PLOS Computational Biology

Charting pathways to climate change mitigation in a coupled socio-climate model
--Manuscript Draft--

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August 21, 2018

Editors, *PLOS Computational Biology*

Dear Editors,

Please consider our manuscript entitled 'Charting pathways to climate change mitigation in a coupled socio-climate model' for publication in *PLOS Computational Biology.*

The influence of human social processes on global climate trends—as well as the feedback of climate change on human populations—are widely appreciated in the climate change research community. However, the opportunities for adding social dynamics to our increasingly sophisticated climate models remain relatively unexplored. As a result, we think there will be significant scholarly interest in research that couples mechanistic models of human social systems to climate models. Here, we develop a coupled socio-climate model that models social processes endogenously, by building on established socio-dynamic models and our previous experience in modelling coupled human-environment systems in other contexts. The paper shows how the timescale of socio-dynamic processes like social learning are crucial determinants of the peak temperature anomaly; how social norms can hurt as well as help climate change mitigation; and how socio-climate models can be used by decision-makers to chart social and economic policy pathways that mitigate climate change more quickly than alternatives.

We hope you are able to consider our manuscript for publication in *PLOS Computational Biology* and we look forward to hearing from you.

Sincerely,

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Charting pathways to climate change mitigation in a coupled socio-climate model

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Abstract

Geophysical models of climate change are becoming increasingly sophisticated, yet less effort is devoted to modelling the human systems causing climate change and how the two systems are coupled. Here we develop a simple socio-climate model by coupling an Earth system model to a social dynamics model. We treat social processes endogenously – emerging from rules governing how individuals learn socially and how social norms develop – as well as being influenced by climate change and mitigation costs. Our goal is to gain qualitative insights into scenarios of potential socio-climate dynamics and to illustrate how such models can generate new research questions. We find that the social learning rate is strongly influential, to the point that variation of its value within empirically plausible ranges changes the peak global temperature anomaly by more than 1°C. Conversely, social norms reinforce majority behaviour and therefore may not provide help when we most need it because they suppress the early spread of mitigative behaviour. Finally, exploring the model's parameter space for mitigation cost and social learning suggests optimal intervention pathways for climate change mitigation. We conclude that socio-climate models should be included in the ensemble of models used to project climate change.

Author summary

The importance of anthropogenic CO_2 emissions on climate change trajectories is widely acknowledged. However, geophysical climate models rarely account for dynamic human behaviour, which determines the emissions trajectory, and is itself affected by the climate system. Here, using a coupled socio-climate model, we show how social processes can strongly alter climate trajectories and we suggest optimal intervention pathways based on the model projections. Policymakers will benefit from a better understanding of how social and climate processes interact, which can be provided by socio-climate models.

Introduction

According to many ancient myths, humans did not invent fire-making de novo but rather learned it from personalities like Prometheus and subsequently spread the practice amongst themselves. These stories reveal how ancient myth-makers already grasped the

fundamental importance of social learning - the process whereby individuals learn new behaviours, values and opinions from others [1]. Social learning is no less relevant in the era of human-environment challenges [2–4]. The importance of social learning and social processes more generally in climate change mitigation and adaptation is well recognized [5–8]. Increasingly sophisticated geophysical climate models are helping us understand the impacts of anthropogenic greenhouse gas (GHG) emissions [9–11], and the importance of these models is hard to understate. However, climate projections depend strongly on the assumed trajectory of GHG emissions [12]. This trajectory is determined by human behaviour and yet climate models generally do not incorporate dynamic social processes relevant to GHG emissions. Rather, GHG emissions are assumed to follow some specified trajectory. These trajectories are constructed with socio-economic factors in mind, (see Representative Concentration Pathways [12] and Shared Socioeconomic Pathways [13] for instance), but are not coupled to climate dynamics and do not capture human responses to climate change in a mechanistic way.

