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Abstract:
Globalization is an important feature affecting the robustness of small-scale social-ecological systems (SESs). Understanding the way globalization affects those systems is crucial for adaptation. In this paper we focus on analyzing how the increased displacement of resource users as a consequence of globalization affects the robustness of SESs. We developed a stylized agent-based model representing a dynamic population of agents moving and harvesting a renewable resource. The individual characteristics and behavior of agents and governments determine the robustness or collapse of the system. We analyzed several scenarios in which we vary the mobility of the agents (i.e., the extent to which agents can move), the distribution of the resource richness and the amount of information governments have regarding potential intruders. Our results showed that agent mobility significantly affects the robustness of the SES. This response is non linear and very sensible to the type of spatial distribution of the resource richness. The attractiveness of rich resource sites (local level) to agents makes them vulnerable to rapid collapse with consequences to the global system. While medium heterogeneous landscapes are very robust to mobility, highly heterogeneous landscapes (i.e., exponential distribution of resource richness) are not able to absorb such a disturbance; the system stability as well as the resource and occupation levels drop as mobility increases. An increase in enforcement is not sufficient for the robustness of such SESs. Results suggest the importance of global governance to deal with governance of resource rich areas, not only for local governments because those areas are more prone to invasions but for global sustainability itself.

Keywords:
Agent-Based Model; Globalization; Mobility; Resilience; Robustness; Social-Ecological Systemsl

Mobility, Resource Harvesting and Robustness of Social-Ecological Systems

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INTRODUCTION

Long-lived small-scale social-ecological systems (SESs) are currently facing a great challenge in adapting to new disturbances due to globalization. Their long-term survival is based on the robustness of their institutions and their adaptation to historical external disturbances (Janssen et al. 2007). However, global social (e.g., global markets) and environmental changes (e.g., climate change) impact the robustness and vulnerability of SESs and threaten the continuity of many long-lived SESs (Young et al. 2006). For example, due to climate change, traditional irrigation systems face a change in the intensity and frequency of rainfall that they had originally adapted to. If they are not able to adapt to this new regime of perturbation the SES may collapse (Anderies et al. 2004). Understanding the vulnerabilities that long-lived SESs face due to globalization is crucial for communities to respond and adapt to global changes.

One of the characteristics of our global era is the increased connectedness and accelerated flow of goods, trade, information, and people. All of this simultaneously causes positive and negative effects on systems. For example, this situation increases the diffusion of knowledge and technology (e.g., Ernst and Kim 2002), and facilitates the arrival of humanitarian aid, but, at the same time, increases the spread of diseases (e.g., flu) (e.g., Dollar 2001) and invasive species (e.g., Gren et al. 2011), and increases the vulnerability of local communities to the encroachment of new resource appropriators (i.e., intruders) (Pérez et al. 2011).

In this paper, we analyzed how the displacement of resource users affects the robustness of SESs. Some documented examples of this widespread consequence of globalization include fisheries worldwide (Berkes et al. 2006, Cudney-Bueno and Basurto 2009), forests in south Asia that are being intensively harvested due to the recent introduction of the shrimp industry (Barbier and Cox 2002) or groundwater in southeast Spain, where traditional farmers have to share the scarce water resource with industrial agrarian companies recently settled in the area (Pedreño and Pérez 2008, Pérez et al. 2011). The driving forces that are behind this intrusion are related with the socio-political and physical accessibility to the resource and to its economic value (Pérez et al. 2011). The incursion of intruders may have positive consequences, such as the transmission of knowledge but also may have severe

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consequences on traditional SESs, and even end in their inevitable collapse, due to, for example, an overexploitation of natural resources.

We use an agent-based model to understand how mobility of agents affects the long-term resource and population levels and to explore specific conditions that increase the robustness of communities to face the incursion of new resource appropriators. Although the model was inspired by case studies of complex SESs, the model itself is highly stylized enabling us to focus on some key mechanisms of mobility and resource use. By mobility we refer to the extent to which agents can move. The model is a stylized representation of a dynamic population of agents moving and harvesting a renewable resource. The individual characteristics and behavior of agents and governments determine the sustainable use or overexploitation of the resource. We analyzed the robustness of the SES under several scenarios in which we vary the mobility of the agents, the landscape configuration and the amount of information governments have towards potential intruders. We hypothesized that higher mobility leads to less robustness of SESs, and that landscape configuration and the reputation of agents modulate those effects.

METHODS

Model description

Our agent-based model is a stylized representation of a SES. A dynamic population of agents moves and harvests a renewable resource in a 50x50 landscape (Fig. 1). Each time step, agents move, harvest and store energy, may reproduce or die, and may imitate other agents' attributes; also during the time step the resource grows and governments collect fines from cheaters and may imitate neighbors (Fig. 2).

Agents move if they think the resource level won't satisfy them. How far they can move is a parameter set by the modeler. Each agent has a different desired amount of resource to be harvested. Agents can change this attribute by imitating more satisfied agents in their same location. Agents store the energy obtained from harvesting not used for metabolism. Movement and reproduction also cost energy to agents. If the energy stored by an agent became 0, the agent will die. Reproduction is asexual, with each agent producing one offspring, which is a copy of its parent. Each location represents a government. Governments differ in their enforcement level that is determined by an attribute that increases the probabilities of detecting cheaters and the amount paid by cheaters. This attribute of governments may change if governments copy the enforcement level of neighbors with higher fitness (i.e., higher population level). Governments encourage agents to harvest a certain amount of resource in order not to deplete it. Agents may ignore sustainable practices and harvest more resource. If a government catches a cheater, the agent will have to pay a fine. Each simulation ends after 5000 time steps or when population or resource become 0.

Below we provide a more detailed description of our model following the ODD (overview, design concepts and details) protocol for describing individual- and agent-based models (Grimm et al. 2006, Grimm and Railsback 2005, Grimm et al. 2010). The model is implemented in NetLogo v.4.1 (Wilensky 1999; http://ccl.northwestern.edu/netlogo/). The model code is available at http://www.openabm.org/model/3175/version/1/view. Table 1 shows the description of all parameter and variables included in this model.

Purpose. The purpose of the model is to analyze how mobility affects the sustainability of SESs and to examine specific conditions that reduce the vulnerability of communities to the incursion of new resource appropriators.

Entities, state variables, and scales. The entities of the model are agents moving and harvesting resources in a 50x50 torus landscape (i.e., when agents approach a border of the landscape, they reenter the system at the opposite border). Agents differ in their location, the amount of resources that they are willing to store, and their stock of energy. Agents may copy the desired storage level of more satisfied agents in their same location. Each patch has an amount of resource and is governed by a government-agent. In this version, few institutional arrangements are included. Government-agents differ in their enforcement level. Government-agents may imitate the enforcement level of neighboring government-agents who have higher fitness (i.e., higher number of agents). Each cell has a logistic growth function for the resource. Each patch might have from 0 to n agents (Fig. 1). The model runs for a period of 3000 time steps. The values of the parameters used in the default model are showed in Table 1.

Process overview and scheduling. Figure 2 shows the activity diagram of our model. Every time step, agents assess the available amount of resources in their patch. If this amount does not satisfy their desired harvest level (*dH*), agents may move to the nearest cell with the highest resource level. The *dH* is:

$$dH_i = met * (1 + S_i)$$

Where *met* is the energy spent in the metabolism. Agents are assumed the desire a harvest level higher than the minimum required to meet their metabolism. The parameter S_i is between 0 and 1 so that the agent will meet the strict metabolism value with S_i =0, or a maximum of double the metabolism rate with S_i =1.

Besides movement due to dissatisfaction, agents can move to another random patch with a fixed probability (p_m). Movement costs energy to the agent. Every time step an agent changes its location, its accumulated energy (E_t) is reduced a certain amount (C_{mov}). Then agents decide how much resource to harvest, they harvest and they store energy. As the resource has a logistic growth, agents are encouraged by the government to harvest an amount near to the maximum sustainable yield (*agMSY*):

$$agMSY_j = \frac{K_j * r}{8} / n_j$$

Where K_j is the carrying capacity at patch *j*, *r* the growth rate of the resource, and n_j the number of agents at the patch *j*.

Agents may ignore sustainable practices and cheat and consequently harvest (*H*) the desired amount of resource (*dH*) when this amount is higher than the *agMSY*. Agents will cheat if they expect to receive a significant benefit of cheating taking into account the expected penalty of being caught:

> Agents cheat if: $Ta * p_{c_j} * F_{ij} > agMSY_{ij}$
> Where *Ta* is the benefit threshold of agents, p_{c_j} is the probability of catching a cheater in patch *j* (see below) and F_{ij} is the fee cheaters will pay if they are caught by the government. F*ij* is proportional to the enforcement level:
>
> $$F_{ij=}(agH_i - agMSY_j) * E_j$$
>
> Where agH_i is the amount of resource harvested by agent *i*. The value of F_{ij} is 0 if agent *i* is not caught or harvests an amount equal or less $agMSY_j$.

We selected as default value a moderate value of *Ta* (Table 1). Low values ($Ta < 0.2$) makes agents decide not cheat, thus in all circumstances the system reaches a stable threshold. On the contrary, high values ($Ta > 0.5$) makes agents decide to cheat and the system rapidly collapse. Agents do not have full knowledge of the probability of being caught (i.e., p_c). The capacity of agents to predict p_c increases the longer they stay in a certain patch, thus newcomers will more frequently predict an erroneous risk of cheating.

The probability of governments to catch a cheater (p_c) is proportional to their enforcement. We consider that the capacity of governments to detect a cheater decreases as the population increases since it require more effort to monitor all the agents. Hence, if the number of agents in a certain patch is 10 or less, p_c is *E*; an increase of 10 agents reduces p_c to 10%:

$$If\ 10(1-i) < \ n_j \leq 10i;\ p_{c_j} = E_j * \left(1 - \frac{i-1}{10}\right)$$

> Where n_j is the number of agents at patch *j*, p_{cj} is the probability of government at patch *j* to catch a cheater, E_j is the enforcement level at patch *j,* and $i \in \{1,2,\ldots,5\}$.

