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Linking models of human behavior and climate alters projected climate change

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Abstract

Although not considered in climate models, perceived risk stemming from extreme climate events may induce behavioral changes that alter greenhouse gas emissions. Here, we link the C-ROADS climate model to a social model of behavioral change to examine how interactions between perceived risk and emissions behavior influence projected climate change. Our coupled climate and social model resulted in a global temperature change ranging from 3.4–6.2 °C by 2100 compared with 4.9 °C for the C-ROADS model alone, and led to behavioral uncertainty that was of a similar magnitude to physical uncertainty (2.8 °C versus 3.5 °C). Model components with the largest influence on temperature were the functional form of response to extreme events, interaction of perceived behavioral control with perceived social norms, and behaviors leading to sustained emissions reductions. Our results suggest that policies emphasizing the appropriate attribution of extreme events to climate change and infrastructural mitigation may reduce climate change the most.

Introduction

Anthropogenic emissions of greenhouse gases (GHGs) over the past two centuries have resulted in rapid global change[1]. Current projections of climate change, driven by fixed emission trajectories (for example, the Special Report on Emissions Scenarios or Representative Concentration Pathways[2,3]) reflect static assumptions of human emissions behaviors in response to climate change. In reality, GHG emissions will be driven by dynamic interactions between physical and human systems as climate change alters the frequency or severity of extreme climate events (for example, heat waves, drought and heavy precipitation), influencing human responses including emissions behaviors[4]. Although some climate models (for example, integrated assessment models) account for linkages with human systems, they primarily consider economic factors such as the costs associated with climate change impacts and are not two-way; for example, feedbacks do not move in both directions[3,5]. While climate models generally do not include a dynamic representation of human emissions behaviors that evolve in response to the perceived risk from worsening climate change, emissions behaviors are not static and are likely to be responsive to changes in extreme weather events. Here, we investigate the potential importance of these feedbacks by linking a model of human behavioral change using the theory of planned behavior[6] with the carbon model of the Climate Rapid Overview and Decision Support climate model[7] (henceforth C-ROADS). The coupling of these two models is predicated on the assertion that climate change drives changes in extreme events, extreme events interact with human perception of risk to influence emissions behaviors and emissions behaviors then feed back into climate change, leading to a fully interacting model.

Modeling Framework

Extreme weather may influence perceived risk of climate change through both experiential and rational routes[8]. Evidence suggests that perceptions of extreme weather or long-term changes in local climate can increase beliefs and concerns about climate change, particularly among those who are less engaged with climate change science[9–13]. At the societal scale, extreme weather may also garner the attention of news media, government agencies and opinion leaders[14]. The social amplification of risk theory illustrates how social processes such as media communication shape the way these extreme events are interpreted by the public[15]. However, extreme weather may not always lead to large behavioral changes[16,17]. Additionally, the influence of any given extreme event on perceived risk fades over time, as evidenced at the individual level by subjective risk assessments and home valuations after hurricanes[18,19] as well as at the societal level by the economic depreciation of homes after floods[20].

We used the theory of planned behavior[6] to create a social model to link perceived risk from climate change to changes in emissions behaviors. The theory of planned behavior posits that behavior can be predicted by people's behavioral intentions and that behavioral intentions are informed by people's attitudes about the behavior (how positively or negatively they evaluate the behavior), the perceived social norm (PSN) surrounding the behavior (how common or widely approved they perceive the behavior to be) and people's perceived behavioral control (PBC; the perception of the ease or difficulty of performing the behavior). This theory provides a generally accepted approach to analyzing human behavior and has been successfully used to address a wide variety of behaviors[21], including such emissions-relevant behaviors as public transportation use[22].

We couple the social model with C-ROADS and refer to this coupled model as the Climate Social Model (CSM). The focus of the CSM is the dynamic feedback between human perception of risk and climate change (Fig. 1). The temperature projection from C-ROADS is used in the CSM to determine the likelihood of extreme events (extreme temperature in the CSM), which are processed by the social model to influence emissions behavior and ultimately GHG emissions (that is, CO2 equivalents in our model). These behaviorally adjusted emissions, in turn, influence global temperature change and the frequency of extreme events in the subsequent time step, leading to new behaviorally adjusted emissions in a dynamic feedback loop.