Just as human behaviour influences climate trends, climate change in turn influences human behaviour concerning GHG emissions, including both climate change mitigation and adaptation [5,6,8,14,15]. Individuals in places with rising average temperatures are more likely to perceive climate change [15], and social effects are apparent when individuals take steps in response to such shifting perceptions [6,8]. There is also an important distinction between social learning and social norms–socially accepted and widely practiced modes of conduct [16]. Social norms are known to have a strong influence on human behaviour [17] including aspects relating to climate change [7,16,18] and therefore play an important role in determining emission trajectories [6]. Multiple studies show a tendency for individuals to conform to emerging norms in support of climate change mitigation [7,16]. Moreover, it appears that individuals are often not consciously aware of the importance of social norms in their decision-making and instead falsely ascribe their decisions to other factors [18]. However, it is important to note that social norms do not automatically promote socially beneficial outcomes. They can equally well force conformity to a destructive norm such as political extremism [19]. This also happens in the context of climate change behaviour, where it has been found that individuals may also conform to a norm of non-mitigation, by adjusting their habits to match those of less environmentally friendly neighbours [18,20].

Hence, Earth's climate and human subsystems are part of a single coupled system where social dynamics play a vital role. Yet, models of Earth's coupled climate-behaviour system remain essentially undeveloped. One such approach [21] couples a sophisticated climate model [11] to a model for individual behavioural change based on the theory of planned behaviour - a dominant paradigm in psychology [22]. The authors find that the sensitivity of global temperature change to human factors such as response to extreme events, social norms and perceived ability to adopt mitigative strategies is of a similar magnitude to its sensitivity to geophysical factors. They deduce that quantifying behavioural uncertainty and physical uncertainty in climate projections deserve equal attention. The model focuses on how individual psychology and behaviour are influenced by extreme weather events. Social effects are modelled phenomenologically (i.e., exogenously imposed): individuals do not learn behaviour or opinions from one another, and social norms are treated as a fixed effect that does not depend on the population's current composition of attitudes.

Here, we treat social learning and social norms endogenously, by modelling their dynamics as they emerge from rules governing how individuals interact, learn and behave. Our first objective is to develop qualitative insights into how different aspects of the system - endogenous social processes, temperature trends, and mitigation costs - separately and together determine possible dynamics of the larger socio-climate system. Our second objective is to illustrate potential uses of coupled socio-climate models to

chart social and economic policy pathways that mitigate climate change as quickly as possible.

Materials and methods

Model

Geophysical models in the climate science literature span a wide range of different complexities depending on the associated research objective. Highly complex models are the state-of-the-art for weather and climate prediction [11, 23, 24], whereas simple models allow us to assess processes and feedbacks, thereby improving our intuition of climate system dynamics [25–29]. Likewise, the behavioural sciences have benefited from a variety of modelling approaches, that address the diverse set of social processes that take place on the individual and societal level [30]. Here, we use minimal models for both social and climate dynamics. Starting simple allows us to build intuition on the effect of socio-climate feedbacks that have yet been considered in the climate change literature. The social model is widespread and, despite its simplicity, captures the salient aspects of social dynamics [2, 30, 31]. Moreover, the simple Earth system model that we use [25] accurately follows the projections of the state-of-the-art CMIP5 models when forced with the IPCC emission scenarios (S1 Text, Fig S1).

Behaviour dynamics

Individuals in our model are either 'mitigators' or 'non-mitigators' and they learn these behaviours from others at a specified social learning rate. They switch to the more attractive behaviour according to a utility function governed by the costs of climate change mitigation (such as the cost of installing solar panels or buying gas-electric hybrid vehicles), the costs associated with the average global temperature anomaly, and the utility associated with social norms that reinforce the majority behaviour, whether it be mitigation or non-mitigation. Social norms strengthen as the majority behaviour becomes more prevalent, consistent with empirical studies [7, 18]. Formally, the utility of being a mitigator is taken as

$$e_M = -\beta + \delta x \qquad (1)$$

where β is the 'cost' of adopting mitigative strategies, δ is the strength of social norms and x is the proportion of mitigators in the population. The utility of being a non-mitigator is taken as

$$e_N = -f(T_f) + \delta(1 - x) \qquad (2)$$

where $f(T)$ is the cost associated with a temperature anomaly of T degrees Celsius, and T_f is a projected temperature anomaly (see below). Social learning is implemented as follows. Each individual samples other members of the population at a fixed rate κ. If 'individual A' samples 'individual B' and B's strategy has a higher payoff that of A, then A will switch to B's strategy with a probability proportional to the difference in payoffs. Thus if there are x mitigators in the population, the rate at which a non-mitigator encounters a mitigator is κx. Should there be a utility gain in switching ($e_M > e_N$), the non-mitigator will switch their strategy with a probability proportional to the payoff difference, $e_M - e_N$. Since there are a total of $1 - x$ non-mitigators in the population, the total rate at which non-mitigators switch to begin mitigators is