In this version of the model, we do not include technological innovation, only learning the local context. Hence unsatisfied agents may copy the attributes (*S*) of the more satisfied agent in the same cell with the highest fitness (i.e., accumulated energy stored).

The enforcement has a cost to governments. Although we don't explicitly model the payment for enforcements by governments, we assume that some governments are more willing to invest in monitoring and sanctioning than others, and that governments do not have infinite resources for monitoring and sanctioning. The net enforcement cost is proportional to the number of agents in the cell but it is reduced by the income from penalties:

$$netCost_j = cost * \ n_j - \sum_{i=1}^{n_j} F_{ij}$$

Where *cost* (=1) is the cost of enforcement, n_j is the number of agents at patch *j*, and $\sum_{i=1}^{n_j} F_{ij}$ is the total revenue from penalties at patch *j*.

The enforcement cost is accumulated each time step. If the accumulated cost of enforcement goes above a certain threshold (*Tg*), governments reduce 10% their enforcement level. With a fixed probability (I_g), governments will look to its neighbors and copy the enforcement value for the neighbor with highest fitness. The fitness of a government is the number of agents.

The energy stored by agents each time steps (E_t) is:

$$E_{t_{ij}} = E_{t-1_{ij}} + agH_i - F_{ij} - met - C_{mov} - C_{rep}$$

Where, H_i is the amount of resource harvested by agent *i* in time step *t*, F_{ij} is the punishment imposed to agent *i* by government of patch *j*, *met* is metabolism, C_{mov} is the cost of movement and C_{rep} the cost of reproduction.

If the energy stored by an agent becomes 0 or lower, the agent will die. With a birth rate (*br*), agents will reproduce. Birth rate depends on the stock of energy of agents:

$$br * \left(\frac{Et}{100}\right)$$

Offspring will reproduce the attributes of its parent. Parent and hatchling share the stock of energy from parent. Offspring will be allocated at the nearest patch (hr_{max}) with the highest resource level to avoid overpopulation in successful patches and to increase the spread of successful strategies.

At the end of each time steps the resource grows accordingly to a logistic equation:

$$R_j - H_j + r * R_j * (1 - \frac{R_j}{K_j})$$

Where R_j is the resource level at patch j, H_j is the total resource harvested at patch *j*, r is the resource growth rate, and K_j is the carrying capacity of the resource at patch *j*.

Initialization. Simulations are initialized with 5000 agents randomly allocated to cells on the landscape of 50x50 cells. Initially, each agent receives an amount of 10 units of energy. The storage rate of agents and the enforcement level of patches are uniformly distributed. Resource is initialized at half of its carrying capacity. Each simulation consists of 5000 time steps to explore the long-term dynamics.

Model experiments

The dynamics of the model are explored by a series of experiments in which we vary the mobility of agents, the landscape structure and the information governments have on potential intruders. We ran 200 iterations for each experiment. Early exploration of our model revealed that around 200 simulations are necessary to reduce the variability of our statistics to an acceptable level. We used as indicators the average of occupied patches and resource levels, as well as other evolved parameters (storage and enforcement levels, number of agents' movements, and proportion of cheaters in the population), over the 200 iterations during the last 1000 time steps. We measured the robustness of the system as the capacity of each run to persist over the 5000 time steps.

Mobility

To analyze how the mobility of agents affects the emergent values of our indicators, we compared the emergent results when we ran the model for different move capacities of the agents. Move capacity (ar_{max}) is the size of the radius that defined the possible set of patches an agent can move to. We ran the model for an ar_{max} of 1, 5, and 25. One means that agents can move to the neighboring patches, while a move capacity of 25 means that agents can move to any patch of the system.

Landscape structure

We run our model for different landscape configurations, i.e. differences in the carrying capacity (K) of the resource between patches. Apart from the default model that does not include landscape heterogeneity (all patches are settled to the same K) we considered 3 different statistical distributions of K: uniform, normal, and exponential. To do this, we first assigned a value to each cell according to a uniform, normal or exponential distribution. Then, we grouped the resulted values in 5 equal intervals. Finally, we assigned to these categories of cells a specific value of very low, low, medium, high and very high K. To compare outcomes between landscapes configuration, these values were adjusted so the total amount of resource at K was the same for the four landscape configurations (Fig. 3). We imported those results from the R statistical package (R Development Core Team 2008) using the NetLogo extension r (Thiele and Grimm 2010).

Reputation

In one of the model experiments, we analyzed how the information governments have on potential intruders affects the outcomes of the model. For this, we added a parameter in the model (*nrmarks*) that indicates whether the agent cheated (*nrmarks* ≥ 1) or not (*nrmarks* = 0) in previous time steps (Table 1). With high enforcement levels, governments have a greater probability of correctly "reading" this information; and by recognizing untrustworthy agents governments can better decide whether or not to let those agents in. In this version of the model, the option of governments to forgive the past unsustainable behaviors of potential intruders is not directly included. Governments predict the expected probability of a potential intruder to cheat (Exp_{ch}) according to past behavior (*nrmarks*):

$$Exp_{ch} = 1 - e^{-nrmarks}$$

In this version of the model, we only included information about the last time step, so *nrmarks* takes values of zero if agent didn't cheat or one if agent cheated last time step.

Agents will have more probabilities entering the selected patch as $Exp_{ch} * E_j$ increases.

Sensitivity analysis

In the sensitivity analysis we varied the values of parameters from low to high values (Table 1) and run the simulations for the different distribution of the resource richness considered. We use as indicator the time steps the simulation are running, and the average occupied patches and resource level over the last 1000 time steps of the 200 runs. We compared these results with results of the default model.

In the result section, we first describe the main dynamics of our default model (Table 1). Then, we analyzed how mobility, landscape structure and reputation of agents affect the outcomes of the model. We used as indicators, the resource level, the number of settlements (i.e., patches with agents), the enforcement level, and the robustness of the system. We measured robustness as the mean duration of the runs before collapse (i.e., number of time steps each simulation is running). We used the number of settlements as an indicator of the outcome of the simulation instead of population (i.e., number of agents) because its value is comparable among different resource richness distributions. Both variables are highly correlated. Finally, we show results of the sensitivity analysis.

RESULTS

Default model

The temporal dynamic of the model shows the interrelationship of the population and the resource level (Fig. 4). Abundant resources cause the population to grow, which, subsequently, causes the resource level to decrease. The fluctuation of the resource level causes periods of frequent movements of the agents when the resource is scarce and periods of stability when the resource level is elevated (Fig. 5). Resource scarcity causes an increase in the proportion of cheaters in the population (Fig. 5). An increase in the enforcement level causes an increase in the resource level and the number of settlements through the decrease of cheaters in the population (Fig. 5)

The system may reach a stable threshold or, on the contrary, collapse (simulations end when the population or the resource become zero). Eighty-five percent of the simulations of the default model collapsed. The mean duration of the collapsed runs was 3111 time steps (median = 3073, range=680-4973). The stable threshold is reached when the sum of the agents' harvesting and sustainable harvesting are very close, thus ending in a low number of cheaters (around less than 20% of the population) and in a more stable system with less agent movement (Fig. 6). The most durable runs support higher number of settlements (i.e., occupied patches) and resource level (Fig. 6). The enforcement level of the system decreases due to a decrease in the enforcement level of the unoccupied patches, while settlements maintain a high value of enforcement level (around 0.6) (Fig. 6). The most robust systems (i.e., durable runs) are those in which the behavior of the agents is controlled, hence the storage level of agents do not reach high levels, though maintaining high values of enforcement (Fig. 6).

The results of the default situation show that the model leads to a variation of outcomes for a fixed parameter setting. In our analysis of the effect of parameter changes we will test whether the changes in outcomes are statistically significant with the default situation.

Mobility and robustness of social-ecological systems

Figure 7a shows the mean time steps that simulations are running (i.e., the system does not collapse) for the different move capacities of the agents and with the rest of the parameters settled as default (Table 1). The probability of the system collapsing is higher with a low move capacity (Table 2, Fig. 7). The mean value of the number of occupied patches (i.e., settlements) and resource level of the last 1000 time steps varies between move capacities of the agents. Lower occupation (i.e., number of settlements) and resource levels are obtained with a move capacity of 25 (Table 2, Fig. 7). With the same resource level, a move capacity of one or five is able to support higher occupation levels. Although the mean storage value of agents is similar for the 3 move capacities, the proportion of cheaters in the population is slightly higher with a move capacity of 25. The enforcement level is lower with a move capacity of 25 while the number of movements is higher (Table 2, Fig. 7). However, these results are very sensitive to the distribution of the resource richness (see below).

Landscape configuration and the impact of mobility

The sensitivity of the system to an increase in the mobility of the agents considerably decreases when low landscape heterogeneity (i.e., uniform and normal distributions) is included in the model. The stability of the system (collapse rate) increases from a homogeneous (default model) to a uniform or normal distribution of the resource richness. However, an exponential distribution of the resource ends in less stable systems (Table 3, Fig. 7). The level of the resource and the number of settlements increase from the default model to any of the three other landscape configurations considered (Table 3, Fig. 7).

There are different sensitivities of resource distributions to mobility. The stability of the system and the value of the evolved parameters at the end of the simulations are higher for the normal distribution (Table 3, Fig. 7) and lower for the exponential landscape structure (Table 3, Fig. 7). For a normal and uniform distribution of the richness of the resource, an increase in mobility produces higher values of resource and occupation levels and more endurable runs (Table 3, Fig. 7). The exponential distribution of the richness of the resource is very sensitive to mobility, and high mobility produces lower values of resource and occupation levels and less endurable runs (Table 3, Fig. 7); while the highest values are obtained with an intermediate or low move capacity of the agents (Table 2, Fig. 7).

