicit landscape with rainfall variability. The code of the model is available at http://www.openabm.org/model-archive/populationaggregationinaridenvironments.

The landscape consists of N x N cells. We assume N to be 20, so the landscape consists of 400 cells. No specific area is simulated, but to calibrate certain parameter values, such as travel costs, we assume that each cell is 10 x 10 km. To avoid edge effects in this artificial closed system, we represent space as a “donut-shaped” torus. The model proceeds in annual time steps, and agents are updated in an asynchronous way.

An agent represents a number of individuals who act as a decision-making unit. This is probably an extended family household or a small number of households. We assume that each agent represents the same number of individuals. In the basic model, agents differ only in location, storage available, and debt (net amount of resource derived from exchange) but not in the decision-making rules. In the last part of the paper, we explore the consequences of heterogeneity of decision-making rules.

Agricultural production

Each settlement receives rainfall each time step. Each cell j has an agricultural production quality Q_j (e.g., soil fertility). We assume that agents occupying the cell harvest an amount proportional to the production quality of the cell and the rainfall at that time step. Thus, the individual harvest of agent i, h_i is defined as:

$$h_i = \tau \cdot Q_j \tag{1}$$

where τ is a rainfall signal as discussed below, and the production quality Q_j depends on the available resources, labor, and technology. In wet years, $\tau > 1$, and the agent’s harvest is higher than in an average year. Note that the rain signal τ is not a linear relation with rainfall as described in the following paragraphs.

Rainfall

The rainfall signal used here is the annual value of the Palmer Drought Severity Index (PDSI). The model uses actual historical sequences of reconstructed PDSI for the period 900–1500 for a typical location in the US Southwest (Fig. 1). We picked the time series of the Cibola region, which covers the period 900–1500 (Dean 2007). The Cibola region was occupied for a very long time, which suggests that these PDSI values are inherently workable. For our simulations of 10,000 years, we use a sequence that repeats the 600 observations. The objective of the PDSI is to provide measurements of moisture conditions that are standardized. This enables comparisons using the index between locations and between months (Palmer 1965) (Table 1).

We define a relative production level as a function of PDSI. We assume that the production level is zero in the case of an extreme drought (PDSI = -8) and a normalized one if PDSI is 0. Furthermore, we assume that in wet years the production level grows toward a maximum of 50% above the yield in normal years. In line with the Mitscherlich-Baule production function (Frank et al. 1990), we define the rainfall-related production adjustment (Fig. 2) as:

$$\tau = 1.5 \cdot \left(1 - \exp\left((\ln(1/3)/8) \cdot (PDSI + 8)\right)\right) \tag{2}$$

Fig. 1. The time series of Palmer Drought Severity Index that is used as input for the model.

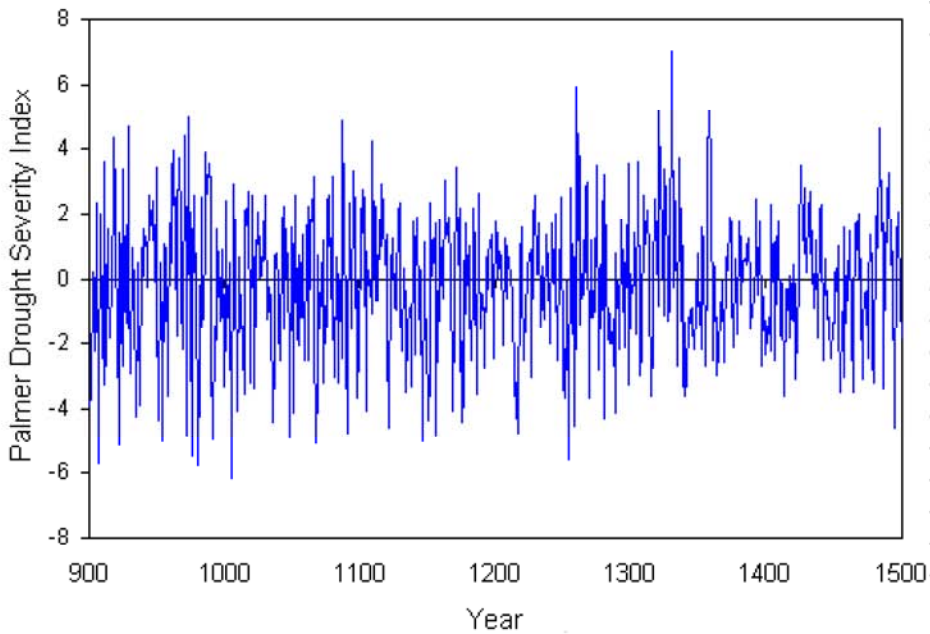


Fig. 2. Relationship between Palmer Drought Severity Index (PDSI) and relative production level according to Equation 2.

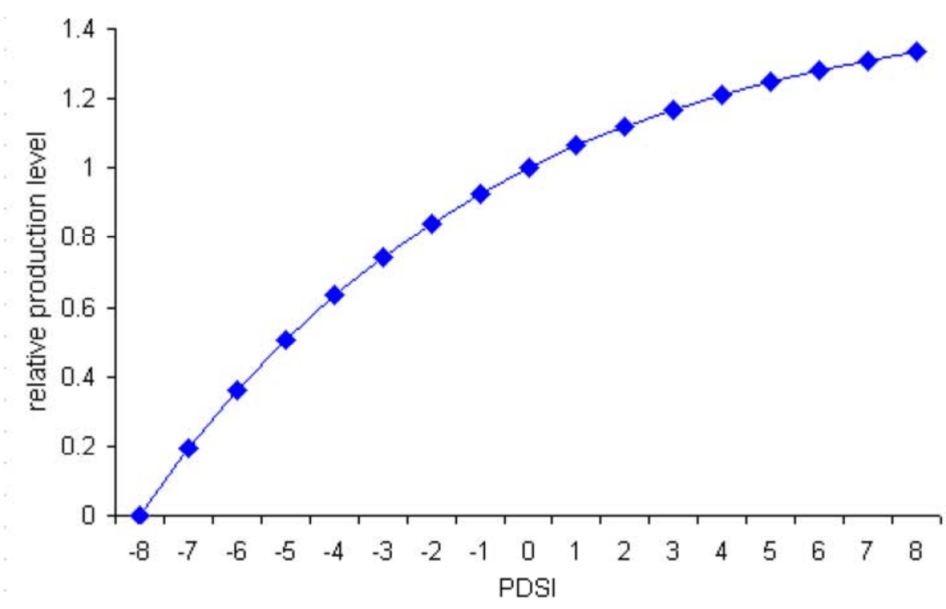


Table 1. Classifications of Palmer Drought Severity Index.

