nature climate change

LETTERS

PUBLISHED ONLINE: 14 JULY 2013 | DOI: 10.1038/NCLIMATE1927

A bottom-up institutional approach to cooperative governance of risky commons

Vítor V. Vasconcelos[1,2,3], Francisco C. Santos[1,3] and Jorge M. Pacheco[1,4,5]*

Avoiding the effects of climate change may be framed as a public goods dilemma[1], in which the risk of future losses is non-negligible[2–7], while realizing that the public good may be far in the future[3,7–9]. The limited success of existing attempts to reach global cooperation has been also associated with a lack of sanctioning institutions and mechanisms to deal with those who do not contribute to the welfare of the planet or fail to abide by agreements[1,3,10–13]. Here we investigate the emergence and impact of different types of sanctioning to deter non-cooperative behaviour in climate agreements. We show that a bottom-up approach, in which parties create local institutions that punish free-riders, promotes the emergence of widespread cooperation, mostly when risk perception is low, as it is at present[3,7]. On the contrary, global institutions provide, at best, marginal improvements regarding overall cooperation. Our results clearly suggest that a polycentric approach involving multiple institutions is more effective than that associated with a single, global one, indicating that such a bottom-up, self-organization approach, set up at a local scale, provides a better ground on which to attempt a solution for such a complex and global dilemma.

To investigate the role of sanctioning institutions, let us consider a finite (and small[1,3]) population of size Z where individuals interact through what has been coined the collective-risk dilemma (CRD), a threshold public goods game—akin to an N-person stag-hunt or coordination game[14]—that mimics the problem at stake[2–4,6]. Individuals organize groups of size N, in which each participant may act as a cooperator (C), defector (D) or punisher (P). Each individual starts with an initial endowment or benefit b. Cs and Ps contribute a fraction c of this benefit, the cost, to reach a common goal, whereas Ds do not contribute. If the overall contribution in the group is insufficient—that is, if the joint number of Cs and Ps in the group is below n_{pg}—everyone in that group will lose their remaining endowments with a probability r (here understood as the perception of risk of collective disaster[2]); otherwise, everyone will keep whatever they have.

The scenario of present-day summits, in which all countries meet in a single group with the aim of establishing long-term goals and commitments by which all must abide[3], is known to be detrimental to cooperation[6]. Hence, it is better to establish smaller groups focused on overcoming shorter-term goals, meant to be revised and reassessed frequently. To this end, we model individual decision-making as an interacting dynamical process, where individuals are embedded in a behavioural ecosystem[15–17], such that decisions and achievements of others influence one's own decisions through time[18–21] (Methods and Supplementary Information for further details). Behavioural experiments[4,5,22], as well as other theoretical models[23,24], have implemented thresholds through repeated interactions, and other authors have highlighted the role played by pledges and communication during negotiations[1,5,25], bringing about additional layers of complexity to this problem (details and comparison with other models in the Supplementary Information).

Besides contributing to this public good, Ps also contribute with a punishment tax (π_t) to an institution that, whenever endowed with enough funding ($n_p\pi_t$) will effectively punish Ds by an amount Δ. Hence, establishing an institution stands as a second-order public good[17,20], which is only achieved above a certain threshold number of contributors n_p (ref. 14). The fact that, in both cases, contributors may pay a cost in vain increases the realism (and the inherent complexity) of the decision process modelled here.

The institution need not be a global one (such as the United Nations)—supported by all Ps in the population—that overviews all group interactions in the population. Institutions may also be local, group-wide, created by Ps within each group to enforce cooperation in that group of individuals. Here we shall consider both cases.

In the absence of Ps, this model reduces to the evolutionary game theoretical model[6] developed to investigate the general role of risk in climate change agreements, and inspired in economic experiments[4] that provided evidence on the unavoidable role of risk perception in the context of climate change. Indeed, the theoretical model not only corroborates the results of the economic experiments[4], but also allows one to extend the analysis to arbitrary group size, risk perception and even group-networked agreements[6]. The new, fundamental changes stemming from the introduction of Ps in this behavioural ecosystem will allow us to assess the role of sanctioning institutions in the presence of risk, a feature that has not been studied before, neither theoretically nor experimentally.

The stochastic evolutionary dynamics of the population occurs in the presence of errors, both in terms of errors of imitation[21] and in terms of behavioural mutations[26], the latter accounting for a free exploration of the possible strategies. We calculate the pervasiveness in time of each possible behavioural composition of the population, the so-called stationary distribution (Methods), which allows the computation of the average fraction of groups that successfully produce (or maintain) the public good—a quantity we designate as group achievement, η_G—and the prevalence in time of a given type of institution—that is, the fraction of time the population witnesses the presence of sanctioning institutions (local or global)—a quantity we designate as institutions prevalence, η_I. It is important to note that both quantities can be directly

[1]ATP-Group, CMAF, Instituto para a Investigação Interdisciplinar, P-1649-003 Lisboa, Portugal, [2]Centro de Física da Universidade do Minho, 4710-057 Braga, Portugal, [3]INESC-ID and Instituto Superior Técnico, Universidade Técnica de Lisboa, IST-Taguspark, 2744-016 Porto Salvo, Portugal, [4]Centro de Biologia Molecular e Ambiental, Universidade do Minho, 4710-057 Braga, Portugal, [5]Departamento de Matemática e Aplicações, Universidade do Minho, 4710-057 Braga, Portugal. *e-mail: pacheco@cii.fc.ul.pt

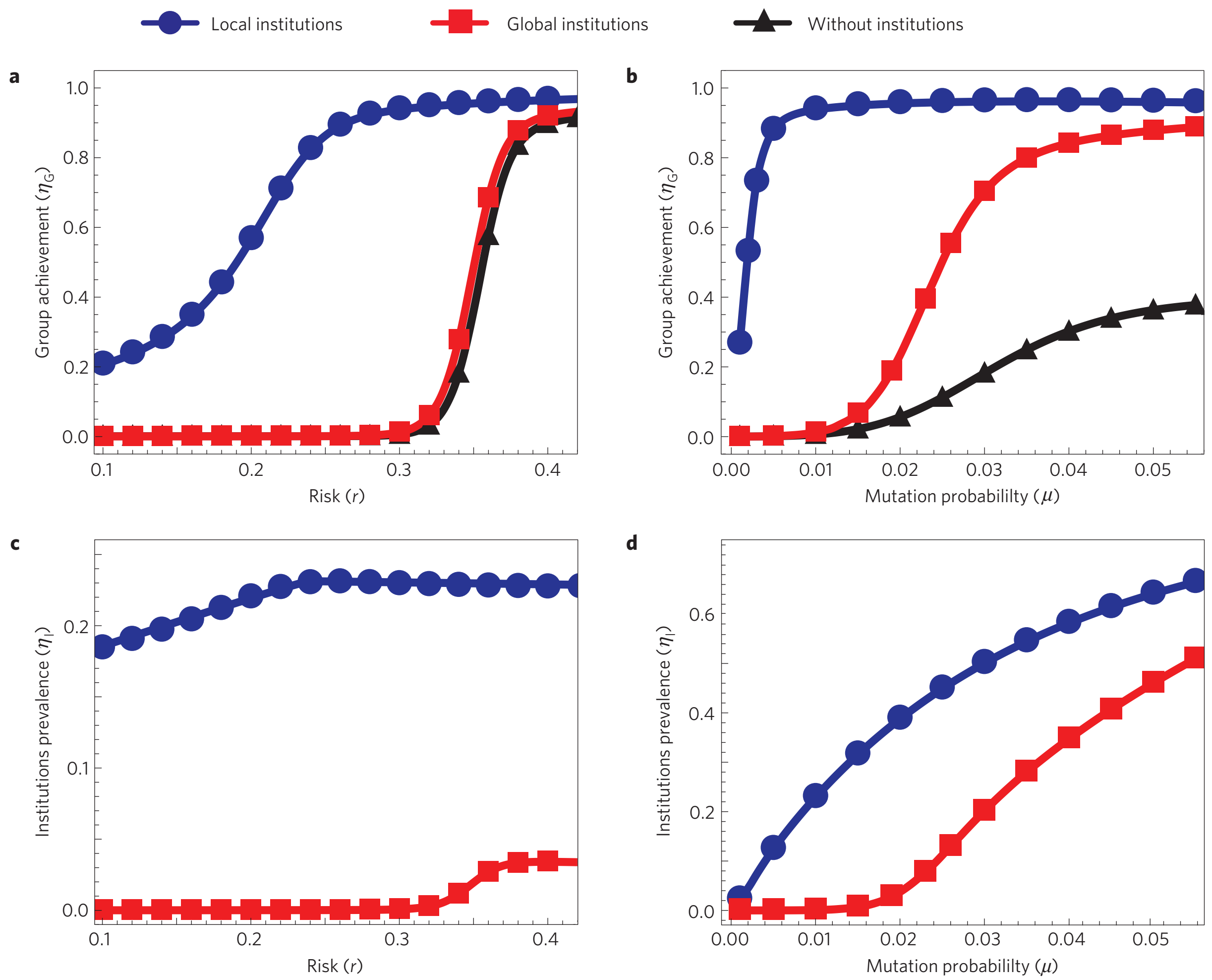

Figure 1 | Group achievement η_G and institutions prevalence η_I. a,**b**, The average fraction of groups that attain the public good (η_G) as a function of perception of risk (r; **a**) and behavioural exploration probability (μ; **b**). Sanctions are enacted by a global institution (red lines and squares) or by local institutions (blue lines and circles). Black lines and triangles: results obtained in the absence of any institution. **c**,**d**, Results for η_I as a function of risk r (**c**) and exploration μ (**d**). Unlike global institutions, often associated with marginal improvements of cooperation, local institutions promote group coordination to avoid a collective disaster, mostly for low perception of risk. The coordination threshold n_{pg} is set to 75% of the group size, whereas local (global) institutions are created whenever 25% of the group (population) contributes to its establishment. Other parameters: $Z = 100$, $N = 4$, $c/b = 0.1$, $\mu = 1/Z$, $\pi_f = 0.3$, $\pi_t = 0.03$ and $r = 0.3$.

compared with data extracted from experiments[2,4]. In particular, the empirical results obtained for the risk dependence[4] (in the absence of any sanctioning) show that the group achievement (η_G in our model) increases with the value of risk, correlating nicely with the dependence shown in Fig. 1a with black lines and symbols.

