Human-environment feedback and the consistency of proenvironmental behaviour

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Abstract

Addressing global environmental crises such as climate change requires the adoption of consistent proenvironmental behaviour by a large part of a population. Identifying the main determinants of proenvironmental behavioural consistency remains challenging. Here, we ask how the individual assessment of environmental actions interacts with social norms to shape the degree of behavioural consistency, and how this feeds back to the perceived environmental state. We develop a stochastic individual-based model involving the coupled dynamics of a population and its perceived environment, assuming that individuals can switch between two alternate behaviours differing in their environmental impact. After showing that the system can be approximated by ordinary differential equations and associated fluctuations, we study the population-environment stationary state. We show that behavioural consistency depends on the balance between individual assessment and social interactions while being little sensitive to the environmental reactivity. Inconsistent proenvironmental behaviour caused by the environmental feedback can be countered by the social context provided the proenvironmental social norm is strong enough. Establishing such a social norm (through e.g. communication or public policy) thus appears critical for consistent proenvironmental behaviour. Noticingly, the combined social and environmental feedbacks then prove effective at establishing consistent proenvironmental behaviour even at high individual cost.

Keywords: Global change, stochastic model, social norms, timescales, fluctuations, payoffs

1 Introduction

Why don't we all act more decisively in the face of global environmental crises such as climate change or biodiversity loss? Achieving climate and biodiversity targets set by international agreements (e.g. Paris accord, Aichi convention) ultimately requires consistent behavioural changes across societies. At the level of individuals, limiting climate change or biodiversity loss requires to make consistent consumer choices with reduced net environmental impact. As citizens, individuals must consistently promote governmental policies that favor proenvironmental actions. Leaders and senior managers, as individuals, should make consistent decisions to influence greenhouse gas emissions and natural resource use by large organizations and industries. For individuals, adopting proenvironmental behaviour is generally a difficult decision. Indeed the decision amounts to accepting certain short-term costs and reductions in living standards in order to mitigate against higher but uncertain losses that may be far in the future [14]. Individual behavioural responses to this collective-risk social dilemma [32] are not all-or-nothing, however. Between those who unconditionally accept or unconditionally deny the need for action towards environmental sustainability, the vast majority of people do not engage consistently in either way. Rather, non-ideologically polarized individuals tend to show inconsistent behaviour as they change opinion, revise their intention, or switch behaviour during their lifetime, possibly on very short timescales [7].

For example, individuals who engage in some kind of proenvironmental action may lose motivation to "take the next step". In this case, action limits intention for more, a pattern called *tokenism* [14]. In the same vein, the *rebound effect* occurs when some mitigating effort is diminished or erased by the individual's subsequent actions [15]. For example, after acquiring a more fuel-efficient vehicle (an active mitigating behaviour), owners tend to drive them farther, in effect reverting to their baseline environmental impact [28]. Other patterns of inconsistent behaviour involve responses to extreme climatic events. Exposure to a climate-related hazard such as wildfires increases support for costly, pro-climate ballot measures in subsequent local elections [20]. But the degree of personal concern about climate change is related to the temperature anomaly only over the past 12 months [10]. Thus, outside of the most politically polarized groups, the influence of environmental anomalies can be strong, but it decays rapidly [19].

Here we propose to analyse the individual dynamics of environmental behaviour in the context of behaviour-environment feedbacks [38]. In this framework, the environment is perceived by individuals as fluctuating and changing, while perceived environmental variations themselves are shaped by individual opinions and actions. Schill and al.'s [38] framework builds on cognitive psychology, behavioural economics, and sustainability science, to develop the two-fold hypothesis: (i) individuals' opinions are made both in relative isolation, given the perceived environmental state, and in response to the socio-cultural context, through interactions with others; and (ii) the socio-cultural and environmental contexts change continuously as individuals form opinions, make decisions, and act. Such a framework is needed to capture the fact that we create socio-cultural and environmental contexts that change dynamically with and feed back continuously to our behaviour.

Recently, several behaviour-environment models, akin to replicator models of game theory, have been analyzed where human behaviour and a natural resource such as farmland [12], water [41] or forest [4] jointly evolve. A key aspect of these behaviour-environment models based on 'imitation dynamics' [21] is that individuals' behavioural decisions are only made in the context of their interaction with others. When interacting with others, individuals evaluate the relative cost of their behaviour or intention, which may depend on the perceived state of the environment; and they respond to social norms (adhere to or reject a specific behaviour). Thus, such imitation dynamics model ignore the individual(istic) component of the decision, based on the perception of the environmental state and not directly tied to social encounters. Moreover, the time scales at which the social and environmental processes operate are not explicitly defined. This makes it difficult to interpret these models in terms of dynamics of *individual* behaviour.

Here we rigorously construct a simple mathematical model based on individual-level rules to investigate the determinants of individual proenvironmental consistency. In particular, we address how the individual assessment of environmental actions interacts with social norms to shape the degree of behavioural consistency, and how this feeds back to the perceived environmental state. To overcome the limitations of previous behaviour-environment models, our model assumes that any given individual impacts the environment to a degree determined by their behaviour, and the individual can change their behaviour stochastically in response to both social interactions and their own perception of the environment. In our model, behaviour can be inconsistent as the individuals can switch behaviour during their lifetime, because of individual assessment of the environmental state, or social pressure; reciprocally, the environmental state changes in response to individuals' behaviour. The environment and the individuals' behaviour are considered as continuous and discrete variables, respectively, and the different processes affecting the state of the behaviour-environment system play out on different time scales. We ask whether larger costs of, or weak social pressure on, proenvironmental behaviour make inconsistency more likely; and whether a slower pace of change in the perceived environmental state can promote consistency.

2 Model

We consider a population of size N. Individual behaviour and perceived environmental state are modeled on a short enough timescale such that N remains constant. The variable E measures the perceived environmental state on a continuous scale, with larger E meaning that the environment is perceived as more degraded. Each individual can express two behaviours: baseline (denoted by B) and active (denoted by A). When expressing the A behaviour, an individual actively seeks to reduce their environmental impact compared to the baseline impact of the B behaviour. An individual in state A increases the perceived environmental impact of the population by an amount l_A, which is less than the environmental impact, l_B, of behaviour B (per capita). Any individual may switch between behaviours A and B.

At any time t, the perceived environmental state and the numbers of individuals who are performing A or B are denoted by E_t^N, $N_t^{A,N}$ and $N_t^{B,N}$, respectively. Since the population size is constant we have $N_t^{B,N} = N - N_t^{A,N}$. Hereafter we derive a model for the joint dynamics of the frequency of the A behaviour in the population, $X_t^N = \frac{N_t^{A,N}}{N}$, and the perceived environmental state, E_t^N. Notations of the model are summarized in Tab. 1.

2.1 Environment dynamics

We assume that the dynamics of the perceived environnemental state E_t^N follows a deterministic continuous process. Each individual in the population has the same perception of the environment. The dynamics of E_t^N is driven by the ordinary differential equation

$$\dot{E}_t^N = h(X_t^N, E_t^N),$$

where h captures the environmental impact of the two behaviours given their frequency, according to

$$h(x, e) = \ell e(l_A x + l_B(1 - x) - e). \tag{1}$$

Parameter ℓ represents the timescale at which individuals' behaviour affects the perceived environmental state E_t^N: the higher ℓ, the faster the perceived environmental state changes due to individuals' behaviour.

The function h is chosen such that in a population where all individuals express behaviour A (B, respectively), the rate of change of the environment perceived as minimally (maximally) degraded is proportional to l_A (l_B) and the stationary value of the perceived environmental state is l_A (l_B). In a population where both behaviours are expressed, the perceived environmental state varies between l_A and l_B.

2.2 Behaviour dynamics

Two factors influence individual behaviour: social interactions and individual assessment of the environmental state.

Social interactions

Any individual may at any time switch between behaviours A and B as a result of social interactions. The rate at which an individual changes its behaviour in the context of social interactions depends on the attractiveness of the alternate behaviour, which is determined by the perceived payoff differential between the two behaviours, and the social norm.