These results can be explained by the difference in the occupation rate of patches. Very high k value ($k > 3$) had significantly lower levels of resource and occupation than patches with smaller k value (Table 4, Fig.8). Agents tend to move to patches with very high k, hence those patches have lower stability. On the contrary, patches with small values of k are more sustainable because they don't attract many agents. As a result, patches with lower k compensate the effect of mobility on patches with very high k, making the system more stable. Hence, landscape configuration with abundant patches with medium level of *k* give rise to higher resource and occupation levels. For low values of k ($k < 3$), the enforcement level of settlements is higher than unoccupied patches. This difference does not occur with higher values of *k*, i.e., there are no differences between the enforcement level of occupied and unoccupied patches. With k values of 3 and higher, even high levels of enforcement are not able to maintain a stable population and the number of cheaters in the population increases significantly.

Agents' reputation and the impact of mobility

A longer duration of systems as well as higher resource and occupation levels are obtained when governments have information about the past behavior of potential intruders (reputation of agents) (Table 5, Fig. 9). The inclusion of reputation significantly reduces the number of movements by creating a barrier to untruthful agents. This higher control on the agents' behavior is obtained because the average enforcement level of the system increases (Fig. 9). As a result, cheaters in the population decrease (especially with high move capacity of the agents) even with a higher storage value of agents (Table 5, Fig. 9).

Sensitivity analysis

We found that frequency of imitation of agents has no effect on our main results when landscape is homogeneous (Table 6). However, when we increase landscape heterogeneity, we found that an increase in the frequency of imitation of agents has a positive effect on the outcomes of the model. This effect is clearer for uniform and exponential distribution of the resource richness (Table 7). As expected, changes in the value of *Ta* (i.e., benefit threshold of agents) have a significant effect on the stability of the system. Lower values originate a decrease in the proportion of cheaters in the population; as a consequence the occupation and resource levels are higher than with the higher values (Tables 6 and 7). High values of *Ta* stabilized the system and lead to higher occupation and resource levels (Tables 6 and 7). An increase in the imitation rate of governments (*Ig*) does not have an effect on the outcomes on the model. A decrease in *Ig* increased the stability of the system and produced higher occupation and resource levels when landscape heterogeneity is null-medium (default and uniform distributions); while it didn't affect the outcomes when the resource richness is normally or exponentially spatially distributed (Tables 6 and 7). Finally, changes in the value of the threshold of governments (*Tg*) have a significant effect on the outcomes of the model. As expected, higher values of *Tg* increased the stability of the system and produced higher occupation and resource levels and vice versa (Tables 6 and 7).

DISCUSSION

Understanding the effects of globalization to SESs is essential to increase their robustness in response to processes such as an increase in agent flow. In this paper we developed a stylized agent-based model to analyze, under a scenario of agent mobility, the conditions that lead to long-term sustainability of SESs and how vulnerabilities to the invasion of intruders might be predicted, hence prevented.

Our results showed that mobility significantly affects the robustness of SESs. This relationship is complex, with non-linear effects and high sensitivity to the resource richness distribution. In general, low mobility capacity of agents destabilizes the system by depleting the local resource. Low mobility increases the isolation of communities and makes the colonization of new areas more difficult. A small increase of the mobility capacity of the agents resulted in better long-term dynamics of the model for all landscape configurations except for highly heterogeneous landscapes (see below). Medium mobility capacity exemplifies a local system in which agents move short distances, or quit the activity for certain periods, to adapt to changes in the resource level. Some examples include nomadic or transhumant pastoralist (e.g., Tyler et al. 2007, Forbes et al. 2009) and rotation of crops and fields in traditional agricultural systems (e.g., Tengö and Belfrage 2004).

When mobility increases to very high levels, landscape configuration (i.e., when we spatially change the carrying capacity [richness] of the resource in our model) is a major factor explaining system outcomes. High mobility represents a globalized world in which people, information, technologies, companies, etc. flow freely. For resources with a low-medium heterogeneous spatial distribution (uniform and normal distributions of resource richness) the average length of simulations suggests that high mobility tended to stabilize the system and better outcomes were obtained in terms of resource and occupation (i.e., number of settlements) levels. For homogeneous landscapes (default setting of our model) this relationship is non-linear since, although medium and high mobility stabilized the system, the resource and occupation levels in the system decreased from medium to high mobility. Lastly, resources with highly heterogeneous distribution (i.e., exponential distribution of the resource richness) were the most sensible to an increase in agents' mobility. An increase in agent mobility (even from low to medium mobility) in highly heterogeneous landscapes destabilized the system and resource and occupation levels decreased. In this situation, both the enforcement level of governments and storage level of agents were not able to stabilize the system. This is what we found in many empirical cases, i.e., intruders focus specifically on very valuable areas (Pérez et al. 2011), for example, shrimp farms in the mangrove forests of Indonesia (Barbier and Cox 2002) or the problem of land grabbing in Africa and other parts of the world (Klopp 2000).

These system level results are a consequence of patch level processes. Richer areas attracted agents that collapsed the local patch but originated a rapid feedback of colonization-depletion-migration that made those areas very unstable and their recovery very difficult. Poorer areas were more sustainable because they didn't attract many agents. As a consequence, the resulting agents' distribution was opposite to the expected ideal free distribution (Fretwell 1972) and rich areas ended with less resource levels due to the less sustainable behavior of agents even with higher level of enforcement. For highly heterogeneous systems, rich patches collapsed rapidly and the system was unable to absorb such a disturbance.

How can we improve the robustness of SESs in a globalized world? The ability to define and enforce boundary rules is key for the long-term sustainability of SESs (Ostrom 1990). In our model, the information governments had on the past behavior of potential intruders significantly reduced the impact of agent mobility. Hence, small investment in surveillance and enforcement might significantly reduce the impact of intruders by limiting the access of untruthful agents. However, in our model, high enforcement's value did not guarantee the preservation of rich areas. This result has implications to the global governance of natural resources: How can areas rich in resources be preserved from resource depletion? In which areas should efforts be focus to conserve natural resources? Accordingly to our results, it becomes important for global governance to deal with governance of resource rich areas, not only for local governments because those areas are more prone to intruders invasions, for example through land grabbing, but for global sustainability itself.

In governing SESs, governments face a tradeoff between short-term benefits (e.g., intruders originate an increases in taxes) versus long-term resource and population maintenance. In our model, governments reaching for short-term benefits reduced the long-term variability of the local system and with consequences to the global system especially for low heterogeneous distribution of resource richness. In our model, heterogeneity avoided the spreading of unsustainable governance. Short-term benefits, like the fitness used in this model (i.e., the number of inhabitants [agents]) caused governments to be unable to preserve the SES. Other government fitness, such as, satisfaction of agents, equality between agents, or sustainable use of natural resources, might increase the long-term outcomes of SESs. Future developments of our model may test differences in results using different government fitness. Other inclusions to our model might be: 1) temporal variability of the resource. Climate change increases uncertainty in resources levels and originates periods of resource scarcity in spatio-temporal scales. This increases migration (Warner 2010, Janssen, 2010); 2) include other attributes of agents that might have significant effects on agent mobility, such us wealth (Katz and Stark 1986) and risk aversion (Stark and Levhari 1982).

CONCLUSION

The model presented here is a stylized representation of an SES used to test how globalization, in particular the increased movement of agents, affects the robustness of SESs. As hypothesized, an increase in agent mobility (i.e. how far an agent can move) significantly impacted the robustness of SES. However, this relationship was complex, with non-linear responses and high sensitivity to the type of spatial distribution of the resource richness. The attractiveness of rich areas made them very sensitive to agent mobility. Some empirical examples are productive lands in Africa subject to land grabbing, oil reserves, or mangrove forest exploited by shrimp farms. The local instability of rich areas (patch level process) had catastrophic consequences on global scales (system level) when rich areas were scarce and exponentially distributed. Governments reaching for short-term benefits (for example increasing tax benefits by intruders) were unable to sustain the local SES and destabilized the global system, especially when the heterogeneity in the resource richness distribution is low. These results have consequences for global governance of natural resources, suggesting that dealing with governance of resource rich areas is essential, not only for the local consequences of invasions but for global sustainability itself.

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Table 1. Variables and parameter definitions of the model and parameters' values of the default setting.

Parameter	Description	Default value
agMSY	Harvest level encouraged by governments	-
ar_{max}	Maximum distance around the patch where agent is located in which agent can set its potential destination	5
br	Birth rate of agents	0.03
C_{mov}	Cost of mobility	-
Crep	Cost of reproduction	-
Cost	Cost of enforcement	-
dH	Desired harvest level of agents	-
E_t	Accumulated energy of agents	-
E	Enforcement level	-
H	Total resource harvested at each patch	-
hr_{max}	Radius around patches as potential destinations for offsprings' settles	5
I_a	Probability of agents coping the attributes of other agents in the same patch	0.5
I_g	Probability of governments imitating the enforcement rate of neighboring patches	0.5
k	Carrying capacity of resource	100
met	Metabolism of agents	0.3
n	Number of agents in patch	-
netCost	Net enforcement cost	-
nrmarks	Number of marks of potential intruders governments can read	0
P	Punishment imposed to cheaters by each government	-
p_c	Probability of each government to catch a cheater	-
p_m	Probability of random movement of agents	0.2
R	Resource level of each patch	-
r	Growth rate of resource	0.075
S	Storage level of agents	-
Ta	Factor that determines the benefit threshold of agents	0.3
Tg	Accumulated enforcement cost threshold. Beyond this threshold governments reduce their enforcement level by 10%	3000

Table 2. Peer comparison (Student's t-test) of the average value of evolved parameters over the last 1000 time steps of 200 runs for different move capacities of the agents and landscape structure.