In Fig. 1a the behaviour of η_G as a function of risk is shown in the absence of any institutions (in black), under one global institution (in red) and under local institutions (in blue). Comparison of the black and red curves shows that global institutions provide, at best, a marginal improvement compared with no institutions at all. This result is surprising, given that most climate agreements attempt to involve all countries at once[1,3,27], in which case a single, global institution constitutes the most natural candidate (further details in the Supplementary Information).

On the contrary, under local, group-wide, sanctioning institutions, associated with a distributed scenario in which global sanctions will result from the joint role of a variety of institutions, group achievement is substantially enhanced, in particular when it is most needed: for low values of the perception of risk and whenever individuals face stringent requirements to avoid a collective disaster (Fig. 1a), as has been pointed out to be the case in the context of climate treaties[1]. One can also show (Supplementary Information) that this result is even more pronounced in a scenario encompassing (many) small groups (and institutions). This aspect is particularly important, as the group size (N) defines both the scale at which agreements should be attempted and the overall scope of each institution.

The success of local institutions is closely connected with their resilience. As shown in Fig. 1c, local institutions prevail for longer periods than a (single) global one, always promoting more widespread cooperation than global ones. The efficiency and prevalence of both kinds of institution, however, can be significantly enhanced for high behavioural mutations (Fig. 1b,d), associated with situations in which participants change their decisions more frequently. This scenario may be relevant, given the multitude of (often conflicting) factors that contribute to the process of decision-making[12,13,19].

The dynamics associated with each type of institution is best characterized by the full stationary distributions, plotted in Figs 2 and 3 and covering the entire configuration space mapped onto the triangular simplexes, in which each (discrete) configuration is represented by a circular dot. Darker dots indicate those configurations visited more often, according to the colour gradient scale indicated in each panel. In each dot the relative frequencies

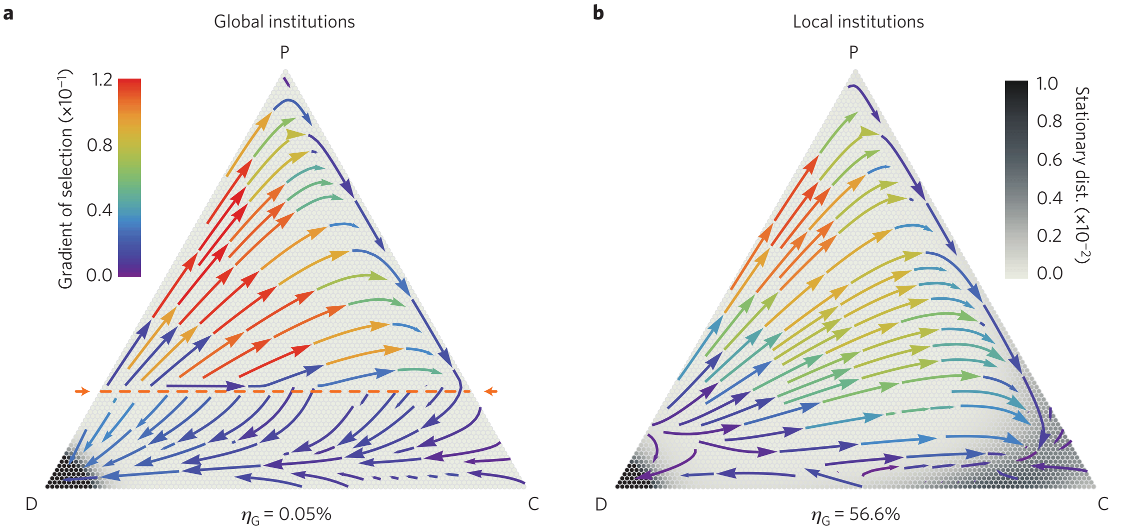

Figure 2 | Behaviour of the CRD in the full configuration space with three strategies—Cs, Ps and Ds—for the same parameters as in Fig. 1 and low risk ($r = 0.2$). a, Global institutions. **b**, Local institutions. The value of the stationary distribution at each configuration is shown using a grey scale; the magnitude of the gradient of selection is shown using the blue–yellow–red scale indicated. For global institutions, the population-wide threshold is indicated using a dashed orange line.

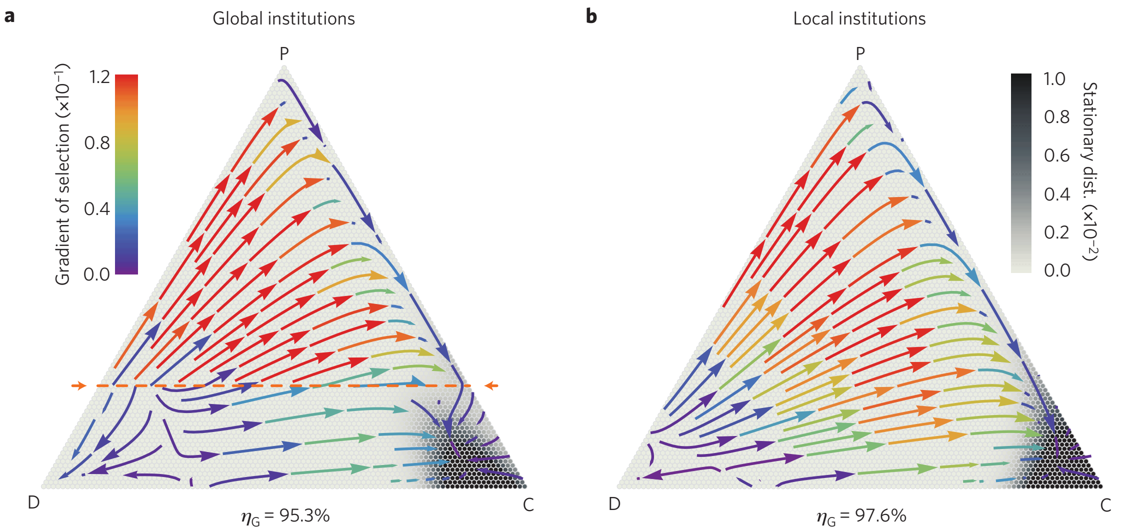

Figure 3 | Behaviour of the CRD in the full configuration space with three strategies: Cs, Ps and Ds. a, Global institutions. **b**, Local institutions. We use the same parameters as in Fig. 2, yet for high values of the perception of risk ($r = 0.5$, in this case), that is, a value of r above which most of the groups manage to coordinate their action, even in the absence of institutions (Fig. 1a).

of Cs, Ds and Ps sum up to one, whereas each vertex of the triangle is associated with monomorphic configurations. Arrows in each simplex represent the most probable direction of evolution, obtained from the computation of the two-dimensional gradient of selection (Methods). We used a continuous colour code associated with the likelihood of such transitions.

The two panels of Fig. 2 show representative examples of the behavioural dynamics of Cs, Ds and Ps under global institutions (Fig. 2a) and local institutions (Fig. 2b), for low values of the perception of risk ($r = 0.2$). For global institutions (Fig. 2a) and whenever the population starts below n_P (the punishment or institution threshold value indicated by a horizontal, orange dashed line), behavioural mutations allow the appearance of Ps in the population (Supplementary Information for further details), such that whenever the composition of the population lies above the threshold line, Ps rapidly outcompete Ds (see arrows), leading the population towards full cooperation, associated with the CP-edge of the simplex. Once in this situation, however, Ps will be outcompeted by Cs as now they contribute to support an institution that has become useless. Hence, the global institution becomes unstable, leading the population (slowly, as shown by the blue arrows along the whole path) to a configuration that falls below the threshold line again. Thus, for low perception of risk, a global institution cannot be maintained for long periods (Fig. 1c) and, as shown by the stationary distributions, the population will remain most of the time under widespread defection. This, in turn, leads to the small value of η_G reported in Fig. 2a.

For local institutions, however, the situation is quite different, as shown in Fig. 2b. Comparison between Fig. 2a and Fig. 2b shows that the role of the threshold line is not so pronounced in this case. Considering that we need the same fraction of Ps (compared to Fig. 2a) to make the institution efficient (25% in this example), but now at the level of the group (and no longer at the level of the population), it is possible that some (although not all) groups have enough Ps for sanctions to become effective. This leads to a marked increase of η_G, as in this case the population evolves towards regimes of widespread cooperation. This happens because the population will stabilize in configurations comprising a sizeable amount of Cs together with enough Ps to prevent Ds from invading. The fact that this happens for low values of risk r is important, given that, at present, the perception of risk regarding climate issues is low[3,7].

For high values of the perception of risk, shown in Fig. 3 ($r = 0.5$), both local and global institutions marginally enhance the positive prospects for cooperation already attained in the absence of any institution, as for high risk the dynamics occurs in the vicinity of the CD-edge of the simplex (Supplementary Information). Notwithstanding, and because local institutions are easier to emerge, they work as catalysers of collective action, while helping to prevent the invasion of Ds, as shown in Fig. 2. Neither local nor global institutions are robust to free-riding, a result that has been recently confirmed experimentally[28]. Finally, behavioural mutations enhance the prevalence of configurations in the inner part of the simplex, which in turn increases the chances of having enough Ps to establish institutions and cooperation, as previously shown in Fig. 1.

