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ANALYSIS

Synchronized deforestation induced by social learning under uncertainty of forest-use value

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ABSTRACT

Deforestation often has been studied in terms of land-use models, in which natural processes such as ecological succession, physical disturbance and human decision-making are combined. In many land-use models, landowners are assumed to make decisions that maximize their utilities. However, since human understanding of ecological and social dynamics is clouded by uncertainty, landowners may not know true utility values, and may learn these values from their experiences. We develop a decision model for forest use under social learning to explore whether social learning is efficient to improve landowners' decisions and can lead to effective forest management. We assume that a forest is composed of a number of land parcels that are individually managed; landowners choose whether or not to cut trees by comparing the expected utilities of forest conservation and deforestation; landowners learn utility values not only from their own experiences, but also by exchanging and sharing information with others in a society. By analyzing the equilibrium and stability of the landscape dynamics, we observed four possible outcomes: a stationary-forested landscape, a stationary-deforested landscape, an unstable landscape fluctuating near an equilibrium, and a cyclic-forested landscape induced by synchronized deforestation. Synchronized deforestation, which resulted in a resource shortage in a society, was likely to occur when landowners employed a stochastic decision and a short-term memory about past experiences. Social welfare under a cyclic-forested landscape can be significantly lower than that of a stationary-forested landscape. This implies that learning and remembering past experiences are crucial to prevent overexploitation of forest resources and degradation of social welfare.

1. Introduction

Forest resources are among the most important natural resources upon which people depend, but have been over-exploited (Moran and Ostrom, 2005; MA, 2005). Forests provide a number of ecosystem services, including supplies of timber, fuel, charcoal, and non-timber forest products, as well as purification of water, stabilization of local climate, and maintenance of biodiversity (Daily, 1997; MA, 2005). Forests are experiencing the increasing pressure of human activities, which are leading to a rapid deforestation and a loss of ecosystem services (Matthews et al., 2000). Many interacting

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processes have been reported to contribute to deforestation, including institutional rules and enforcement, opportunities for local landowners, market prices of cash crops, and ecological conditions (e.g. Dietz et al., 2003; Geist and Lambin, 2001; Lambin et al., 2003).

In previous publications, deforestation has been studied in terms of land-use models, in which natural processes such as ecological succession, physical disturbance and human decision-making are combined (Parker et al., 2003; Veldkamp and Fresco, 1996; Walker, 1999, 2003; Walker et al., 2004). The land-use decisions by individual landowners are usually considered to follow utility maximization associated with land conversion (e.g. Bockstael, 1996). For example, Satake and Iwasa (2006) developed a Markov chain model in which landowners are assumed to make decisions to choose a land-use option that produces larger expected utility under the situation where complete knowledge of utility values and perfect foresight about future landscape changes are available. However the ecosystem values of forest and economic benefits of deforestation (e.g. timber extraction) are often difficult to know in advance and may be misunderstood. This is especially so when forest succession occurs very slowly and forest restoration after deforestation takes longer than the generation time of human decision-makers. To cope with uncertainty about forest-use values, landowners may learn these utility values from their experiences. We might envision that landowners learn not only from their own experiences, but also by exchanging and sharing information with others in a society. This is called "social learning" (Boyd and Richerson, 1985; Sobel, 2000).

The aim of this paper is to develop a simple decision model for deforestation under social learning. We explore whether social learning is efficient in improving landowners' decision about forest-use and lead to an effective forest management. Models for learning have long been used by psychologists (Bush and Mosteller, 1955; Iosifescu and Theodorescu, 1969; Lakshmivarahan, 1981; Norman, 1972), and have been applied to the problem of cooperation in games (Erev and Roth, 1998; Macy, 1991; Macy and Flache, 2002; Roth and Erev, 1995). The process of learning is known in mathematical terms as a reinforcement process (e.g. reinforced random walks; Davis, 1990; Limic, 2001).

Learning by resource users has been an important topic during the last 30 years in natural resource management as well. In particular, adaptive management focuses on learning by resource managers by the iterative process of experimentation and decision-making (e.g. Holling, 1978; Walters, 1986). In recent years, this also resulted in a series of agent-based models that formalize the iterative learning process in a more realistic and complex manner (e.g. Bodin and Norberg, 2005; Janssen and de Vries, 1998; Peterson et al., 2003).

We build on a simple model studied by Satake and Iwasa (2006), and extend the previous model by incorporating strategic behaviors under social learning. In doing so, we address the potentiality that social learning with short-term memory may give rise to unstable and synchronized deforestation, and may lead to a resource shortage in a society. In view of our results, we discuss the importance of developing a social system within which a cumulative body of knowledge about forest values is handed down through generations to prevent recurrence of overexploitation of forest resources. This style of problem typifies the issues faced by small-holder deforestation at the local scale (as reviewed by Angelsen and Kaimowitz (1999)), but we see the model as having broader applications.

2. Model description

2.1. *Two-state Markov chain: deforestation and forest recovery*

We assume that a forest is composed of N land parcels. For simplicity, we assume that a landowner i, $i \in \{1,\ldots, N\}$, owns only one parcel i. This landowner agent may represent a single person, a household, or a group of people. Let $S_i(t)$be the state variable of the ith land parcel in year t:

$$S_i(t) = \begin{cases} 1 & \text{if parcel i is forested} \\ 0 & \text{if parcel i is deforested} \end{cases} \tag{1}$$

A state change of an individual parcel is described by a two-state Markov chain. A forested parcel becomes deforested following the landowners' decision to cut trees (called "deforestation decision") (Fig. 1a). The deforestation decision is made with probability $r(t)$ in year t, and is controlled by the net gain of deforestation. We will explain how to calculate $r(t)$ and the net gain of deforestation in the next section. Once the forested parcel is deforested, the resultant deforested parcel will develop secondary vegetation and will finally revert back to forested land (Fig. 1a). We assume that the transition probability from forested to deforested state is given by μ. We call μ "the forest recovery rate" per year. The expected number of years needed for forest recovery is $1/\mu$.