$$r_{N \to M} = \kappa x(1 - x) \max\{e_M - e_N, 0\}. \qquad (3)$$

Using similar arguments, one can show

$$r_{M \to N} = \kappa x(1 - x) \max\{e_N - e_M, 0\} \qquad (4)$$

and so the net rate of change in mitigators is

$$\frac{dx}{dt} = r_{N \to M} - r_{M \to N} = \kappa x(1-x)(e_M - e_N), \tag{5}$$

which has an equivalent form to the replicator equations of evolutionary game theory [32]. The behaviour model then reads

$$\frac{dx}{dt} = \kappa x(1-x)(-\beta + f(T_f) + \delta(2x-1)). \tag{6}$$

Temperature projection

Because long-term climate forecasts are known to influence individual decisions on whether to support mitigation [14], the utility function assumes that individuals base decisions on long-term extrapolations of recently experienced climate trends. The projected temperature takes the form

$$T_f(t) = T(t) + \left(\frac{t_f}{t_p}\right)(T(t) - T(t - t_p)) \tag{7}$$

where t_p is the number of years back to extrapolate from and t_f is the number of years forward to extrapolate to.

Perceived costs associated with climate change

We assume a sigmoidal relationship between costs and temperature anomaly. This is motivated by the slow mitigative response to global warming over the past decade (S1 Text, Figs S6-S8) and the anticipated non-linear alterations in the Earth system with increasing temperature [33]. Specifically

$$f(T) = \frac{f_{\max}}{1 + e^{-\omega(T - T_c)}}, \tag{8}$$

where $f_{\max}$ corresponds to a maximum cost, ω is the degree of nonlinearity of the sigmoid, and T_c is the critical temperature about which costs are most sensitive to change (S1 Text, Fig S3).

Earth system model

We couple the social model to an Earth system model [25] with reduced ocean dynamics [34]. Dynamics for atmospheric CO_2 is modified to include an anthropogenic emission term, dependent on the proportion of non-mitigators. Specifically

$$\frac{dC_{\mathrm{at}}}{dt} = \epsilon(t)(1-x) - P + R_{\mathrm{veg}} + R_{\mathrm{so}} - F_{\mathrm{oc}} \tag{9}$$

where C_{at} is the deviation in atmospheric CO_2 from pre-industrial values, $\epsilon(t)$ is the baseline rate of CO_2 emissions in the absence of mitigation, P is the rate of carbon uptake via photosynthesis, R_{veg} is the outward carbon flux via plant respiration, R_{so} is the outward carbon flux via soil respiration and F_{oc} is the net uptake of carbon by the oceans. Functional forms for the transfer of carbon via these processes are provided in Supplementary Information. Global surface temperature is assumed to evolve with the carbon cycle according to [25]

$$c\frac{dT}{dt} = (F_d - \sigma T^4)a_E \tag{10}$$

where T is the deviation in global surface temperature from pre-industrial values, c is the thermal capacity specific heat capacity of the Earth's surface, F_d is the net downward flux of radiation absorbed at the planet's surface (which depends on the opacity of CO_2), σ is the Stefan-Boltzmann constant, and a_E is the Earth's surface area. Full details are provided in S1 Text.

Simulation

Over the period from 1800 to 2014, the socio-climate model is simulated with a fixed social component, forced with historical anthropogenic carbon emissions. Initial conditions for all climate variables are zero since they represent deviations from pre-industrial values. Social dynamics are initiated in 2014 with an initial proportion of mitigators $x_0 = 0.05$. The ensuing dynamics of $\epsilon(t)$ follow an increasing but saturating trend corresponding to the world's increasing but saturating population size and energy demands. Specifically

$$\epsilon(t) = \begin{cases} \text{linear interpolation of historical emissions} & t \leq 2014 \\ \epsilon_{2014} + \frac{(t-2014)\epsilon_{\max}}{t-2014+s} & t \geq 2014 \end{cases} \qquad (11)$$

where $\epsilon_{\max}$ is the saturating value, and s the half-saturation constant, of $\epsilon(t)$. This expression is shown graphically in S1 Text, Fig S5. The system of (delay) ordinary differential equations is simulated using the NDSolve package in Wolfram Mathematica. Historical CO_2 emissions were obtained from the CDIAC data repository [35].