Our results support the conclusion that a decentralized, polycentric, bottom-up approach[10], involving multiple institutions instead of a single global one, provides better conditions both for cooperation to thrive and for ensuring the maintenance of such institutions. This result is particularly relevant whenever perception of risk of collective disaster, alone, is not enough to ensure global cooperation. In this case, local sanctioning institutions may provide an escape hatch to the tragedy of the commons humanity is facing. In this context, it is worth stressing that the mechanisms discussed here operate optimally whenever groups are small. Present-day local initiatives, such as the Western Climate Initiative[29], have started with a small group of US states. As time went by, the Western Climate Initiative group size has grown to include additional Canadian states and Mexican provinces. Although the reasons and motivations for such an evolution are comprehensible, one should not overlook that larger groups are more difficult to coordinate into widespread cooperation (Supplementary Information). Similar dynamics, in which cooperation nucleating in a small group expands into a larger and larger group, can be found in policies beyond climate governance with mixed results, from the major transitions in evolution[30] to the recent evolution of the European Union, stressing the common ground shared by governance and a variety of ecosystems[15]. In this context, it might be easier to seek a multi-scale (and multi-step) process, in which coordination is achieved in multiple small groups or climate blocks[12], before aiming, if needed, at agreements encompassing larger groups (or, alternatively, inter-group agreements). Hence, although most causes of climate change result from the combined action of all inhabitants of our planet, the solutions for such complex and global dilemma may be easier to achieve at a much smaller scale[10]. In light of our results, the widely repeated motto 'Think globally, act locally' would hardly seem more appropriate.

Methods

We consider a population of Z individuals, who set up groups of size N, in which they engage in the CRD public goods game[4,6], being capable of adopting one of the three strategies: C, P and D. Following the discussion in the main text, the payoff of an individual playing in a group in which there are j_C Cs, j_P Ps and $N - j_P - j_C$ Ds, can be written as $\Pi_C = -c + b\Theta(j_C + j_P - n_{pg}) + (1-r)b[1 - \Theta(j_C + j_P - n_{pg})]$, $\Pi_P = \Pi_C - \pi_t$ and $\Pi_D = \Pi_C + c - \Delta$ for Cs, Ps and Ds, respectively. In the equations above, $\Theta(k)$ is the Heaviside function (that is, $\Theta(k) = 1$ whenever $k \geq 0$, being zero otherwise), $0 < n_{pg} \leq N$ is a positive integer not greater than N, and r (the perception of risk) is a real parameter varying between 0 and 1; the parameters c, π_t and b are all real positive; Δ corresponds to the punishment function, which depends on whether the institution is global or local. For local institutions, punishment acts at the group level, and Δ yields $\Delta_{local} = \pi_f\Theta(j_P - n_P)$, which means that a punishment fine π_f is applied to each D in the group whenever $N \geq j_P \geq n_P \geq 0$. For global institutions, punishment acts at the population level; in a population with i_C Cs, i_P Ps and $Z - i_P - i_C$ Ds, the punishment function for global institutions can be written as $\Delta_{global} = \pi_f\Theta(i_P - n_P)$, applying a punishment fine π_f now to every D in the population, whenever $Z \geq i_P \geq n_P \geq 0$. Finally, the fitness f_X of an individual adopting a given strategy, X, will be associated with the average payoff of that strategy in the population. This can be computed for a given strategy in a configuration $i = \{i_C, i_P, i_D\}$ using a multivariate hypergeometric sampling (without replacement; Supplementary Information for details). The number of individuals adopting a given strategy will evolve in time according to a stochastic birth–death process combined with the pairwise comparison rule[21], which describes the social dynamics of Cs, Ps and Ds in a finite population. Under pairwise comparison, each individual of strategy X adopts the strategy Y of a randomly selected member of the population, with probability given by the Fermi function $(1 + e^{\beta(f_X - f_Y)})^{-1}$, where β controls the intensity of selection ($\beta = 5.0$ in all figures). In addition, we consider that, with a mutation probability μ, individuals adopt a randomly chosen strategy. As the evolution of the system depends only on its actual configuration, evolutionary dynamics can be described as a Markov process over a two-dimensional space. Its probability distribution function, $p_i(t)$, which provides information on the prevalence of each configuration at time t, obeys a master equation, a gain–loss equation involving the transition rates between all accessible configurations. The stationary distribution $\bar{p}_i$ is then obtained by reducing the master equation to an eigenvector search problem (Supplementary Information for details). Another central quantity, which portrays the overall evolutionary dynamics in the space of all possible configurations, is the gradient of selection Δ_i. For each configuration i, we compute the most likely path the population will follow, resorting to the probability to increase (decrease) by one the number of individuals adopting a strategy S_k, $T_i^{S_k+}$ ($T_i^{S_k-}$) in each time step. In addition, for each possible configuration i, we make use of multivariate hypergeometric sampling to compute both the (average) fraction of groups that reach n_{pg} contributors, that is, that successfully achieve the public good—which we designate by $a_G(i)$—and the (average) fraction of groups that reach n_p punishers (for local institutions) or whether for that configuration i a global institution will be formed—in both cases, we designate this quantity by $a_I(i)$. Average group achievement—η_G—and institution prevalence—η_I—are then computed averaging over all possible configurations i, each weighted with the corresponding stationary distribution: $\eta_G = \sum_i \bar{p}_i a_G(i)$ and $\eta_I = \sum_i \bar{p}_i a_I(i)$.

Received 9 January 2013; accepted 16 May 2013; published online 14 July 2013

References

1. Barrett, S. *Environment and Statecraft: The Strategy of Environmental Treaty-Making* (Oxford Univ. Press, 2005).
2. Milinski, M., Semmann, D., Krambeck, H. J. & Marotzke, J. Stabilizing the Earth's climate is not a losing game: Supporting evidence from public goods experiments. *Proc. Natl Acad. Sci. USA* **103,** 39 94–3998 (2006).
3. Barrett, S. *Why Cooperate? The Incentive to Supply Global Public Goods* (Oxford Univ. Press, 2007).
4. Milinski, M., Sommerfeld, R. D., Krambeck, H. J., Reed, F. A. & Marotzke, J. The collective-risk social dilemma and the prevention of simulated dangerous climate change. *Proc. Natl Acad. Sci. USA* **105,** 2291–2294 (2008).
5. Tavoni, A., Dannenberg, A., Kallis, G. & Löschel, A. Inequality, communication and the avoidance of disastrous climate change in a public goods game. *Proc. Natl Acad. Sci. USA* **108,** 11825–11829 (2011).
6. Santos, F. C. & Pacheco, J. M. Risk of collective failure provides an escape from the tragedy of the commons. *Proc. Natl Acad. Sci. USA* **108,** 10421–10425 (2011).
7. Heal, G. & Kristrom, B. Uncertainty and climate change. *Environ. Resour. Econom.* **22,** 3–39 (2002).
8. Levin, S. A. Learning to live in a global commons: Socioeconomic challenges for a sustainable environment. *Ecol. Res.* **21,** 328–333 (2006).
9. Levin, S. A. The trouble of discounting tomorrow. *Solutions* **4,** 20–24 (2012).
10. Ostrom, E. Policy Research Working Paper, *Background Paper to the 2010 World Development Report, WPS5095*, The World Bank (2009).
11. Walker, B. *et al.* Looming global-scale failures and missing institutions. *Science* **325,** 1345–1346 (2009).
12. Poteete, A. R., Janssen, M. A. & Ostrom, E. *Working Together: Collective Action, the Commons, and Multiple Methods in Practice* (Princeton Univ. Press, 2010).
13. Young, O. R., King, L. A. & Schroeder, H. (eds) in *Institutions and Environmental Change* (MIT Press, 2008).
14. Pacheco, J. M., Santos, F. C., Souza, M. O. & Skyrms, B. Evolutionary dynamics of collective action in n-person stag hunt dilemmas. *Proc. R. Soc. B* **276,** 315–321 (2009).
15. May, R. M., Levin, S. A. & Sugihara, G. Ecology for bankers. *Nature* **451,** 893–895 (2008).
16. Rendell, L. *et al.* Why copy others? Insights from the social learning strategies tournament. *Science* **328,** 208–213 (2010).

17. Sigmund, K., De Silva, H., Traulsen, A. & Hauert, C. Social learning promotes institutions for governing the commons. *Nature* **466,** 861–863 (2010).
18. Fowler, J. H. & Christakis, N. A. Cooperative behavior cascades in human social networks. *Proc. Natl Acad. Sci. USA* **107,** 5334–5338 (2010).
19. Carman, K. G. Discussion Paper 02–13 (Stanford Institute for Economic Policy Research, 2003).
20. Sigmund, K. *The Calculus of Selfishness* (Princeton Univ. Press, 2010).
21. Traulsen, A., Nowak, M. A. & Pacheco, J. M. Stochastic dynamics of invasion and fixation. *Phys. Rev. E* **74,** 011909 (2006).
22. Milinski, M., Röhl, T. & Marotzke, J. Cooperative interaction of rich and poor can be catalyzed by intermediate climate targets. *Climatic Change* 1–8 (2011).
23. Chakra, M. A. & Traulsen, A. Evolutionary dynamics of strategic behavior in a collective-risk dilemma. *PLoS Comput. Biol.* **8,** e1002652 (2012).
24. Van Segbroeck, S., Pacheco, J. M., Lenaerts, T. & Santos, F. C. Emergence of fairness in repeated group interactions. *Phys. Rev. Lett.* **108,** 158104 (2012).
25. Barrett, S. & Dannenberg, A. Climate negotiations under scientific uncertainty. *Proc. Natl Acad. Sci. USA* **109,** 17372–17376 (2012).
26. Traulsen, A., Hauert, C., De Silva, H., Nowak, M. A. & Sigmund, K. Exploration dynamics in evolutionary games. *Proc. Natl Acad. Sci. USA* **106,** 709–712 (2009).
27. Schroeder, H., Boykoff, M. T. & Spiers, L. Equity and state representations in climate negotiations. *Nature Clim. Change* **2,** 834–836 (2012).
28. Traulsen, A., Röhl, T. & Milinski, M. An economic experiment reveals that humans prefer pool punishment to maintain the commons. *Proc. R. Soc. B* **279,** 3716–3721 (2012).
29. Western Climate Initiative (http://www.westernclimateinitiative.org/).
30. Maynard-Smith, J. & Szathmáry, E. *The Major Transitions in Evolution* (Freeman, 1995).