Landowners receive utility depending on the state of their land. Let $u_i(t)$ be the actual utility received by landowner i in year t:

$$u_i(t) = \begin{cases} b & \text{if } S_i(t) = 1 \\ c & \text{if } S_i(t) = 0 \text{ and } t_D = 0, \\ 0 & \text{if } S_i(t) = 0 \text{ and } t_D > 0 \end{cases} \tag{2}$$

where t_D is the length of the time that has elapsed since deforestation; b is a positive constant that indicates the utility caused by ecosystem services when the parcel is in forested state (i.e. $S_i(t)=1$); and c is the utility of deforestation, which is the total revenue received (e.g. monetary benefits by timber sales) minus the cost incurred (e.g. harvesting/transportation cost) when the landowner is engaged in deforestation (i.e. $S_i(t)=0$). We assume that landowners receive the utility c just after deforestation (i.e. $t_D=0$), but afterwards (i.e. $t_D>0$) the utility of deforested land declines to a level of 0 that is even lower than that of forested land, because bare land does not produce the same range of ecosystem services (Fig. 1b). Although we assume constant levels of utility, this assumption can be relaxed to allow time variant utility in a future.

2.2. *Individual decision about deforestation*

At each time step, the landowner who manages a forested parcel makes binary decisions-whether or not to cut trees.

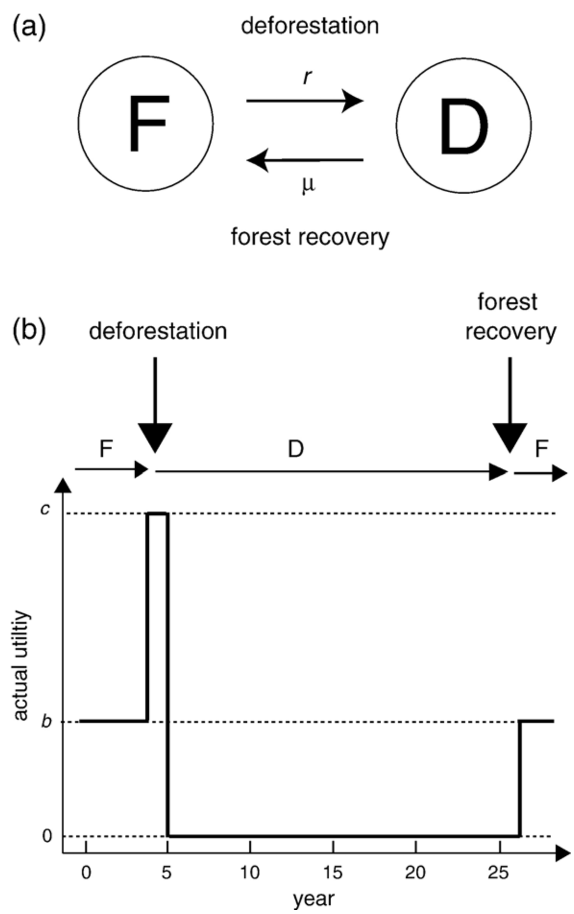

Fig. 1 – (a) Diagram of two-state Markov chain at a single land parcel. The parcel is in either forested (F) or deforested (D). r and μ are the deforestation and forest recovery rate respectively. (b) The change of actual utility at a single land parcel. The landowner will receive utility of b if he manages forested land. He will obtain utility of c when he cuts trees, but utility of deforested land stays at a low level of 0 after deforestation until the parcel reverts back to forested state.

This decision is influenced by the net gain of deforestation, defined as the expected utility received by deforestation minus that of forested parcel lost by deforestation:

$$[\text{Net gain of deforestation}] = V_D(t) - V_F(t), \tag{3}$$

where $V_D(t)$and $V_F(t)$are the expected utilities of deforestation and that of forest conservation in year t.

We assume that the landowner is more likely to choose deforestation option if it results in a larger net gain. The rate of deforestation in year t is:

$$r(t) = \frac{1}{1 + e^{-\beta(V_D(t) - V_F(t))}}, \tag{4}$$

where β is a positive constant that is homogeneous among different landowners. $r(t)$ is the transition probability from forested to deforested state in a year. We call this "deforestation rate" per year. Eq. (4) represents probabilistic decision called *logit* dynamics in evolutionary game theory (Hofbauer and Sigmund, 2003), and has been used to describe individual land-use decisions (Satake and Iwasa, 2006; Satake et al., in review; Walker et al., 2004). β is a positive constant that controls the degree of stochasticity in decision-making. If β approaches ∞, the landowners' behavior resembles deterministic decision, i.e. he chooses the forest-use option that produces the larger value with certainty, and the inferior option is selected with zero probability. Otherwise, the choice becomes probabilistic—the option producing larger utility is more likely to be selected than the inferior option, but the best choice is not selected with certainty. The probabilistic choice models were introduced by mathematical psychologists (e.g. Luce, 1959), and McKelvey and Palfrey (1995) provided a general framework to extend the probabilistic choice approach to the case of multiple decision-makers (called the Quantal Response Equilibrium). We assume probabilistic rather than deterministic decision because of the existence of attitudinal heterogeneity (i.e. heterogeneity in the need for immediate income, preferred level of risk, and interest in conservation) and the existence of errors in evaluating the utility of forested and deforested land. We will see that this stochastic decision plays a key role in destabilizing a forested landscape, and leads to a resource shortage in the society.

2.3. *Social learning: overcome environmental uncertainty*

We assume that landowners' knowledge about the utilities of forest conservation and deforestation is incomplete because of uncertainty about social and ecological dynamics. The landowner, therefore, must learn these utility values by experiences.

