



Adaptive self-organization of Bali's ancient rice terraces

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Spatial patterning often occurs in ecosystems as a result of a self-organizing process caused by feedback between organisms and the physical environment. Here, we show that the spatial patterns observable in centuries-old Balinese rice terraces are also created by feedback between farmers' decisions and the ecology of the paddies, which triggers a transition from local to global-scale control of water shortages and rice pests. We propose an evolutionary game, based on local farmers' decisions that predicts specific power laws in spatial patterning that are also seen in a multispectral image analysis of Balinese rice terraces. The model shows how feedbacks between human decisions and ecosystem processes can evolve toward an optimal state in which total harvests are maximized and the system approaches Pareto optimality. It helps explain how multiscale cooperation from the community to the watershed scale could persist for centuries, and why the disruption of this self-organizing system by the Green Revolution caused chaos in irrigation and devastating losses from pests. The model shows that adaptation in a coupled human-natural system can trigger self-organized criticality (SOC). In previous exogenously driven SOC models, adaptation plays no role, and no optimization occurs. In contrast, adaptive SOC is a self-organizing process where local adaptations drive the system toward local and global optima.

self-organization | criticality | irrigation | evolutionary games | Pareto optimality

The geometric precision of Balinese rice terraces has inspired generations of postcard photographers. Viewed from above, a changing mosaic of colors appears: green when the rice is young, yellow as it nears harvest, silver when the paddies are flooded, and brown when they are drained. These colors are not uniform across the island, because Bali is an equatorial island with only two seasons, wet and dry. Consequently, farmers can plant their crops at any time, although they avoid harvesting in the rainy season. The colored patches that make up the mosaics are visible in Google Earth. Like many natural phenomena, patches show a characteristic power-law distribution of sizes. However, in this case, the patches are created by the farmer's decisions about when to synchronize irrigation schedules with their neighbors: Each patch displays the outcome of these choices. Adjacent patches tend to be correlated. This correlation weakens with distance, a relationship that also follows a specific power law (Fig. 1). To discover why harvests approach a maximum when both the size distribution of patches and the corresponding correlation functions fit power-law distributions, we need a model that relates the decisions of the farmers to the consequences for irrigation flows and rice growth.

In Bali, water is regarded as a public good, the gift of the Goddess of the Lakes. Rice is grown in paddy fields fed by irrigation systems dependent on rainfall. Rainfall varies by season and, in combination with groundwater inflow, determines river flow. By virtue of their location, upstream farmers can influence

how much water reaches their downstream neighbors. Across the island, farmers recognize two management systems. In *tulak sumur* ("reject the wellspring"), everyone is free to plant whenever they like, which gives upstream farmers an advantage over their downstream neighbors. Alternatively, in *kerta masa* ("lawful/good timing"), farmers agree to adopt synchronized irrigation schedules.

Kerta masa is sustained by local water-user groups called *subak*, which have existed since the 11th century (1). Irrigation schedules are chosen by consensus in *subak* meetings. In prior research on a group of 10 *subaks* practicing *kerta masa*, we measured irrigation flows and found that they correlated perfectly with the agreed-upon irrigation schedules (*SI Appendix, Fig. S3*). *Kerta masa* tends to equalize rice harvests, and, in a typical survey, 39 of 40 farmers agreed that their harvests are about the same as those of their neighbors (*SI Appendix, Table S1*) (2). However, to sustain *kerta masa*, upstream farmers must give up their advantage in irrigation control. How, then, did it become the norm in Bali, whereas *tulak sumur* is regarded as a rare and problematic condition?

To find out, in prior research, we modeled the emergence of cooperation in a simple game involving only two rice farmers, one upstream from the other (2). We allow the upstream farmer to have first claim on any water in the system. To simplify

Significance

In Bali, the cooperative management of rice terraces extends beyond villages to whole watersheds. To understand why, we created a model that explores how cooperation can propagate from pairs of individuals to extended groups, creating a resilient system of bottom-up management that both increases and equalizes harvests. Spatial patterns of collective crop management—observable in Google Earth—closely match the predictions of the model. The spatial patterning that emerges is nonuniform and scale-free. Although the model parameters here are tuned to Bali, similar mechanisms of emergent global control should be detectible in other anthropogenic landscapes using multispectral imagery. Recognizing this signature of emergent system-wide cooperation may help planners to avoid unproductive changes to successful bottom-up systems of environmental management.

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water into the subak and the scale at which groups of farmers synchronize irrigation. Consequently, the pest–water trade-off for each farmer varies depending on where his farm is located and the outcome of the irrigation schedules chosen by his neighbors. Whether both farmers choose to cooperate (synchronize irrigation) depends on the magnitude of ρ and δ .

To explore how patterns of irrigation scheduling emerge from this mutual dependence, we created an adaptive version of the game in which farms are embedded on the sites of an $L \times L$ lattice, with dimension $L=100$. Parameters a and b specify the relative weights of pest and water stress, respectively, for the entire lattice and are set in advance. The lattice represents a rice-growing region such as shown in Fig. 1B.