Value	Classifications of Palmer Drought Severity Index
4.0 or more	Extremely wet
3.0 to 3.99	Very wet
2.0 to 2.99	Moderately wet
1.0 to 1.99	Slightly wet
0.5 to 0.99	Incipient wet spell
0.49 to -0.49	Near normal
-0.5 to -0.99	Incipient dry spell
-1.0 to -1.99	Mild drought
-2.0 to -2.99	Moderate drought
-3.0 to -3.99	Severe drought
-4.0 or less	Extreme drought

In addition to the calculation of τ for the landscape, we assume that there is some spatial heterogeneity in the value of τ. We introduce this heterogeneity by multiplying τ by $(1 + \varepsilon)$ for each cell, where ε is a draw every time step from a normal distribution with mean 0 and a standard deviation of 10% (= 0.15).

Agricultural production quality

The agricultural production quality of a cell is assumed to change with the number of agents occupying the cell. More labor will lead to modest increasing returns to scale as they can help each other prepare the land and harvest the resources. Furthermore, the production quality of a cell depends on the relative soil quality. With increasing use of the cell, soil quality will be reduced because of erosion processes. In a formal way, the agricultural production quality of a cell is represented by a production function with input resources R_j (representing soil quality), population size (P_j), and technology, and is formulated as:

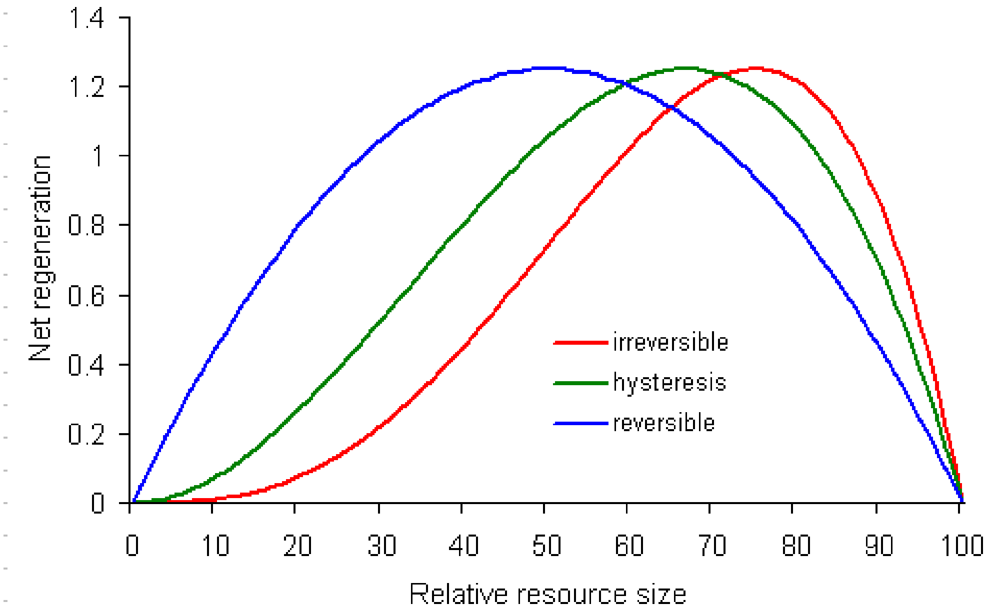
$$Q_j = a \cdot R_j \cdot P_j^{\alpha} \quad (3)$$

With P_j the population level at the cell j agent i is located, α the elasticity to labor input, and a is the relative level of soil quality an agent uses per unit of food harvested depending on the experience available within the settlement. For an elasticity of α equal to 0.2, a doubling of the population on a cell leads to a 14% increase in production.

Resource dynamics

The relative resource level R_j represents the quality of the soil. It will decline due to agricultural use and recover when left fallow. The relative level of the soil quality on time step t depends on the regeneration level g_r, the degradation factor of the resource γ, the carrying capacity C_j, and the depletion by use, depletion rate η times population level jP_j. The relative resource level is now defined as a non-linear finite difference equation with density-dependent regeneration:

Fig. 3. Net growth curves, *Rj* (*t*+1) – *Rj(t)*, for different assumptions of depletion rate and recovery rate of the resource levels in each cell. For irreversible, we assume γ = 2 and gr = 0.1188; for hysteresis, we assume γ = 1 and gr = 0.0844; and for reversible, we assume γ = 0 and gr = 0.05.



$$R_j(t) = R_j(t-1) + g_r R_j(t-1)\left(\frac{R\ (t-1)}{C_j}\right)^{\gamma} \cdot \left(1 - \frac{R_j(t-1)}{C_j}\right) - \eta \cdot P_j\ (t-1) \quad (4)$$

If $\gamma = 0$, the soil quality follows a traditional logistic equation of resource dynamics of time. This means that without use of the land, the soil quality recovers back toward the original level leading to the carrying capacity C_j. This recovery is like an S curve, with the faster regeneration rate around half the level of C_j. Thus, soil quality will always recover. However, we expect that the ability of soil quality to recover can decline the more it is depleted. That is why we also consider cases where $\gamma > 0$. With values of $\gamma > 0$, soil quality regenerates more slowly when it is depleted. This is included to mimic erosion processes. In the model simulation, we used a default value of $\gamma = 1$ and $g_r = 0.0844$ (Fig. 3). As extreme conditions, we use $\gamma = 0$ and $g_r = 0.05$, and $\gamma = 2$ and $g_r = 0.1188$, where we adjust g_r to remain at the same maximum regeneration rates (see Appendix). Figure 3 shows the different effects of the parameters on the net regeneration levels. With higher values of degradation, the maximum recovery rate occurs at higher levels of the soil quality *R*. Thus, when soil quality *R* is depleted to a lower level, it will regenerate very slowly, and thus, it takes much longer to recover when depletion is included ($\gamma > 0$). The depletion of the soil quality depends only on the number of agents in the cell. It mimics loss of nutrients, vegetation, and other resources.

We acknowledge that this formulation is extremely simplistic, and more comprehensive models of the ecological processes need to be explored in the future. For now, it is important that a group of agents cannot productively use a location forever because this will lead to depletion of the soil quality.

Local knowledge

Agents have a certain efficiency in using the soil quality. The efficiency rate of harvesting *a* depends on the cumulative experience of harvesting on that location. The more experience is accumulated, the higher the efficiency. This is formulated as follows:

$$a = \frac{tl}{tl + lf} \tag{5}$$

For each agent, the number of time steps staying at the cell is taken into account. This enables us to calculate, *tl* the sum of the durations of all current agents at the cell. The parameter *lf* is the learning parameter. Agents lose experience in harvesting in a cell when they leave that cell. Thus, if *lf* is 1, *a* is equal to 0.5 for a new agent exploring a pristine cell. The second year, *a* increases to 2/3 and, after 10 years, the relative efficiency is 10/11. When more agents occupy the cell, the improvement in efficiency appreciates more rapidly.

Decision making of agents

Agents are assumed to strive to consume a minimum level of resources, h_{min}. These resources are derived from the annual harvest and from storage. When some settlements have a shortage, they will try to obtain food through exchange (see below). However, settlements with a surplus will keep a minimum amount in storage as a buffer level, *b*. Settlements with a production beyond this level may choose to exchange. We update each step of an activity for all agents before moving on to the next activity in the sequence: harvesting, sharing, exchange, and migration.