Formally, an individual with behaviour i switches to behaviour j via social interactions at rate

$$\lambda^N_{i\to j}(X^N) = N^2\kappa X^N(1-X^N)\lambda^N_j(X^N), \tag{2}$$

where $\lambda^N_i(x)$ is the individual attractiveness of behaviour i, $N^2\kappa X^N(1-X^N)$ is the number of potential encounters, and κ is a scaling parameter controlling the rate of switching behaviour via social interactions. For example, only a fraction κ of the total population may be observable by any given individual at any given time. The individual attractiveness of behaviour i is taken of the form

$$\lambda^N_i(X^N) = \frac{1}{N}\left(\gamma_i + \delta_i g_i(X^N)\right), \tag{3}$$

where γ_i is the payoff from adopting behaviour i, and δ_i is the social pressure for behaviour i. As a result, the individual rate of behavioural switch from i to j is

$$\lambda^N_{i\to j}(X^N) = N\kappa X^N(1-X^N)(\gamma_j + \delta_j g_j(X^N)). \tag{4}$$

We further assume

$$\begin{aligned} g_A(X^N) &= X^N, \\ g_B(X^N) &= 1 - X^N \end{aligned} \tag{5}$$

reflecting that social influence is a coercive mechanism which encourages conformism.

Individual assessment

Any individual may also switch behaviour at any time based on their assessment of the state of the environment. Such behavioural switch occurs at the individual rate

$$\tau^N_{i\to j}(X^N, E^N) = N g_i(X^N)\tau_j(E^N), \tag{6}$$

where $g_A(X^N) = X^N$ and $g_B(X^N) = 1 - X^N$ (as above). τ_A and τ_B must capture the fact that individuals tend to adopt the alternate behaviour when they perceive the environmental impact of their current behaviour as relatively high, compared to the alternate behaviour. The simplest form then is

$$\begin{aligned} \tau_A(E^N) &= \tau(E^N - l_A) \\ \tau_B(E^N) &= \tau(l_B - E^N) \end{aligned} \tag{7}$$

where parameter τ sets the timescale of behavioural switch from individual assessment.

2.3 Dynamics of the behaviour-environment stochastic process

The dynamics of the coupled behaviour-environment process $\left(X^N_t, E^N_t\right)$ are stochastic, driven by the probabilistic events of individual switch between the baseline (B) and active (A) behaviours, under the joint effects of social interactions and individual assessment, and the deterministic response of the perceived environmental state. Mathematically, the effects of all possible events (individual behavioural switches, change in perceived environment) on the state of the Markovian system $\left(X_t^N, E_t^N\right)_{t\geq 0}$ are captured by the infinitesimal generator L^N of the stochastic process $\left(X_t^N, E_t^N\right)$. For $(x,e) \in [\![0, \frac{1}{N}, \cdots, 1]\!] \times \mathbb{R}_*^+$ and a test function $f \in \mathcal{C}_b^1([\![0, \frac{1}{N}, \cdots, 1]\!] \times \mathbb{R}_*^+, \mathbb{R})$, we have

$$\begin{aligned} L^N f(x,e) =& N^2\kappa x(1-x)\lambda_A^N(x)\left[f\left(x+\frac{1}{N},e\right)-f\left(x,e\right)\right] \\ &+ N^2\kappa x(1-x)\lambda_B^N(x)\left[f\left(x-\frac{1}{N},e\right)-f\left(x,e\right)\right] \\ &+ N(1-x)\tau_A(x,e)\left[f\left(x+\frac{1}{N},e\right)-f\left(x,e\right)\right] \\ &+ Nx\tau_B(x,e)\left[f\left(x-\frac{1}{N},e\right)-f\left(x,e\right)\right] \\ &+ h(x,e)\frac{\partial f(x,e)}{\partial e}. \end{aligned} \tag{8}$$

Individuals switch behaviour at a given time t for a given state of the system (X_t, E_t) with a probability given by Eq. (8). In this expression, the first and second rows account for individual behavioural switches due to social interactions (from B to A or A to B, respectively). For instance, the rate at which a $B \to A$ switch occurs because of social interactions (first row) is proportional to $N(1-x)$, the number of individuals adopting behaviour B; $\kappa N x$, the rate of social interaction between a single individual adopting B and individuals adopting A; and $\lambda_A(x)$, the social attractiveness of a single individual adopting A. The third and fourth rows account for switches because of individual assessment of the perceived environment state. For instance, the rate at which a $B \to A$ switch occurs because of the environment (third row) is proportional to $N(1-x)$, the number of individuals adopting B; and $\tau_A(x,e)$, the rate at which an individual in state B adopts the alternative behaviour A after assessing the impact of its behaviour on the perceived state of the environment. Finally, the last row accounts for changes in the perceived environmental state depending on the frequency. The process defined by Eq. (8) is called a Piecewise Deterministic Markov Process where the population state (frequencies of behaviours) probabilistically jumps at each change in individual behaviour while the environmental state deterministically and continuously changes between jumps.

Equation (8) captures the fact that individuals' behaviour is generally inconsistent, *i.e.* individuals can change their behaviour depending on their ecological and social environments, and their own experience [13, 7]. For individual behaviour to be consistent, social interactions with the alternate behaviour must be rare, the attractiveness of the alternate behaviour must be low, and/or individuals rarely evaluate their behaviour against the perceived environment state. Note that the model assumes that individuals do not differ in personality: all individuals have the same intrinsic propensity to change their behaviour (or not) across time.

2.4 Dynamical system approximation for large populations

In the Supplementary Note [11], we provide a mathematical proof that, assuming that the population size N is very large, the sequence of stochastic processes $(X^N, E^N)_{N\in\mathbb{N}^*}$ converges in distribution to the unique solution of the following system (x, e) of ordinary differential equations

$$\begin{aligned} \frac{dx}{dt} &= \kappa x(1-x)[\lambda_A(x) - \lambda_B(x)] + [\tau_A(e)(1-x) - \tau_B(e)x]\,, \\ \frac{de}{dt} &= \ell e(l_A x + l_B(1-x) - e). \end{aligned} \tag{9}$$

with initial conditions denoted by (x_0, e_0). The first equation governs the frequency x of the active behaviour, A. In the right hand side, the first term measures behavioural switch due to social interactions; the second term measures behavioural switch due to individual assessement. The second equation in System (9) drives the dynamics of the perceived environmental state, e. The terms $\lambda_A(x)$ and $\lambda_B(x)$ follow from Eq. (3), (4) and (5)

$$\begin{aligned} \lambda_A(x) &= \gamma_A + \delta_A x, \\ \lambda_B(x) &= \gamma_B + \delta_B(1-x) \end{aligned} \tag{10}$$

and $\tau_A(e)$ and $\tau_B(e)$, from Eq. (7)

$$\begin{aligned} \tau_A(e) &= \tau(e - l_A), \\ \tau_B(e) &= \tau(l_B - e). \end{aligned} \tag{11}$$

In the rest of the paper, the payoff differential, or payoff difference between behaviours A and B, will be denoted by β

$$\beta = \gamma_A - \gamma_B. \tag{12}$$

We say that the active behaviour A is *costly* when the payoff differential, β, is negative. The payoff differential may be positive if, for example, the active behaviour A is actually incentivized. Combining Eq. (10)-(12) in Eq. (9) lead to the following model equations

$$\begin{aligned} \frac{dx}{dt} &= \kappa x(1-x)[\beta + \delta_A x - \delta_B(1-x)] + \tau\,[e - l_A(1-x) - l_B x]\,, \\ \frac{de}{dt} &= \ell e(l_A x + l_B(1-x) - e). \end{aligned} \tag{13}$$

We will denote the deterministic solution of Eq. (9) by (x, e). If x converges to 1, individuals perform behaviour A most of the time, which means that the individual switching rate from A to B vanishes. In other words, behaviour A is expressed consistently. If x converges to 0, the individual switching rate from B to A vanishes and behaviour B is expressed consistently. In all other cases, individual behaviour is inconsistent.