		1 *versus* 5			**5 *versus* 25**			**1 *versus* 25**		
		t	**df**	**p**	**t**	**df**	**p**	**t**	**df**	**p**
Default	**Steps**	-7.51	331.83	***	-0.23	357.07	n.s.	-8.26	271.65	***
	Settlements	-0.47	397.04	n.s.	4.02	336.12	***	3.59	345.90	***
	Resource	-0.28	396.91	n.s.	3.37	349.73	***	3.17	359.90	**
	Enforcement	-0.68	396.36	n.s.	3.12	357.10	**	2.46	369.03	*
	Cheaters	-0.91	372.29	n.s.	-1.07	384.53	n.s.	-1.98	336.17	*
	Movements	-0.82	363.33	n.s.	-2.90	280.87	**	-3.47	243.66	***
	Storage	-1.41	391.52	n.s.	0.53	395.09	n.s.	-0.78	380.85	n.s.
Uniform	**Steps**	-4.79	783.15	***	-25.60	399.00	***	-43.54	599.00	***
	Settlements	-7.76	587.60	***	-37.92	412.63	***	-93.17	678.85	***
	Resource	-6.55	624.01	***	-40.49	429.27	***	-85.75	732.81	***
	Enforcement	-43.66	634.21	***	7.07	349.94	***	-41.64	644.41	***
	Cheaters	-9.19	201.11	***	10.90	151.32	***	2.55	606.92	*
	Movements	-5.19	235.22	***	9.18	151.06	***	6.61	599.90	***
	Storage	-18.02	631.94	***	-20.72	259.73	***	-37.56	781.43	***
Normal	**Steps**	-7.64	314.67	***	-2.63	199.13	**	-10.71	184.05	***
	Settlements	-8.19	75.55	***	-5.74	215.55	***	-12.42	47.13	***
	Resource	-5.45	66.30	***	-6.18	226.74	***	-8.83	47.34	***
	Enforcement	11.90	71.40	***	0.54	357.46	n.s.	11.26	98.16	***
	Cheaters	6.62	48.30	***	3.86	260.15	***	7.35	46.41	***
	Movements	4.95	46.32	***	0.57	391.90	n.s.	5.00	46.32	***
	Storage	17.74	78.96	***	-17.91	388.00	***	5.79	73.48	***
Exponential	**Steps**	5.68	554.61	***	3.30	843.78	**	9.75	509.46	***
	Settlements	-3.07	527.03	**	0.51	862.49	n.s.	-2.84	482.27	**
	Resource	-0.99	425.25	n.s.	-0.41	900.61	n.s.	-1.38	393.62	n.s.
	Enforcement	-17.96	223.19	***	16.47	267.41	***	-12.62	219.45	***
	Cheaters	-5.81	206.13	***	7.79	141.42	***	2.06	292.72	*
	Movements	-3.10	224.20	**	4.74	143.62	***	1.71	282.50	n.s.
	Storage	-11.12	293.50	***	19.67	333.97	***	1.48	295.16	n.s.

Table 3. Peer comparison of landscape structure with different move capacities of the agents. Results of the Student's t-test of the average value of evolved parameters over the last 1000 time steps of 200 runs are shown.

		1			5			25		
		t	df	p	t	df	p	t	df	p
Default *versus* Uniform	**Time steps**	6.23	394.13	***	9.68	596.04	***	-29.57	199.00	***
	Settlements	-3.92	246.45	***	0.96	377.50	n.s.	49.15	206.61	***
	Resource	-3.94	248.37	***	0.21	353.65	n.s.	43.28	211.81	***
	Enforcement	-1.36	328.30	n.s.	20.45	202.29	***	32.896	207.53	***
	Cheaters	1.95	459.24	n.s.	8.64	273.54	***	-2.0447	199.65	*
	Movements	1.33	467.92	n.s.	4.51	326.79	***	-4.86	199.02	***
	Storage	-0.93	333.08	n.s.	7.86	254.08	***	16.585	217.61	***
Default *versus* Normal	**Time steps**	-15.52	275.79	***	-18.01	280.30	***	-29.56	199.06	***
	Settlements	-14.01	167.66	***	-23.04	282.84	***	-51.56	208.16	***
	Resource	-12.85	120.93	***	22.48	295.98	***	-47.18	214.80	***
	Enforcement	-23.52	216.21	***	-18.82	203.24	***	-31.53	215.84	***
	Cheaters	-6.03	64.23	***	1.34	229.65	n.s.	3.50	202.78	***
	Movements	-2.76	70.32	**	3.76	202.01	***	4.97	199.65	***
	Storage	-21.91	206.14	***	-8.19	253.58	***	-16.30	238.14	***
Default *versus* Exponential	**Time steps**	-3.14	386.47	**	10.72	597.56	***	18.62	796.81	***
	Settlements	2.03	362.92	*	0.05	385.78	n.s.	-5.01	530.57	***
	Resource	1.66	377.40	n.s.	1.26	331.51	n.s.	-3.48	435.97	***
	Enforcement	-0.38	397.11	n.s.	-17.28	222.41	***	-21.86	238.37	***
	Cheaters	-2.10	362.22	*	-6.67	197.73	***	1.91	270.12	n.s.
	Movements	-1.72	349.35	n.s.	-3.80	211.74	***	3.48	219.06	***
	Storage	-1.21	388.85	n.s.	-11.12	296.48	***	0.96	283.76	n.s.
Uniform *versus* Exponential	**Time steps**	-10.78	473.04	***	0.68	797.12	n.s.	39.54	599.00	***
	Settlements	-2.03	291.23	*	1.27	797.51	n.s.	47.50	627.00	***
	Resource	-2.39	279.74	*	2.02	792.94	*	51.79	663.95	***
	Enforcement	-1.78	316.21	n.s.	10.48	155.37	***	29.40	225.26	***
	Cheaters	0.71	334.66	n.s.	0.809	252.66	n.s.	0.04	610.29	n.s.
	Movements	-0.82	321.49	n.s.	-0.23	225.35	n.s.	-5.84	600.30	***
	Storage	-2.27	296.36	*	-6.396	220.09	***	36.10	782.36	***
Uniform *versus* Normal	**Time steps**	-30.24	759.96	***	-23.70	469.26	***	1.00	199.00	n.s.
	Settlements	-23.76	59.61	***	-29.83	598.00	***	-12.34	394.61	***
	Resource	-19.53	54.18	***	-31.225	583.84	***	-15.42	393.66	***
	Enforcement	-43.22	607.94	***	11.776	344.00	***	4.19	359.35	***
	Cheaters	-5.21	57.01	***	11.11	161.39	***	13.91	265.13	***
	Movements	-2.08	61.23	*	9.308	152.77	***	2.77	212.21	**
	Storage	-30.43	110.15	***	-0.608	337.19	n.s.	-0.32	352.63	n.s.
Exponential *versus* Normal	**Time steps**	-13.55	302.99	***	-25.37	473.65	***	-39.54	599.06	***
	Settlements	-18.44	112.46	***	-30.80	597.67	***	-50.18	632.53	***
	Resource	-15.49	91.71	***	-34.91	565.74	***	-56.83	677.61	***
	Enforcement	-21.96	214.80	***	-4.23	165.61	***	-24.39	280.44	***
	Cheaters	-4.30	82.32	***	8.31	127.89	***	3.41	661.37	***
	Movements	-1.25	101.84	n.s.	6.75	122.68	***	6.26	636.87	***
	Storage	-18.38	229.34	***	5.95	223.81	***	-33.03	771.62	***

Table 4. Peer comparison of patches with different k values in a uniform distribution. Results of the Student's t-test of the average value of evolved parameters over the last 1000 time steps of 200 runs are shown.

	1 *versus* 2			**2 *versus* 3**			**3 *versus* 4**			**4 *versus* 5**		
	t	**df**	**p**	**t**	**df**	**p**	**t**	**df**	**p**	**t**	**df**	**p**
Settlements	0.45	398.00	n.s.	1.43	397.48	n.s.	2.78	391.22	**	4.27	350.62	***
Resource	0.56	398.00	n.s.	1.37	397.81	n.s.	2.80	391.29	**	4.41	345.46	***
Enforcement	0.70	283.33	n.s.	2.09	282.86	*	3.68	283.74	***	5.27	256.82	***
Settlements' enforcement	0.91	269.36	n.s.	-0.61	275.47	n.s.	0.73	242.57	n.s.	-0.91	245.93	n.s.
Unoccupied patches' enforcement	0.71	206.57	n.s.	-4.88	229.53	***	0.35	185.86	n.s.	-1.19	201.38	n.s.
Cheaters	1.97	274.81	n.s.	1.17	283.73	n.s.	-2.09	283.67	*	-2.66	276.03	**

Table 5. Peer comparison between results of the default model and when reputation is included for different move capacities of the agents. Results of the Student's t-test of the average value of evolved parameters over the last 1000 time steps of 200 runs are shown.

	1			**5**			**25**		
	t	**df**	**p**	**t**	**df**	**p**	**t**	**df**	**p**
Time steps	-23.52	200.26	***	-23.07	199.39	***	-28.42	199.00	***
Settlements	-27.89	238.32	***	-25.54	255.83	***	-55.02	201.18	***
Resource	-26.05	288.46	***	-25.26	278.85	***	-51.72	200.98	***
Enforcement	-16.56	215.06	***	-15.93	209.65	***	28.26	219.61	***
Cheaters	-0.62	371.93	n.s.	0.60	336.15	n.s.	5.22	199.22	***
Movements	2.81	265.61	**	1.71	281.60	n.s.	5.16	199.00	***
Storage	-22.96	287.19	***	18.01	261.09	***	-14.80	210.03	***

Table 6. Results of the sensitivity analysis. Average number of settlements and resource level over the last 1000 time steps of 200 runs and average duration of the runs for different parameter and initial conditions combinations and comparison (Student's t-test) with the default model.