Acknowledgements

The authors thank F. L. Pinheiro for useful discussions. This research was supported by FCT-Portugal through grants SFRH/BD/86465/2012, PTDC/FIS/101248/2008 and PTDC/MAT/122897/2010, by multi-annual funding of CMAF-UL and INESC-ID (under the project PEst-OE/EEI/LA0021/2013) provided by FCT-Portugal, and Fundação Calouste Gulbenkian through the Stimulus to Research programme for young researchers.

Author contributions

V.V.V., F.C.S. and J.M.P. have contributed equally to this work: they all designed and performed the research, analysed the data and wrote the paper.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to J.M.P.

Competing financial interests

The authors declare no competing financial interests.

nature climate change

SUPPLEMENTARY INFORMATION
DOI: 10.1038/NCLIMATE1927

A bottom-up institutional approach to cooperative governance of risky commons

Vítor V. Vasconcelos[1,2,3], Francisco C. Santos[3,1] and Jorge M. Pacheco[4,5,1]

[1] ATP-Group, CMAF, Instituto para a Investigação Interdisciplinar, P-1649-003 Lisboa, Portugal

[2] Centro de Física da Universidade do Minho, 4710 - 057 Braga, Portugal

[3] INESC-ID and Instituto Superior Técnico, Universidade Técnica de Lisboa, IST-Taguspark, 2744-016 Porto Salvo, Portugal

[4] Centro de Biologia Molecular e Ambiental, Universidade do Minho, 4710 - 057 Braga, Portugal

[5] Departamento de Matemática e Aplicações, Universidade do Minho, 4710 - 057 Braga, Portugal

 DOI: 10.1038/NCLIMATE1927

1. Collective risk dilemma and pool punishment

Following the discussion in the main text the payoff an individual within a group of j_C ***C***s, j_P ***P***s and $N - j_P - j_C$ ***D***s, can be written as

$$\Pi_C = -c + b\,\Theta(j_C + j_P - n_{pg}) + (1-r)b\left[1 - \Theta(j_C + j_P - n_{pg})\right] \quad (1)$$

$$\Pi_P = \Pi_C - \pi_t \quad (2)$$

$$\Pi_D = \Pi_C + c - \Delta \quad (3)$$

In the Equations above, $\Theta(k) = \{^{0\,(k<0)}_{1\,(k\geq 0)}$ is the Heaviside function, $0 < n_{pg} \leq N$ a positive integer, and r is a real number between 0 and 1; the parameters c, π_t, and b are all positive real numbers. In Eq. 3, Δ corresponds to the "punishment function", which depends on whether the *institution* is *global* or *local*. For *local institutions* punishment acts at the group level, and Δ yields

$$\Delta = \pi_f\,\Theta(j_P - n_p) \quad (4)$$

which means that a *punishment fine* π_f is applied to each ***D*** in the group whenever $j_P \geq n_p$.

For *global institutions* punishment acts at the population level; in a population with i_C ***C***s, i_P ***P***s and $Z - i_P - i_C$ ***D***s, the punishment function for *global institutions* can be written as

$$\Delta = \pi_f\,\Theta(i_P - n_p) \quad (5)$$

applying a *punishment fine* π_f now to every ***D*** in the population, whenever $i_P \geq n_p$.

If one models individual decision process as purely rational (as is usually done in conventional game theoretical analysis), one will ignore existing evidence that peer-influence plays a determinant role in strategy revision[1-3]. Hence, we assume here a simpler, short-term behavioural revision process conveniently modelled in the framework of evolutionary game theory. As a result, our framework allows agreements to become vulnerable to (or to benefit from) such short-term behavioural updates, as individuals assess the consequences of their choices. Thus, our approach contrasts with that implemented in behavioural experiments[4-7] and alternative theoretical models[8,9], where a repeated-game scenario is implemented, involving a wide repertoire of strategies and contingency plans[4-14]. As a result, theoretical models are no longer amenable to be dealt with analytically[8].

In fact, short-term commitments and strategy revision are presumably more realistic. The fact that different countries (and different political actors in each country) do not agree on long term policies[15], suggests that defining short term time scales may prove beneficial, giving decision makers more room to change their mind and (hopefully) reach a consensus. This is also the best framework in which to adopt an evolutionary game theoretical approach, as we do here. Such an approach has been employed before, although sanctioning institutions have not been analysed[16,17]. Needless to say, other mechanisms are certainly relevant, and may even prove crucial, given the time frame at stake[18], as discussed at length in Refs.[10,12,19-30]. In this context, our work provides the barest framework establishing conditions that naturally favour widespread cooperation in attempting to mitigate the adverse effects of global warming.

The variable n_{pg} imposes a minimum number of contributions needed to achieve a common goal[5,17] or an intermediate climate target[7]. In line with a previous model[17], individuals engage in several (preferably small scale) **CRD** games with the aim of coordinating to establish *short term* goals in each of them. The extent to which individuals cooperate in these games will ultimately dictate the solution (or not) of the (*long term*) problem of Climate Change.

DOI: 10.1038/NCLIMATE1927

To let the entire population form a single group engaging in the **CRD** is detrimental to cooperation[17], and hence it is much better to establish smaller (eventually local) groups focussing on coordinating to overcome more modest, common interest and shorter term targets. Short-term commitments are meant to be revised and re-assessed frequently in subsequent instances of the **CRD** game, whereby individual decisions may naturally change in time. Because individual decisions are known to all in the population, it is natural to assume that previous decisions will influence future decisions, which also means that communication between participants actually takes place in such a setting. Although such type of communication is different from, e.g., that studied explicitly in Ref.[11], there is some correspondence between these two forms of "pre-play" signalling[31,32]. Needless to say, a detailed theoretical model of the process of pre-play communication would require signalling to be explicitly incorporated (honest signalling would perhaps suffice, in face of the results of Ref. [11]), which would render the model analytically intractable[31]. In this sense, the present model, making information of individuals' successes and failures available to all between different games, can be understood as a first (and much simpler) step in that direction. For this reason, we model individual decision making as an interacting dynamical process, such that decisions and achievements of others may influence one's own decisions through time[3,33-38]. Such (stochastic) dynamical system is discussed in detail in the following section.

2. Evolutionary dynamics in finite populations

We consider a population of Z individuals. Each individual can adopt one of $s+1$ strategies: $S_1,\ldots,S_{s+1}$, such that, at each time-step t, we have a given configuration (or state) $\mathbf{i}(t)=\{i_1,\cdots,i_k,\cdots,i_s\}$ of a population, specified by the number of individuals adopting each particular strategy (we need only the first s strategies – and hence, an s-dimensional simplex – as the frequency of players using strategy s+1 can be obtained through normalization). The fitness of a strategy will be associated, as usual[39], with the average payoff of any individual using this strategy. Let $\mathbf{j} = \{j_1, \cdots, j_k, \cdots, j_s\}$ be the configuration of players in a group of size N and ($\mathbf{j}$; j_k=q) designating any group configuration in which there are specifically q players with strategy j_k; with these definitions, we may write down the average fitness of a strategy S_k in a population characterized by configuration $\mathbf{i}$, $f_{S_k}(\mathbf{i})$, as[9,17,40-43]

$$f_{S_k}(\mathbf{i}) = \binom{Z-1}{N-1}^{-1} \sum_{(\mathbf{j};\, j_k=0)}^{(\mathbf{j};\, j_k=N-1)} \Pi_{S_k}(\mathbf{j}) \binom{i_k - 1}{j_k} \prod_{\substack{l=0 \\ (l \neq k)}}^{s+1} \binom{i_l}{j_l} \qquad (6)$$

where $\Pi_{S_k}(\mathbf{j})$ stands for the payoff of a strategy S_k in a group with composition $\mathbf{j}$.

For each configuration $\mathbf{i}$, we may also compute other population-wide variables of interest making use of variants of Eq. 6. In particular, the average fraction of groups $a_G(\mathbf{i})$ that reach n_{pg} contributors (see Methods and previous section) is obtained replacing $\Pi_{S_k}(\mathbf{j})$ by $\Theta(j_C + j_P - n_{pg})$ in Eq. 6 for the case of 3 strategies (s=2, ***C***s, ***P***s and ***D***s) and by $\Theta(j_C - n_{pg})$ for the case 2 strategies (s=1, ***C***s and ***D***s). Similarly, the average fraction of groups $a_I(\mathbf{i})$ that reach n_p punishers (for local institutions) is also provided by Eq. 6 with $\Pi_{S_k}(\mathbf{j})$ replaced by $\Theta(j_P - n_p)$. For global institutions, $a_I(\mathbf{i})$ is simply given by $\Theta(i_P - n_p)$, as described in the previous section and main text.