Parameters and sensitivity analysis.

Baseline climate parameters are obtained from the original Earth system model [25] where they were fitted to obtain historical trends of temperature and carbon dynamics. Social parameters are more speculative and so are given wide upper and lower bounds. For sensitivity analyses we draw parameters from triangular distributions that peak at baseline values and extend to upper and lower bounds (S1 Text, Table 2). Parameters are kept fixed preceding 2014 to retain historical trends in the simulations.

Results

The model demonstrates how the social learning rate can strongly determine temperature trends. We first consider a null hypothesis where adaptive behaviour is removed from the model by forcing the proportion of mitigators in the population to remain constant. In this case of fixed behaviour, emissions saturate and the temperature anomaly increases indefinitely (S1 Text, Fig S2). However, once social learning is added and the proportion of mitigators is allowed to evolve dynamically as in our baseline model, the predicted average global temperature anomaly can peak anywhere from 2.2°C, near the Intergovernmental Panel on Climate Change (IPCC) limit [36] (in the case of very rapid social learning) to 3.5°C (in the more realistic case where social learning unfolds on a generational timescale) (Fig 1a-c). Whether people discuss climate change more or less often can therefore strongly influence temperature trends. Because we model social norms as something that tends to reinforce majority behaviour and attitudes - whatever they might be - one might think that social norms act as a double-edged sword. In fact, they operate more like an unhelpful scimitar, as illustrated by comparing cases of low and high strength of social norms. Because the population starts off from a state of largely non-mitigating behaviour, increasing the strength of social norms suppresses the spread of mitigating behaviour for decades by

entrenching non-mitigation as a norm, even when rising temperatures strongly justify an ₁₆₉
immediate shift (Fig 1d-f). (This model dynamic echoes not only current climate norms ₁₇₀
reinforcing non-mitigation [20] but also past social shifts occurring on decadal ₁₇₁
timescales, such as evolving social norms about when and where smoking is acceptable.) ₁₇₂
However, when mitigating behaviour eventually does become widespread, a higher ₁₇₃
strength of social norms does not significantly accelerate its spread. Rather, the two ₁₇₄
curves for cases of high and low social norm strength simply move in parallel to one ₁₇₅
another because by this time, the utility function that determines behaviour change is ₁₇₆
dominated by the large temperature anomaly (Fig 1d). In this parameter regime, social ₁₇₇
norms generate a perverse asymmetry, in contrast to findings from other socio-climate ₁₇₈
models that assume social norms can only support climate change mitigation [20]. ₁₇₉

Fig 1. Endogenous social dynamics influence climate trajectories. Shown are
ensembles of model simulations comparing two parameter values for the social learning
rate (κ) (a-c), strength of social norms (δ) (d-f), and costs associated with mitigation
(β) (g-i). All other parameters are drawn from triangular probability distributions with
defined upper, lower and baseline values (S1 Text, Table 2). Displayed are median
trajectories with 95% confidence intervals from an ensemble of 100 realisations.
Additional details in Methods.

The model also shows how a reduction in mitigation cost can significantly accelerate ₁₈₀
the onset of social change. For instance, a 67% reduction in the mitigation cost ₁₈₁
increases the percentage of mitigators by 2075 from 10% to 90% (Fig 1g-i). Therefore, ₁₈₂
policies that reduce the cost of mitigation (through e.g. subsidies, tax cuts) will benefit ₁₈₃
from the accelerating effects of social learning and must be timed correctly. ₁₈₄
Our baseline model assumes that individuals' perceived cost of climate change ₁₈₅
impacts depends on a linear extrapolation of the recent temperature anomaly over the ₁₈₆
previous ten years (Methods). If individuals instead base their decisions only on the ₁₈₇
current temperature anomaly, the simulated global temperature anomaly lies well above ₁₈₈
the 2°C target set by the IPCC, and exhibits wide variation in sensitivity analysis (Fig ₁₈₉
2). This contrasts with our baseline model where the population movement towards ₁₉₀
mitigative strategies ignites earlier, significantly reducing the global temperature ₁₉₁
anomaly. This predicted dynamic stems from the multi-decadal lag between GHG ₁₉₂
emissions and the consequent global temperature rise [37]. ₁₉₃