Emissions behaviors in the CSM are driven by the frequency of extreme events, but are mediated by a set of social processes. The occurrence of extreme temperatures on an annual time scale is stochastically related to the average global temperature based on empirical observations[23]. The number of extreme events in memory reflects the conflicting processes of sensing and forgetting. Sensing refers to the assimilation of extreme events after accounting for habituation, modelled as the perception of excess extreme events relative to their recent frequency as given by a moving average.

Forgetting refers to the rate at which past extreme events fade from memory, determined by a shorter or longer ‘time to forget’ in years. The events in memory are translated into an attitude towards emissions behaviors that reflects the influence of both the perceived risk of climate change and the perceived efficacy of behavioral responses, meaning the belief that one’s behavioral choices can meaningfully influence GHG emissions. Attitude is combined with the PSN and constrained by PBC to result in emissions behaviors. Change in emissions behavior is modulated by the societal structural capacity for changing emissions to determine anthropogenic emissions of GHG. GHG concentration is translated into average global temperature using C-ROADS, and the updated global temperature leads to a frequency of extreme events, closing the feedback loop in the model (Fig. 1 and Table 1).

While the theory of planned behavior has generally been implemented using a linear functional form[6], we used three different mathematical forms (linear, logistic and cubic; see Supplementary Fig. 1) to bracket the likely range of human responses to climate extremes. All components of the social model are combined using the same functional form within a model run. The logistic form is characterized by sensitivity to initial changes in extreme events, but with little additional response to an increasing frequency of events. Conversely, the cubic functional form leads to little initial sensitivity to changes in extreme events, but results in a strong response to increasing frequency. The linear functional form represents a constant but moderate sensitivity that is midway between the logistic and cubic responses.

We examine two general modes of emissions behavioral change in our model: non-cumulative and cumulative mitigation responses. Non-cumulative mitigation responses are short-term adjustments to GHG emissions that result from emissions behaviors such as adjusting thermostats or driving fewer miles in vehicles. These shifts occur rapidly, can be reversed quickly and hence do not accumulate over time. Cumulative mitigation responses are longer-term adjustments in GHG emissions that are harder to reverse, such as insulating homes or adopting hybrid vehicles, or changing public policy and associated regulations for economy-wide changes. These represent long-term commitment to GHG reductions and accumulate over time.

We used the CSM to investigate the influence of human risk perception and associated behavioral changes on projections of global temperature change. We compared the resultant temperature projections of the CSM to the baseline run of C-ROADS without the social model. We identified the components of the CSM that exert the greatest influence on temperature projections by varying the model parameters (for example, sensing, forgetting, perceived efficacy, PSN and PBC) and structure (for example, functional form and the mode of emissions behavior change) resulting in 766,656 simulations, each representing a unique combination of model structure and parameter values. We used a regression tree to partition the variation in final projected global temperature across model parameters and structure[24].

The CSM offers one example of the incorporation of human behavioral responses into a single climate model (C ROADS) and relies heavily on the theory of planned behavior. While we have been careful to explore the sensitivity of the CSM to changes in parametrization and structure, further efforts to couple social and climate models should explore the robustness of our results to other choices of social and climate models.

Behavioral responses influence projected climate change

The change in mean global temperature in the year 2100 compared with the pre-industrial (circa 1850) temperature was in the range 3.4–6.2 °C across the CSM model set, which compared with a 4.9 °C temperature increase in the baseline run. The regression tree (Fig. 2) shows that the greatest temperature change (highest 3% of CSM simulations; a mean temperature change of 5.7 °C) is associated with a logistic functional form, cumulative mitigation response, relatively high PBC (≥ 0.45) and low PSN (< 0.35). The smallest temperature change (lowest 4% of CSM simulations; a mean temperature change of 3.8 °C) shows a similar pattern with logistic functional form, cumulative mitigation responses, relatively high PBC (≥ 0.45), but high PSN (≥ 0.55). These results consistently demonstrate that high sensitivity in perceived risk to initial changes in extreme events, long-lasting carbon mitigation responses and the interaction of PBC and PSN are influential factors in emissions behaviors. An analysis of the runs with the lowest and highest temperature change (that is, the top or bottom 5%) showed that both the lowest and highest temperatures (3.8 and 6.1 °C) were associated with high PBC (≥ 0.85; Supplementary

Figs. 2 and 3), while the highest temperature increases were additionally associated with higher forgetting (shorter 'time to forget') of past extreme events.