2.5 Quantifying the effect of individual stochasticity

Even though the individual rates of behavioural switching are deterministic functions, the actual switches occur probabilistically. As a consequence, in a finite population the actual proportion of the population expressing one or the other behaviour at any point in time departs from the deterministic expectation. How much randomness there is in the behaviour's frequency in the population can be evaluated by analysing the fluctuations of the stochastic model around the deterministic limit.

To this end, we use the central limit theorem associated to the convergence of the stochastic process $(X_t^N, E_t^N)_{t\in[0,T]}$ to the deterministic solution of Eq. (9). We therefore introduce $(\eta_t^N)_{t\in[0,T]} = (\eta_t^{A,N}, \eta_t^{E,N})_{t\in[0,T]} = (\sqrt{N}(X_t^N - x_t, E_t^N - e_t))_{t\in[0,T]}$, where (x,e) is the deterministic solution of Eq. (9) and (X^N, E^N) is the stochastic process. Assuming that η_0^N converges in law to η_0, when $N \to \infty$, the process $(\eta_t^N)_{t\in[0,T]}$ converges in law to a Ornstein-Uhlenbeck type process $(\eta_t)_{t\in[0,T]} = (\eta_t^A, \eta_t^E)_{t\in[0,T]}$ and we have

$$(X_t^N, E_t^N) = (x_t, e_t) + \frac{1}{\sqrt{N}}(\eta_t^A, \eta_t^E) + o\left(\frac{1}{\sqrt{N}}\right).$$

The process $(\eta_t)_{t\in[0,T]} = (\eta_t^A, \eta_t^E)_{t\in[0,T]}$ satisfies, $\forall t \in [0,T]$:

$$\begin{aligned}
\eta_t^A &= \eta_0^A + \int_0^t [(\kappa(1-2x_s)(\gamma_A - \gamma_B - \delta_B + (\delta_A + \delta_B)x_s) - \tau(l_B - l_A))\eta_s^A + \tau\eta_s^E]ds \\
&\quad + \int_0^t \sigma(x_s, e_s)dW_s, \\
\eta_t^E &= \eta_0^E + \int_0^t \ell[(l_A - l_B)e_s\eta_s^A + (l_A x_s + l_B(1-x_s) - 2e_s)\eta_s^E]ds.
\end{aligned} \tag{14}$$

where

$$\sigma(x,e) = \sqrt{\kappa x(1-x)(\lambda_A(x) + \lambda_B(x)) + \tau_A(e)(1-x) + \tau_B(e)x}, \tag{15}$$

and W is a standard Brownian motion (see Supplementary Note [11] for mathematical detail).

Note that the drift and variance are functions of the solution of the deterministic system (9). The variance is the sum of the overall jump rates in the population and only affects the behaviour frequency (not the perceived environmental state).

2.6 Simulations and numerical analysis

For the stochastic process, the dynamics of individual behaviours' frequency (by stochastic jumps) is jointly simulated with the dynamics of the perceived environment (by deterministic changes, continuously in time between the population stochastic jumps). Random times are for any N drawn according to an exponential distribution of parameters ξ^N, where

$$\xi^N > N \sup_{x,e}(\kappa(\lambda_A(x) + \lambda_B(x)) + \tau_A(e) + \tau_B(e)). \tag{16}$$

At each of these times, we update our variables of interest. There are three possible cases: either no individual changes their behaviour in the population, or one individual switches from B to A, or one individual switches from A to B. The perceived environment is changed using a Euler scheme between two events in the population.

Without loss of generality, parameters κ and l_B are fixed to 1 (default values for parameters used in numerical analyses are summarized in Tab. 1). We analyse the properties of the stochastic and deterministic models for values of δ_A and γ_A spanning the whole range of possible values while keeping δ_B and γ_B constant. Parameters are varied across a discrete grid. We search for fixed points by computing the zeros of the polynomial given by Eq. (18). Local stability is tested by computing the Jacobian of the system. We use the Poincaré-Bendixson theorem to check the absence of limit cycle (Th.1.8.1 in [18], see also Supplementary Material [11]). When the existence of a stable limit cycle in addition to an attractive fixed point cannot be excluded, we simulate the dynamical system for different initial conditions. Would there be a limit cycle crossing the trajectory of the simulations, the trajectory would be trapped around the limit cycle and not converge to its stable fixed point. Otherwise, all trajectories converge to the equilibrium, thus excluding the existence of a limit cycle.

3 Results

We first describe the dynamics of the large-population model in the absence of environmental feedback ($\tau = 0$ in Eq. (9)). When the environmental feedback is included, we investigate the effect of all parameters to identify those that control behavioural consistency: payoff differential, social norm threshold, individual environmental impacts and environmental impact differential, individual sensitivity to the environmental state, and reactivity of the environment. Then, we study the individuals behaviour and its variance at the stationnary state. Finally, we ask how incremental behavioural changes would affect the perceived environmental state.

3.1 Behaviour dynamics in the absence of environmental feedback

In the absence of environmental feedback (i.e. no individual assessment, $\tau = 0$), individuals may switch behaviour only upon encountering other individuals, i.e. through social interactions. Equation (9) then reduces to the standard imitation dynamics (or replicator) equation

$$\frac{dx}{dt} = p_0(x) = \kappa x(1-x)[\beta + \delta_A x - \delta_B(1-x)]. \tag{17}$$

The model admits three fixed points, $x_0^* = 0$, $x_1^* = 1$ and $x^* = \frac{\beta+\delta_B}{\delta_A+\delta_B}$. If $x^* < 0$ (resp. $x^* > 1$), then $x_1^* = 1$ (resp. $x_0^* = 0$) is globally stable. If $0 < x^* < 1$, then the system is bistable; convergence to $x_1^* = 1$ occurs if the initial frequency of the active behaviour is higher than x^*. In other words, the whole population may stick to the active behaviour A either if A is perceived as rewarding compared to B ($\gamma_A > \gamma_B$) or, otherwise, if the cost of A is not too large and the social pressure on behaviour A is strong enough ($\gamma_A + \delta_A > \gamma_B$). When neither condition is satisfied, the baseline behaviour B will prevail in the population. Note that when the payoff differential β is null, the outcome is entirely determined by social pressures and in this case, the frequency threshold x^* is equal to $\frac{\delta_B}{\delta_A+\delta_B}$, a term that we call *social norm threshold*. In general ($\beta \neq 0$), the probability of behavioural switch betwen A and B depends on the payoff differential, β, and the social norm threshold, $\frac{\delta_B}{\delta_A+\delta_B}$.

3.2 Effect of environmental feedback on behaviour dynamics

As expected, environmental feedback alone can explain behavioural inconsistency. By taking $\tau > 0$ in Eq. (7) and $\kappa = 0$ in Eq. (9), individual behaviour is influenced by the perceived environmental state and not by social interactions. In this case, the Eq. (9) possesses only one stable equilibrium $(x^*, e^*) = (\frac{1}{2}, \frac{l_B+l_A}{2})$. Thus, as individuals switch behaviour, each of them will in the long run spend as much time adopting behaviour A as B, irrespective of the environment reactivity, ℓ, or individual environmental impacts, l_A and l_B. With no social interactions ($\kappa = 0$), the payoffs γ_A and γ_B do not affect the individuals' inconsistency either, since the payoffs only play a role when individuals can compare them, which is assumed to require social interactions.

By setting both $\tau > 0$ in Eq. (7) and $\kappa > 0$ in Eq. (9), the effect of environmental feedback combines with the effect of social interactions. As in the case without environmental feedback (cf. previous subsection), the model predicts up to three equilibria, given by the zeros of

$$p(x) = p_0(x) + \tau(l_B - l_A)(1 - 2x), \tag{18}$$

that are nonegative and less than (or equal to) one. The effect of the environmental feedback on its own can be highlighted by comparing Eq. (17) at its stable equilibria with the value of Eq. (18) at the same state (i.e. $x^* = 0$ or $x^* = 1$). The effect of the environmental feedback is then given by the sign of $p(0) = \tau(l_B - l_A) > 0$ and $p(1) = -p(0) < 0$ showing that the equilibria of the system necessarily become internal, as illustrated by the disappearance of the yellow region between Fig. 1b to Fig. 2d.