Storage

Agents store surplus for up to y_s years. When agents have consumed food from their stock, they first deplete the oldest stock in storage before they use resources from more recent years. Each year, a fraction l_s of the storage of the previous years is lost or not suitable for consumption. If agents share or exchange, they will only do so with the surplus of resources beyond the stock level *b*.

Sharing

A settlement is defined as one or more agents in a cell. We distinguish three variations of distribution strategies within a settlement after Hegmon (1996):

- Independent—There is no sharing of harvest or storage among the households within a settlement.
- Pooling—All storage and harvest is pooled each year and distributed equally among the participants.
- Restricted sharing—Surplus of households is shared with households who have a shortage, up to the point that those households meet the minimum requirement h_{min}. When surplus within a settlement is greater than the shortage, each agent with a surplus provides the same share of surplus to those agents with a shortage. When surplus in a settlement is less than the shortage, each agent with a shortage receives an amount so that each agent with a shortage has the same level of resources.

Exchange between settlements

After calculating the sharing of food for all agents in all settlements, the model starts calculating the exchange of resources between settlements. Between settlements, there is exchange of food in periods of stress and when the settlements have exchange relationships. For each location, we calculate whether there is a shortage. We randomly draw which settlement with a shortage will be first to initiate exchange of resources. When there are other settlements where an exchange is possible, the agents will obtain resources from a settlement with a surplus. This procedure is repeated until no exchange can be made anymore before moving on to another settlement with a shortage. We acknowledge that the order in which exchange between settlements is updated might have some minor effects on the results if there are many settlements with shortages. Using data from Malville (2001), we assume that a fraction of 0.02 * distance in number of cells is lost, by assuming a cell size of 10 x 10 km.

However, settlements do not always agree to provide food to other settlements who ask for it. For each agent, we track how much it gives and receives during exchange interactions. When settlements exchange, we calculate the average level of debt (more received than given) for each settlement. A settlement does not receive additional resources from another settlement if the average level of debt of the cell is beyond a maximum tolerable level of debt d_{max}.

Moving to another cell

If an agent does not receive the minimum level of resources it requires (h_{min}) or when storage is below a minimum level of the buffer (b_m*b), the agent may consider moving to another location. The agent will only move to another location when it finds a location within a radius r_{max} that is better than its present location. The agent evaluates a location in the following way.

Agents take into account that resources are depleting and calculate what will be the impact of them moving to that location. They calculate the expected value of the relative resource R at timestep t+1. To calculate the expectation, the agent uses the current level of the soil quality and calculates the consequence of adding one additional agent moving to that cell, using the following relationship:

$$R_j^E(t+1) = R_j(t) + g_{r0} R_j(t) \left(\frac{R_j(t)}{C_j}\right)^{\gamma} \cdot \left(1 - \frac{R_j(t)}{C_j}\right) - \eta \cdot \{P_j^E(t+1) + 1\} \tag{6}$$

This expectation depends on the expected number of agents in the cell, which is assumed to be equal to the number of agents at that moment, using asequential updating, plus the agent moving to the cell. This leads to the expected production, defined as:

$$Q_j^E(t+1) = a \cdot R_j^E(t+1) \cdot \{P_j^E(t+1) + 1\}^{\alpha} \tag{7}$$

If the expected value of production is:

$$Q_j^E(t+1) > T_{\min} \cdot Q_j(t) \tag{8}$$

the location is considered to be an option. T_{min} might be higher than 1 if we include transaction costs of movement and if the agent wants to move to another location that is at least better than the current location. The agent moves to the best location drawn from the options and the relative values of expected production.

Population dynamics

The total number of agents—the population of the system—changes over time. Agents have offspring and can die. Although agents represent a group of individuals, the proportional level can be mimicked by assuming that each agent has a chance to die or to generate offspring. The annual levels of death and birth rates are based on the amount of food produced by the agent during the year.

The death rate is defined as r_d * (2 – h_i/100), with r_d equal to 0.02. The birth rate is defined as r_b * h_i/100, with r_b equal to 0.03. This leads to a linear relationship between expected population change and level of corn consumption. The expected population change is zero for a consumption level of 80, and 0.25% a year when the consumption level is equal to 85, the values of h_{min} in the base case simulations. Thus, the population growth rate is 0.25% at the maximum growth rate when no food shortages are experienced, which is in line with the maximum "natural" level of population growth as observed in historical data (Cowgill 1975).

Parameter values

The parameter values used in the default case are listed in Table 2. We also list the boundaries of the parameter ranges we will explore in the sensitivity analysis. The stylized model is not based on specific empirical data, so we tried to define a set of relative values that would enable us to explore the consequences of different assumptions on the spatial and temporal population dynamics.

Table 2. Parameter values of the default version of the model.

Parameter	Description	Range	Default value
γ	Degradation factor	[0, 2]	1
g_r	Regeneration level of soil per year	[0.05, 0.1188]	0.0844
η	Annual depletion rate of resource per household		0.5
α	Production elasticity		0.2
y_s	Years of storage	[1, 9]	5
l_s	Loss rate storage	[0,0.5]	0.25
lf	Learning factor	[0,2]	1
T_{min}	Threshold of expected food available in other cell in order to migrate	[1,2]	1.5
h_{min}	Minimum level of food a year		85
d_{max}	Maximum level of debt	[0, 100000]	100
r_{max}	Radius around existing settlement as migration opportunities	[1, 9]	5
b	Buffer	[0,100]	50
b_m	Minimum relative size of buffer	[0, 1]	0.5
r_d	Annual death rate		0.02
r_b	Annual birth rate		0.03

RESULTS

Default case

We ran the model for a 10,000-year period to explore the long-term population dynamics. Before discussing a sensitivity analysis of the parameter values, we discuss a few individual runs in more detail. We ran the model for each of the three types of sharing mechanisms. Figure 4 shows that the population size in the whole landscape is fluctuating and experiencing periods of overshoot and collapse (Fig. 5). There are no clear statistically significant differences between the various assumptions of sharing if we compare the average population levels of many runs. In all cases, population size builds up over a long period and triggers a resource scarcity that causes the population level to decline.

These population cycles are 1,000 to 2,000 years long. Over a shorter period, several decades, there are cycles of aggregation and disaggregation (Fig. 6). Figure 6 shows clearly the short- and long-term cycles. The long-term cycles are caused by decline and recovery of soil quality, whereas the short-term cycles are triggered by climate variability as we will show in the next paragraphs.

We analyze how precipitation affects aggregation, measured as the density of agents per occupied cell. If there are 400 agents in 200 cells, leaving 200 cells unoccupied, the density of agents per occupied cell is 2. We expect that a change in population density is caused by precipitation changes. More specifically, we expect an increase in density during periods of low precipitation because larger settlements are more efficient (economics of scale in technological knowledge and expertise, the value

Fig. 4. Population sizes for typical runs for three types of sharing mechanisms within the settlement.