**Fig 2. Peak temperature anomaly strongly depends on individual time
horizon.** SBox-and-whisker plots show the peak temperature anomaly measured over
100 realisations for fixed time horizons and all other parameters drawn from triangular
probability distributions with defined upper, lower and baseline values (S1 Text, Table
2). Boxes span the interquartile range, whiskers span the entire set of realisations and
box dividers mark the median. Additional details in Methods.

Our model predicts medium-term GHG emission trajectories (Figure 1b,e,h) that are ₁₉₄
qualitatively similar to those often assumed under various future emissions scenarios. ₁₉₅
This raises the question of how such models can be useful. The socio-climate model ₁₉₆
enables us to explore how socio-climate dynamics might respond to changes that are ₁₉₇
under the control of policymakers. For instance, it is possible to compare social and ₁₉₈
economic policy interventions by considering the effects of simultaneous parameter ₁₉₉
changes, instead of one at a time. This enables us to chart out the quickest pathways ₂₀₀
from highest to lowest temperature anomalies. The relative merits of increasing the ₂₀₁
social learning rate vs. reducing the cost of mitigation are illustrated with a contour ₂₀₂
plot where the contours represent peak temperature anomaly as a function of the two ₂₀₃
parameters (Fig 3). Increasing the social learning rate (e.g. through media coverage and ₂₀₄

public fora devoted to climate change) is particularly effective when social learning is slow, but has saturating benefits, as indicated by the increasing vertical spacing of contour lines for at higher learning rates. In contrast, reducing the mitigation cost (e.g. through tax breaks) drives a more linear response in peak temperature anomaly. Crucially, it should be noted that both a reduction of mitigation cost and an increase in the social learning rate are required to achieve the IPCC target. The arrows in Fig 3 show the 'path of steepest descent' – the most efficient combination of the two measures. Starting from a situation of high projected temperature anomalies, the contour plot predicts that increasing the social learning rate should first be prioritized, followed by a reduction in mitigation costs once the benefits of social learning begin to saturate. This approach gets us to the region of parameter space corresponding to the IPCC target faster than alternative trajectories.

Fig 3. Optimal pathways to mitigation via increasing social learning and reducing mitigation costs. Contour plot showing peak temperature anomaly at specified values of cost of mitigation (β) and rate of social learning (κ). Arrows indicate the direction of steepest descent – the most efficient combination of the two measures to reduce temperature anomalies. All other parameters are fixed at baseline values (S1 Text, Table 2). Additional details in Methods.

A sensitivity analysis reveals the relative influence of each parameter on the peak temperature anomaly (Fig 4). The time horizon of individuals' temperature projection, social learning rate and costs of mitigation are major factors, all of which may be influenced by appropriate intervention. The importance of social parameter uncertainties in determining climate predictions indicated by our model has also been predicted by other socio-climate models [21]. Sensitivity analyses such as these can help investigators determine priorities for data collection: the parameters exhibiting the greatest influence on predictions should be targeted for data collection so we can best reduce model uncertainty.

Fig 4. Peak temperature anomaly is sensitive to both social and climate parameters. Tornado plot showing the deviation in peak temperature anomaly when parameters are varied individually. A red (blue) bar indicates the deviation when the specified parameter adopts its upper (lower) bound, while all other parameters are fixed at baseline values (S1 Text, Table 2). Parameters ordered by relative impact from top to bottom. Additional details in Methods.