The individuals' expected utility about forest conservation is updated according to the following learning dynamics:

$$V_F(t+1) = (1-\alpha)V_F(t) + \alpha\pi_F(t), \tag{5a}$$

where α is the parameter ranging from 0 to 1 and $\pi_F(t)$ is the information input from experiences about the utility of forested parcel at time t. The expected utility is determined over a period $T \sim 1/|\log(1-\alpha)|$. As α increases, the period is reduced. The shortest memory is realized when $\alpha = 1$, where the landowners' expected utility is determined based only on the current information input. Similarly, the individuals' expected utility about a deforested parcel changes according to:

$$V_D(t+1) = (1-\alpha)V_D(t) + \alpha\pi_D(t), \tag{5b}$$

where $\pi_D(t)$ is the information input from experiences about the utility of deforested parcel at time t.$\pi_F(t)$ and $\pi_D(t)$ are considered as experienced utilities averaged in the society:

$$\pi_F(t) = \sum_{i=1}^{N} S_i(t)u_i(t) / \sum_{i=1}^{N} S_i(t), \tag{6a}$$

$$\pi_D(t) = \sum_{i=1}^{N} (1-S_i(t))u_i(t) / \sum_{i=1}^{N} (1-S_i(t)), \tag{6b}$$

where $S_i(t)$ and $u_i(t)$ are the state variable (Eq. (1)) and the actual utility received by landowner i in year t (Eq. (2)). The learning dynamics in Eqs. (5a) (5b) (6a) and (6b) assume that

the agents all share their information about utilities received as the outcomes of their decisions. As the number of forested land increases, the denominator of Eq. (6b) decreases, which in turn increases the per capita contribution by landowners who manage deforested lands in updating the expected utility of deforested land. We acknowledge that this is a simplified implementation of social learning (Boyd and Richerson, 1985; Sobel, 2000). In future work we will explore the consequences of various types of knowledge exchange via different social network structures as studied by Bodin and Norberg (2005).

α in Eqs. (5a) and (5b) is called the "learning rate" in the studies of reinforcement learning (Bradtke and Duff, 1994), because a large α indicates a greater application of present information in developing expectations. α is also called a "forgetting" rate according to the learning dynamics in game theory (Erev and Roth, 1998; Roth and Erev, 1995) because a larger α implies a smaller memory about past experiences. In this paper, we adopt the term "forgetting rate" after the learning dynamics in game theory. Our formulation is also equivalent to the learning model in Rapoport and Chammah (1970), who studied the Prisoner's Dilemma game under learning dynamics.

2.4. Linking individual decision with macroscopic landscape dynamics

In order to investigate macroscopic landscape patterns emerging from individual decisions, we infer a landscape dynamics at the system level by assuming a large number of landowners (i.e. N is sufficiently large), all making decisions about their parcels. Let $x(t)$ be the density of forested parcel, and $y(t)$ be the density of just-deforested parcel. Then $1-x(t)-y(t)$ represents the density of parcel that were deforested more than a year ago, and have not recovered to forest yet.

The landscape dynamics are given as follows:

$$x(t+1) = \mu(1-x(t)) + \left(1-\frac{1}{1+\exp[-\beta(V_D(t)-V_F(t))]}\right)x(t), \qquad (7a)$$

$$y(t+1) = \frac{1}{1+\exp[-\beta(V_D(t)-V_F(t))]}x(t), \qquad (7b)$$

$$V_F(t+1) = (1-\alpha)V_F(t) + \alpha b, \qquad (7c)$$

and

$$V_D(t+1) = (1-\alpha)V_D(t) + \alpha\frac{cy(t+1)}{1-x(t+1)}. \qquad (7d)$$

The expected utility of forest conservation ($V_F(t)$) converges to b according to Eq. (7c), and then the dynamics are reduced to three variables: $x(t)$, $y(t)$, and $V_D(t)$.

In the following, we perform equilibrium and stability analysis of this landscape dynamics. We also perform computer simulation of the model by assuming a finite number of agents (N=10,000). We assume that initial expected utilities of forest conservation and deforestation ($V_F(0)$ and $V_D(0)$) are random values that are evenly distributed between 0 and 1. We update these values using Eqs. (5a) (5b) (6a) and (6b), and then simulate individual decisions about deforestation.

3. Result

3.1. Equilibrium state of landscape dynamics

The landscape dynamics in Eqs. (7a) (7b) (7c) and (7d) have a single positive equilibrium:

$$(x^*, y^*, V_F^*, V_D^*) = \left(\frac{1+\exp[-\beta(\mu c-b)]}{1+\exp[-\beta(\mu c-b)]+1/\mu}, \frac{1}{1+\exp[-\beta(\mu c-b)]+1/\mu}, b, \mu c\right). \qquad (8)$$

At equilibrium, the net gain of deforestation ($V_D^*-V_F^*$) is given by $\mu c-b$, which is an increasing function of forest recovery rate (μ). This means that forested parcels become more likely to be deforested as μ increases. The equilibrium is independent of the forgetting rate (α), although α greatly influences the stability of the equilibrium, as we will explain later.

From Eq. (8), the relative fraction of forested and deforested parcels is given by:

$$x^* : 1-x^* = 1+\exp[-\beta(\mu c-b)] : 1/\mu. \qquad (9)$$

The above equation is interpreted as follows: each land parcel experiences state change regarding forest use; the expected time a parcel stays in a forested state is $1+\exp[-\beta(\mu c-b)]$, and in a deforested state (including both just-harvested parcels and those harvested more than a year before) is $1/\mu$. If $\mu c-b<0$ (i.e. the net gain of deforestation is negative), the expected time staying in a forested state is increased, which results in an increase of forest density. On the contrary, if $\mu c-b>0$, the expected time staying in the forested state is reduced because of enhanced deforestation, leading to a decline of forest density. As β increases, the expected time in a forested state becomes more sensitive to the change of $\mu c-b$. For example, in the limit of infinitely large β (i.e. $\beta\to\infty$), the expected time in a forested state becomes infinitely long if $\mu c-b<0$, but it is as short as 1 if $\mu c-b>0$.

3.2. Best choice vs. stochastic choice at equilibrium

In this section, we highlight the difference between the deterministic (i.e. $\beta\to\infty$) and the stochastic choice (i.e. finite β) by comparing the equilibrium forest densities. Without stochasticity, landowners always select the option that produces the larger utility. This is called the "best choice".

According to Eqs. (4) and (8), the best choice about deforestation under social learning is given by;

$$r_{best} = \begin{cases} 1 & \text{if } c>b/\mu \\ 0 & \text{otherwise} \end{cases}. \qquad (10)$$

Here c represents the one-year return received by deforestation (see Eq. (2)). In contrast, b/μ is the net loss of utility being forested due to deforestation, which is given by the one-year return received by forest conservation (b)multiplied by the expected time needed for forest recovery ($1/\mu$).