The functional form mediates behavioral responses to extreme events and is a large determinant of future temperature change (Fig. 2). The largest range in CSM temperature projections (3.4–6.2 °C) was associated with the logistic functional form, while more modest ranges of temperature variation were associated with the linear (3.4–5.9 °C) and cubic (3.6–5.2 °C) functional forms (Fig. 3). Both the logistic and linear functional forms allowed for a wide range of global temperature change, but the logistic functional form had the largest proportion of the simulations in the extreme tails (Supplementary Fig. 4). The cubic functional form, in contrast, was associated with temperatures clustered near the baseline run. The largest shifts in mean global temperature were associated with cumulative mitigation responses (Fig. 3), leading to mean global temperature changes in the range 3.4–6.2 °C. Simulations including non-cumulative mitigation responses resulted in little change to the projected global temperature (4.8–5.0 °C) compared with the baseline run of 4.9 °C, regardless of the functional form. The combination of cumulative mitigation and logistic functional form thus leads to the largest potential reduction in global temperature in response to extreme events.

Effects of PSN and PBC on the projected temperature change

The simulations also demonstrate that the direction and magnitude of global temperature change are strongly dependent on PSN and PBC (Fig. 4). The smallest increase in global temperature occurred with concurrent moderate-to-high values of both PSN and PBC, while the largest increase was associated with moderate-to-high PBC and low PSN. PSN and PBC interact with the functional form such that the temperature response to PSN and PBC is greater with the logistic and linear functional forms compared with the cubic functional form (Supplementary

Figs. 5–7). PBC mediates the effect of PSN on the projected global temperature change (Fig. 4). The global temperature increases with declining PBC even at very high values of PSN. For example, with a high PSN (0.9–1.0), decreasing PBC results in a rapidly increasing global temperature that approaches the baseline of 4.9 °C. Conversely, with high PBC (0.8–1.0), there is little change in global temperature with declining PSN until PSN approaches mid-range values (0.5–0.6). The sensitivity to PBC is again particularly pronounced with the logistic and linear functional forms as the cubic has a narrow range of temperature change (see Supplementary Figs. 5–7). This sensitivity to PBC is similar to what might be expected in other theory of planned behavior models, since PBC can influence behaviors above and beyond that of attitudes and PSN[21].

Changes in PSN in either direction from 0.5 lead to an asymmetric response in global temperature change (Fig. 4). Other theory of planned behavior models predict PSN to have an increasingly large but similar effect moving away from the mean in either direction (for example, PSNs of 0.3 and 0.7 would have similar-sized but opposite impacts). In the CSM, however, even a moderate change in PSN towards emissions-increasing behaviors (that is, low PSN) led to a lowered global temperature when accompanied by a high PBC. This may partially result from the continually increasing global temperature (albeit at different rates across runs) leading to a general trend of increasing extreme climate events, and therefore increasing risk perception and positive attitudes towards emissions reducing behavior. The resulting positive attitudes can then override a relatively weak PSN (that is, slightly below 0.5).

Other social components had less influence on the global temperature projections in our model runs. Personal efficacy, sensing and forgetting had little overall impact on temperature projections except in the upper and lower tails of the temperature distribution (Supplementary

Figs. 2 and 3), where (increased) forgetting was associated with the highest temperatures.

Sensitivity to mitigation constraints and uncertainty

We examined the sensitivity of the results to structural constraints within the CSM on carbon mitigation: a ± 5% limit to annual shifts in carbon flux and a 20 Gt minimum level of annual anthropogenic emissions. We found that CSM simulations that resulted in the minimum global temperature were constrained by the 20 Gt minimum and that its removal (set to 0 Gt) lowered the temperature by an additional 0.6 °C (Supplementary Fig. 8). The 5% limit in annual change influenced the time to reach this limit. Therefore, establishing empirically well-supported values of these structural constraints could improve model projections.