The roots of Eq. (18) also show that the number of equilibria is likely influenced by the social interaction rate, κ, the payoff differential, β, the social norm threshold, $\frac{\delta_B}{\delta_A+\delta_B}$, and the combination (product) of the individual sensitivity to the environment, τ, and differential environmental impact, $l_B - l_A$. Parameter ℓ, the environment reactivity, does not affect the number of equilibria but it affects their stability.

The mathematical stability analysis of Eq. (18) finally shows that the combination of individual sensitivity to the environment, τ, and environmental impact differential, $l_B - l_A$, is indeed a key determinant of the system dynamics, qualitatively. When the product $\tau(l_B - l_A)$

are small enough, there is one (globally stable) or three (two stable, one unstable) equilibria; the stable equilibrium always being close to $x^* = 0$ or $x^* = 1$, or the two stable equilibria being close to $x^* = 0$ and $x^* = 1$. When the product $\tau(l_B - l_A)$ is large enough, there is only one equilibrium, this equilibrium can be stable or unstable (here necessarily a limit cycle) depending on environmental reactivity ℓ. In other words, if the individual sensitivity to the environment is strong enough and/or the environmental impact differential is large, the model, as expected, predicts behavioural inconsistency, with individuals frequently switching between active and baseline behaviours. In contrast, with a relatively weak sensitivity to the environment and a small environmental impact differential, the model predicts that individuals will adopt a consistent behaviour, either expressing the active behaviour most of the time, or the baseline behaviour most of the time.

3.3 Conditions for propagation and consistency of active behaviour

Figure 2 shows that environmental feedback by itself can cause behavioural inconsistency even when one of the behavioural options is highly beneficial. In contrast, active behaviours that are low-incentivized or even costly can be propagated and stabilized when the environmental feedback is combined with strong conformism for the active behaviour. Indeed, on the one hand, low-incentivized active behaviour (i.e. β slightly positive) can be propagated unconditionally (no bistability) and adopted consistently (yellow regions in Fig. 2a-c). If the individual sensitivity to the environment is low or the behavioural difference is sufficiently small (yellow vertical strip corresponding to β slightly positive in Fig. 2a-c), then the social norm threshold has a minor influence on the outcome; otherwise, the consistent adoption of low-incentivized active behaviour requires a low social norm threshold, i.e., strong enough conformism among active individuals (yellow area in the bottom right of Fig. 2d-f). On the other hand, the active behaviour can be propagated unconditionally (no bistability) and adopted consistently even if it carries a net cost (i.e. negative payoff differential), provided environmental reactivity is fast enough and the social norm threshold is sufficiently low, i.e., conformism among active individuals is strong enough (yellow area in bottom left of Fig. 2a-c).

Changing the balance between social interaction and individual assessment (i.e. the balance between the parameter κ and τ) affects the consistency of active behaviour. The higher τ is, the more inconsistent the active behaviour gets (Fig. 2g-i). Each column of the Figure 2 illustrates a different balance between the parameter κ and τ.

Decreasing environmental reactivity causes the globally stable equilibrium to lose its stability and be replaced with a limit cycle. In this case, individuals will switch behaviour at a rate that is itself changing over a slower timescale set by the environmental reactivity. The slow timescale of environmental reactivity creates a time lag between the perceived environmental state and individuals' behaviour, generating periodic oscillations in the switching rates.

3.4 Behavioural inconsistency due to stochasticity at stationnary state

The finite size of a population causes random fluctuations in the frequency of the behaviours, even asymptotically around the equilibrium values predicted by the deterministic model. The variance of the asymptotic fluctuations is always large when the environmental feedback is strongest (large product $\tau(l_A - l_B)$), in relation with the equilibrium frequency being close to 0.5 (results not shown). With weaker environmental feedback, the asymptotic fluctuation variance is influenced by the payoff differential and the social norm threshold (Fig.(3)). It is relatively large for low positive payoff differential combined with medium to large social norm threshold (i.e. medium to low social pressure among active individuals) (lighter areas in Fig. 3). In contrast, the variance is very small at low values of the social norm threshold, irrespective of the payoff differential (dark blue horizontal strip at the bottom of Fig. 3a-c). In conclusion, behavioural inconsistency due to stochasticity at stationnary state depends on a subtle balance between the payoff differential β and the social norm threshold, $\frac{\delta_B}{\delta_A+\delta_B}$. The variance at stationnary state is the hightest when the payoff differential and the social norm threshold have similar intensity but favour different behaviours.

3.5 Robust environmental impact reduction through incremental behavioural change

Environmental feedback tends to generate behavioural inconsistency, which eventually limits the environmental impact reduction of active behaviour. This is especially true if the environmental impact differential is large (Fig. 4a,b), in which case active behavioural consistency in conjunction with a large environmental impact reduction can be achieved only if the social pressure in favor of the active behaviour is extremely strong (yellow horizontal strip at the bottom of Fig. 4a). However, by allowing for the unconditional propagation of low-incentivized or even costly active behaviour with a small environmental impact differential, the environmental feedback opens a path towards robust environmental impact reduction (Fig. 4c-f).

The general principle is to target a sequence of incremental behavioural change, each contributing a small reduction of environmental impact. According to the results presented in the previous subsections, an active behaviour A with a slightly smaller environmental impact than baseline behaviour B (small $l_A - l_B$) will propagate and be expressed consistently provided A is sufficiently incentivized (positive payoff differential, $\beta > 0$) or its net cost (negative payoff differential, $\beta < 0$) is compensated by social pressure (high enough δ_A hence low $\frac{\delta_B}{\delta_A+\delta_B}$). Once behaviour A is established, it becomes the common baseline behaviour where individuals may start expressing a new active behaviour A', with lower environmental impact, and, in the worst case scenario, a larger cost. In the latter case, a stronger social pressure (higher δ_A hence lower $\frac{\delta_B}{\delta_A+\delta_B}$) may compensate for the larger cost and ensure that the active behaviour A' propagates and becomes expressed consistently, instead of A.

Thus, in a system where social conformism for active behaviour can increase (increasing δ_A hence decreasing $\frac{\delta_B}{\delta_A+\delta_B}$) in relation with more effective active behaviour (lower l_A) and/or the perception of reduced environmental impact (lower E^*), a substitution sequence of gradually more active (lower l_A) and more costly (more negative β) behaviours can take place, driving a significant decrease in the perceived environmental impact (E^* decreasing to arbitrarily low levels).

Finally, potentially small populations, social pressure on the more active behaviour is also an important factor of the robusteness of this pathway towards reduced enviromental impact. As shown in the previous section, the finiteness of the population generates stochastic fluctuations in behaviour frequency, and the amount of fluctuations is sensitive to social pressure (Fig. 3). While very little stochastic fluctuation is expected in the active behaviour frequency once costly active behaviour is established in conjunction with strong social pressure for this behaviour (negative β, high δ_A, see dark blue horizontal strip at the bottom of Fig. 3a-c), the initial state and steps of the incremental sequence could be affected by the large fluctuations that are expected with a positive payoff differential and weak social pressure for A (large social norm threshold, see light areas in upper right region of Fig. 3a-c). Whether a new behaviour A' more active than A could propagate in a system where A has not been adopted consistently (reflected by x significantly fluctuating away from 1) is beyond the scope of this model and warrants furher mathematical investigation.

