

# Adaptive self-organization of Bali's ancient rice terraces

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Edited by William C. Clark, Harvard University, Cambridge, MA, and approved May 15, 2017 (received for review April 1, 2016)

**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 detectable 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.**

Author contributions: J.S.L. designed research; J.S.L., S.T., N.N.C., and L.Y.C. performed research; J.S.L., S.T., N.N.C., A.C.-C., C.K., K.A.F., and L.Y.C. analyzed data; J.S.L., S.T., and L.Y.C. wrote the paper; J.S.L. created the model; and S.T., N.N.C., and L.Y.C. extended and analyzed the model.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at [www.pnas.org/lookup/suppl/doi:10.1073/pnas.1605369114/-DCSupplemental](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1605369114/-DCSupplemental).



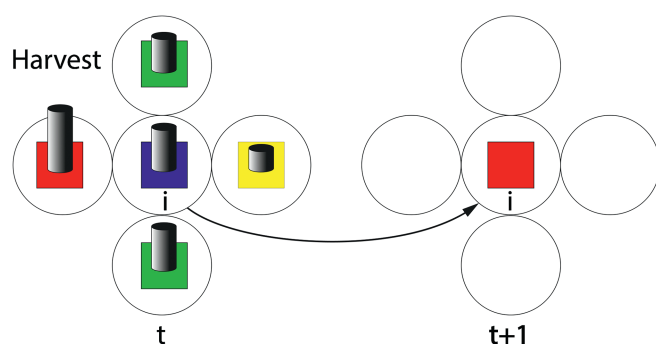
water into the subak and the scale at which groups of farmers synchronize irrigation. Consequently, the pest–water trade-off for each farmer varies depending on where his farm is located and the outcome of the irrigation schedules chosen by his neighbors. Whether both farmers choose to cooperate (synchronize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

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  $\rho$  and  $\delta$  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.

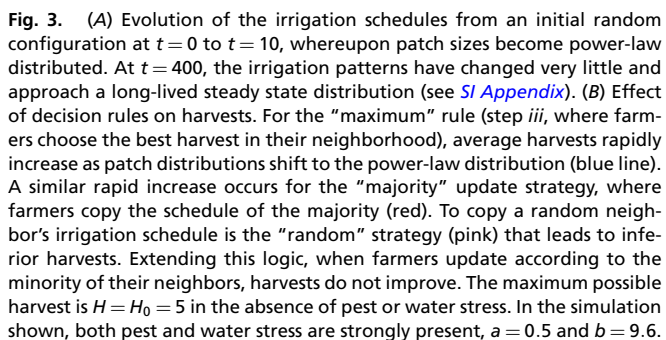
representing the initial harvest before loss. Here  $f_p^i(t)$  denotes the fraction of neighbors of farmer  $i$  within a radius  $r$  who share the same cropping pattern as  $i$  at the previous time step  $t$ , which reduces local pest damage, and  $f_w^i(t)$  is the fraction of all lattice sites 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.



### Comparison with Satellite Imagery

The cumulative patch size distribution is visible in the power law (Fig. 1C). The model results (blue squares) for the phase transition (when  $b/a \approx 20$  at  $t = 400$ ) closely matches the empir-

We performed a systematic study of the dependence of the average harvests  $H$ , the power-law exponents  $\alpha$ , and the correlation lengths  $\varepsilon$  on the parameters  $a$  and  $b$ . The results are shown in Fig. 4. Here, we observe the emergence of critical behavior at a region where water stress and pest stress balance as adaptation progresses in the simulation. This region is highlighted with white lines in Fig. 4B. A comparison with the observed data for the power-law exponent  $\alpha$  in [SI Appendix, Table S2](#) suggests that model results from this parameter region are compatible with the empirical data. At the critical region, the entire system of farms becomes correlated as global control emerges from simple local interactions between farmers.

We suggest that the dynamics captured in the lattice model described above show that self-organized criticality (SOC) can emerge from an adaptive process. The evidence that this finding tells us something about the Balinese subak system is based on the remarkable similarity of the distributions of patch sizes and correlation distances in the satellite imagery and the model. However, power-law distributions can occur for many reasons. For example, they often occur in vegetation patches in dryland ecosystems under stress (5–8). However, vegetation patches in natural ecosystems are functionally similar, differing only in size. For the vegetation patches that make up the mosaics of the rice terraces, size matters, but so does the age of the rice crop in each patch, which depends on the irrigation schedules selected by the farmers. Any explanation for the observed power-law distribution of patches in the rice terraces needs to account for this functional coupling of irrigation schedules and ecosystem dynamics. Our adaptive SOC model tests the hypothesis that the observed mosaic patterns might arise from the farmers' efforts to optimize the pest–water trade-off. The model shows that, if the adaptive dynamics are driven by the pest–water trade-off, there exist critical points where the power-law distribution is the attractor. Because approximate Pareto optimality emerges at this point, where the pest–water trade-off is optimized at all scales, the model also suggests an explanation for the historical persistence of this attractor. For these reasons, we suggest that the emergence of power-law mosaics is not a purely biological phenomenon but is the outcome of ongoing coupled human–natural dynamical interactions. Two further assumptions of the model can be evaluated with historical data.

First, the model assumes that subaks actively cooperate to minimize losses due to pests and water shortages by synchronizing their irrigation schedules. This assumption can be evaluated in light of historical evidence. From the ninth to the 14th