	Time steps					**Settlements**					**Resource level**				
Parameter	Mean	Sd	t	df	p	Mean	Sd	t	df	p	Mean	Sd	t	df	p
Default model	3416	1030	-	-	-	0.14	0.31	-	-	-	0.15	0.29	-	-	-
K = default; I_a= 0.2	3227	1247	-1.25	155.18	n.s.	0.12	0.27	0.29	178.96	n.s.	0.17	0.29	0.43	173.62	n.s.
K = default; I_a= 0.7	3550	1011	0.77	198.01	n.s.	0.15	0.32	0.27	197.82	n.s.	0.16	0.30	0.25	197.88	n.s.
K = default; T_a= 0.1	5000	0.00	14.94	99.00	***	1.00	0.00	35.20	99.00	***	0.85	0.00	27.32	99.00	***
K = default; T_a= 0.5	3361	1902.25	0.19	155.94	n.s.	0.37	0.38	5.96	174.32	***	0.33	0.33	4.54	188.66	***
K = default; I_g= 0.2	3944	1143.35	3.30	195.16	**	0.23	0.36	2.10	193.09	*	0.29	0.32	3.34	195.42	**
K = default; I_g= 0.7	3415	1019.95	-0.17	197.99	n.s.	0.14	0.30	-0.01	197.82	n.s.	0.15	0.28	0.04	197.93	n.s.
K = default; T_g= 1000	945	173.25	-22.97	104.37	***	0.01	0.01	4.30	99.20	***	0.00	0.00	-5.20	99.00	***
K = default; T_g= 5000	4316	1039.57	5.01	91.07	***	0.47	0.46	4.45	66.52	***	0.44	0.37	4.80	73.16	***

Table 7. Results of the sensitivity analysis for different landscape structures. Average number of settlements and resource level over the last 1000 time steps of 200 runs and average duration of the runs for different parameter and comparison (Student's t-test) with the default settings for the different landscape structures.

	Time steps					**Settlements**					**Resource level**				
Parameter	Mean	Sd	t	df	p	Mean	Sd	t	df	p	Mean	Sd	t	df	p
Default settings but with k = normal	4907	495.34	-	-	-	0.85	0.17	-	-	-	0.71	0.15	-	-	-
K = normal; I_a= 0.2	4934	257.58	-0.67	299.29	n.s.	0.84	0.21	0.70	378.45	n.s.	0.70	0.19	0.40	381.07	n.s.
K = normal; I_a= 0.7	4909	601.97	-0.03	383.77	n.s.	0.88	0.15	-1.80	393.11	n.s.	0.74	0.13	-2.34	390.72	*
K = normal; T_a= 0.1	5000	0.00	-2.65	199.00	**	0.94	0.02	-6.81	210.48	***	0.85	0.01	-12.97	200.76	***
K = normal; T_a= 0.5	606	767.30	51.00	141.50	***	0.02	0.12	49.67	267.42	***	0.02	0.09	48.90	291.73	***
K = normal; I_g= 0.2	4867	745.60	0.49	144.03	n.s.	0.87	0.17	-0.88	196.43	n.s.	0.73	0.15	-1.25	201.13	n.s.
K = normal; I_g= 0.7	4970	190.20	-1.58	284.02	n.s.	0.88	0.14	-1.58	229.23	n.s.	0.74	0.13	-1.98	227.22	*
K = normal; T_g= 1000	729	238.74	107.47	286.72	***	0.00	0.00	71.33	199.00	***	0.00	0.00	64.58	199.00	***
K = normal; T_g= 5000	4936	523.20	-0.56	396.81	n.s.	0.93	0.12	-5.20	352.92	***	0.80	0.10	-6.82	343.27	***
Default settings but with k = uniform	4154	1337.04	-	-	-	0.47	0.35	-	-	-	0.34	0.29	-	-	-
K = uniform; I_a= 0.2	3396	1554.19	5.23	389.31	***	0.23	0.33	7.22	397.11	***	0.17	0.27	6.22	395.88	***
K = uniform; I_a= 0.7	4275	1485.20	-0.86	393.68	n.s.	0.61	0.37	-3.82	396.32	***	0.48	0.31	-4.62	395.92	***
K = uniform; T_a= 0.1	5000	0.00	-8.95	199.00	***	0.79	0.02	-13.00	200.72	***	0.88	0.00	-26.41	199.11	***
K = uniform; T_a= 0.5	468	37.12	38.96	199.61	***	0.00	0.00	19.20	199.00	***	0.00	0.00	16.85	199.00	***
K = uniform; I_g= 0.2	4118	1649.11	0.19	165.86	n.s.	0.60	0.38	-2.89	182.75	***	0.47	0.31	-3.56	182.58	***
K = uniform; I_g= 0.7	4121	1540.41	0.18	175.26	n.s.	0.53	0.39	-1.28	178.69	n.s.	0.41	0.32	-1.87	178.81	n.s.
K = uniform; T_g= 1000	627	38.83	37.29	199.34	***	0.00	0.00	19.20	199.00	***	0.00	0.00	16.85	199.00	***
K = uniform; T_g= 5000	4569	1295.92	-3.16	397.61	**	0.84	0.28	-11.77	382.81	***	0.70	0.24	-13.66	384.33	***
Default settings but with k = exponential	3936	1414.08	-	-	-	0.41	0.40	-	-	-	0.27	0.29	-	-	-
K = exponential; I_a= 0.2	3885	1183.85	0.39	386.06	n.s.	0.28	0.36	3.42	394.66	***	0.19	0.26	2.93	394.79	**
K = exponential; I_a= 0.7	4106	1541.15	-1.15	395.09	n.s.	0.51	0.39	-2.55	397.69	*	0.34	0.28	-2.40	397.93	*
K = exponential; T_a= 0.1	4950	500.00	-9.07	276.24	***	0.87	0.12	-15.26	258.67	***	0.84	0.09	-25.97	260.17	***
K = exponential; T_a= 0.5	450	462.90	31.64	268.64	***	0.01	0.1	13.37	242.25	***	0.01	0.08	11.90	251.67	***
K = exponential; I_g= 0.2	4086	1511.43	-0.91	272.18	n.s.	0.48	0.39	-1.66	287.80	n.s.	0.32	0.28	-1.54	292.28	n.s.
K = exponential; I_g= 0.7	3850	1640.34	0.45	174.27	n.s.	0.42	0.39	-0.18	200.72	n.s.	0.28	0.29	-0.32	198.26	n.s.
K = exponential; T_g= 1000	798	681.78	28.27	286.78	***	0.00	0	14.49	199.00	***	0.00	0.07	12.53	222.72	***
K = exponential; T_g= 5000	4580	1269.39	-4.79	393.45	***	0.78	0.29	-10.60	365.68	***	0.54	0.23	-10.62	376.37	***

Fig. 1. Example of views of the default model at time step zero and 5000. A) Resource: Initially all the patches are settled to half of the carrying capacity. Darker green means higher resource level; B) Government agent. Each patch represents a government agent with a different enforcement level. Darker blue means higher enforcement level. Initially the enforcement level is uniformly distributed. At the end of the simulation, group of patches with similar enforcement level appear as a results of governments imitating other governments of higher fitness (i.e. population level); C) Population. Darker pink means higher density of agents. Initially 5000 agents are randomly allocated. Red dots are agent, blue dots are agents that have moved, and yellow dots are offspring. The views are from different runs of the default model.

A)

B)

C)

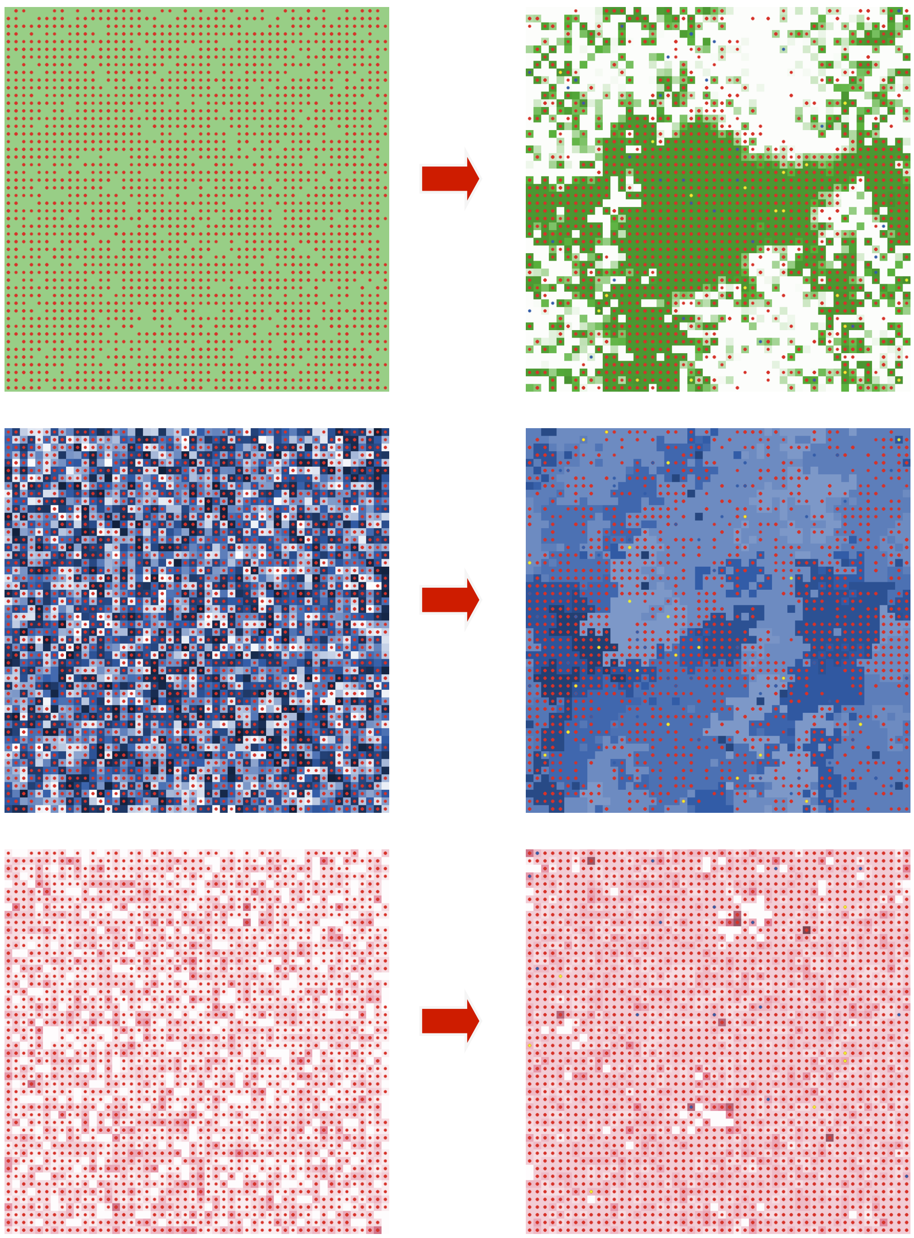


Fig. 2. Activity diagram. For a legend of parameters and variables see Table 1.