4 Discussion

In the face of global environmental crises such as anthropogenic climate change, many people who are not ideologically polarized may form proenvironmental intentions and yet fail to engage consistently in proenvironmental action. Using Schill and al.'s [38] conceptual framework of behaviour-environment feedbacks, we developed a simple mathematical model to study how social and environmental feedbacks jointly influence proenvironmental behavioural consistency. Individuals are modeled as agents who can engage in and switch repeatedly between two behaviours: the baseline behaviour B with environmental impact measured by l_B and the active behaviour A with (reduced) environmental impact l_A. As individuals interact among themselves and with their environment, they shape their social and environmental context; the social context then feeds back to individual behaviour via social interactions, while the state of the environment feeds back to behaviour via individual assessment. The social feedback is positive: conformism tends to promote behavioural consistency among individuals expressing the same behaviour. The environmental feedback is negative: individuals favour proenvironmental behaviour when the environmental state is perceived as worsening; they are more likely to shift to baseline behaviour when the environmental state is perceived as improving. As expected, the negative environmental feedback by itself is a cause of behavioural inconsistency whereas the positive feedback of conformism can promote behavioural consistency.

To resolve the joint influence of these two feedbacks, we rescaled our stochastic individual-level model to obtain a macroscopic model of behaviour-environment dynamics. The macroscopic model takes the form of a system of ordinary differential equations in the state variable x (frequency of active behaviour at any time t) and e (perceived level of environmental degradation at any time t). This derivation, whereby a simple differential equation model is obtained rigorously from a stochastic model, highlights three important timescales in the system, which control the behaviour-environment dynamics: the timescale of social interactions, set by the encounter rate κ; the timescale of individual assessment, set by parameter τ; and the timescale of change in the perceived environment, set by parameter ℓ.

When the timescale of individual assessment is fast relative to social interactions, the environmental feedback dominates the system dynamics, maintaining inconsistent behaviour. The relative cost of proenvironmental behaviour has no influence on the outcome, which is also largely independent of the level of proenvironmental conformism. This is because both factors (set by the payoff differential β and the social norm threshold) only influence behavioural decisions in the context of social interactions. The relatively fast individual assessment timescale may originate from individuals having more confidence in their own evaluation of costs and benefits than in others' influence. This is known to occur, for instance, when the decision to be made carries a lot of personal weight [3, 33] or when individuals have grown up in a very favourable environment [24].

When individual assessment is slow compared to social interactions, the social feedback dominates. The outcome of social interactions is parametrized by the social norm threshold and the payoff differential, β. When analysed with respect to these two parameters, the coupled human-behaviour system dynamics are similar to the purely social interaction model, with stable equlibria (possibly coexisting in a bistable regime) corresponding to a behaviour that is consistently baseline or consistently active. However, the coupled human-environment system exhibits a notable difference: low-incentivized or even costly proenvironmental behaviour (i.e. small-positive or negative β) can spread unconditionally (with respect to initial frequency) and be adopted consistently, provided the conformism of proenvironmental behaviour is strong enough. This raises the question of whether, in practice, social influence could be stronger among individuals who engage in proenvironmental behaviour than among individuals who do not. One can speculate that this could be the case if the active behaviour is individually costly and perceived as a moral duty. In this case, the active individuals behave as cooperators whose efforts (measured in terms of opportunity cost) are influenced the most by the observation of the others' efforts [35, 5].

Overall, the timescale of perceived environmental change has little effect on the behaviour-environment dynamics. Thus, whether individuals assume that their actions are environmentally meaningful in the short term (high environmental reactivity) or the long term (low environmental reactivity) generally has no significant effect on behavioural consistency. The case of social interactions and individual assessment occurring on similar timescales is special, however. In this case, low environmental reactivity creates a time lag between behavioural and environmental changes, causing behaviour-environment cycles when the proenvironmental behaviour is costly and levels of conformism are not too different between behaviours. A similar effect of slow environmental reactivity relative to social interactions promoting oscillations was also detected by [40] in their model of forest growth and conservation opinion dynamics. Contrasted environmental impacts of behaviours A and B (i.e. large $l_B - l_A$) favour the limit cycle regime over bistability which is reminiscent of previous findings of behaviour-environment cycles replacing bistability when the human influence on the environment is strong [23].

A question of interest is how the magnitude of environmental impact reduction associated with the active behaviour affects consistency. The model shows that for active behaviours causing only a small environmental impact reduction, the bistable regime is favoured, which leads to consistency (of behaviour A or behaviour B). In fact, a small environmental impact reduction by the active behaviour has the same effect on the system dynamics as a slow timescale of individual assessment. Once such a 'small step' active behaviour is established consistently, the perceived level of environmental degradation is only decreased by a small amount; but if more behavioural options were available, the socio-environmental context would be set to promote individuals engaging consistently in 'the next small step'. If the process were repeated, leading to the consistent adoption of active behaviours of gradually smaller environmental impact, we would expect the perceived level of environmental degradation to decrease. Interestingly, this might happen even if the relative cost of active behaviour was increasing, provided conformism for active behaviour increased concommitently.

Our consideration of gradual behavioural change through a sequence of 'small steps' raises the empirical question of whether the perceived change in environmental state could in turn affect the repertoire of individual behaviours, and in particular motivate behaviours more active than A. In practice, the existence and direction of such an additional feedback may depend on whether each small step is individually beneficial and thus considered by people as a self-serving decision, or individually costly and considered as a form of cooperation. In the first case, there is no obvious reason for the perceived change in environmental state to affect individual decisions, so it is unlikely that such feedback would exist. In the second case, however, the question relates to the rich empirical literature on the influence of the perceived environmental state on cooperation. The majority of studies in this field, and in particular the highest powered studies, report a positive relationship between the quality of the environment experienced by indidivuals and their level of investment in cooperation [25, 39, 2, 34, 30, 37, 45, 26]; although some studies report opposite effects [1, 27, 36] or no effect at all [42, 44]. We may thus hypothesize the existence of the additional positive feedback whereby the perception of an improved environmental state would enlarge the behavioural repertoire and motivate more active behaviours. The improvement or, on the contrary, the deterioration of the perceived environment could lead individuals to invest more, or, on the contrary, less in proenvironmental behaviour, thus generating the kind of behavioural sequence that we envisioned in this analysis.

Our work builds on the fundamental distinction between the individual's stable characteristics and the subset of situational characteristics which capture the social and environmental situatedness of behaviour [9]. In the model, all parameters, except the rate of environmental reactivity, l, are set as individual characteristics. A key assumption is that all individuals are identical in their stable characteristics. Our framework could be extended to relax this assumption and investigate the consequences of diversity in individual social status or personalities [8, 43]. For example, the same objective cost of the active behaviour (e.g. buying or maintaining an electric car) may be perceived very differently depending on the individual's wealth [31, 17]. Likewise, individuals of different social status may vary in their experience of social pressure from individuals expressing the active vs. baseline behaviour; this in the model would manifest through inter-individual variation of δ_A and δ_B [24]. Given the predicted importance of the individual sensitivity to the environment, τ, and environmental impact differential, $l_A - l_B$, the outcome (consistency of the active behaviour) is likely to be influenced by inter-individual heterogeneity in these two parameters. It is known that individuals can differ greatly in their perception and assessment of the state of degradation of their environment, due to differences in social origin, education, or information [17, 16]; and in their potential proenvironmental response to perceived environmental degradation [16]. This heterogeneity could result in wide variation of both τ and $l_A - l_B$ among individuals, with contrasted personalities such as being little responsive and acting weakly (small τ and $l_A - l_B$), or responding fast and strongly (large τ and $l_A - l_B$).

In previous human-environment models, the environment is a natural renewable resource such as forests [4] or fisheries [29], or physical variables such as atmospheric greenhouse gases concentration or temperature [6]. In these models, the environmental dynamics are driven by their own endogenous processes and impacted by human activities (harvesting, gas emissions...). These models typically ask how human behavioural feedbacks alter the stability properties of the perturbed (exploited, polluted...) ecosystem. An important difference between our approach and previous human-environment system models lies in our definition of the environmental state in terms of perceived information. This information changes under the influence of individuals' intentions or behaviours. This may be an actual, physical change, in the sense that some actual component of the environment is impacted by human behaviour; or it may be virtual (informational) as inferred from the distribution of behaviours in the population. Given this representation of the environmental state, we assumed the simplest behavioural response, a linear negative feedback. Psychological studies suggest that alternate or additional responses warrants further investigation, such as positive reinforcement (improved environmental state encourages to do more [22, 17]) or "giving up" (environment degradation leads to less effort, rather than more [22, 17]).