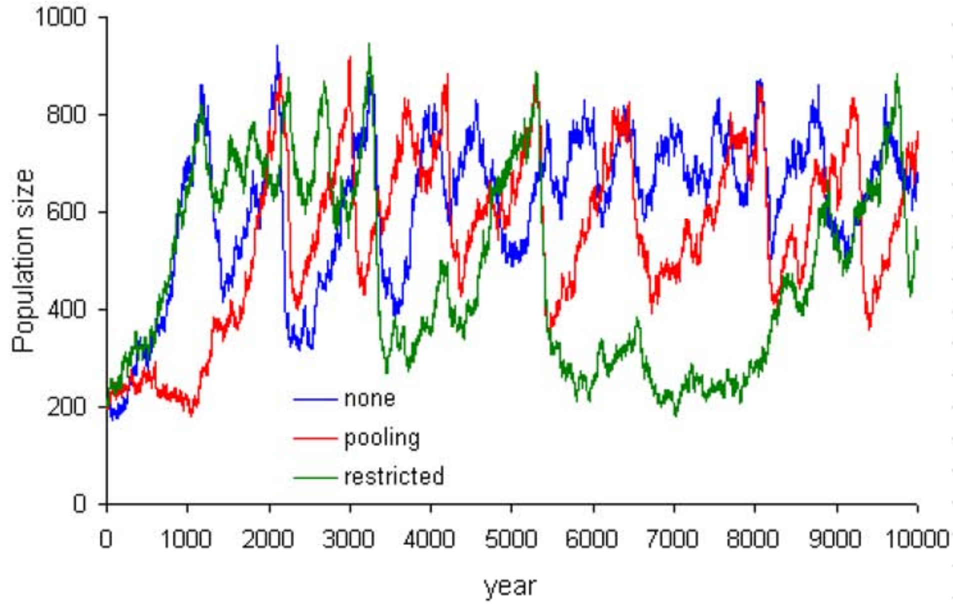


Fig. 5. Relative resource level for typical runs for three types of sharing mechanisms within the settlement.

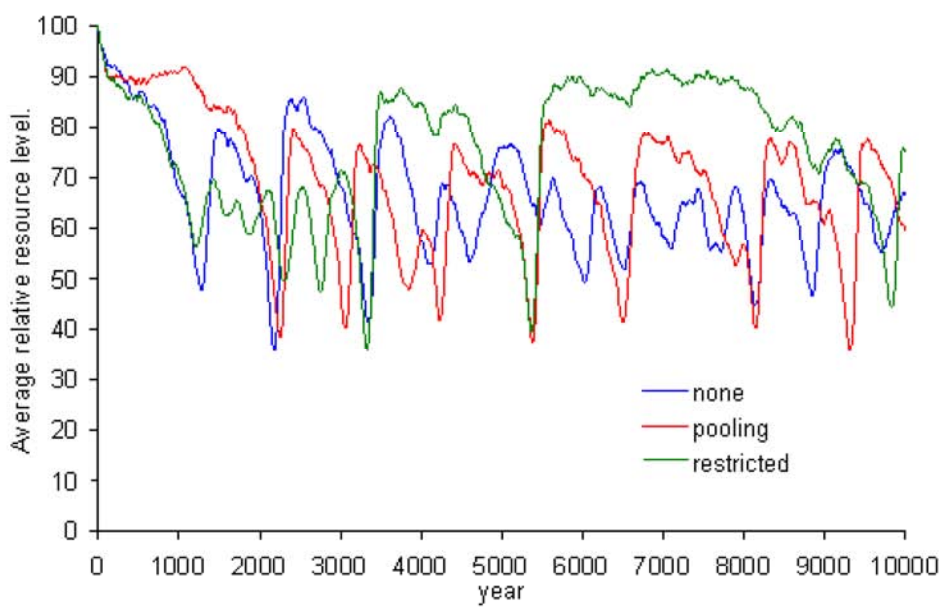


Table 3. Results of linear regressions for three types of sharing.

	None	Pooling	Restricted
a_0	2.1761***	1.4607***	0.5494***
a_1 (density_{t-1})	0.8066***	0.8502***	0.9310***
a_2 (PDSI)	-0.0873***	-0.0630***	-0.0289***
i	2	2	2
R^2	0.6814	0.7362	0.8698

***Significant with $p < 0.001$.

of α in eq. (3)). For the last 5,000 time steps of the three simulations, we estimate the following functions:

$$\text{Density}_t = a_0 + a_1 * \text{Density}_{t-1} + a_2 * \text{PDSI}_{MA(i)} \tag{9}$$

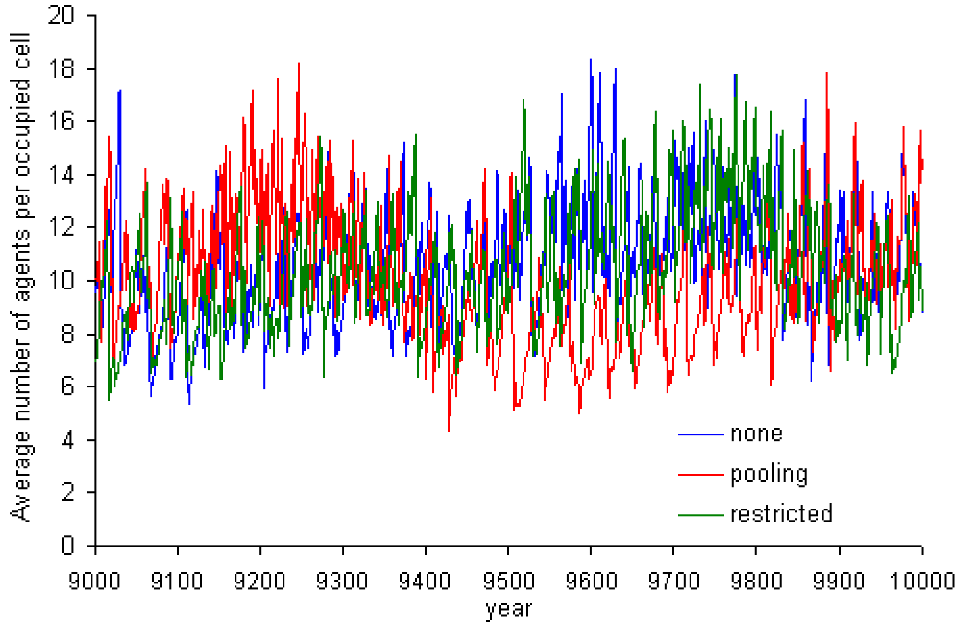
Where $\text{PDSI}_{MA(i)}$) is the moving average of the last *i* timesteps. We check for different values of *i* which moving average leads to the best fit.

The average aggregation per occupied cell increases after a few (2) years of droughts (Table 3). There is not much variation between the cases, but the case without sharing seems to be more sensitive to fluctuations in precipitation. Restricted sharing is least sensitive to fluctuations in precipitation because agents within the settlements have different histories and levels of storage available. Note that in all three cases the average PDSI of the last 2 years is used, which indicates that aggregation is a response to a multiyear drought. This result explains the short-term variations in densities as depicted in Fig. 6.