Strategies evolve according to a mutation-selection process. At each time step, the strategy of one randomly selected individual X is updated. With probability μ, X undergoes a mutation, adopting a strategy drawn randomly from the space of available strategies. With probability $1-\mu$, another randomly selected individual Y acts as a

DOI: 10.1038/NCLIMATE1927

potential role model of *X*. The probability that *X* adopts the strategy of *Y* equals $\varphi = \left[1 + e^{\beta(f_X - f_Y)}\right]^{-1}$, whereas *X* maintains the strategy with probability $1-\varphi$. We use f_X and f_Y to denote the fitness of individual *X* and *Y*, respectively. This update rule is known as the pairwise comparison rule[35,44]. The parameter $\beta \geq 0$, measures the contribution of fitness to the update process, i.e., the selection pressure. In the limit of strong selection ($\beta \to \infty$), the probability φ is either zero or one, depending on how f_X compares with f_Y. In the limit of weak selection ($\beta \to 0$), φ is always equal to $1/2$, irrespective of the fitness of *X* and *Y*.

For the sake of mathematical convenience, analysis of evolutionary dynamics in finite populations and arbitrary number of strategies have been mostly dealt with either in the limit of rare mutations[9,38,40,45-47] — in which the population will never contain more than two different strategies simultaneously — and/or in the limit of weak selection ($\beta \to 0$)[34,35,44,48-54]. Here we do not restrict our analysis to any of these approximations. Instead, as the pairwise comparison relies solely on the present configuration of the population[35], the dynamics of $\mathrm{i}(t) = \{i_1,\ldots,i_s\}$ corresponds to a Markov process over a *s*–dimensional space[35,46,50,55-57], and hence its probability density function, $p_{\mathbf{i}}(t)$, i.e., the prevalence of each configuration at time *t*, evolves in time according to the Master-Equation[55],

$$p_{\mathbf{i}}(t+\tau) - p_{\mathbf{i}}(t) = \sum_{\mathbf{i}'} \{T_{\mathbf{i}\mathbf{i}'} p_{\mathbf{i}'}(t) - T_{\mathbf{i}'\mathbf{i}} p_{\mathbf{i}}(t)\} \qquad (7)$$

a gain-loss equation that allows one to compute the evolution of $p_{\mathbf{i}}(t)$ given the transition probabilities per unit time between configurations $\mathbf{i}$ and $\mathbf{i}'$, $T_{\mathbf{i}'\mathbf{i}}$ and $T_{\mathbf{i}\mathbf{i}'}$. The stationary distribution $\bar{p}_{\mathrm{i}}$ analysed in the main text, is obtained by making the left side zero, which transforms Eq. 7 into an eigenvector search problem[55], namely, the eigenvector associated with the eigenvalue 1 of the transition matrix $\Lambda = \left[T_{ij}\right]^T$.

Besides providing the prevalence in time of each configuration **i**, the stationary distribution $\bar{p}_{\mathrm{i}}$ also allows the direct computation of an average measure of group achievement (η_G) and institution prevalence (η_I) given by $\eta_G = \sum_{\mathrm{i}} \bar{p}_{\mathrm{i}} a_G(\mathrm{i})$ and $\eta_I = \sum_{\mathrm{i}} \bar{p}_{\mathrm{i}} a_I(\mathrm{i})$, respectively, where $a_I(\mathbf{i})$ and $a_G(\mathbf{i})$ were defined before.

We are then left with the task of computing the transition probabilities among all possible configurations that define Λ. The nature of the birth-death process we defined imposes that, if the configuration of strategies at a given time is

$$\mathbf{i} = \{i_1, \ldots, i_s, i_{s+1} = N - i_1 - \ldots - i_s\},$$

it can only move to a configuration

$$\mathbf{i}' = \{i_{1'}, \ldots, i_{s'}, i_{s+1}' = N - i_{1'} - \ldots - i_{s'}\} = \{i_1 + \delta_1, \ldots, i_{s+1} + \delta_{s+1}\},$$

where either all δ_k are zero, or only two of them are non-zero being, respectively, 1 and -1. When all $\delta_k = 0$, the configuration remains unchanged, $\mathbf{i}' = \mathbf{i}$, and the transition probability corresponding to this event can be calculated from the remaining transitions as $T_{\mathbf{ii}} = 1 - \sum_{\mathbf{i}' \neq \mathbf{i}} T_{\mathbf{i}'\mathbf{i}}$. The missing transition probabilities are associated with events in which an element with a given strategy, S_l, changes into another specific strategy, S_k, which, for the pairwise comparison rule with an arbitrary mutation rate μ, is given by

$$T_{S_l \to S_k} = (1-\mu)\left[\frac{i_l}{Z}\frac{i_k}{Z-1}\left(1 + e^{\beta\left(f_{S_l} - f_{S_k}\right)}\right)^{-1}\right] + \mu \frac{i_l}{sZ}. \qquad (8)$$

 DOI: 10.1038/NCLIMATE1927

Hence, for a given configuration $\mathbf{i} = \{i_1,...,i_s\}$, we can compute the probability to increase (decrease) by one the number of individuals adopting a strategy S_k, which we denote by $T_{\mathbf{i}}^{S_k+}$ and $T_{\mathbf{i}}^{S_k-}$, as

$$T_{\mathbf{i}}^{S_k\pm} = \sum_{i_1',...,i_{k-1}',i_{k+1}',...i_s'} T_{\mathbf{i}\{i_1',...,i_k\pm 1,...,i_s'\}} \ . \qquad (9)$$

These transitions constitute a central quantity to compute the gradient of selection ($\nabla_{\mathbf{i}}$) — i.e., the most likely path the population will follow when leaving configuration **i** — as pictured in the main text.

In a 2-strategy case, each configuration **i** — e.g., *i* ***C***s and *Z-i* ***D***s — would have two neighbours, and therefore two possible transitions, one with one ***C*** more ($i \rightarrow i+1$) and another with one ***C*** less ($i \rightarrow i-1$). Hence, we will have $\nabla_{\mathbf{i}} = T_{D\rightarrow C}(i) - T_{C\rightarrow D}(i)$, where $T_{D\rightarrow C}(i) = (1-\mu)\left[\frac{i}{Z}\frac{Z-i}{Z-1}\left(1+e^{\beta(f_D-f_C)}\right)^{-1}\right] + \mu\frac{Z-i}{Z}$ for the probability to increase from *i* to *i*+1 ***C***s and $T_{C\rightarrow D}(i) = (1-\mu)\left[\frac{i}{Z}\frac{Z-i}{Z-1}\left(1+e^{\beta(f_C-f_D)}\right)^{-1}\right] + \mu\frac{i}{Z}$ for the probability to decrease to *i*-1[58].

For the 3-strategy case – e.g., when configurations are given by $\mathbf{i} = \{i_C, i_P\}$, standing for the number of ***C***s, ***P***s (and Z–i_C–i_P ***D***s) — the evolutionary dynamics occurs in a 2-dimensional simplex (see Figures 2 and 3 in the main text). To every adjacent configuration **i'** in the simplex (the ones accessible in a single update), we associate a vector with magnitude $T_{\mathbf{i'i}}$ and with the direction of $\mathbf{i'}-\mathbf{i}$. Performing the sum of these vectors leads to a new local vector, $\nabla_{\mathbf{i}}$, which contains information about all possible transitions, and which can be written as

$$\nabla_{\mathbf{i}} = (T_{\mathbf{i}}^{C+} - T_{\mathbf{i}}^{C-})\mathbf{u_C} + (T_{\mathbf{i}}^{P+} - T_{\mathbf{i}}^{P-})\mathbf{u_P} \qquad (10)$$

where $\mathbf{u_C}$ ($\mathbf{u_p}$) are unit vectors defining a basis of the 2 dimensional simplex in which evolution proceeds (see Fig. S1). The entries of $\nabla_\mathbf{i}$ correspond to a balance of transitions along each direction and, therefore, we call $\nabla_\mathbf{i}$ the gradient of selection (or *drift*)*.

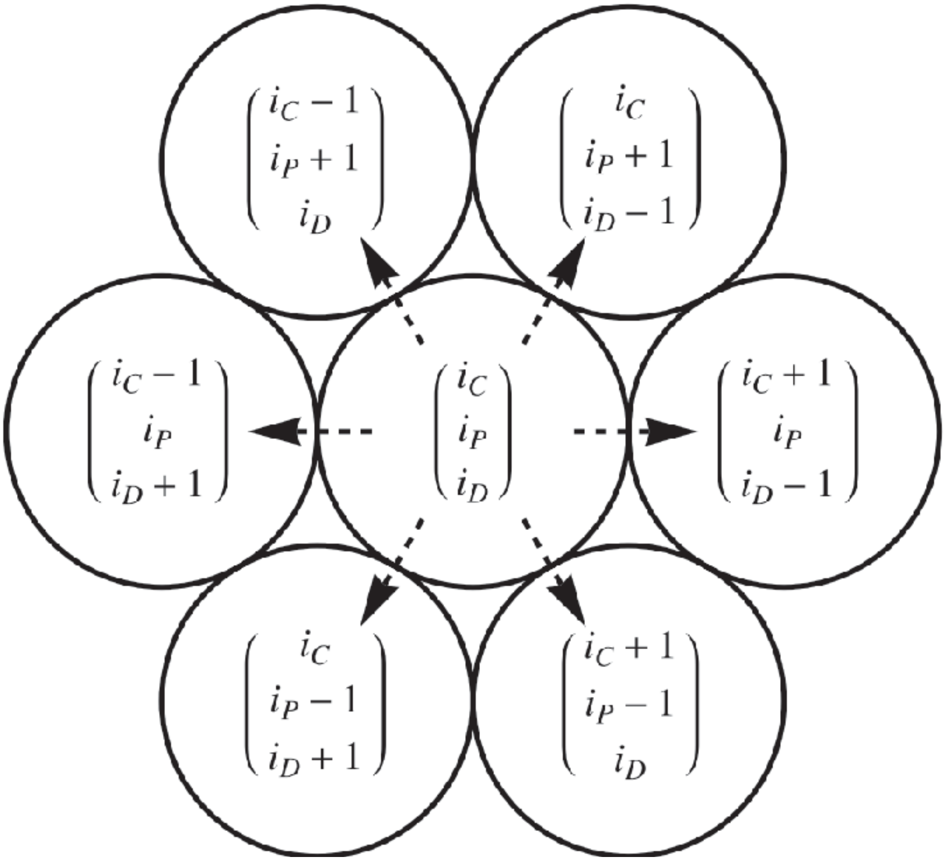

Figure S1 | Local representation of the phase space and possible transitions for a bi-dimensional one-step process. A vector can be associated with every transition between the element ***i*** and each adjacent element. The sum of these vectors corresponds to the gradient of selection, $\nabla_\mathbf{i}$, in the configuration ***i***, i.e., the *drift* (see above).