This model proceeds through a process of trial-and-error adaptation. Losses from water stress are calculated based on the distribution of irrigation schedules for the entire lattice: The fewer the farmers following a given schedule, the more water they have to share. However, this reward for asynchronous irrigation is balanced by the need to reduce losses from pests, which depends on the fraction of neighboring farmers (f_p) within a given radius (r) that synchronize their irrigation schedules. When pest damage is at least half as bad as water damage, does cooperation spread and do aggregate harvest yields increase?

The model is initialized with random irrigation patterns for all sites at $t=0$, when every farmer i chooses one of four possible irrigation schedules C_i with probability $1/4$. At the end of a time step (representing one simulated irrigation cycle), each farmer compares his harvest with those of his closest neighbors, and uses this information to choose his irrigation schedule for the next cycle (Fig. 2). Because the farmers do not know ρ and δ in advance, they must guess. Anticipating future pest outbreaks or water shortages is challenging, and the actual decision-making process in subaks typically involves lengthy discussions (3, 4). Irrigation flows along the tiny canals that connect adjacent fields are also complex, involving bargains similar to the game described above. We do not attempt to replicate this level of complexity in the model. Instead, we implement very simple strategies to discover whether they are sufficient to enable successful adaptation (Fig. 2). Once the decision rule and the background pest and water levels are determined, the model proceeds in the following steps:

- i) Assume we are at the beginning of time step $t+1$. Calculate the rice harvest for each individual farmer i by debiting his losses from pest damage and water stress, according to $H^i(t+1) = H_0 - a/0.1 + f_p^i(t) - b f_w^i(t)$, where H_0 is a constant

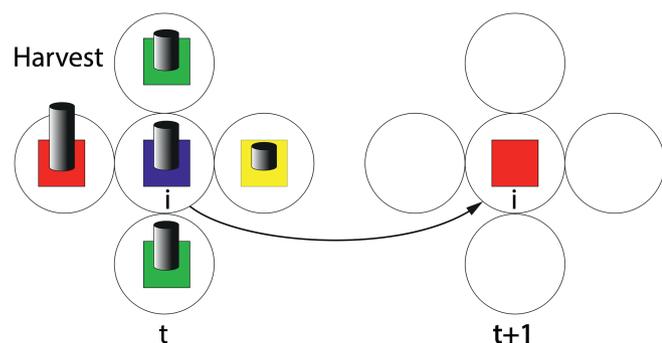


Fig. 2. Update rule for farmer i . Colors denote irrigation schedules. For example, green might signify planting in January, and blue might signify planting in March. At time $t+1$, farmer i compares his harvest with those of his four closest neighbors at time t . Because the red schedule produced the best harvests, he adopts it for the next cycle. This update corresponds to step *iii* in the model.

representing the initial harvest before loss. Here $f_p^i(t)$ denotes the fraction of neighbors of farmer i within a radius r who share the same cropping pattern as i at the previous time step t , which reduces local pest damage, and $f_w^i(t)$ is the fraction of all lattice sites that have the same cropping pattern as i . The number 0.1 in the formula is to ensure that H_i is positive. The parameters a and b specify the relative weights of the pest loss and water stress, respectively. We set $H_0=5$ and $r=2$ (lattice units) for all simulations. Details are provided in *SI Appendix*.

- ii) Pick one specific farmer i randomly.
- iii) Farmer i compares his harvest $H^i(t+1)$ with the harvests of his four nearest neighbors and copies the irrigation schedule of one or more neighbors according to the decision rule (Fig. 2). In the simplest case, it is the neighbor who had the best harvest in the previous irrigation cycle j : $C_i(t+1) = C_j(t)$ (Fig. 3). For an explanation of the reasons for the difference between these decision rules and the game, see *SI Appendix, Game and Lattice Models*.
- iv) Pick next farmer until all are updated (synchronously).
- v) For a small fraction of lattice sites, the irrigation schedules are randomly updated, to simulate empirically observed nonconformity (see *SI Appendix*).
- vi) Perform the next time step.
- vii) Repeat for more time steps until harvests converge to maximum.

Model Results

The model evolves through a process of trial-and-error adaptation by the farmers. At first, in the initial random state ($t=0$), the correlation between farms is close to zero (Fig. 3A). What happens next depends on the ecological parameters pests (a) and water stress (b), and on the decision rule followed by the farmers. There are three trivial attractors (“phases”) (*SI Appendix, Fig. S4*): (i) If water stress is negligible ($b \ll 1$) eventually all farms adopt the same irrigation schedule to control pests, resulting in a single uniform patch that spans the entire lattice. (ii) If $b > 20a$, water stress dominates, and many small patches appear; this increases the variance of irrigation schedules, reducing water stress, but allows pests to migrate between adjacent patches. (iii) For $b < 20a$, after a very long transient phase (thousands of cycles), a quadrant state is reached that separates the lattice into four quadrants with the same irrigation schedules.