We now compare the baseline simulation with other simulations to assess the impact of climate variability and population dynamics. If we reduce climate variability, assuming τ of eq. (1) to be equal to 1, the level of fluctuations in population size increases (Fig 7). Climate variability acts as a stabilizer of the population level by perturbing the settlements regularly. When there is no climate variability, there is less aggregation and less local depletion of soil quality. This leads to longer population growth periods and deeper declines because the soils have been depleted more evenly. This can also be seen in Fig. 8, where the aggregated soil depletion is more severe for the simulation without climate variability. Note that with a stable population level of 650 the relative resource level declines to a stable level.

Figure 9 shows that, with a constant population level and no climate variability, we still have periods of aggregation and disaggregation. Above, we have related the change in density to climate variability, so how can we explain this? As we will see in the sensitivity analysis, a crucial assumption in the model is that agents need to accumulate knowledge of a location to reach maximum productivity of that location. This leads to agents holding on to their land until the productivity declines to such a level that replacement and loss of local knowledge is outweighed by the value of a more productive location. If we exclude the experience component of the model, we still see fluctuations in densities. Just the initial random allocation of agents on the landscape leads to differences in soil quality among the settlements and contributes to the spatial dynamics.

Fig. 6. Population density for typical runs for three types of sharing mechanisms within the settlement.



Settlement sizes of up to 50 agents are observed, but most of the settlement sizes are between 10 and 15 agents. In the simulation without climate variability, there is a larger number of small settlements because this simulation experiences large collapses of the population level (Fig. 10).

In sum, we can synthesize what is happening in the model. When a cell is occupied for a longer period, it becomes used more efficiently, by which we mean the same production can be derived with a lower soil quality. This attracts more agents, which increases the relative production level due to increasing levels to scale. But this depletes the soil, and when the agents cannot meet the minimum level of production and cannot derive food from other sources, they will leave if a better spot is nearby. Consequently, depending on the assumed resource dynamics, the depleted soil will have time to recover.

Rainfall variability leads to short-term shocks that lead to agents leaving, on average, at a lower level of depletion, meaning the soil is able to recover faster. Note that we assume that, due to erosion, the soil recovers slowly and, therefore, regular movement increases long-term productivity. Thus, climate variability shakes the system regularly to redistribute the pressure on the landscape. From a resilience perspective, climate variability maintains the resilience of the system and reduces severe overshoot and collapse at the system level.

Sensitivity analysis

In the sensitivity analysis, we vary the parameters in Table 2 from relatively low to high in the uncertainty range. For each parameter combination, the model is run 100 times, each for 10,000 time steps. Although we could analyze the data using many indicators, the basic statistic we will look at is the average population level over the 10,000 time steps (Table 4).

The standard deviation of the population size is typically about 10% and, thus, the differences between the different assumptions of sharing (no

Fig. 7. Population size for typical simulations with constant population size, and no climate variability, next to the default scenario.

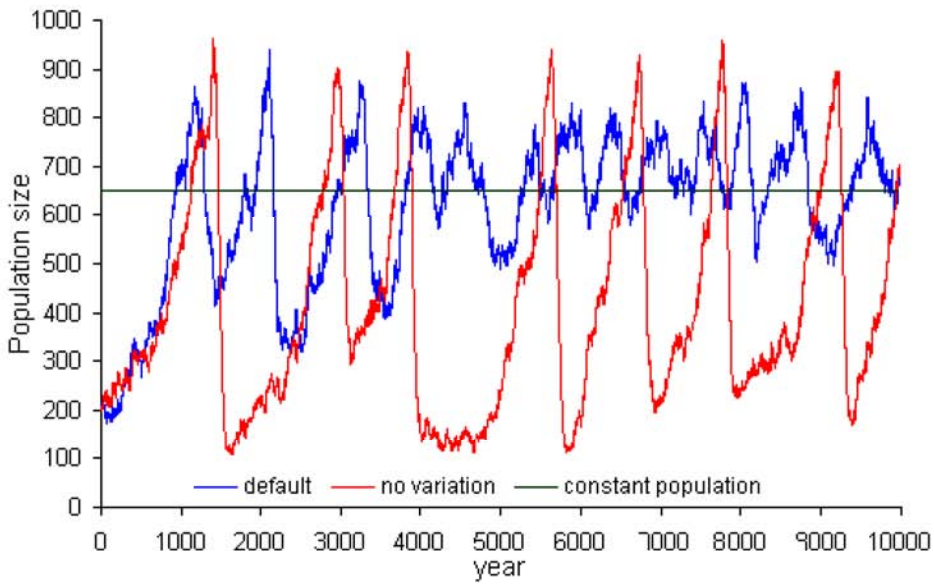


Fig. 8. Average relative resource level for different runs with alternative assumptions about population dynamics and climate variability. Aside from the default case, we assume a simulation without climate variability, a simulation with a constant population size, and a simulation with both constant population size and no climate variability

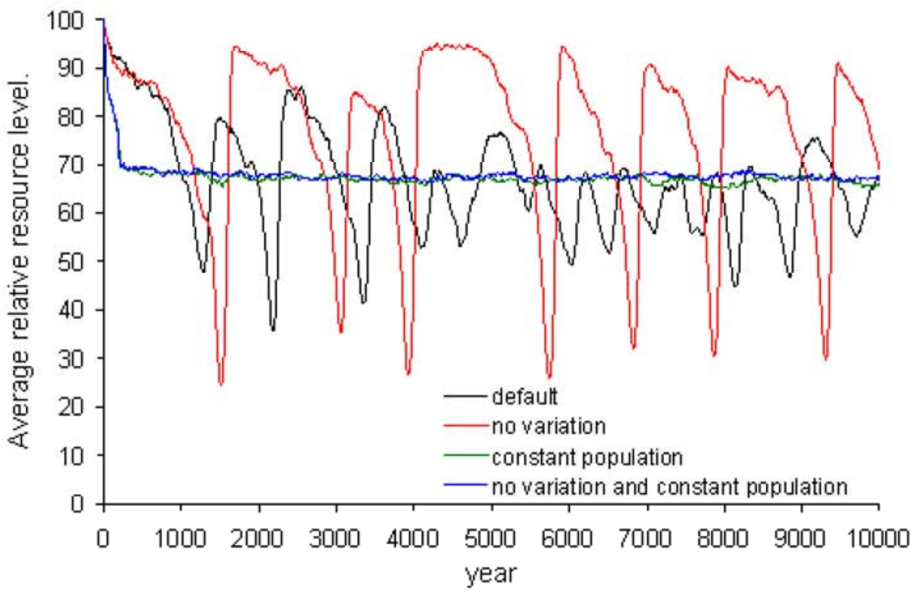


Fig. 9. Even a flat landscape with a fixed number of agents without rainfall variability has periods of aggregation and disaggregation.