* It can be shown that $\nabla_\mathbf{i}$ corresponds to the first coefficient of the Kramers-Moyal expansion of the Master Equation for this birth-death process which, in the limit $N \rightarrow +\infty$, gives the drift term of the Fokker-Planck equation and the corresponding meaning of the most probable direction.

 DOI: 10.1038/NCLIMATE1927

3. Evolutionary dynamics in populations with two strategies

A natural first step to describe the role of sanctioning defectors is to understand in detail the evolutionary dynamics of populations in which only one of the cooperating strategies is present in the population — namely ***P***s and ***D***s, and ***C***s and ***D***s. In the absence of ***P***s, we recover the *N*-person **CRD** game recently proposed[17], where the risk of collective failure is explicitly introduced and where it is was shown how the perception of risk plays a central role in the emergence of cooperation. The different panels in Fig. S2 show the stationary probability distribution function together with the gradient of selection $\nabla_{\mathbf{i}}$ for populations in which only 2 strategies are present — ***C***s and ***D***s (left) and ***P***s and ***D***s (right). Whenever $\nabla_{\mathbf{i}} = 0$ is zero, at i_C^*, the transition probabilities to a configuration with more ***D***s and to a configuration with fewer ***D***s are the same. Furthermore, if the configuration to the right (decreasing the number of ***D***s) has a negative (positive) $\nabla_{\mathbf{i}}$ and the one to the left has a positive (negative) $\nabla_{\mathbf{i}}$, this system is preferentially pushed into (pulled out of) this configuration. Intuitively, the configurations with less ***C***s, to the left of i_C^*, tend to have their number of ***C***s increase (decrease), whereas the configurations to the right, with more ***C***s, tend to have less (more). In this sense, those configurations associated with i_C^* are analogous to the stable (unstable) fixed points obtained from the replicator equation[39], the stable analogues being probability attractors (repellers). Hence, the maximum of the stationary distribution is nearly coincident with the configuration i_C^*, whenever the gradient crosses zero with negative slope. Consequently, the population will spend most of the time around i_C^*.

Fig. S2 shows how risk (decreasing from top to bottom) plays a crucial role in the overall population dynamics, given the sensitivity of cooperation to risk. The left panels reproduce the scenarios obtained in the absence of ***P***s[17], which will be used here as references.

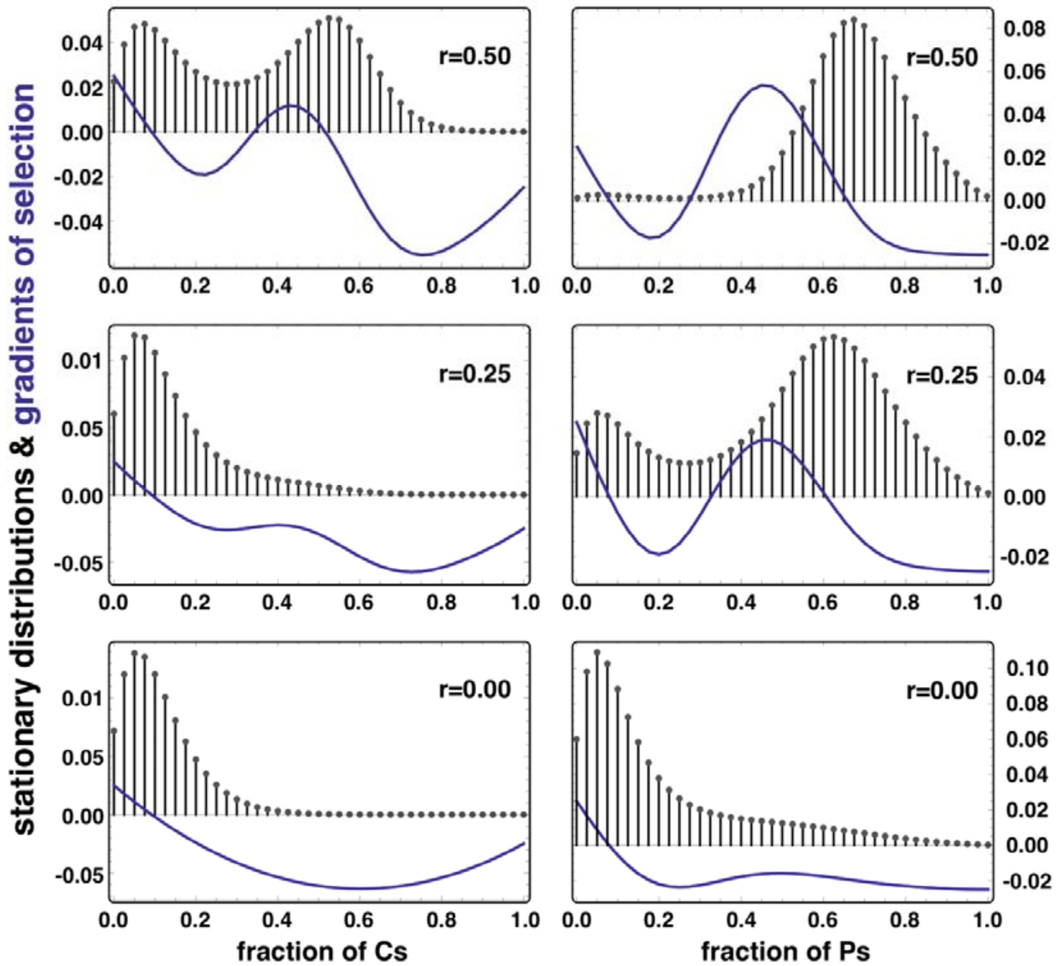

Figure S2 | The role of risk in populations made of ***C***s and ***D***s (left), and ***P***s and ***D***s (right) under local institutions. From top to bottom, each panel shows the stationary distributions (black vertical lines) and respective gradients of selection (blue solid curves) for r = 0.5, r = 0.25 and r = 0. (Z=40, N=10, n_{pg}=5, b=1, c=0.1, π_t=0.02, π_f=0.1, n_p=3, μ=1/Z and β = 5).

The right panels show the impact of punishment on the levels of cooperation — implemented here in the *local institution* version, see Eq. 4 — as ***P***s now co-evolve with ***D***s in the population. In the absence of risk (bottom), the gradient of selection is nearly half as negative compared to the reference scenario. This means that the strength with

DOI: 10.1038/NCLIMATE1927

which the population is driven into defection is smaller and, as a result, the stationary distribution grows a heavy tail towards punishment, meaning that the population actually spends a significant amount of time in configurations with less than 50% ***D***s. This is a rather impressive result, revealing the power of punishment[20] in hindering (in this case) defection. As we increase risk (center and top panels) populations adopt more and more the punishment behaviour.

An overall view of the results is provided in Fig. S3, where we plot the internal roots of the gradient of selection for different values of *r*. We compare again the two strategies against ***D***s: ***C***s and ***P***s with *local institutions*.

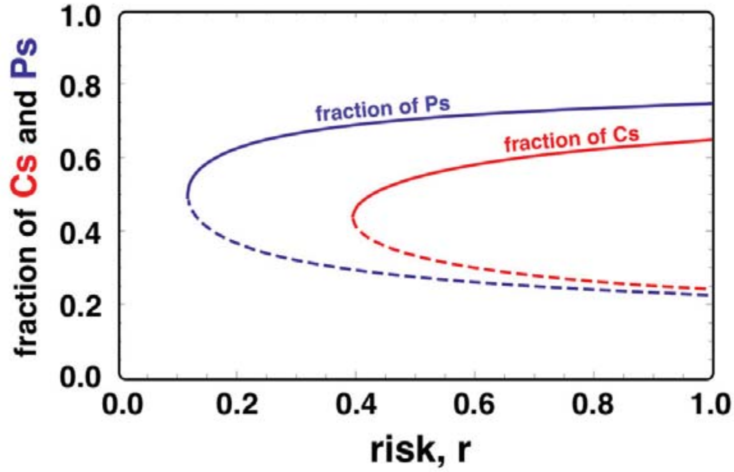

Figure S3 | Interior roots i_C^* of the gradient of selection for populations made of ***C***s and ***D***s (red lines), and ***P***s and ***D***s (blue lines) under local institutions. For each value of *r,* the solid (dashed) lines represent the finite analogues of stable (unstable) fixed points, that is, probability attractors (repellers). (Z=40, N=10, $n_{pg} = 5$, b=1, c=0.1, $\pi_t = 0.02$, $\pi_f = 0.1$, $n_p = 3$, $\mu = 1/Z$ and $\beta = 5$).