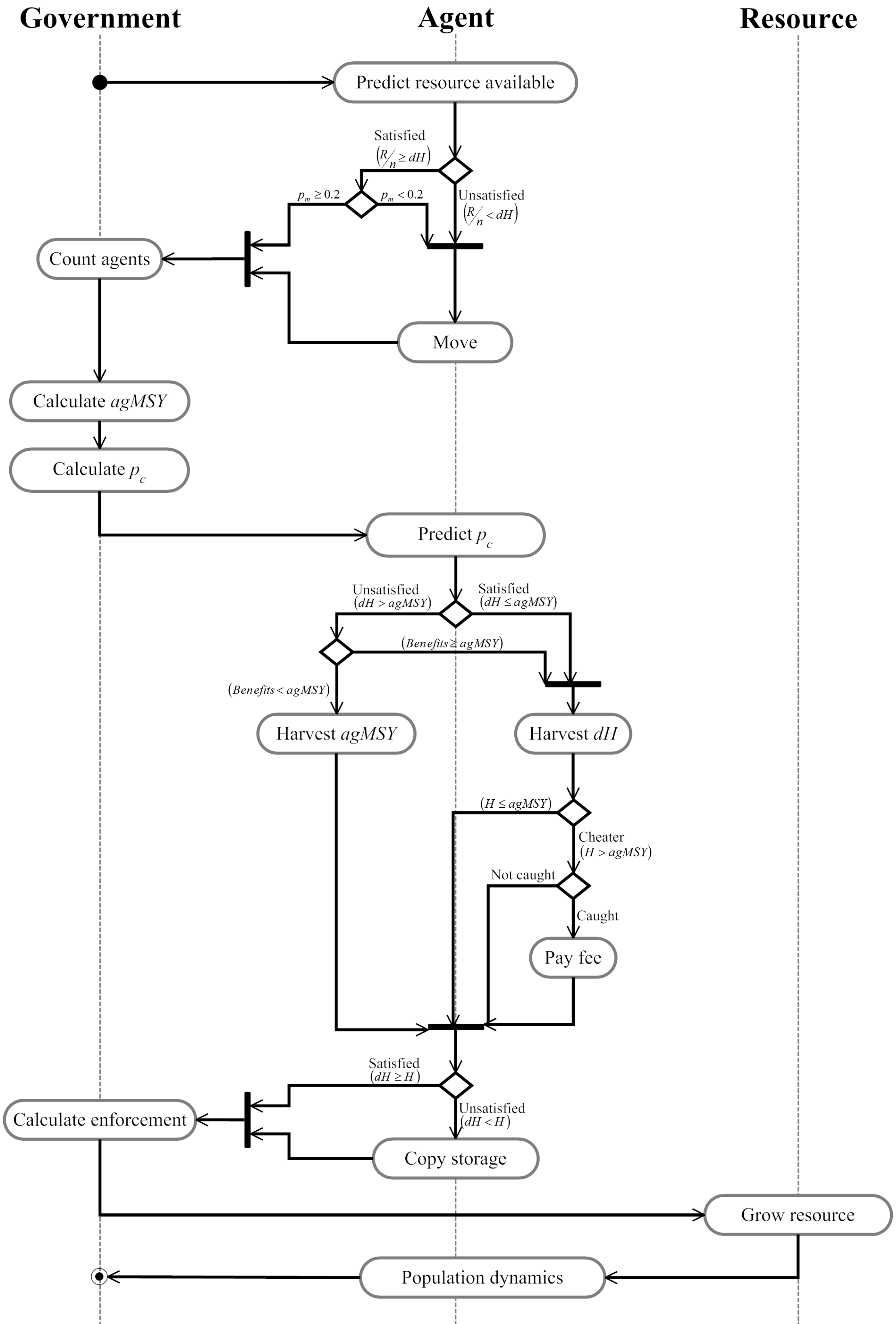


Fig. 3. Landscape structure. Graphs show the number of patches in the system for each carrying capacity of the resource (*k*). In read is the mean and in blue the standard deviation for 200 runs. The right size of the figure shows the resource view of the model at time step zero for each landscape structure.

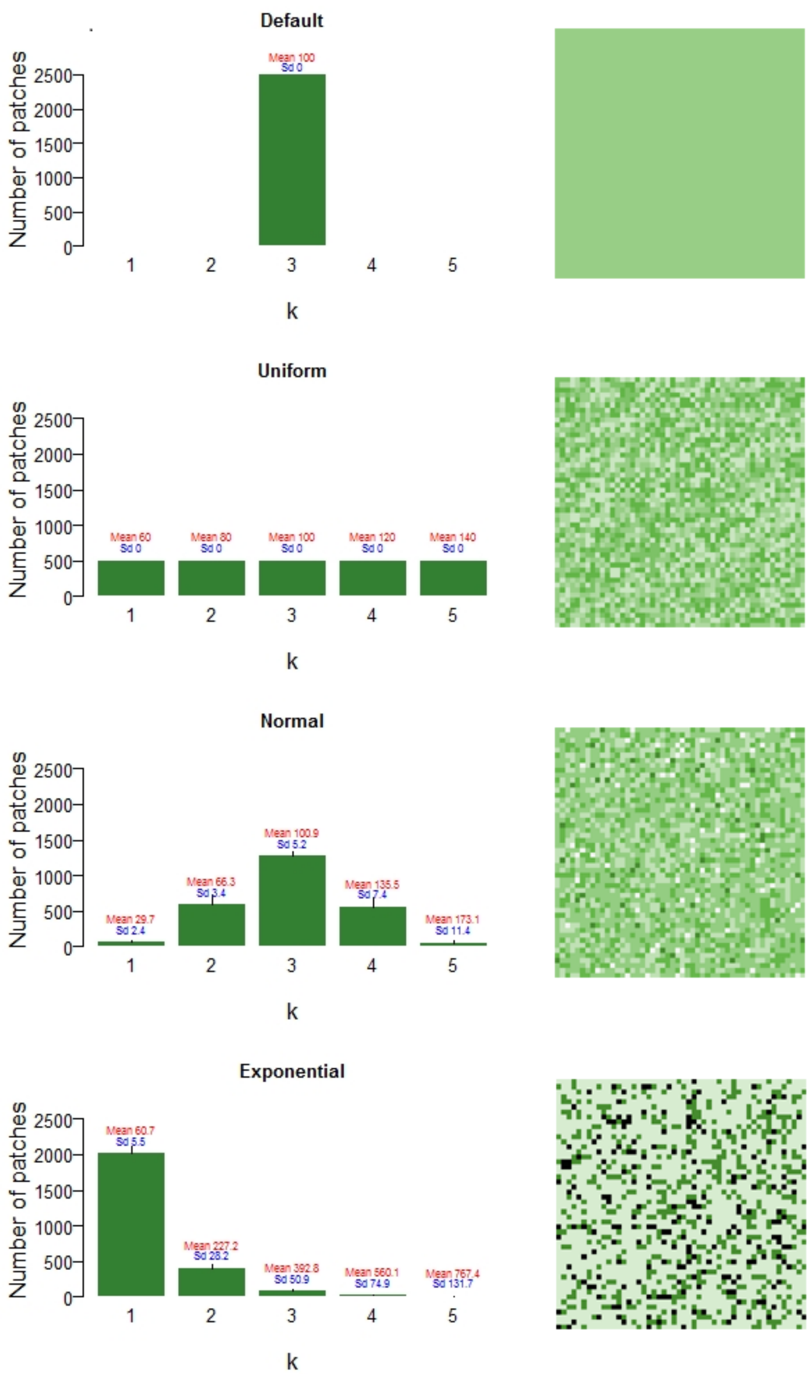


Fig. 4. Percentage of resource level (green lines) and occupied patches (pink lines) in two typical runs of a non-collapsed (solid lines) and collapsed (dotted lines) simulations. A resource level of 100% means that all patches reached their carrying capacity. The first 2000 time steps are omitted.

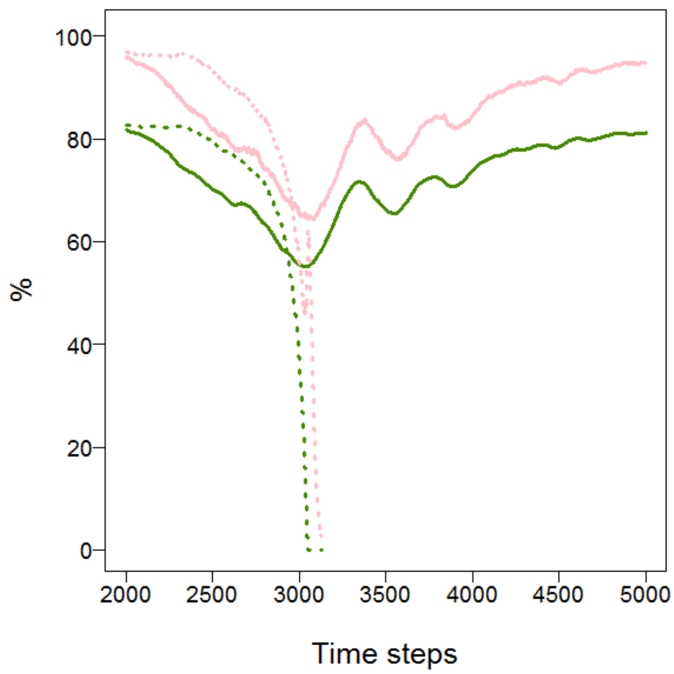


Fig. 5. Relationship between the average enforcement level of the system and resource level of the system (A), number of settlements (B), and percentage of cheaters in the population (C) and between resource level and number of agents' movements (D) and percentage of cheaters (E). Each dots represents the average value of the system in each time steps of the 200 runs. The first 2000 time steps are omitted.