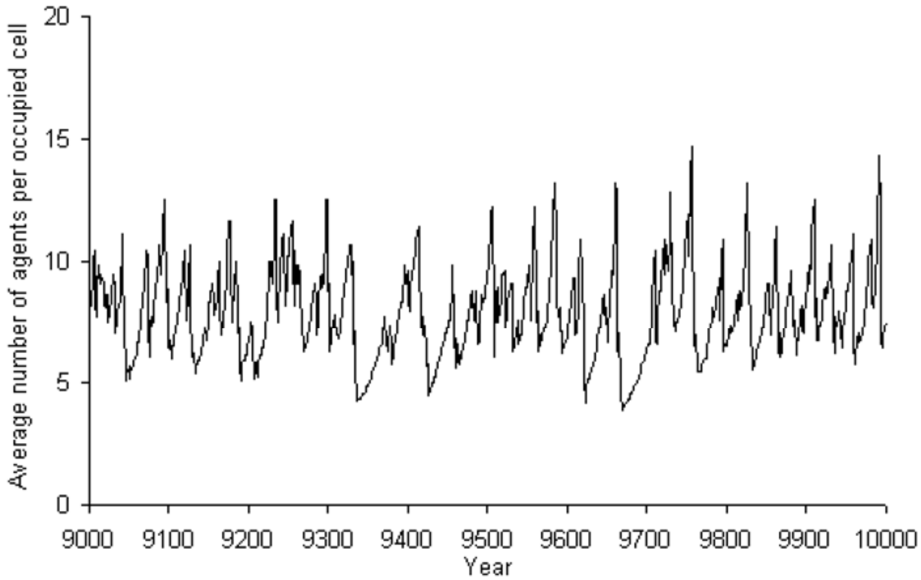


Fig. 10. Distribution of settlement size for the four simulations discussed in Figure 8.

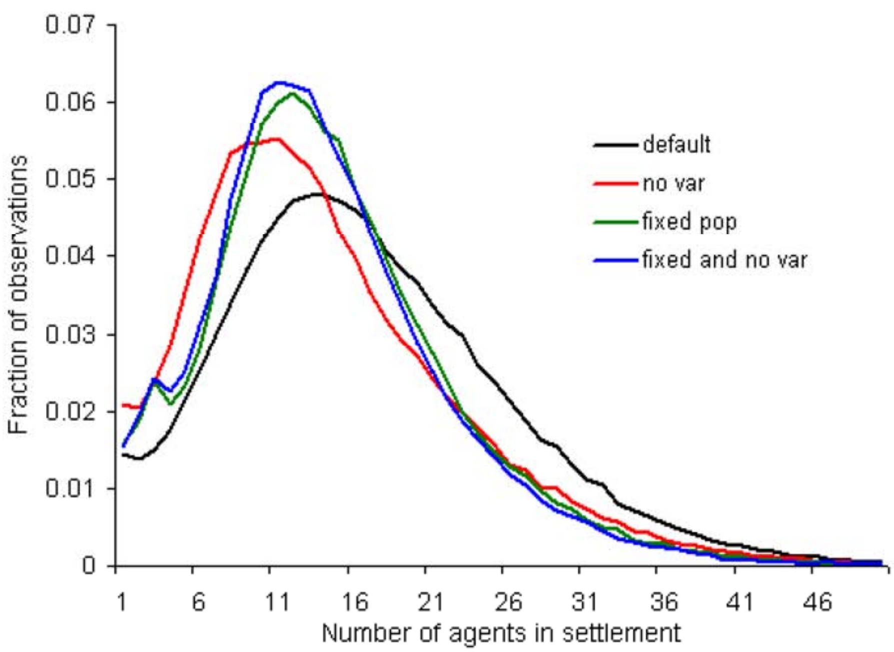


Table 4. The average population level over 10,000 time steps of 100 runs for various parameter combinations and assumptions.

	None	Pooling	Restricted
Default	238	304	303
Degradation factor = 0 , regeneration rate 0.05	24	76	24
Degradation factor = 2, regeneration rate 0.1188	96	70	96
Loss rate storage = 0	385	273	361
Loss rate storage = 0.5	20	35	19
Learning factor = 0	749	763	744
Learning factor = 2	12	19	14
Radius = 1	13	15	13
Radius = 9	311	342	266
No rain variability	333	296	352
More variability	583	565	587
Years of storage = 1	9	16	9
Years of storage = 9	285	385	243
T_{min} = 1	461	491	461
T_{min} = 2	10	13	11
d_{max} = 0	16	18	19
d_{max} = 1000000	407	420	413
Buffer = 0	250	233	270
Buffer = 100	40	123	38
B_m = 0	146	274	156
B_m = 1	289	357	289

sharing, pooling, and restricted sharing) are in general not significant. In the sharing case where resources are pooled together in settlements, higher population levels are derived. There are some notable exceptions such as when there is no climate variability, when agents do not keep a buffer before exchanging resources, when erosion increases, and when storage is not lost. Pooling can, therefore, be considered the most resilient strategy of sharing at the system level. This conclusion is in contrast to Hegmon (1996), who concludes that pooling leads more households to fall below the minimum nutrition level. However, in Hegmon (1996), agents could neither move to another location during periods of scarcity nor exchange resources with other settlements.

The effect of different assumptions of sharing is relatively small compared with a number of other assumptions. The most sensitive assumption is the learning factor, which indicates how much agents need to learn from the local environment before reaching maximum productivity. If there is no delay, and agents immediately have all the necessary knowledge when they move to a new location, the population levels more than double. There is less benefit from aggregation and economies of scale, and agents are more spread over the landscape. Another sensitive assumption is the threshold level T_{min}, which determines when agents will move to another location. If agents are more selective about when to move to another location, a high value of T_{min}, the agent will stay longer in one place and locally deplete the soil before moving on. This local depletion leads to a long recovery time, too long for the population to be able to use this location again when other cells are depleted. Thus, the population collapses rapidly, leading to a low average population level.

The third most influential parameter is the assumption about how much debt settlements can accept until they will refuse to donate resources to settlements with shortages. If settlements will accept no debt, no exchange will happen and the population will collapse rapidly. This indicates that exchange is necessary for this environment to persist at the system level. Allowing a very high debt load, encouraging agents always to give when asked for a donation, leads to a somewhat higher population level.

When we assume that the carrying capacity C_j is drawn from a uniform distribution [0,200] instead of being 100 for each cell, the population level increases, and there is a higher density of agents per occupied cell. Thus, heterogeneity again leads to an increase in capacity of the system. The assumptions of soil quality regeneration rate and erosion are varied, and we found that population levels are much lower in both scenarios (no erosion but low regeneration rate, and high degradation and higher regeneration rate). This indicates that more detailed information about the resource dynamics can have important consequences for the results when using a model like this.