The behavioral and physical uncertainty in global temperature change were of similar magnitudes in the CSM. The behavioral sensitivity, defined as the range for global mean temperature in 2100 across the set of social and behavioral parameters, was 2.8 °C (3.4–6.2 °C). Physical uncertainty of 3.5 °C (2.9–6.4 °C) was calculated by varying the climate sensitivity parameter of the C-ROADS climate model across the Intergovernmental Panel on Climate Change 'likely' range of 1.5–4.5 °C (ref. 25) and recording the resultant range of global temperatures of the baseline run. The similar ranges of uncertainty imply that a similar level of effort should be spent on quantifying behavioral uncertainty and physical uncertainty.

Emissions behavior strongly interacted with climate sensitivity in our model (Supplementary Fig. 9). High values of climate sensitivity were substantially offset by feedbacks with emissions behavior in some parameterizations of the CSM. A climate sensitivity of 6 °C, for example, was reduced to an effective climate sensitivity of 3.3 °C through climate change feedbacks on emissions behavior. Our results indicate that the climate sensitivity of the physical system needs to be considered in the context of social and behavioral responses that together yield the effective climate sensitivity.

Scientific and policy implications

Perceived risk of climate change has traditionally been emphasized in the realm of adaptation policy, but has rarely been considered in climate policy mechanisms that address mitigation[26–28]. Our results underscore the need to include perceived risk as a component of mitigation policy with the intent of leveraging and reinforcing behavioral responses to climate change in order to enhance mitigation response impacts.

Policies that facilitate the timely and reliable attribution of extreme events to climate change may increase perceived risk of climate change rather quickly and facilitate changes in emissions behaviors. Climate change attribution research has progressed sufficiently such that the likelihood that a particular extreme event would have occurred in the absence of anthropogenic GHG emissions can be assessed[29–32.] Specifically, attribution science could help shift the functional form of the societal response more towards a logistic curve, increasing sensitivity by rapidly identifying the fingerprint of climate change in individual extreme weather events. Further investing in climate communication education for media members might also be helpful, so that the media can make climate change consequences more concrete and locally relevant to the public. Weather forecasters in particular have been found to effectively increase concern and belief about climate change among political moderates and conservatives by emphasizing local extreme weather changes[33,34].

Furthermore, policies should focus on mitigation actions that are cumulative. Concern about climate change that leads to noncumulative mitigation behaviors that are easily reversed results in little long-term impact on global temperature in our model. Short-term responses are subject to the vagaries of climate variability and habituation to climate change. Cumulative mitigation responses, in contrast, represent longer-term systemic shifts in mitigation infrastructure that are not easily reversed and are critical to reducing climate change in our simulations. Support for cumulative responses may be further increased through emphasis of the co-benefits of modernizing infrastructure to reduce GHG emissions. Health benefits, including reduced lung disease and asthma related to atmospheric pollutants, could occur from transitioning from fossil fuels to residential or community renewables[35], and the economic benefits often include job creation and cost savings from implementation of energy efficiency programmes[36,37]. Additionally, infrastructural mitigation projects can be designed to simultaneously increase PBC and PSN. For example, community solar organizations reduce the cost and difficulty of purchasing residential solar photovoltaics by offering education and financing options (increasing PBC), and increase the local social acceptability of adopting solar by hosting community meetings and encouraging adopters to communicate with neighbors (increasing PSN)[38].

Conclusions

Social processes are important and dynamic components of the Earth system that have been largely absent from climate and integrated assessment models. Two-way linkages between human behavior and climate have the potential to strongly influence GHG emissions and temperature change in ways that static models cannot capture. The perception of risk from extreme events associated with climate change can influence emissions behaviors to reduce GHGs. We find that the temperature uncertainty associated with the social component of climate change is of a similar magnitude to that of the physical certainty and thus merits comparable attention. Our model results suggest that simultaneously addressing a set of human social processes is key to understanding mitigation behaviors and curbing future climate change.