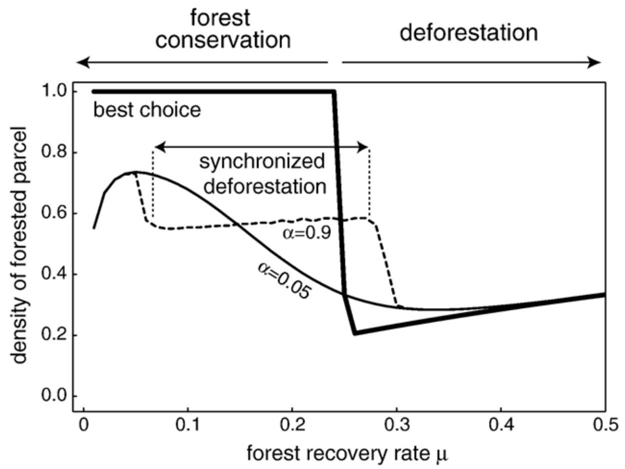

Fig. 2 – Plot of the density of forested parcel along the forest recovery rate (μ). α is the forgetting rate. A solid-thick line: best choice ($\beta=\infty$). A solid-thin line: stochastic choice with $\alpha=0.05$ and with $\beta=10$; A dashed line: stochastic choice with $\alpha=0.9$ and with $\beta=10$. A two-sided arrow indicates the unstable region where synchronized deforestation prevails. We illustrate the region of forest conservation and deforestation regimes by one-sided arrows. Other parameters are $b=0.5$, $c=2.0$, and $\mu=0.1$.

Therefore Eq. (10) indicates that the best choice under social learning is to cut his trees when the one-year return of deforestation exceeds the net loss of forested utility.

The decision depends critically on the magnitude of forest recovery rate (μ). For instance if μ is close to 0, the net loss of forested utility is considered as enormous because the forest would recover very slowly once deforested, and consequently the best choice is not to deforest. On the contrary, if μ is larger than b/c, the one-year return of deforestation exceeds the net loss of forested utility, and the best choice is to cut trees immediately after forest recovery.

The equilibrium forest density created by the best choice under social learning is:

$$x^*_{\text{best}} = \begin{cases} \mu/(1+\mu) & \text{if } c > b/\mu \\ 1 & \text{otherwise} \end{cases}. \tag{11}$$

x^*_{best} shows a sharp transition from perfectly forested to partly deforested landscape as μ increases (Fig. 2) — when $\mu<b/c$, everyone decides to conserve the forest, leading to a forest-dominated system (we call this the “forest conservation regime”); otherwise the density of forested parcel stays at a low level because everyone decides to cut trees immediately after forest recovery (we call this the “deforestation regime”).

The equilibrium density of forested parcel created by stochastic decision (x^*) is also illustrated in Fig. 2. Because stochasticity exists, a transition from the forest conservation to deforestation regime is obscured (a solid-thin line in Fig. 2). The stochastic choice creates the landscape that has significantly less forested parcels when it is in the forest conservation regime. But if it is in the deforestation regime, the deviation between the best choice and the stochastic choice is small.

A general trend observed in x^* is as follows: when μ is close to 0, x^* stays at a relatively low level due to the longer expected time needed for forest recovery. As μ increases, x^* first increases and has a peak and then decreases as μ increases further. This behavior is explained by considering the relative speed of forest recovery against that of deforestation. As μ increases, both forest recovery rate and deforestation rate increase. The former shows a linear increase, but the latter represents a nonlinear increase that is given by an S-shaped function defined in Eqs. (5a) and (5b). At the first stage of increase of μ, the increase of forest recovery rate is faster than that of deforestation, which results in an increase of x^*. As μ increases further, the increase of deforestation rate becomes faster than that of forest recovery, leading to a decrease of x^*. When μ becomes sufficiently large, the deforestation rate is satiated, approaching unity. x^*, therefore, gradually increases again with an increase of μ (Fig. 2).

3.3. *Synchronized deforestation*

In the preceding sections we derived the equilibrium of landscape dynamics, but this equilibrium may be stable or unstable. In the following sections, the stability of the equilibrium will be analyzed. We illustrated three examples of the landscape dynamics (Fig. 3). $V_F(t)$, the expected utility of forest conservation, converged to a constant level of b regardless of the magnitude of α (dashed lines in Fig. 3a,b, and c). $V_D(t)$, the expected utility of deforestation, also converged to a constant value that is equivalent to the equilibrium value (V^*_D) if α is small ($\alpha=0.05$; a solid line in Fig. 3a). However, for larger values of α ($\alpha=0.2$ and 0.9), V^*_D is destabilized and an oscillation-cyclic increase and decrease of expected utility-prevails (Fig. 3b and c). As a consequence, the fraction of forested ($x(t)$) and that of just-deforested parcels ($y(t)$) converged to constant levels if α is small (Fig. 3d), but for larger α, $x(t)$ showed a drastic decline (sometimes the density was below 10%) and then recovery to a very high level (almost 80% forested), which was repeated quasi-periodically (Fig. 3e and f). The drastic decline of $x(t)$ is due to synchronized deforestation. For example, when $\alpha=0.9$, more than 40% of landowners decide to cut trees synchronously (Fig. 3f).

Different values of α (0.05, 0.2, and 0.9) represent the different situations about how far back into time landowners look. For example, a time interval with which landowners evaluate past information is about up to 50 yrs prior to the present when $\alpha=0.05$, but it reduces to about 10 yrs when $\alpha=0.2$, and further reduces to 1 yr when $\alpha=0.9$. Large α reduces the memory size of past experiences. The oscillation of the density of forested parcel therefore, occurs when landowners have a short-term memory.