Figures 11 and 12 provide more information about the sensitivity analysis. In general, we see that there is more migration for higher levels of aggregation (Fig. 12). This means that there are larger settlements, which are of shorter duration as they lead to rapid decline in local soil quality. The most extreme case is with T_{min} = 1, which leads to a migration rate of 25% a year and an average density of 12 agents per cell. In fact, groups of agents are hopping around on the landscape. More reasonable migration rates are around 10% for the American Southwest, which is observed for most of the parameter settings. We see that higher population levels coincide with higher levels of aggregation, except when the average population level is really high and agents are spread over the landscape more evenly, which is the case when the learning factor is equal to zero (agents have perfect knowledge of local conditions of new locations).

Evolution of strategies

We close the model analysis by examining agents with different strategies and let those strategies evolve over time. We are interested in what mix of strategies evolve and how they differ for various assumptions of the environment and resource dynamics.

Agents differ in the strategy of sharing, the years of storage, the buffer level of storage before they exchange, the relative buffer below which they will decide to move to another location, the maximum debt tolerated, and the threshold T_{min} when to move to another location. The initial values of the agents are drawn from uniform distributions as defined in Table 2, and with a one-third probability that an agent will have one of the three sharing strategies. Every time a new agent is generated, it copies the values of its parents and adds some white noise (standard deviation 1%) or changes the sharing strategy with a probability of 1%.

Some decisions of agents are settlement based, such as the decision whether to exchange with another settlement. We assume that the most intolerant agent in a settlement with a surplus defines the average level of debt it will tolerate from a settlement with a shortage. When agents like to pool resource, they only pool with other agents in the settlement who also like to pool. Similar agents who restrictedly share their resources within the settlement do this only with other agents with a similar strategy in the settlement.

We ran the model 100 times for 10,000 time steps and found that no dominant sharing strategies

Table 5. Average values of the evolved parameters during the last 1,000 time steps. Based on 100 simulations of 10,000 time steps. Rows with an x indicate that less than 5% of the simulations did not collapse before 9,000 time steps, and thus, no data could be derived.

						Distribution		
	ys	Buffer	B_m	d_{max}	T_{min}	None	Pooling	Restricted
Default	5.3	70.3	0.67	468	1.10	0.31	0.41	0.28
Degradation factor = 0, regeneration rate 0.05	5.3	73.0	0.71	534	1.09	0.31	0.37	0.32
Degradation factor = 2, regeneration rate 0.1188	x	x	x	x	x	x	x	X
Loss rate storage = 0	5.3	69.2	0.70	535	1.14	0.26	0.40	0.34
Loss rate storage = 0.5	5.8	66.8	0.67	614	1.08	0.34	0.34	0.32
Learning factor = 0	5.8	57.2	0.55	536	1.08	0.35	0.34	0.32
Learning factor = 2	x	x	x	x	x	x	x	x
Radius = 1	x	x	x	x	x	x	x	x
Radius = 9	5.3	66.8	0.65	554	1.12	0.30	0.37	0.34
No rain variation	4.7	64.4	0.63	515	1.12	0.36	0.32	0.32
More variation	5.5	74.6	0.71	576	1.11	0.30	0.36	0.34

emerged (Table 5). The reason for this is that benefits can only be derived when multiple agents with the same strategy are in the same settlement for a longer period, which is not common in a landscape where the population is so dynamic. The most significant evolved parameter is the threshold T_{min}, which evolves to a value around 1.1 for all scenarios. Another finding is that the buffer level is around 70 and lower than the default case, whereas b_m is higher than the default situation.

When degradation is more severe than in the default case, or the radius of movement is small, or it takes more time to derive local knowledge, the evolution of individual strategies goes too slowly to avoid collapse of the population before 9,000 time steps, after which we define the evolved parameter values. The differences in evolved parameters are modest, partly because the agents experience many different conditions and evolutionary pressures. In future, we may include cultural transmission of strategies, which may lead to domination of certain strategies.

DISCUSSION

This paper presents an initial version of a stylized agent-based model to capture population dynamics on an artificial landscape that mimics some basic characteristics of the ancient American Southwest. We find that the temporal and spatial population dynamics are affected by many assumptions of the model. Resource dynamics affect the long-term population levels, whereas climate variability affects the short-term aggregation levels. Assumptions about how much learning is needed to reach maximum productivity, when agents move to another location, and when to exchange resources, affect the long-term population levels.

Fig. 11. Average density vs. population size for the different cases of Table 4.

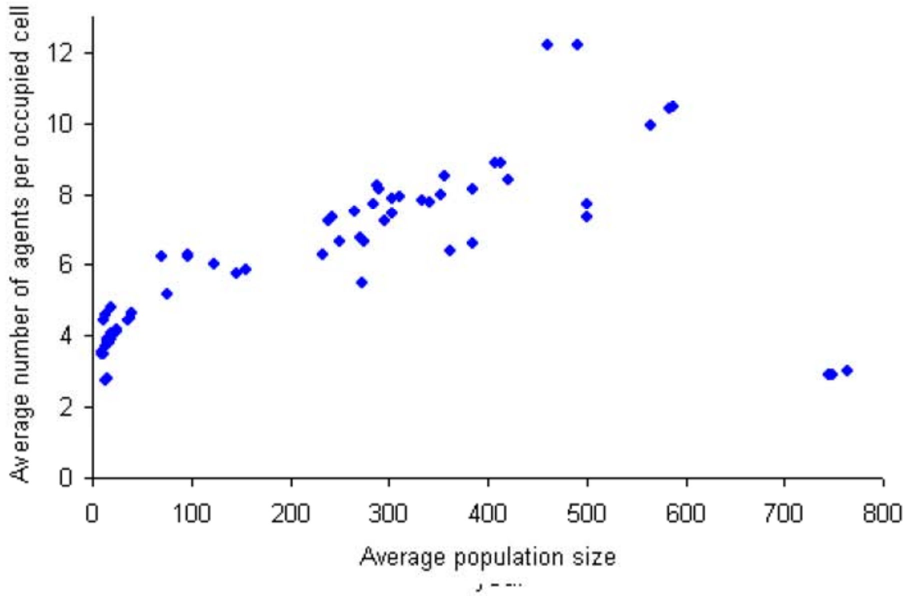
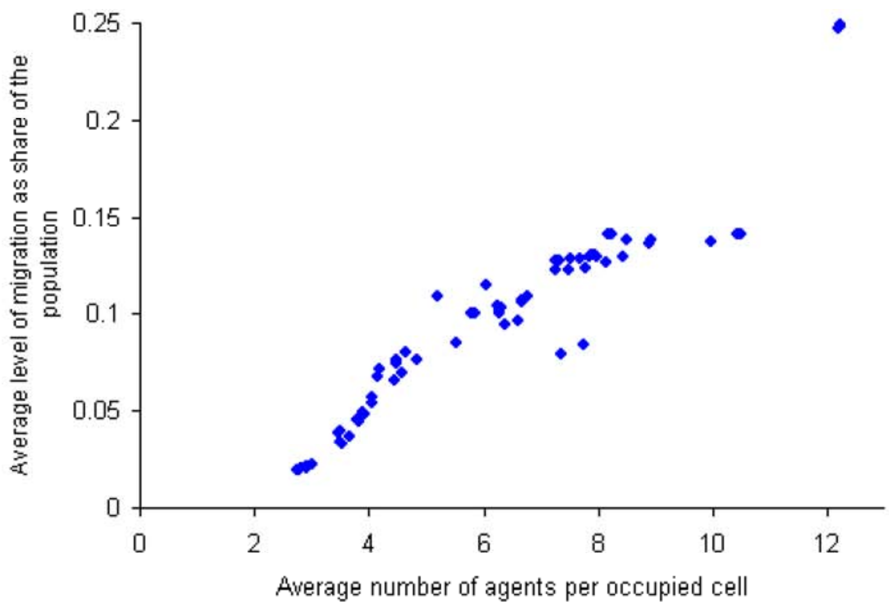


Fig. 12. Average migration level vs. population density for the different cases of Table 4.