In conclusion, behavioural consistency depends on the balance between two different feedbacks: individual assessment and social interactions. The model highlights the importance of the timescales for these two feedbacks and provides valuable information in reinforcing proenvironmental behaviour. In order to promote consistency in pro-environmental behaviour, environmental policies should invest in improving the perceptions, or decreasing the costs, of proenvironmental behaviours. Achieving climate targets needs the right policies to be done and the informations that coupled human-environment models provide are crucial.

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References

[1] Dorsa Amir, Matthew R Jordan, and David G Rand. “An uncertainty management perspective on long-run impacts of adversity: The influence of childhood socioeconomic status on risk, time, and social preferences”. In: *Journal of Experimental Social Psychology* 79 (2018), pp. 217–226.

[2] James Andreoni, Nikos Nikiforakis, and Jan Stoop. *Are the rich more selfish than the poor, or do they just have more money? A natural field experiment*. Tech. rep. National Bureau of Economic Research, 2017.

[3] Robert S Baron, Joseph A Vandello, and Bethany Brunsman. “The forgotten variable in conformity research: Impact of task importance on social influence.” In: *Journal of personality and social psychology* 71.5 (1996), p. 915.

[4] Chris T Bauch et al. “Early warning signals of regime shifts in coupled human–environment systems”. In: *Proceedings of the National Academy of Sciences* 113.51 (2016), pp. 14560–14567.

[5] Mélusine Boon-Falleur et al. “Leveraging social cognition to promote effective climate change mitigation”. In: *Nature Climate Change* 12.4 (2022), pp. 332–338.

[6] Thomas M Bury, Chris T Bauch, and Madhur Anand. “Charting pathways to climate change mitigation in a coupled socio-climate model”. In: *PLoS computational biology* 15.6 (2019), e1007000.

[7] Robert B Cialdini and Robert B Cialdini. *Influence: The psychology of persuasion*. Vol. 55. Collins New York, 2007.

[8] Susan Clayton et al. “Psychological research and global climate change”. In: *Nature climate change* 5.7 (2015), pp. 640–646.

[9] Sara M Constantino and Elke U Weber. “Decision-making under the deep uncertainty of climate change: The psychological and political agency of narratives”. In: *Current Opinion in Psychology* 42 (2021), pp. 151–159.

[10] Simon D Donner and Jeremy McDaniels. “The influence of national temperature fluctuations on opinions about climate change in the US since 1990”. In: *Climatic change* 118.3 (2013), pp. 537–550.

[11] Claire Ecotière et al. “Supplementary materials”. In: (2022).

[12] Joana Figueiredo and Henrique M Pereira. “Regime shifts in a socio-ecological model of farmland abandonment”. In: *Landscape ecology* 26.5 (2011), pp. 737–749.

[13] D. C. Funder. “Towards a resolution of the personality triad: Persons, situations, and behaviors”. In: *Journal of Research in Personality* 40 (2006), pp. 21–34.

[14] Robert Gifford. “The dragons of inaction: psychological barriers that limit climate change mitigation and adaptation.” In: *American psychologist* 66.4 (2011), p. 290.

[15] Robert Gifford, Karine Lacroix, and Angel Chen. “Understanding responses to climate change: Psychological barriers to mitigation and a new theory of behavioral choice”. In: *Psychology and climate change*. Elsevier, 2018, pp. 161–183.

[16] Aurore Grandin, Melusine Boon-Falleur, and Coralie Chevallier. “The belief-action gap in environmental psychology: How wide? How irrational?” In: (2021).

[17] Aurore Grandin et al. “Socioeconomic status, time preferences and pro-environmentalism”. In: *Journal of Environmental Psychology* 79 (2022), p. 101720.

[18] John Guckenheimer and Philip Holmes. *Nonlinear oscillations, dynamical systems, and bifurcations of vector fields*. Vol. 42. Springer Science & Business Media, 2013.

[19] Lawrence C Hamilton and Mary D Stampone. “Blowin’in the wind: Short-term weather and belief in anthropogenic climate change”. In: *Weather, Climate, and Society* 5.2 (2013), pp. 112–119.

[20] Chad Hazlett and Matto Mildenberger. “Wildfire exposure increases pro-environment voting within democratic but not republican areas”. In: *American Political Science Review* 114.4 (2020), pp. 1359–1365.

[21] Josef Hofbauer, Karl Sigmund, et al. *Evolutionary games and population dynamics*. Cambridge university press, 1998.

[22] Mehran Homayounfar, Rachata Muneepeerakul, and John Anderies. "Resilience-performance trade-offs in managing social-ecological systems". In: *Ecology and Society* 27.1 (2022).

[23] Clinton Innes, Madhur Anand, and Chris T Bauch. "The impact of human-environment interactions on the stability of forest-grassland mosaic ecosystems". In: *Scientific reports* 3.1 (2013), pp. 1–10.

[24] Pierre O Jacquet et al. "The ecological roots of human susceptibility to social influence: A pre-registered study investigating the impact of early-life adversity". In: *Royal Society open science* 6.1 (2019), p. 180454.

[25] Martin Korndörfer, Boris Egloff, and Stefan C Schmukle. "A large scale test of the effect of social class on prosocial behavior". In: *PloS one* 10.7 (2015), e0133193.

[26] Niels Lettinga et al. "Environmental adversity is associated with lower investment in collective actions". In: *PloS one* 15.7 (2020), e0236715.

[27] Daniel Lim and David DeSteno. "Suffering and compassion: The links among adverse life experiences, empathy, compassion, and prosocial behavior." In: *Emotion* 16.2 (2016), p. 175.

[28] Joshua Linn. "The rebound effect for passenger vehicles". In: *The Energy Journal* 37.2 (2016).

[29] Jean-Denis Mathias et al. "Exploring non-linear transition pathways in social-ecological systems". In: *Scientific reports* 10.1 (2020), pp. 1–12.

[30] Michael E McCullough et al. "Harsh childhood environmental characteristics predict exploitation and retaliation in humans". In: *Proceedings of the Royal Society B: Biological Sciences* 280.1750 (2013), p. 20122104.

[31] Hugo Mell, Nicolas Baumard, and Jean-Baptiste André. "Time is money. Waiting costs explain why selection favors steeper time discounting in deprived environments". In: *Evolution and Human Behavior* 42.4 (2021), pp. 379–387.

[32] Manfred Milinski et al. "The collective-risk social dilemma and the prevention of simulated dangerous climate change". In: *Proceedings of the National Academy of Sciences* 105.7 (2008), pp. 2291–2294.

[33] Olivier Morin. "Is cooperation a maladaptive by-product of social learning? The docility hypothesis reconsidered". In: *Biological Theory* 9.3 (2014), pp. 286–295.

[34] Daniel Nettle, Agathe Colléony, and Maria Cockerill. "Variation in cooperative behaviour within a single city". In: *PloS one* 6.10 (2011), e26922.

[35] Karine Nyborg. "No man is an island: social coordination and the environment". In: *Environmental and Resource Economics* 76.1 (2020), pp. 177–193.

[36] Paul K Piff et al. "Having less, giving more: the influence of social class on prosocial behavior." In: *Journal of personality and social psychology* 99.5 (2010), p. 771.

[37] Lou Safra et al. "Neighborhood deprivation negatively impacts children's prosocial behavior". In: *Frontiers in psychology* 7 (2016), p. 1760.

[38] Caroline Schill et al. "A more dynamic understanding of human behaviour for the Anthropocene". In: *Nature Sustainability* 2.12 (2019), pp. 1075–1082.