The **CRD** played between ***C***s and ***D***s, shows two kinds of behaviours. In the first scenario, for low values of the perception of risk, the system is driven into a configuration in which defection dominates. As one increases the perception of risk, one reaches a critical value above which the analogues of stable and unstable fixed points

DOI: 10.1038/NCLIMATE1927

emerge, allowing the system to spend longer periods of time in more cooperative configurations. Note that the stable point drives the population into configurations in which ***D***s are a minority.

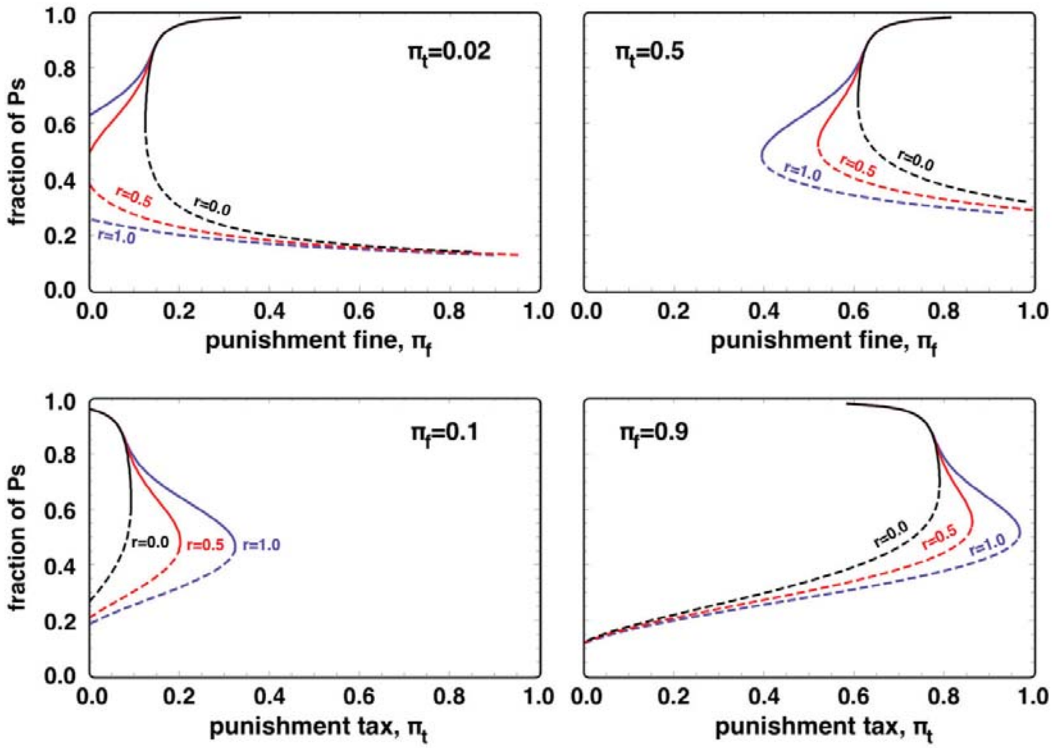

Figure S4 | Effect of punishment under local institutions and sensitivity to risk. The top panels show the internal roots of ∇_i as functions of the punishment fine π_f; the bottom panels show the same quantity now as a function of the punishment tax, π_t; left panels show results for low π_t (top) and low π_f,(bottom), respectively, whereas right panels show results for high values of these parameters. Different line colours represent increasing values of risk: r=0 with black lines, r=0.5 with red lines and r=1 with blue lines, respectively. (Z=40, N=10, c=0.1, b=1, n_{pg}=5, n_p=3, β=5.0 and μ=1/Z).

Whenever ***P***s co-evolve with ***D***s, we also obtain a change in the relative size of the basins of attraction, in particular for low values of risk, as the critical perception of risk r needed to create a cooperative basin of attraction decreases. Furthermore, with ***P***s, the stable equilibrium where few ***D***s co-exist with ***P***s occurs for lower fraction of ***D***s.

 DOI: 10.1038/NCLIMATE1927

Overall, this means that the population will spend a greater amount of the time in a more cooperative configuration. Additionally, and compared to ***C***s, ***P***s also push the unstable fix point to lower fractions of ***D***s, rendering collective coordination an easier task.

In Fig. S4 we adopt the same notation scheme of Fig. S3 to show the dependence of the position of the internal roots of $\nabla_{\mathbf{i}}$ on the punishment fine π_f and punishment tax π_t. This analysis is repeated for different values of risk (low risk, r=0.0, black lines; intermediate risk, r=0.5, red lines; high risk, r=1.0, blue lines).

In the top panels we see how π_f affects the positions of the fixed points, for both low (left panel) and high (right panel) *punishment fine* π_t. As expected, if the taxes for the maintenance of institutions are low, a considerable amount of punishers pervades; however, as we increase the tax, punishment eventually fades. When the *punishment fine* applied to the ***D***s is smaller, punishment vanishes for smaller values of the tax (left panel).

In the bottom panels we show how the *punishment tax* π_t affects the positions of the internal roots of $\nabla_{\mathbf{i}}$, for both low (left panel) and high (right panel) *punishment fine* π_f. If the tax for the punishment institution is low enough, a small *punishment fine* leads to the appearance of a coexistence root further away from the full defection configuration. However, if the *punishment fine* is high, once again we regain the two different scenarios: for very low (or none) *punishment tax*, the population falls into the tragedy of the commons, whereas above a critical value the coexistence point will arise. Both left and right panels show that a small increase on the *punishment tax* can drastically wipe-out defection. As a final point, all panels contain the location of the internal roots for the three values of risk indicated before, showing the importance of risk in the emergence collective action.

DOI: 10.1038/NCLIMATE1927

4. Group size dependence in the 3-strategy case

As discussed in the main text, one does not expect that all the parties (e.g. countries, regions or cities[59]) will be willing to pay in order to punish others, despite being perhaps willing to undertake the necessary measures to mitigate climate change effects (***C***s). In other words, an analysis of a 2-strategy case fails to provide a complete overview of the overall dynamics, as players who are willing to pay towards mitigating the climate change effects may free-ride in a 2^{nd} order cooperation dilemma, by refusing to pay a tax in order to create an institution (local or global), able to punish defectors. Consequently, in the main text we discussed the evolutionary dynamics of the population considering the entire set of strategies (***C***s, ***P***s and ***D***s), from which we showed that the adoption of multiple institutions instead of a single, global one provides better conditions for cooperation to thrive.

In this context, the group size N constitutes an important variable, as it defines not only the scale at which agreements should be tried but also the overall dimension and scope of each institution. In particular, a local sanctioning system converges to a single global institution whenever $N \rightarrow Z$. Hence, one should expect that the evolutionary advantage provided by a polycentric approach vanishes for increasing N. Fig. S5 shows, however, that the results in the main text are robust, as local institutions provide a significant advantage in the promotion of cooperation for a wide range of values of N, when compared with a global institution. Furthermore, for a given group size, local institutions are always able to promote higher group achievements for lower values of risk.

 DOI: 10.1038/NCLIMATE1927

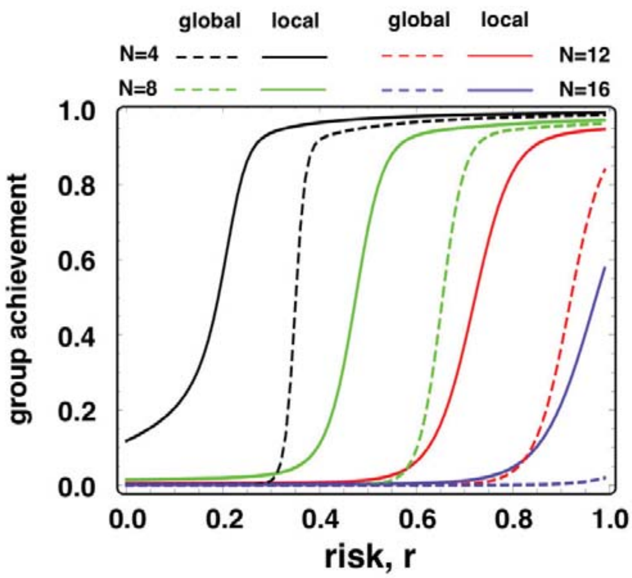

Figure S5 | Group achievement for different group sizes and institution types. Group achievement — η_G —standing for the average fraction of groups that are able to attain the public good, is shown as a function of the perception of *risk* (*r*) for global institutions (dashed lines) and local institutions (full lines). Each colour corresponds to a different group size, as indicated. The coordination threshold (n_{pg}) is set to 75% of the group size, whereas local (global) institutions are created whenever 25% of the group (population) contributes to its establishment. Punishment tax is π_t=0.03, whereas the punishment fine for defecting is π_f=0.3. Other parameters: *Z*=100, *N*=4, *c/b*=0.1, μ=1/*Z*=0.01.