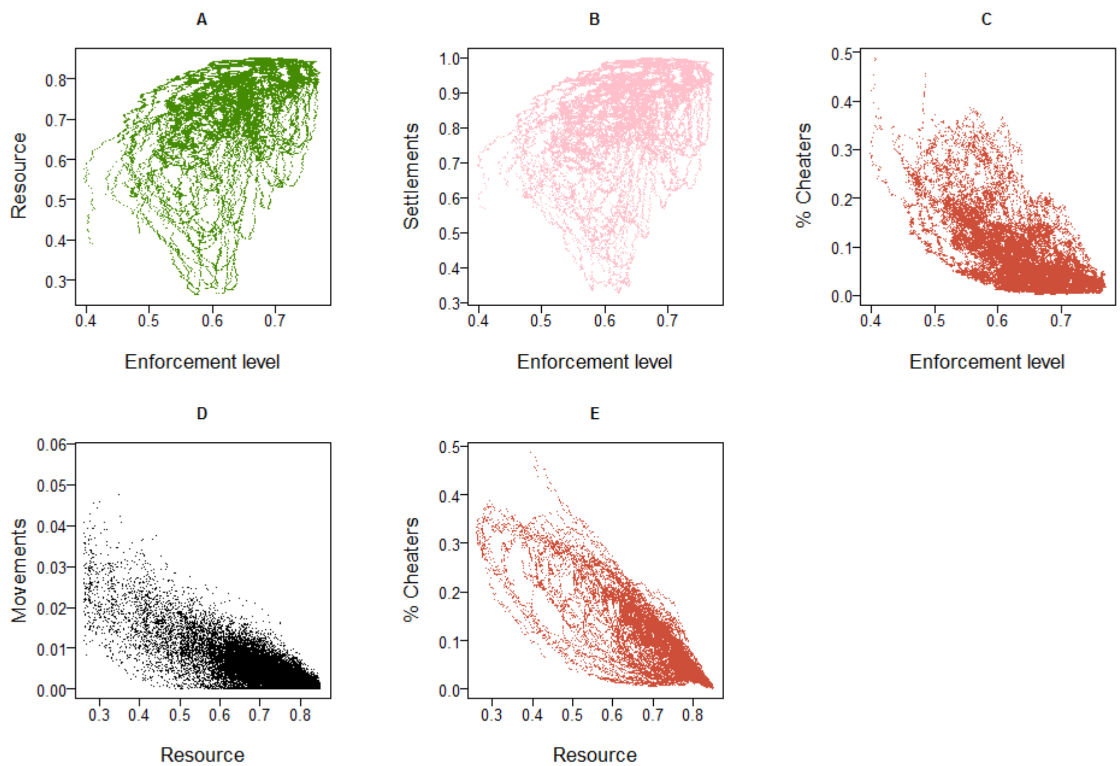


Fig. 6. Average value of the evolved parameters of the default model during the last 20% steps of each run. A: proportion of occupied patches (i.e. settlements); B: resource level; C: proportion of cheaters in the population; D: proportion of agents that moved; E: mean storage level of agents; F: enforcement level; G: enforcement level of settlements; H: enforcement level of patches. Results from the Pearson´s correlation between the duration of the runs and the evolving parameters are shown.

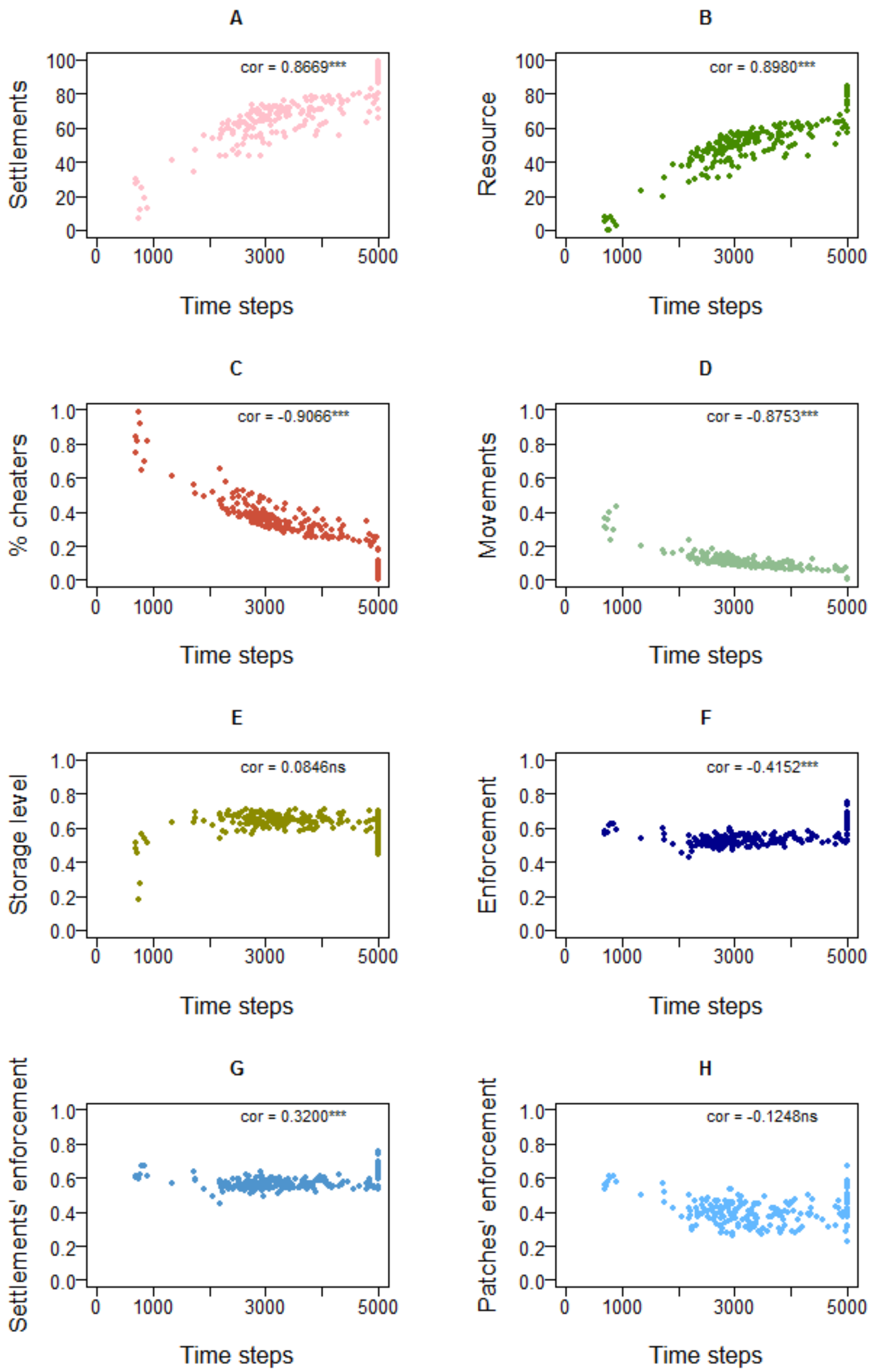


Fig. 7. Mean of the duration of the runs (A) and value of evolved parameters (B-I) for different move capacities of the agents and landscape configuration. Lines represent the standard deviation. Black bars: default landscape; from left (light bars) to right (dark bars): uniform, normal, exponential.

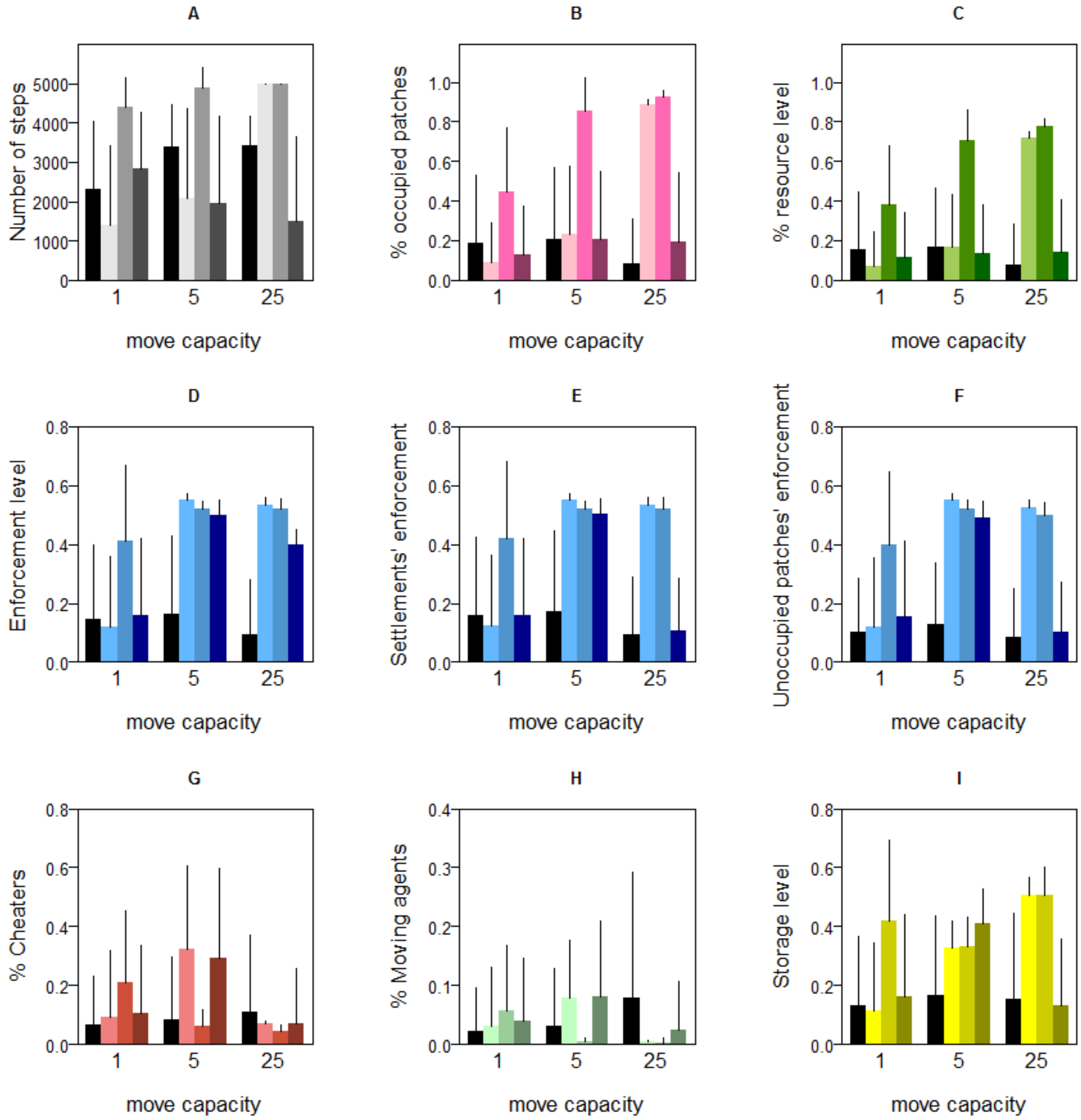


Fig. 8. Percentage of occupied patches (A), resource level (B), enforcement level (C) of occupied (dark blue) and unoccupied (light blue) patches, and percentage of cheaters (D) in patches with each value of K. Simulations are for a uniform distribution and with the rest of parameters settled as the default model. Lines represent the standard deviation.