We investigated how periodicity will be altered by the change of magnitude of α and forest recovery rate (μ) (Fig. 4). We calculated auto-correlation functions with time lags (ACFs) using time series of the density of forested parcel ($x(t)$) generated from computer simulations. We then detected periodicity by counting the number of lags that showed the largest positive correlation. The interval between subsequent synchronized deforestations became shorter as landowners employed shorter memories (i.e. large α), or also as the forest recovers faster (i.e. large μ). The cycle of deforestation is predicted to be periodic if

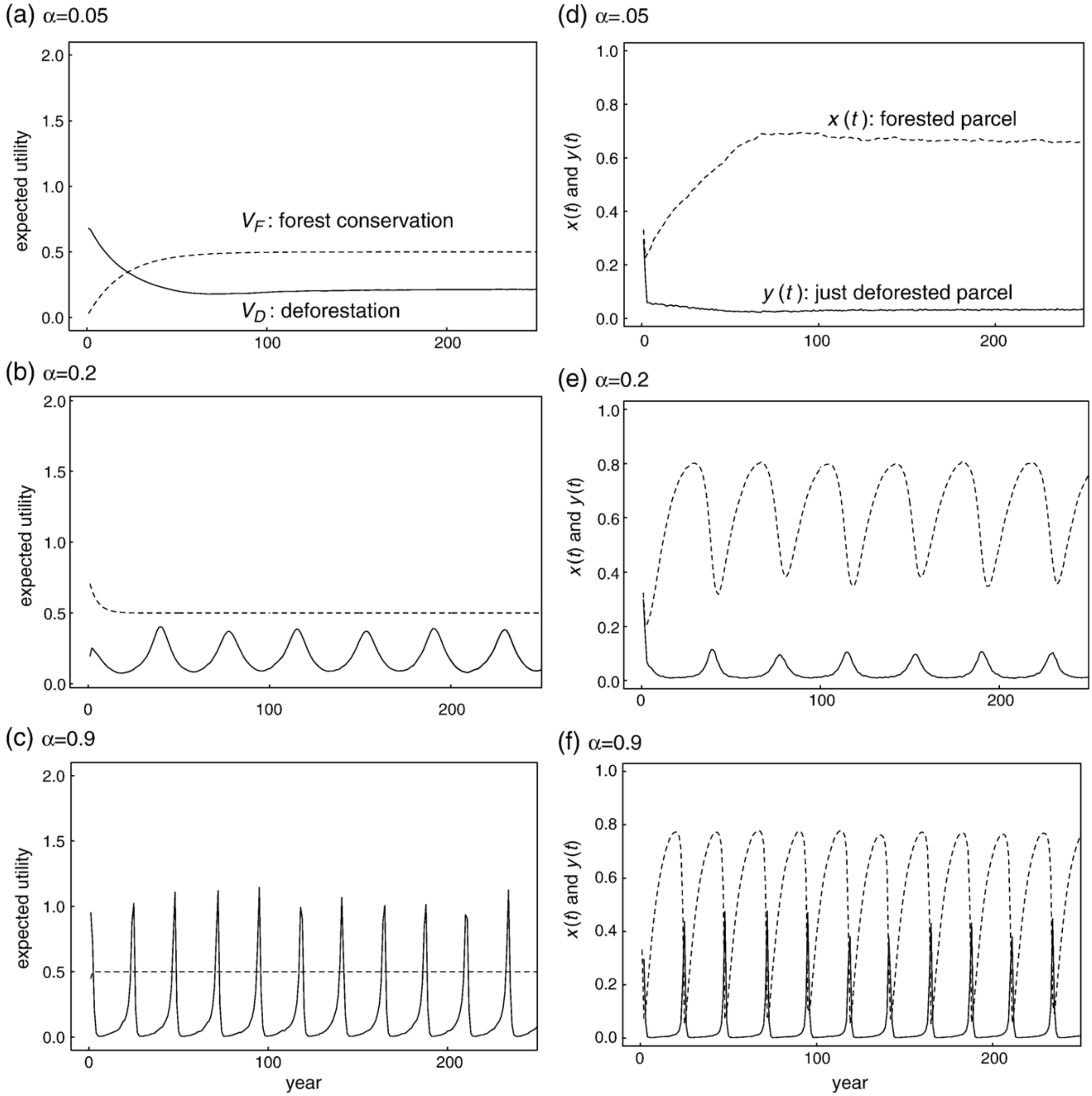

Fig. 3 – (a), (b), and (c): The expected utility of forest conservation (V_F : dashed lines) and that of deforestation (V_D : solid lines). (d), (e), (f): The density of forested parcel ($x(t)$: dashed lines) and that of just-deforested parcel ($y(t)$: solid lines). Other parameters are $b=0.5$, $c=2.0$, $\mu=0.1$, and $\beta=10$.

an infinitely large number of agents are included, as formalized in Eqs. (7a) (7b) (7c) and (7d); however, because of the finite number of agents in the computer simulations we observed only a quasi-periodic cycle.

3.4. *When does synchronized deforestation occur?*

In this section, we investigate when synchronized deforestation occurs. If the equilibrium (Eq. (8)) is stable, the landscape converges to a stationary state in which the density of forested parcel is constant across time due to a balanced fraction of forest recovery and deforestation. In contrast, if the equilibrium is unstable, the density of forested parcel oscillates. We analyzed the stability of landscape dynamics by calculating eigenvalues of the Jacobian Matrix (see Appendix A), and illustrated the boundary that separates the stable and unstable regions (Fig. 5).

When the equilibrium is unstable, there are two different situations, which can be classified according to the nature of eigenvalue(s) with the greatest magnitude (i.e. dominant eigenvalue(s)). One is the case in which there is a single real eigenvalue that is negative with the magnitude larger than 1.

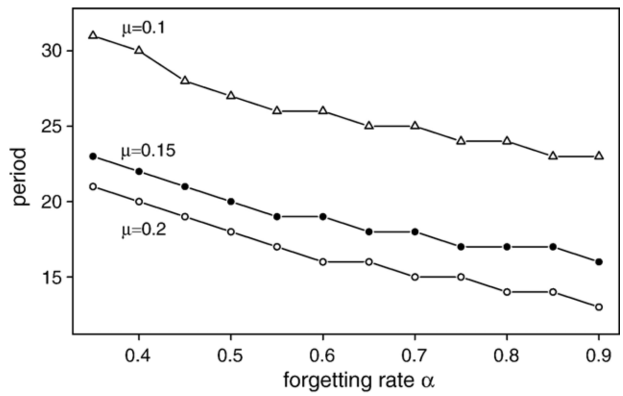

Fig. 4 – Plot of intervals of subsequent synchronized deforestation along the forgetting rate (α). μ is the forest recovery rate. Triangles: $\mu=0.1$; solid circles: $\mu=0.15$; open circles: $\mu=0.2$. Other parameters are $b=0.5$, $c=2.0$, $\mu=0.1$, and $\beta=10$.