Discussion

This study has shown how social processes can influence climate dynamics, according to one possible way of modelling social dynamics and norms. However, other frameworks for modelling human behaviour could yield different predictions. For instance, the socio-climate model of Ref. [21] does not include social learning. Individuals respond directly to changes in the climate, and not through interactions with one another. As a consequence, the rate at which individuals adopt mitigative strategies only varies with the current climate situation, and not with current population consensus. Mitigation efforts can therefore be expected to closely follow the severity of climate change in the model. In our model, social learning manifests as a feedback within the social system, resulting in qualitatively different socio-climate trajectories. Mitigative behaviour is initially suppressed–even as temperatures rise to levels that should incentivise mitigation–due to low numbers of mitigating individuals and therefore little turnover of

behaviour in the population. However, social learning creates a positive feedback loop ₂₃₉ once there is a net positive utility to mitigate, and so as the numbers of mitigators ₂₄₀ increases, so too does the rate at which non-mitigators switch to being mitigators. This ₂₄₁ results in a sharp non-linear increase in mitigators, as a combined outcome of both the ₂₄₂ social and the climate system dynamics. We note that, all else being equal, adding ₂₄₃ social learning to a model has the effect of slowing down behaviour change in the ₂₄₄ human population (since a process takes time, by definition), and therefore the ₂₄₅ mitigation response of human populations. ₂₄₆

Conversely, the case of very rapid social learning recovers a 'best response' model ₂₄₇ similar to those assumed in classical economics, where individuals immediately adopt ₂₄₈ the highest payoff strategy without learning the behaviour from others. Whether or not ₂₄₉ this assumption can approximate behaviour in real human populations hinges upon how ₂₅₀ fast social learning occurs - individuals would need to sample others rapidly enough to ₂₅₁ enable complete population behaviour change within 5 years for this approximation to ₂₅₂ work in our model, which seems implausible (Fig 1a-c). ₂₅₃

In a different vein, we assumed a homogeneous population with respect to mixing ₂₅₄ and individual utilities. More complex models could include different types of ₂₅₅ individuals with correspondingly different utilities. For instance, the model could ₂₅₆ include industrial corporations with utilities biased toward shareholder profit, and social ₂₅₇ institutions (such as laws, taxes, the education system) that reflect the current ₂₅₈ governmental stance. Social learning may also take on different forms due to diverse ₂₅₉ individual psychologies and values [38–40]. Such heterogeneities are known to affect the ₂₆₀ dynamics of a wide variety of systems [41] and can prevent population consensus by ₂₆₁ permitting development of echo chambers [42]. Extending socio-climate models to ₂₆₂ include these finer details should prove valuable in these investigations. ₂₆₃

Climate change is a manifestation of coupled human-environment dynamics and ₂₆₄ therefore we should start coupling climate models to social models [5,43]. Our simple ₂₆₅ coupled socio-climate model shows that the rate at which individuals learn socially ₂₆₆ strongly influences the peak global temperature anomaly, to the point that variation of ₂₆₇ this parameter within plausible ranges changes the peak temperature anomaly by more ₂₆₈ than 1°C. Therefore, it matters whether social processes cause slow or fast uptake of ₂₆₉ climate change mitigation measures. We found that social norms may not provide help ₂₇₀ when we most need it, although this finding could be nuanced by adding social ₂₇₁ heterogeneity. Finally, we illustrated how exploring the parameter space of socio-climate ₂₇₂ models suggests optimal paths for mitigating climate change. A more sophisticated ₂₇₃ policy impact assessment model based on a coupled socio-climate approach could ₂₇₄ therefore be useful to decision-makers facing a mandate to reduce GHG emissions with ₂₇₅ a fixed budget. In summary, it is essential for climate change research to account for ₂₇₆ dynamic social processes in order to generate accurate predictions of future climate ₂₇₇ trends, and the paradigm of coupled socio-climate modelling could help us address this ₂₇₈ challenge. ₂₇₉

Supporting information ₂₈₀

S1 Text. Supplementary figures, tables and full model details. Includes full ₂₈₁ description of the socio-climate model and its parameters, comparison with the CMIP5 ₂₈₂ climate models, and historical climate and CO_2 trajectories. ₂₈₃

Acknowledgments ₂₈₄

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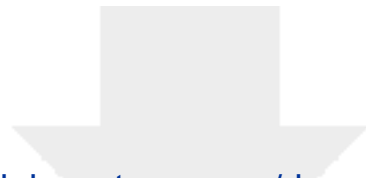
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