Methods

The CSM consists of a collection of relationships that link the social model to the C ROADS climate model as expressed in Fig. 1. The key assumptions of the CSM are: (1) human emissions behaviors feed back to climate through a modification in CO2 emissions; (2) human emissions behaviors arise from perceptions of risk established through experiencing and then remembering a progression of extreme events; (3) the annual number of extreme events is characterized from temperature conditions, with the number of extreme events occurring per time step being stochastic, but increasing with mean temperature; (4) modification of emissions due to behavior change can be maintained in a pool representing cumulative changes that continue to impact future emissions independent of additional changes in emissions due to further behavior change; (5) the annual change in global CO2 emissions is limited to 5% of previous year emissions, reflecting our assumption that there is only a limited capacity for behavioral factors to modify emissions in a short time period, given limits to individual or infrastructural change; and (6) there is a minimum level of CO2 emissions (20 Gt CO2 year–1) that no behavioral changes can modify. This represents a minimum amount of anthropogenic emissions that are required by our current society. Full details of the model structure are given in the Supplementary Information, but the key components are illustrated in Fig. 1 and defined in Table 1.

The CSM uses the mean global temperature output of C-ROADS at each time step to generate the number of extreme events. It uses an empirical relationship between the average global temperature and the baseline year of 2010 to compute the mean number of extreme events expected. The annual number of extreme events is then a random variate from a Poisson distribution with a mean that is a linear function of this ratio. The mean and variance of the number of annual extreme events thus increases with rising global temperature and declines with falling global temperature. The collective societal ‘memory’ is a balance between sensing and forgetting extreme climate events. We model ‘sensing’ as the difference between the number of extreme events in the current year and the rolling average over a previous number of years. We employ the rolling average to represent habituation to changing numbers of extreme events. A proportion of the events in memory are removed at each time step and this represents ‘forgetting’. The forgetting parameter specifies the proportion of the events in memory that are removed at each time step; for example, a value of 10 leads to the removal of one-tenth of all events still in ‘memory’ per year. It is the pool of remembered extreme events that modifies downstream behavior through risk perception, perceived efficacy, attitude, perceived social norm and perceived behavioral control to mediate the magnitude of behavior change resulting in either a reduction or an increase in CO2 emissions.

To implement the two different modes of emissions behavior change, we divided the total annual CO2 emissions into two parts: a minimum emission portion that could not be reduced but was fixed, and the remainder of emissions that could be modified. The fixed portion of emissions represents CO2 emissions that would be very difficult to reduce given current societal structure, while the other pool could be reduced by the actions possible in today’s societal context. In a non-cumulative mitigation response, the CSM determines the percentage change (increase or decrease) in the modifiable emissions. The percentage change is recalculated each year and is not cumulative, and so it is representative of easily reversible changes in emissions behavior. Cumulative mitigation response also identifies a proportion of the modifiable emissions based on the CSM, but this proportion is added to a pool of accumulating modifications that sum the effect of current and past modifications to the system. In both methods, the CSM generates the magnitude and direction of the emissions modification as constrained by the annual maximum change allowed. The respective emissions modification is incorporated into C-ROADS and the resultant global temperature is returned for the next iteration of the model.

Data availability

The authors declare that models and data supporting the findings of this study are available within the article and its Supplementary Information files at: https://doi.org/10.1038/s41558-017-0031-7.

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Author Contributions

B.B. directed the development of the computational model, conducted the model analyses and wrote the final version of the manuscript. L.J.G. contributed to writing the manuscript, supported the model development and interpretation, and wrote the supplementary materials. K.L. helped write the manuscript and contributed psychological expertise to the model development. E.C. implemented the computational model and ran simulation experiments. S.S.M. provided dynamic modeling expertise to support model implementation and analysis. J.M.W. contributed climate modeling expertise and helped articulate model insights. P.D.H. contributed expertise regarding human perceptions of climate change. N.F. provided modeling and mathematical expertise, detailed feedback and references. T.F. developed a preliminary social model and provided the linkage to C-ROADS. A.Z. contributed ideas about how to model the theory of planned behavior. A.K. helped to frame real-world implications of the model. F.H. provided climate modeling expertise that clarified the contribution of the model. All authors contributed to the development of the conceptual model.