In this case, the system would fluctuate around the equilibrium, but amplitude is small staying near the equilibrium. We call this "the fluctuation near the equilibrium". Another is the case in which there is a pair of dominant eigenvalues with complex conjugate that have the magnitude larger than 1. In this case, the system would show a fluctuation with large amplitudes. We call this "synchronized deforestation".

Synchronized deforestation is not likely when the landscape is in deforestation regime. However, in forest conservation regime, synchronized deforestation is observed in a large parameter region where α is large (Fig. 5a). The degree of stochasticity in decision-making (β) negatively influences the likelihood of synchronized deforestation — as β decreases (i.e. as the degree of stochasticity increases), unstable parameter region diminishes (Fig. 5b). When stochastic deforestation occurs frequently, the fraction of bare land increases. In such a situation, landowners observe bare lands that produce low profit as well as just-deforested lands producing large profit. By taking average of these observations, landowners identify that deforestation does not produce a large profit over the long term. This expectation reduces the landowners' motivation to cut trees, and consequently prevents synchronized deforestation. In other words, the probability of a decision to cut down trees when this is not expected to be the best decision should be low to trigger synchronized deforestation. The stable region expanded with a decline of μ (Fig. 5). This occurs due to the same mechanism: if forested land recovers very slowly, landowners always observe bare land that produces low profit, which reduces the motivation of deforestation, and prevents synchronized deforestation.

"Best choosers" do not decide to cut trees under the forest conservation regime because they choose the forest conservation option that produces larger utility than deforestation with certainty. Therefore we will not observe synchronized deforestation in the society that is composed of only best choosers. However, such a society may be fragile to deforestation that is externally imposed. In order to investigate the robustness of the forest conservation regime created by the best chooser under social learning, we examine whether or not a small fraction of deforestation imposed externally, i.e. "noise", induces synchronized deforestation. We found that the noise ends up with a synchronized deforestation if the following inequality holds (Appendix B):

$$\alpha > \frac{b-\mu c}{c(1-\mu)}. \tag{12}$$

The above equation implies that a lack of long-term memory about past experiences (i.e. large α) makes the forest

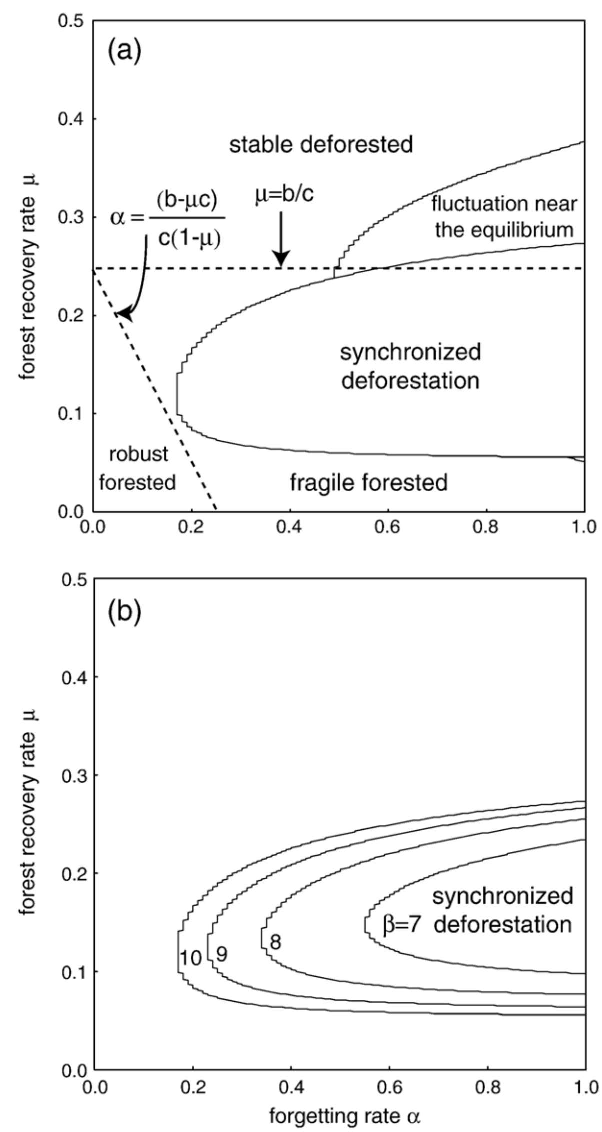

Fig. 5 – (a) Stability of the model. Solid lines indicate the boundary that separates stable, synchronized deforestation, and the fluctuation near the equilibrium. Two dashed lines separate the forest conservation and deforestation regime (the line of $\mu=b/c$) and robust and fragile forested landscape (the line of $\alpha=(b-\mu c)/c(1-\mu)$). $\beta=10$. (b) The impact of stochasticity on the region of synchronized deforestation. Solid lines indicate the boundary that separates stable-forested landscape and cyclic-forested landscape caused by synchronized deforestation. The numbers attached these lines are magnitude of β. Other parameters are $b=0.5$ and $c=2.0$.

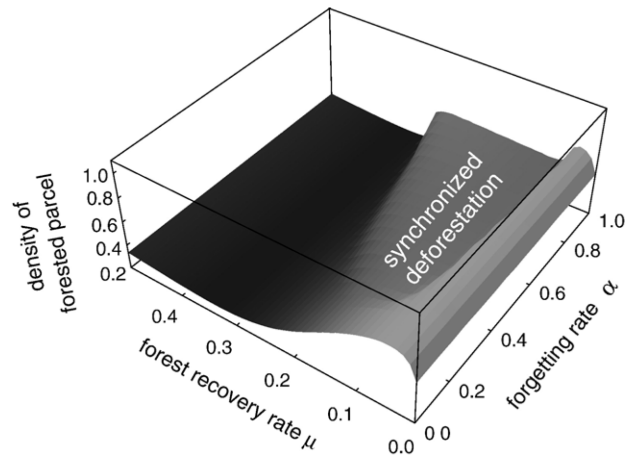

Fig. 6 – 3-Dimensional plot of long-term average of the density of forested parcel. Parameters are $b=0.5$, $c=2.0$, and $\beta=10$.