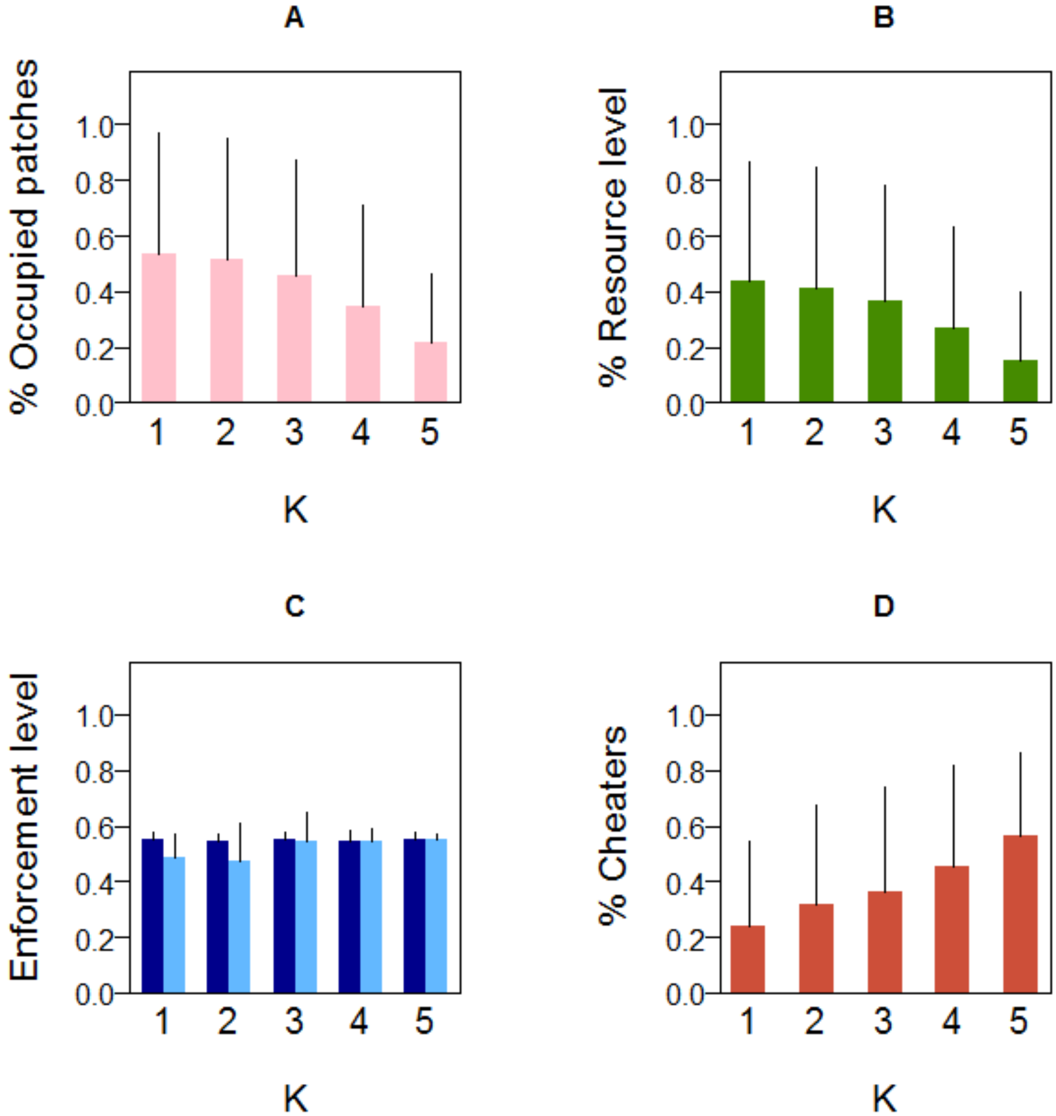
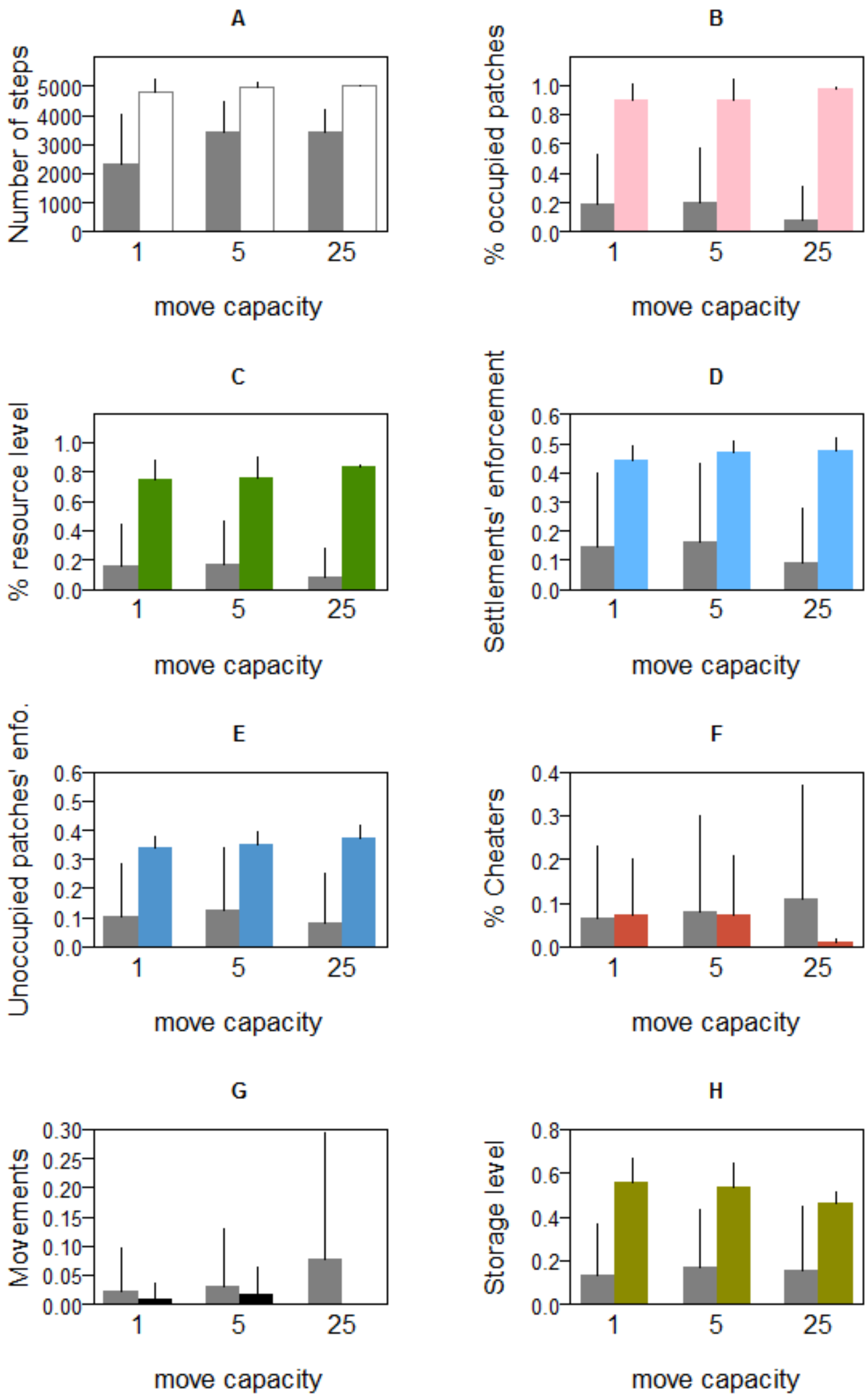


Fig. 9. Mean of the duration of the runs and value of evolved parameters for different move capacities of the agents when reputation of the agents is included. Gray bars represent the default model. Lines represent the standard deviation.



Appendix1. Video of the first 1000 time steps of the model using the default settings (see Table 1).

In the video agents (red dots) as well as agents that have moved each time steps (blue dots) and offspring (yellow dots) can be seen. At the beginning of the video, the evolution of the resource is showed. Agents harvest resource and resource growth accordingly to a logistic growth function. In the video darker green patches represent higher level of resource. At time step 100, the evolution of the enforcement level is shown. Governments (patches) may copy the enforcement level of other patches with higher fitness (i.e. higher population level). In the video darker blue represent higher enforcement level. At time step 200, the evolution of the population is shown. Agents move if they consider that the available amount of resources of their patch will not satisfy them. They move to the closest cell with the higher resource level. In the video, darker pink patches represent higher population level. At time step 300, the video show the resource again until the end of the simulation. In the video there are seven graphs representing: the population and resource levels, the number of settlements (i.e. occupied patches), the percentage of agents moving, the percentage of cheaters in the population, the mean storage level of agents, and the mean enforcement level of the system and of the settlements.

https://dl.dropbox.com/u/11065899/MOVIE1.mp4