Table 1. Description of the CSM components depicted in Fig. 1

Factor	**Description**
Frequency of extreme events	Poisson distribution with a mean based on the empirical distribution of temperature as a function of the average global temperature
Sensing	Perception of excess extreme events relative to the recent frequency of extreme events; that is, habituation
Forgetting	Rate at which extreme events leave the memory
Events in memory	Number of events pooled as a stock with inflow from sensing and outflow from forgetting
Perceived risk	Perceived adverse effects of climate change
Functional form	Three alternative forms (linear, logistic, & cubic) for transforming memory to perceived risk and for combining other social components of the model
Perceived efficacy	Perceived extent to which a behavior influences GHG emissions
Attitude	Positive or negative evaluation of emissions behaviors
Perceived social norm	Perceived extent to which a behavior is commonly performed or approved of by others
Perceived behavioral control	Perceived ability to perform behavior
Emissions behavior change	Behaviors taken to adjust GHG emissions
Capacity for changing emissions	Constraint on the effect of behavioral change on emissions
GHG emissions	Emissions adjusted for behavioral change and structural constraints
Average global temperature	Temperature computed using the carbon cycle model of C-ROADS

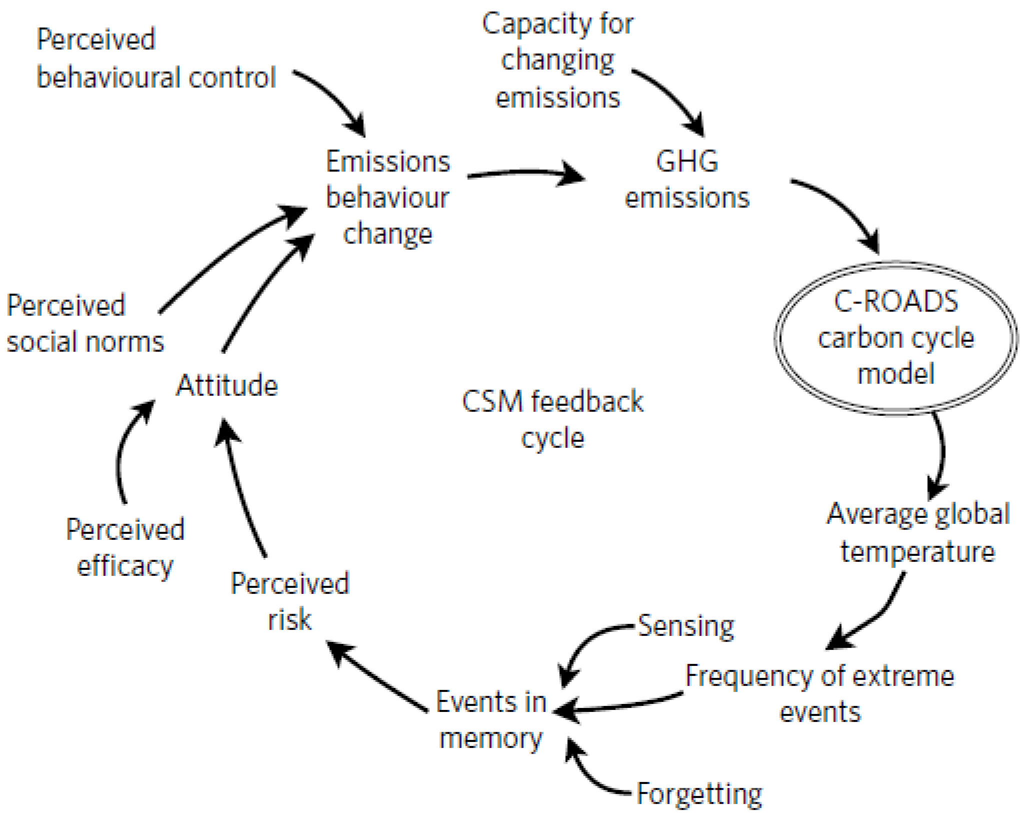

Fig. 1. Conceptual model. Linkages between temperature, extreme events, perceived risk, social components and GHG emissions in the CSM. Average global temperature is calculated from the GHG concentration using the carbon cycle model of C-ROADS[7]