Despite the many shortcomings of the model, we conclude that climate variability had an important impact on the possible factors leading to aggregation and abandonment in the ancient Southwest. Climate variability leads to an increased resilience of the population at the system level. Although individual settlements are abandoned due to climate fluctuations, this causes the soils to recover quickly. If there were no climate variability, settlements would be occupied for a very long time, leading to severe soil degradation and causing the settlement to collapse.

Populations in the American Southwest are known for their mobility to adapt to the harsh arid environment. The limited ability of settlements to derive resources over large distances led them to degrade local resources. Climate variability, such as long-term droughts, is thought to have led to abandonment of settlements and collapse of ancient societies. The results of the model described in this paper suggest that, without climate variability, the rise and fall of societies would have been more severe. Thus, climate variability may have triggered the regular reorganizations that maintained the resilience of the prehistoric populations in American Southwest.

Responses to this article can be read online at:
http://www.ecologyandsociety.org/vol15/iss2/art19/responses/

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LITERATURE CITED

Axtell, R. L., J. M. Epstein, J. S. Dean, G. J. Gumerman, A. C. Swedlund, J. Harburger, S. Chakravarty, R. Hammond, J. Parker, and M. Parker. 2002. Population growth and collapse in a multi-agent model of the Kayenta Anasazi in Long House Valley. *Proceedings of the National Academy of Sciences of the United States of America* **99**(3):7275–7279.

Cowgill, G. L. 1975. On the causes and consequences of ancient and modern population changes. *American Anthropologist* **77**(3):505–525.

Dean, J. 2007. Zuni-area paleoenvironment. Pages 77–94 *in* D. A. Gregory and D. R. Wilcox, editors. *Zuni origins: toward a new synthesis of Southwestern archaeology.* University of Arizona Press, Tucson, Arizona, USA.

Frank, M. D., B. R. Beattie, and M. E. Embleton. 1990. A comparison of alternative crop resource models. *American Journal of Agricultural Economics* **72**(3):597–603.

Fretwell, S. D. 1972. *Populations in a seasonal environment.* Princeton University Press, Princeton, New Jersey, USA.

Gunderson, L. H., and C. S. Holling, editors. 2002. *Panarchy: understanding transformations in human and natural systems.* Island Press, Washington, D.C., USA.

Hegmon, M. 1996. Variability in food production, strategies of storage and sharing, and the pithouse-to-Pueblo transition in the northern Southwest. Pages 223–250 *in* J. A. Tainter and B. B. Tainter, editors. *Evolving complexity and environmental risk in the prehistoric Southwest.* Addison-Wesley Publishing Company, Reading, Massachusetts, USA.

Janssen, M. A. 2009. Understanding artificial Anasazi. *Journal of Artificial Societies and Social Simulation* **12**(4):13. [online] URL: http://jasss.soc.surrey.ac.uk/12/4/13.html.

Janssen, M. A., J. M. Anderies, and E. Ostrom. 2007. Robustness of social–ecological systems to spatial and temporal variability. *Society and Natural Resources* **20**(4):307–322.

Kelly, R. L. 1983. Hunter–gatherer mobility strategies. *Journal of Anthropological Research* **39**(3):277–306.

Kobti, Z., R. G. Reynolds, and T. A. Kohler. 2006. The emergence of social network hierarchy using cultural algorithms. *International Journal on Artificial Intelligence Tools* **15**(6):963–978.

Kohler, T. A., J. Kresl, C. van West, E. Carr, and R. Wilshusen. 2000. Be there then: a modeling approach to settlement determinant and spatial efficiency among late ancestral Pueblo populations of the Mesa Verde region, U.S. Southwest. Pages 145–178 *in* G. J. Gumerman and T. A. Kohler, editors. *Dynamics in human and primate societies: agent-based modeling of social and spatial processes.* Santa Fe Institute, Santa Fe, New Mexico, USA and Oxford University Press, Oxford, UK.

Kohler, T. A., and S. A. van der Leeuw, editors. 2007. *The model-based archaeology of socionatural systems.* School for Advanced Research Press, Santa Fe, New Mexico, USA.

Kohler, T. A., M. D. Varien, A. Wright, and K. A. Kuckelman. 2008. Mesa Verde migrations: new archaeological research and computer simulation suggest why ancestral Puebloans deserted the northern Southwest United States. *American Scientist* **96**:146–153.

Luck, M. A., G. D. Jenerette, J. Wu, and N. B. Grimm. 2001. The urban funnel model and the spatially heterogeneous ecological footprint. *Ecosystems* **4**:782–796.

Malville, N. L. 2001. Long-distance transport of bulk goods in the pre-Hispanic American Southwest. *Journal of Anthropological Archaeology* **20**:230–243.

McAllister, R. R. J., D. M. S. Smith, C. J. Stokes, and F. J. Walsh. 2009. Patterns of accessing variable resources across time and space: desert plants, animals and people. *Journal of Arid Environments* **73**:338–346.

Niamir-Fuller, M., editor. 1999. *Managing mobility in African rangelands: the legitimization of transhumance.* Intermediate Technology Publications, London, UK.

Palmer, W. C. 1965. *Meteorological drought.* Research Paper No. 45, U.S. Department of Commerce Weather Bureau, Washington, D.C., USA.

Rautman, A. E. 1993. Resource variability, risk, and the structure of social networks: an example from the prehistoric Southwest. *American Antiquity* **58**:403–424.

Reynolds, R. G., T. A. Kohler, and A. Kobti. 2003. The effects of generalized reciprocal exchange on the resilience of social networks: an example from the Prehispanic Mesa Verde region. *Computational and Mathematical Organization Theory* **9**:227–254.

Young, D. A. 2002. A new space–time computer simulation method for human migration. *American Anthropologist* **104**(1):138–158.

Appendix

Maximum regeneration rate for

$$R = C \cdot \left(\frac{\gamma + 1}{\gamma + 2} \right)$$

Regeneration rate is normalized via

$$g_r = \frac{0.25 * g_{r,n}}{\left(\frac{1}{\gamma + 2} \right) \cdot \left(\frac{\gamma + 1}{\gamma + 2} \right)^{\gamma + 1}}$$