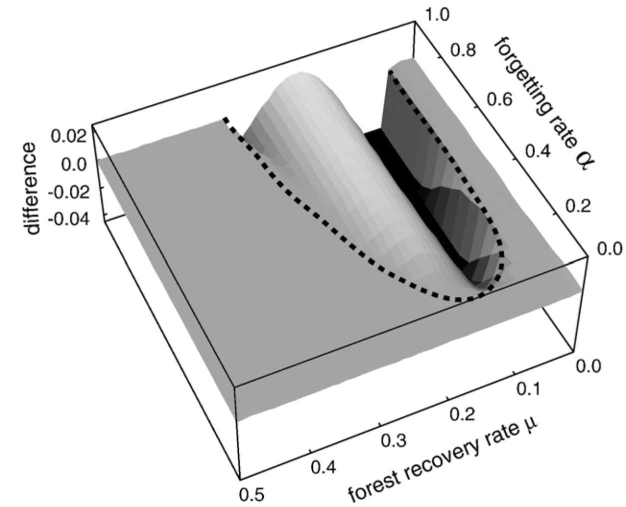

Fig. 8 – 3-Dimensional plot of the difference between the temporal average of social welfare (i.e. $\overline{W}$) and the social welfare at equilibrium (i.e. W^*). Dotted line indicates the boundary that separates stable- and cyclic-forested landscapes. Parameters are $b=0.5$, $c=2.0$, and $\beta=10$.

conservation regime more likely to be fragile to the external deforestation. The boundary between two regimes (robust forested and fragile forested) is indicated as a dashed line in Fig. 5a.

The long-term average of $x(t)$ (the density of forested parcel) is investigated as well in order to show the difference between stable and unstable landscape dynamics (Fig. 6). The temporal mean of $x(t)$ was calculated by sampling 1000 time points. If the equilibrium is stable (i.e. small α), $x(t)$ is equivalent to the equilibrium value illustrated in Fig. 2 showing a gradual shift from forest conservation to deforestation as μ increases. On the other hand, in a region of synchronized deforestation, the average density of forested parcel did not change much (Fig. 6), appearing a flat shape when it is plotted against μ (a dashed line in Fig. 2).

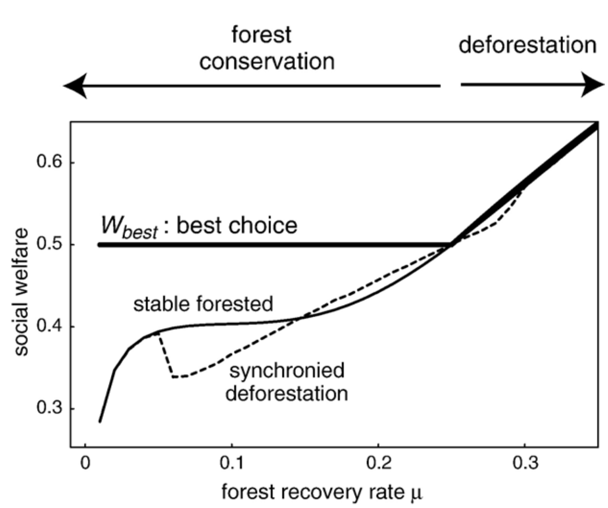

Fig. 7 – Plot of social welfare along the forest recovery rate (μ). A solid-thick line: best choice (W_{best}: $\beta=\infty$); A solid-thin line: stochastic choice with $\alpha=0.05$ and with $\beta=10$; A dashed line: stochastic choice with $\alpha=0.9$ and with $\beta=10$.We illustrate the region of forest conservation and deforestation regimes by one-sided arrows. Other parameters are $b=0.5$, $c=2.0$, and $\mu=0.1$.

3.5. *Comparison of social welfare between stable- and cyclic-forested landscapes*

We analyzed how social welfare changes according to stochasticity (β), forest recovery (μ), and forgetting rate (α). We define a social welfare in year t as the average utility received by landowners in the society:

$$W(t) = \sum_{i=1}^{N} u_i(t)/N = bx(t) + cy(t), \tag{13}$$

where $u_i(t)$is the actual utility received by landowner i in year t (Eq. (2)); N is the total number of individuals in the society; $x(t)$ and $y(t)$ represent the density of forested and just-deforested parcel in year t; b and c are introduced in Eq. (2).

If a society is composed of only best choosers, $W(t)$ is constant across time:

$$W_{\text{best}} = \begin{cases} \dfrac{b+c}{1+1/\mu} & \text{if } c>b/\mu \\ b & \text{otherwise} \end{cases}. \tag{14}$$

Eq. (14) means that in a deforestation regime (i.e. $c>b/\mu$), the averaged welfare increases as μ increases; otherwise it is constant and is as large as b (Fig. 7).

We compare W_{best} with the social welfare in a society of landowners who make stochastic decisions (Fig. 7). We also

explore the deviation of stable- and cyclic-forested landscapes in terms of social welfare (Fig. 8). The social welfare under stochastic decisions are determined as the temporal average of social welfare that is calculated by sampling 1000 time points (i.e. $\bar{W} = \frac{1}{T}\sum_{t=0}^{T-1}(bx(t) + cy(t))$ where $T=1000$). If the equilibrium is stable (i.e. small α), $\overline{W}$ is equivalent to W^* that is given as $W^*=bx^*+cy^*$ where x^* and y^* are the density of forested and just deforested parcel at equilibrium (Eq. (8)). Regardless of the stability of landscape dynamics, $\overline{W}$ was substantially below W_{best} when the system is in the forest conservation regime (Fig. 7). The cyclic-forested landscape (a dashed line in Fig. 7) induced by synchronized deforestation caused significantly lower social welfare than that of stable-forested landscape (a solid-thin line in Fig. 7) when μ was small, but this difference was reduced as μ increased. This trend is also illustrated in Fig. 8 where the difference between the temporal average of social welfare ($\overline{W}$) and the social welfare at equilibrium W^* (i.e. $\overline{W}-W^*$) was plotted; when the system was in a cyclic-forested landscape, $\overline{W}$ was significantly smaller than W^* if μ is small; but as μ increases, $\overline{W}$ quickly increased to the level even slightly larger than W^*. This implies that the impact of synchronized deforestation on the social welfare is significantly negative only when forest regenerates slowly. As μ increased further, $\overline{W}$ finally approached W^* (Fig. 7).