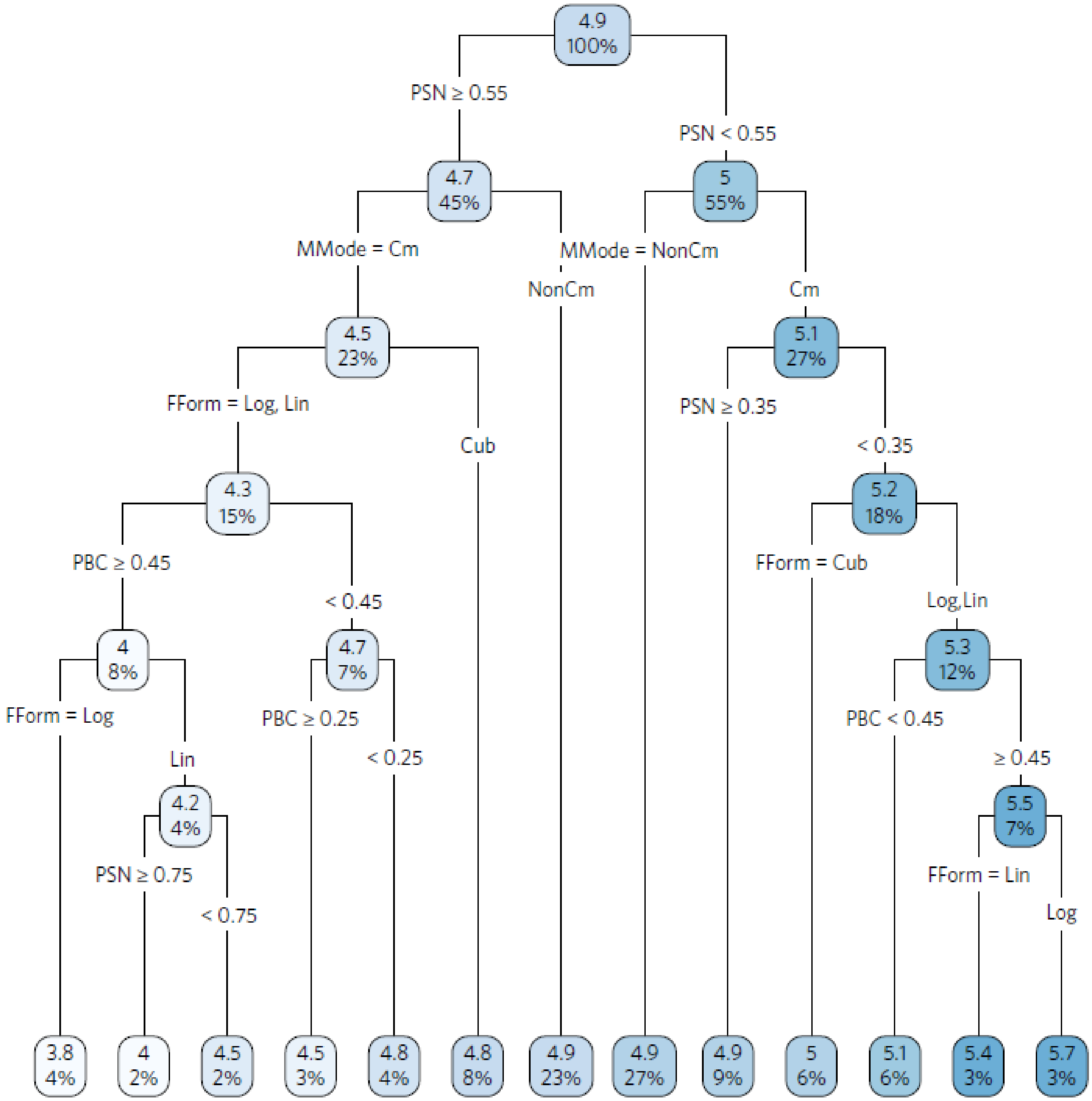

Figure 2. Regression tree partitioning of variation in mean global temperature change relative to the pre-industrial baseline period (approximately 1850). Simulations of the CSM resulted in increases in mean global temperature in the range 3.4–6.2 °C across 766,656 simulations. Each simulation was carried out with a unique model structure (that is, functional form and mode of emissions behavior change) and parameter values (that is, PSN, PBC and so on). Cm, cumulative; Cub, cubic; FForm, functional form; Lin, linear; Log, logistic; MMode, mode of emissions behavior change; NonCm, non-cumulative.