[39] Stefan C Schmukle, Martin Korndörfer, and Boris Egloff. "No evidence that economic inequality moderates the effect of income on generosity". In: *Proceedings of the National Academy of Sciences* 116.20 (2019), pp. 9790–9795.

[40] Ram P Sigdel, Madhur Anand, and Chris T Bauch. "Competition between injunctive social norms and conservation priorities gives rise to complex dynamics in a model of forest growth and opinion dynamics". In: *Journal of theoretical biology* 432 (2017), pp. 132–140.

[41] Murugesu Sivapalan and Günter Blöschl. "Time scale interactions and the coevolution of humans and water". In: *Water Resources Research* 51.9 (2015), pp. 6988–7022.

[42] Angelos Stamos et al. "Having less, giving more? Two preregistered replications of the relationship between social class and prosocial behavior". In: *Journal of Research in Personality* 84 (2020), p. 103902.

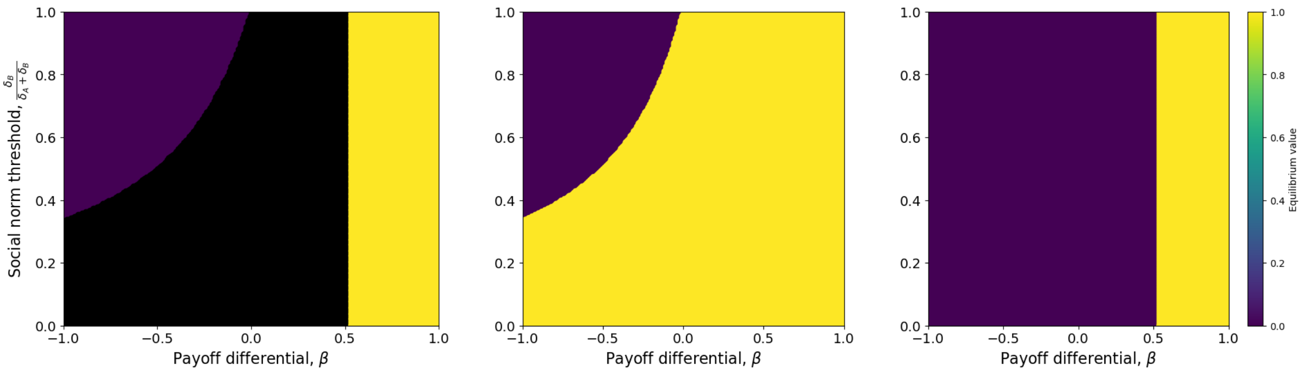
[43] Ralph H Turner. "Personality in society: Social psychology's contribution to sociology". In: *Social Psychology Quarterly* (1988), pp. 1–10.

[44] Junhui Wu et al. "Life history strategy and human cooperation in economic games". In: *Evolution and Human Behavior* 38.4 (2017), pp. 496–505.

[45] Elena Zwirner and Nichola Raihani. "Neighbourhood wealth, not urbanicity, predicts prosociality towards strangers". In: *Proceedings of the Royal Society B* 287.1936 (2020), p. 20201359.

Notations	Description	Default parameter value
Behaviours A vs. B	Active vs. Baseline behaviours	
N	Size of the population	
$N_t^{A,N}, N_t^{B,N}$	Number of individuals with behaviour A, B at time t	
X_t^N, E_t^N	Frequency of individuals with behaviour A and Environment state at time t	
x_t, e_t	Deterministic frequency individuals with behaviour A and environment state at time t	
κ	Encounter rate	1
τ	Individual sensitivity to the environment	
ℓ	Environmental reactivity	
γ_A (resp. γ_B)	Payoff of behaviour A (resp. B)	$\gamma_B = 1$
δ_A (resp. δ_B)	Social pressure of behaviour A (resp. B)	$\delta_B = 0.5$
l_A (resp. l_B)	Individual environmental impact of behaviour A (resp. B)	$l_B = 1$
$\beta = \gamma_A - \gamma_B$	Payoff differential	
$\frac{\delta_B}{\delta_A+\delta_B}$	Social norm threshold (SNT)	
$l_A - l_B$	Environmental impact differential	

Table 1: Summary of notations



(a) (b) (c)

Figure 1: **Frequency of active behaviour at equilibrium in the absence of environmental feedback (Eq.** (17)**), with respect to the payoff differential** (β) **and social norm threshold** ($\frac{\delta_B}{\delta_A+\delta_B}$)**.** (a) Bistability occurs in the black filled area (depending on the initial conditions, the equilibrium is either $x^* = 0$ or $x^* = 1$). (b) The upper equilibrium value ($x^* = 1$) is plotted across the bistability area. (c) The lower equilibrium value ($x^* = 0$) is plotted across the bistability area. Other parameters: $\kappa = 1,\ \tau = 0,\ \ell = 0.1,\ l_B = 1$ et $\delta_B = 0.5$.

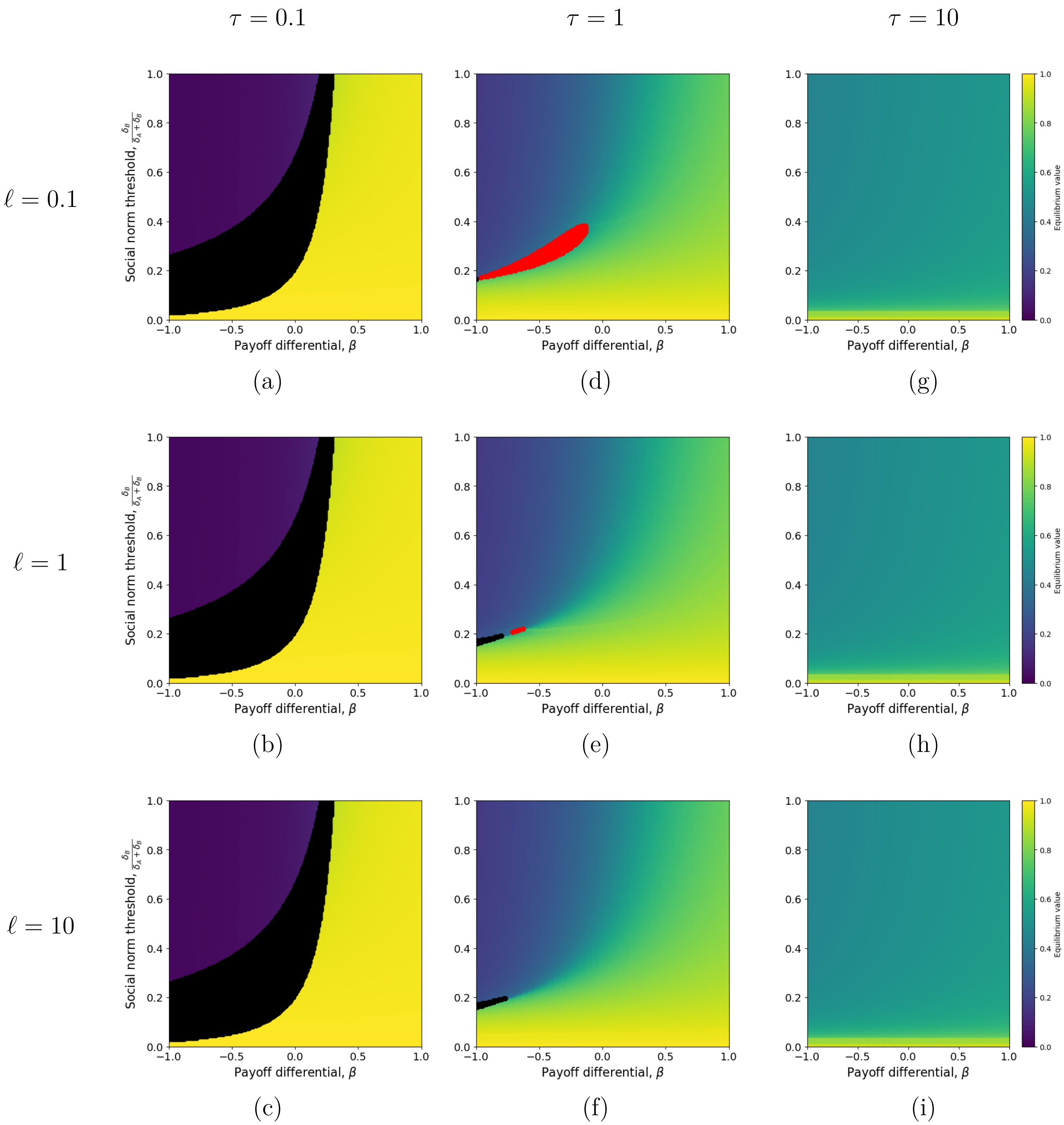
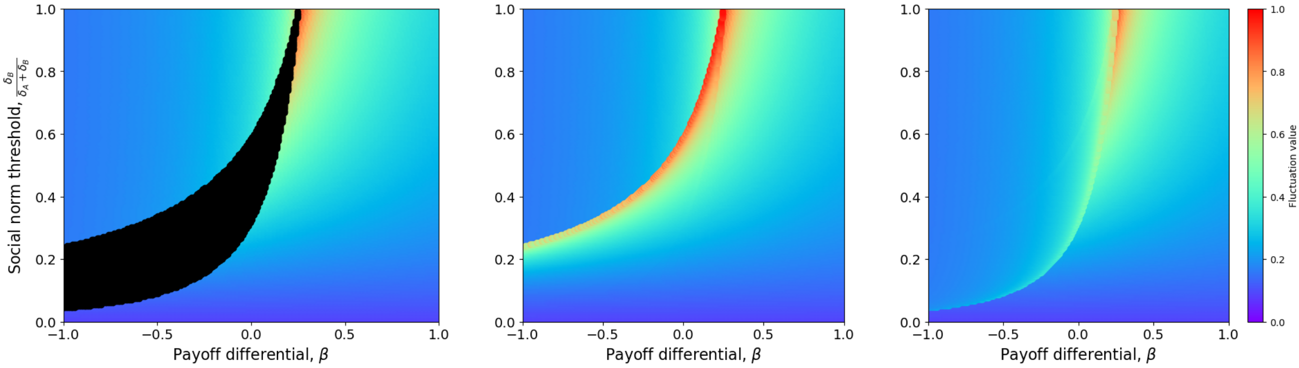