4. Discussion

This paper presents a simple decision model of forest use under social learning. Our analysis shows that when forest regeneration is slow, the landowner learns that the best decision (which we define in Section 2.2) is forest conservation because the loss of forest exceeds the gain by deforestation (as abbreviated by the “forest conservation regime” in Fig. 2). But if there are errors in decision-making, landowners may make decisions to cut trees even if the best decision is not to cut trees. We illustrated that such stochastic decisions could trigger synchronized deforestation by others, causing cyclic occurrence of large-scale deforestation.

Two important factors inducing synchronized deforestation are stochastic decision and short-term memory. If a single landowner decides to cut trees by chance under forest conservation regime, other landowners will observe the outcome and identify a currently high utility of deforestation. But if landowners have long-term memory, they do not alter their decisions to conserve forests even after the observation because they remember that there is a period of low profitability immediately after deforestation. However, if landowners employ only short-term memory, observation of currently high profitability of deforestation triggers an increase of their motivations to cut trees, and eventually leads to synchronized deforestation.

The cyclic deforestation in a landowners' population is similar to economic studies on herding behavior and bubbles in financial markets. When speculative investors in markets start imitating each other's attitudes about the future price change, overvaluation (or undervaluation) of market values occurs, leading to a cyclic development and breakdown of bubbles (Lux, 1995). This herding behavior has been identified as similar to the foraging and recruitment behavior in ant populations—a switching of food sources from one to another (Kirman, 1993). In forest management, Bodin and Norberg (2005) reported that synchronized catastrophes could occur when landowners share information in a tightly connected network.

The common factors included in models of synchronized (or collective) behaviors are stochastic decisions (in a sense that the system involves agents making different choices) and communication (mimicking or contagion) among individuals. The model presented in this paper demonstrates that a lack of long-term memory about the past is another important factor inducing synchronized decision (this is also mentioned by Giardina and Bouchaud (2003) in the context of bubble formation). From ecosystem management perspectives, societies embedded in forested landscape should avoid synchronized deforestation in order to prevent overexploitation that would reduce the social welfare. In this sense, conservative decision-makers who employ a long-term memory and are reluctant to change opinions are better off than the trend followers who have short-term memory and are apt to change their mind very easily.

When regeneration of forest resources is slow, recovery of forest may take longer than the generation time of the landowner. Because of this slow process, it may be difficult to observe directly how decisions made by previous generations affect the state of forest in the present time. This implies that social learning within the same generation is not enough to learn from the events that occurred long ago and that have been experienced by previous generations. A society needs to develop a system within which a cumulative body of knowledge about ecological value is handed down through generations by cultural transmission (as discussed in Berkes and Folke, 1998; Folke, 2004). For example, for the White Mountain Apache Tribe, knowledge about causes and consequences of widespread ecological deterioration that occurred in the early part of the 20th century has been passing on from elders to youths to restore health and productivity of ecosystems (Long et al., 2003). The traditional knowledge will allow future human generations to learn to sacrifice short-term gains to obtain long-term benefits. This would be critical to prevent recurrence of overexploitation of renewable resources.

Humans learn from the past and anticipate the future. Combining these backward-and forward-looking perspectives, people make sophisticated decisions. In this paper, we examined only the backward-looking aspect, but in future work we intend to examine how the two features can be combined.

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Appendix A. Stability analysis

The Jacobian matrix J of the dynamics in Eqs. (7a) (7b) (7c) and (7d) in the text is given by:

$$J=\begin{vmatrix} -\mu+1-\dfrac{1}{1+e^{-\beta(V_D^*-V_F^*)}} & 0 & \dfrac{-\beta e^{-\beta(V_D^*-V_F^*)}}{(1+e^{-\beta(V_D^*-V_F^*)})^2}x^* \\ \dfrac{1}{1+e^{-\beta(V_D^*-V_F^*)}} & 0 & \dfrac{\beta e^{-\beta(V_D^*-V_F^*)}}{(1+e^{-\beta(V_D^*-V_F^*)})^2}x^* \\ \dfrac{\alpha c y^*}{(1-x^*)^2} & \dfrac{\alpha c}{1-x^*} & 1-\alpha \end{vmatrix}, \qquad (A1)$$

where x^*, y^*, V_F^*, and V_D^* are given in Eq. (8) in the text. We obtained eigenvalues of the Jacobian matrix J numerically because characteristic equation is not tractable analytically. If absolute values of all of the eigenvalues are less than 1, the system is stable. The unstable landscape is further classified into the two, "synchronized deforestation" and "the fluctuation near the equilibrium", according to the nature of eigenvalue(s) with the greatest magnitude (i.e. dominant eigenvalue(s)) as explained in the text.

Appendix B. Stability analysis under the best choice

We investigate the robustness of the forest conservation regime under the best choice by observing whether or not a small fraction of deforestation imposed externally (i.e. noise) induces synchronized deforestation.

Consider that a single landowner decides to deforest his land when all landowners manage forested land. After this noise, the expected utility of deforestation by all landowners is updated as $(1-\alpha)V_D^*+\alpha c$(see Eqs. (5a) and (5b) in the text). Given $V_D^*=\mu c$, the updated expected utility of deforestation is given by $(1-\alpha)\mu c+\alpha c$. Landowners decide to cut tree when the expected utility of deforestation exceeds that of forest conservation (b). Therefore the condition to induce synchronized deforestation is:

$$\alpha>\frac{b-\mu c}{c(1-\mu)}. \qquad (B1)$$

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