References

1. Carman, K.G., Social influences and the private provision of public goods: Evidence from charitable contributions in the workplace. *Manuscript, Stanford University* (2003).
2. Rees, M. *et al.*, A nonsimultaneous, extended, altruistic-donor chain. *New England Journal of Medicine* 360 (11), 1096 (2009).
3. Fowler, J.H. & Christakis, N.A., Cooperative behavior cascades in human social networks. *Proc Natl Acad Sci U S A* 107 (12), 5334-5338 (2010).
4. Milinski, M., Semmann, D., Krambeck, H.J., & Marotzke, J., Stabilizing the Earth's climate is not a losing game: Supporting evidence from public goods experiments. *Proc Natl Acad Sci U S A* 103 (11), 3994-3998 (2006).
5. Milinski, M., Sommerfeld, R.D., Krambeck, H.J., Reed, F.A., & Marotzke, J., The collective-risk social dilemma and the prevention of simulated dangerous climate change. *Proc Natl Acad Sci U S A* 105 (7), 2291–2294 (2008).
6. Traulsen, A., Röhl, T., & Milinski, M., An economic experiment reveals that humans prefer pool punishment to maintain the commons. *Proceedings of the Royal Society B: Biological Sciences* 279 (1743), 3716-3721 (2012).

7. Milinski, M., Röhl, T., & Marotzke, J., Cooperative interaction of rich and poor can be catalyzed by intermediate climate targets. *Climatic change*, 1-8 (2011).
8. Chakra, M.A. & Traulsen, A., Evolutionary Dynamics of Strategic Behavior in a Collective-Risk Dilemma. *PLoS Computational Biology* 8 (8), e1002652 (2012).
9. Van Segbroeck, S., Pacheco, J.M., Lenaerts, T., & Santos, F.C., Emergence of fairness in repeated group interactions. *Phys Rev Lett* 108, 158104 (2012).
10. Milinski, M., Semmann, D., & Krambeck, H.J., Reputation helps solve the 'tragedy of the commons'. *Nature* 415 (6870), 424-426 (2002).
11. Tavoni, A., Dannenberg, A., Kallis, G., & Löschel, A., Inequality, communication and the avoidance of disastrous climate change in a public goods game. *Proc Natl Acad Sci U S A* 108, 11825-11829 (2011).
12. Tavoni, A., Schlüter, M., & Levin, S., The survival of the conformist: social pressure and renewable resource management. *Journal of theoretical biology* 299, 152-161 (2012).
13. Nikiforakis, N., Punishment and counter-punishment in public good games: Can we really govern ourselves? *Journal of Public Economics* 92 (1), 91-112 (2008).
14. Hilbe, C. & Traulsen, A., Emergence of responsible sanctions without second order free riders, antisocial punishment or spite. *Scientific reports* 2 (2012).
15. Portuguese Comission for Climate Change (personal communication).
16. McGinty, M., International Environmental Agreements as Evolutionary Games. *Environmental and Resource Economics* 45 (2), 251-269 (2010).
17. Santos, F.C. & Pacheco, J.M., Risk of collective failure provides an escape from the tragedy of the commons. *Proc Natl Acad Sci U S A* 108 (26), 10421-10425 (2011).
18. Walker, B. *et al.*, Looming global-scale failures and missing institutions. *Science* 325 (5946), 1345-1346 (2009).
19. Ostrom, E., *Governing the Commons: The Evolution of Institutions for Collective Action* (Cambridge University Press, 1990).
20. Boyd, R. & Richerson, P., Punishment allows the evolution of cooperation (or anything else) in sizable groups. *Ethology and Sociobiology* 13 (3), 171-195 (1992).
21. Poteete, A.R., Janssen, M.A., & Ostrom, E., *Working together: collective action, the commons, and multiple methods in practice*. (Princeton Univ Pr, 2010).
22. Barrett, S., *Environment and statecraft: the strategy of environmental treaty-making*. (Oxford University Press, USA, 2005).
23. Barrett, S., *Why cooperate?: the incentive to supply global public goods*. (Oxford University Press, USA, 2007).
24. Osés-Eraso, N. & Viladrich-Grau, M., On the sustainability of common property resources. *Journal of Environmental Economics and Management* 53 (3), 393-410 (2007).
25. Sethi, R. & Somanathan, E., The evolution of social norms in common property resource use. *The American Economic Review*, 766-788 (1996).
26. Nowak, M.A., Five rules for the evolution of cooperation. *Science* 314 (5805), 1560-1563 (2006).
27. Nowak, M.A. & Sigmund, K., Evolution of indirect reciprocity. *Nature* 437 (7063), 1291-1298 (2005).
28. Pacheco, J.M., Santos, F.C., & Chalub, F.A.C., Stern-judging: A simple, successful norm which promotes cooperation under indirect reciprocity. *PLoS Computational Biology* 2 (12), e178 (2006).
29. Barrett, S., Avoiding disastrous climate change is possible but not inevitable. *Proc Natl Acad Sci U S A* 108 (29), 11733 (2011).
30. Barrett, S. & Dannenberg, A., Climate negotiations under scientific uncertainty. *Proc Natl Acad Sci U S A* 109 (43), 17372-17376 (2012).
31. Skyrms, B., *Signals: Evolution, learning, and information*. (OUP Oxford, 2010).
32. Santos, F.C., Pacheco, J.M., & Skyrms, B., Co-evolution of pre-play signaling and cooperation. *Journal of theoretical biology* 274 (1), 30-35 (2011).

DOI: 10.1038/NCLIMATE1927

33. Carman, K.G., Social infuences and the private provision of public goods: Evidence from charitable contributions in the workplace. *Discussion paper 02–13 (Stanford Institute for Economic Policy Research, Stanford, CA).* (2003).
34. Sigmund, K., *The Calculus of Selfishness*. (Princeton University Press, 2010).
35. Traulsen, A., Nowak, M.A., & Pacheco, J.M., Stochastic dynamics of invasion and fixation. *Phys Rev E* 74 (1), 011909 (2006).
36. Rendell, L. *et al.*, Why Copy Others? Insights from the Social Learning Strategies Tournament. *Science* 328, 208-213 (2010).
37. Tomasello, M. & Call, J., *Primate Cognition*. (Oxford University Press, New York, 1997).
38. Sigmund, K., De Silva, H., Traulsen, A., & Hauert, C., Social learning promotes institutions for governing the commons. *Nature* 466 (7308), 861-863 (2010).
39. Hofbauer, J. & Sigmund, K., *Evolutionary Games and Population Dynamics*. (Cambridge Univ. Press, Cambridge, UK, 1998).
40. Hauert, C., Traulsen, A., Brandt, H., Nowak, M.A., & Sigmund, K., Via Freedom to Coercion: The Emergence of Costly Punishment. *Science* 316, 1905-1907 (2007).
41. Hauert, C., Michor, F., Nowak, M.A., & Doebeli, M., Synergy and discounting of cooperation in social dilemmas. *J Theo Bio*, 195-202 (2006).
42. Pacheco, J.M., Santos, F.C., Souza, M.O., & Skyrms, B., Evolutionary dynamics of collective action in n-person stag hunt dilemmas. *Proc R Soc B* 276 (1655), 315 (2009).
43. Gokhale, C.S. & Traulsen, A., Evolutionary games in the multiverse. *Proc Natl Acad Sci U S A* 107 (12), 5500 (2010).
44. Traulsen, A., Nowak, M.A., & Pacheco, J.M., Stochastic payoff evaluation increases the temperature of selection. *Journal of theoretical biology* 244 (2), 349-356 (2007).
45. Fudenberg, D. & Imhof, L., Imitation Processes with Small Mutations. *J Econ Theory* 131, 251-262 (2005).
46. Imhof, L.A., Fudenberg, D., & Nowak, M.A., Evolutionary cycles of cooperation and defection. *Proc Natl Acad Sci U S A* 102 (31), 10797-10800 (2005).
47. Van Segbroeck, S., Santos, F., Lenaerts, T., & Pacheco, J., Reacting differently to adverse ties promotes cooperation in social networks. *Phys Rev Lett* 102 (5), 58105 (2009).
48. Wild, G. & Traulsen, A., The different limits of weak selection and the evolutionary dynamics of finite populations. *Journal of theoretical biology* 247 (2), 382-390 (2007).
49. Traulsen, A., Pacheco, J.M., & Nowak, M.A., Pairwise comparison and selection temperature in evolutionary game dynamics. *Journal of theoretical biology* 246 (3), 522-529 (2007).
50. Traulsen, A., Pacheco, J.M., & Imhof, L.A., Stochasticity and evolutionary stability. *Phys Rev E* 74 (2), 021905 (2006).
51. Wu, B., Altrock, P.M., Wang, L., & Traulsen, A., Universality of weak selection. *Physical Review E* 82 (4), 046106 (2010).
52. Nowak, M.A., *Evolutionary Dynamics: Exploring the equations of life*, 1st ed. (Belknap Press of Harvard University Press, Cambridge, Massachussets, 2006a).
53. Tarnita, C.E., Wage, N., & Nowak, M.A., Multiple strategies in structured populations. *Proc Natl Acad Sci U S A* 108 (6), 2334-2337 (2011).
54. Antal, T., Traulsen, A., Ohtsuki, H., Tarnita, C.E., & Nowak, M.A., Mutation-selection equilibrium in games with multiple strategies. *Journal of theoretical biology* 258 (4), 614-622 (2009).
55. Kampen, N.V., *Stochastic processes in physics and chemistry*. (North-Holland, 2007).
56. Traulsen, A., Claussen, J.C., & Hauert, C., Coevolutionary dynamics: from finite to infinite populations. *Phys Rev Lett* 95 (23), 238701 (2005).
57. Vasconcelos, V. *et al.*, Principal axes for stochastic dynamics. *Phys Rev E* 84 (3), 031103 (2011).

58. Traulsen, A., Hauert, C., De Silva, H., Nowak, M.A., & Sigmund, K., Exploration dynamics in evolutionary games. *Proc Natl Acad Sci U S A* 106 (3), 709-712 (2009).
59. Hoornweg, D., *Cities and Climate Change: An urgent agenda*. (The World Bank, 2010).