Figure 2: **Frequency of active behaviour at equilibrium in the presence of environmental feedback (Eq. 18), with respect to the payoff differential (β) and social norm threshold ($\frac{\delta_B}{\delta_A+\delta_B}$)**, for low to high individual sentivity to the environment (τ) and environmental reactivity (ℓ). Environmental reactivity takes on values $l = 0.1$, 1 and 10 with $\tau = 0.1$ in panels a-c, $\tau = 1$ in d-f, and $\tau = 10$ in g-i. Bistability occurs in the black filled areas. Stable limit cycles occur in the red filled areas.The environmental impact differential is fixed ($l_B = 1, l_A = 0.7$). Other parameters: $\kappa = 1$ et $\delta_B = 0.5$.



(a) (b) (c)

Figure 3: **Behavioural inconsistency due to stochasticity at stationnary state.** The variance of the asymptotic fluctuation around the equilibrium x^* is given by Eq. 15 . (a) Variance outside the parameter region of bistability. (b) Variance calculated in the bistability parameter region for fluctuations around the upper stable equilibrium x^* (close to one). (c) Variance calculated in the bistability parameter region for fluctuations around the lower stable equilibrium x^* (close to zero). Other parameters: $\kappa = 1,\ \tau = 1,\ \ell = 0.1$, $l_B = 1$ et $\delta_B = 0.5$.

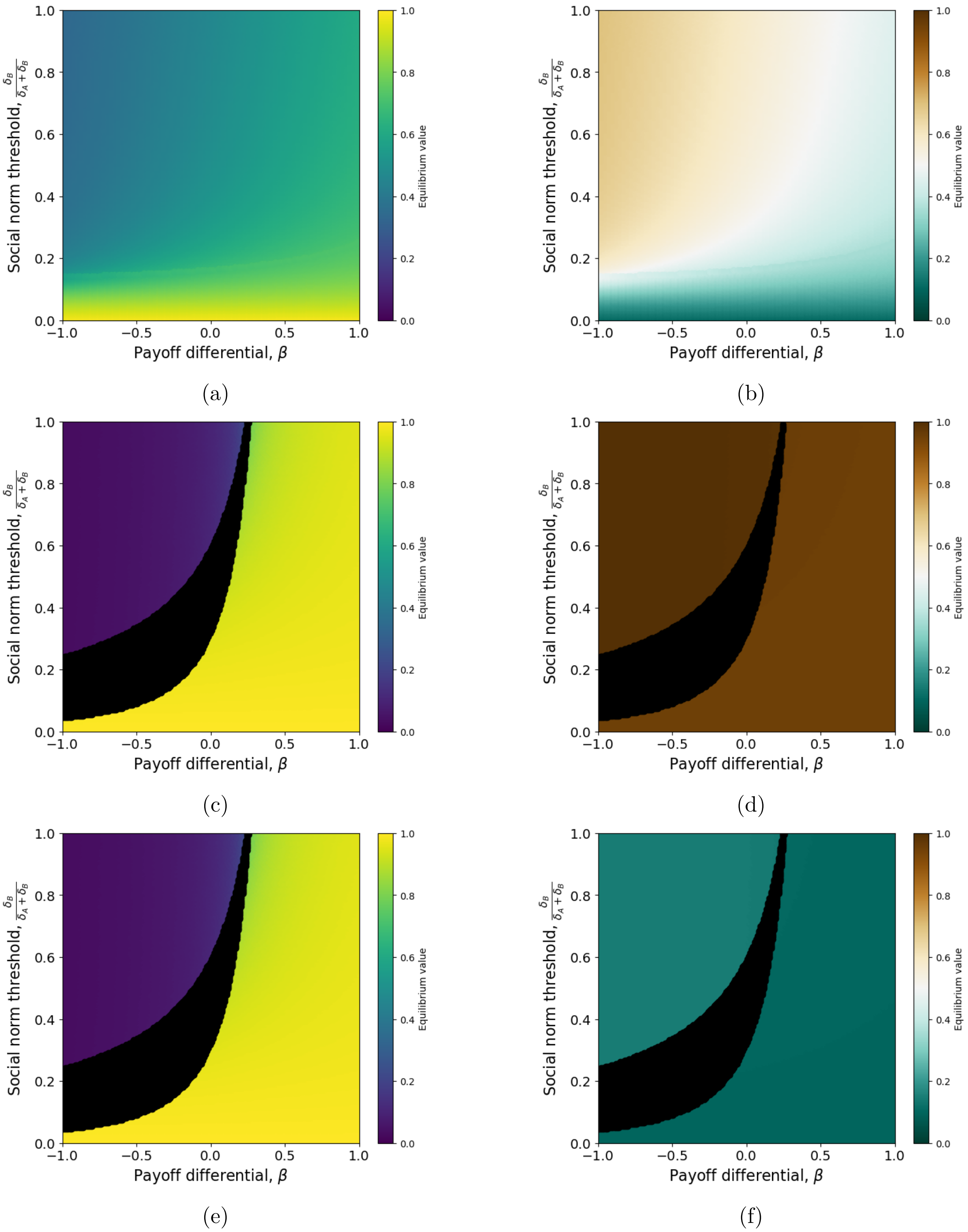


Figure 4: **Influence of the environmental impact differential, $l_B - l_A$, on the frequency of active behaviour (a, c, e) and perceived environmental state (b, d, f) at equilibrium.** For (a) and (b), the parameters are $l_B = 1$ and $l_A = 0.1$. For (c) and (d), $l_B = 1$ and $l_A = 0.95$. For (e) and (f), $l_B = 0.15$ and $l_A = 0.1$. Other parameters: $\kappa = 1,\ \tau = 1,\ \ell = 0.1$ et $\delta_B = 0.5$.