The fourth attractor, which is nontrivial, emerges at the phase transition, exactly at the boundary where the water and pest stress phases equalize. Correlation lengths increase as the cycles of planting and harvest progress, and farms coalesce into small, irregularly sized patches with identical irrigation schedules. Patches form very quickly, as seen in Fig. 3A, and soon become large enough to dramatically reduce pest damage. Uniformly short correlation distances indicate that the patches are functionally independent: Each patch discovers its own solution to the pest–water trade-off. Rice harvests improve rapidly within the first time steps, and correlations between farms increase. However, there is still some variation in harvests, so farms on the borders of the patches continue to experiment with different irrigation schedules. Adaptation ceases when no farm can improve its harvest by changing its irrigation schedule. The geographic scale at which the pest–water trade-off is solved shifts from many small independent patches (small correlation length) to the entire lattice by ($t=10$), equivalent to 5 y of double cropping. Subsequently there is little change: At $t=400$, the situation is very similar to $t=10$. In Fig. 3B, we study the average harvest $H = 1/L^2 \sum_{i=1}^{L^2} H^i$ as a function of simulation time steps (blue line, maximum strategy). We see that the maximum of H is reached very soon.

correlations span the entire system. For this reason, we call the model dynamics “adaptive SOC.”

We conclude with the question of whether these results are likely to be unusual, perhaps even unique to Bali. The scope of the model is limited by the physical geography of Bali. The four crater lakes store rainfall that feeds the groundwater system, but they have no river outlets. On the steep porous volcanic slopes, rivers recharge very quickly. Irrigation systems consist of one to six closely spaced weirs and springs that provide water for one or more subaks. These local irrigation systems are functionally independent: Although they remove most or all of the flow, a kilometer or two downstream, it will be replenished from groundwater flows. Our model captures the adaptive process at this scale, where local groups of farmers meet face to face to solve the pest–water trade-off. The concept of emergent global-scale connectivity in our model, which we borrow from physics, does not refer to all of the subaks on a river but to these smaller functionally independent groups of subaks, such as those shown in Fig. 1B and *SI Appendix, Figs. S3 and S6–S17*. This configuration of water distribution contrasts with a typical desert river, where the effects of upstream irrigation may be felt far downstream.

If several subaks share water resources, their elected leaders meet to negotiate irrigation schedules. Although this higher-level coordination between subaks is not explicitly included in the model, the decision-making process is the same: a trial-and-error adaptation to reduce pest and water stress. These meetings take place in regional water temples and make use of a sophisticated permutational calendar to plan and implement staggered irrigation schedules (14, 16). These cultural innovations undoubtedly facilitate adaptation to changing pest–water dynamics. However, the model does not require calendars or water temples; instead, it helps to clarify the functional significance of these social constructs for sustaining approximate Pareto optimality. Our model shows that the simple pest–water trade-off triggers continuous transitions that turn adaptive agents on a two-dimensional lattice into a coevolving system capable of solving the pest–water trade-off by means of local decision-making. Unlike Gunderson and Holling’s well-known model of adaptive cycles (17), here increasing connectivity does not cause collapse but stabilizes at a scale-free distribution of functionally varied patches. This is quite a general result that may be common in coupled human–natural systems. In any anthropogenic landscape, correlations between patches will provide some information about the scale of human management (see *SI Appendix* for code). If Bali’s subaks are not

unique, and adaptive SOC occurs in the management of the commons elsewhere, it should be readily detectible from correlated patch distributions.

Methods

Correlation Functions. We use a definition of correlation function $C(d)$ that is based on the mutual information between the cropping pattern X at site i and the cropping pattern Y at site j , where the distance from site i to j is d . The mutual information measures how much the knowledge of the cropping pattern at one site reduces the uncertainty on the knowledge of the cropping pattern at the other site. It is defined as

$$C(d) = \frac{1}{\mathcal{N}} \sum_{X=1}^4 \sum_{Y=1}^4 P_d(X, Y) \log_2 \frac{P_d(X, Y)}{P_d(X)P_d(Y)}, \quad [1]$$

where $P_d(X, Y)$ is the probability of cropping patterns X and Y occurring at sites that are a distance d apart. Note that X and Y take values from 1 to 4 with ‘1 = green’, ‘2 = red’, ‘3 = blue’ and ‘4 = yellow’. Operationally, the joint probability $P_d(X, Y)$ is determined by taking the relative frequency of the cropping patterns X and Y against all possible combinations of cropping patterns between sites at a relative distance d . Note that the site here refers either to a pixel in the satellite image or to a lattice site for the model. The marginal probability of cropping pattern X (or Y) is $P_d(X)$ [or $P_d(Y)$]. \mathcal{N} is the normalization constant. It is equal to the Shannon entropy of the cropping pattern X , i.e., $\mathcal{N} = -\sum_{X=1}^4 P_0(X) \log_2 P_0(X)$. It ensures that the correlation is normalized, so that $C(d=0) = 1$. We use this definition for the correlation function because it is applicable to random variables in symbolic form. The standard correlation function in two dimensions is inappropriate, as it needs random variables in numeric form. However, these two definitions for the correlation functions are closely related if the joint probability distribution is Gaussian (18).

Correlation Length. The correlation length ε is defined as the variance (second moment) of the correlation function from Eq. 1,

$$\varepsilon = \left(\frac{\sum_d d^2 C(d)}{\sum_d C(d)} \right)^{\frac{1}{2}}. \quad [2]$$

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