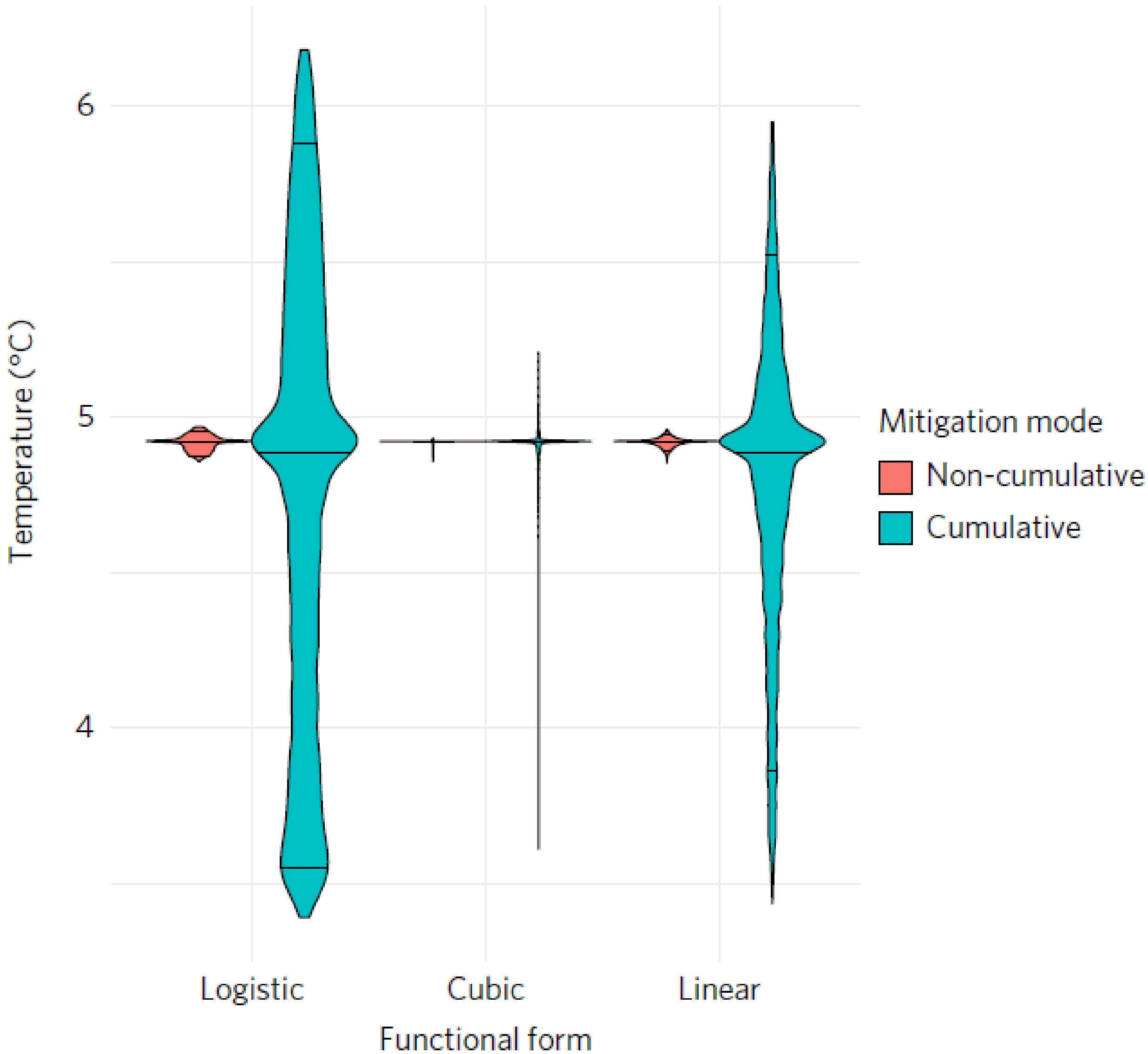

Figure 3. Effect of functional form on mean global temperature in 2100. Functional form by which social processes respond to extreme climate events (logistic, linear or cubic) and mode of emissions behavior change (non-cumulative or cumulative).

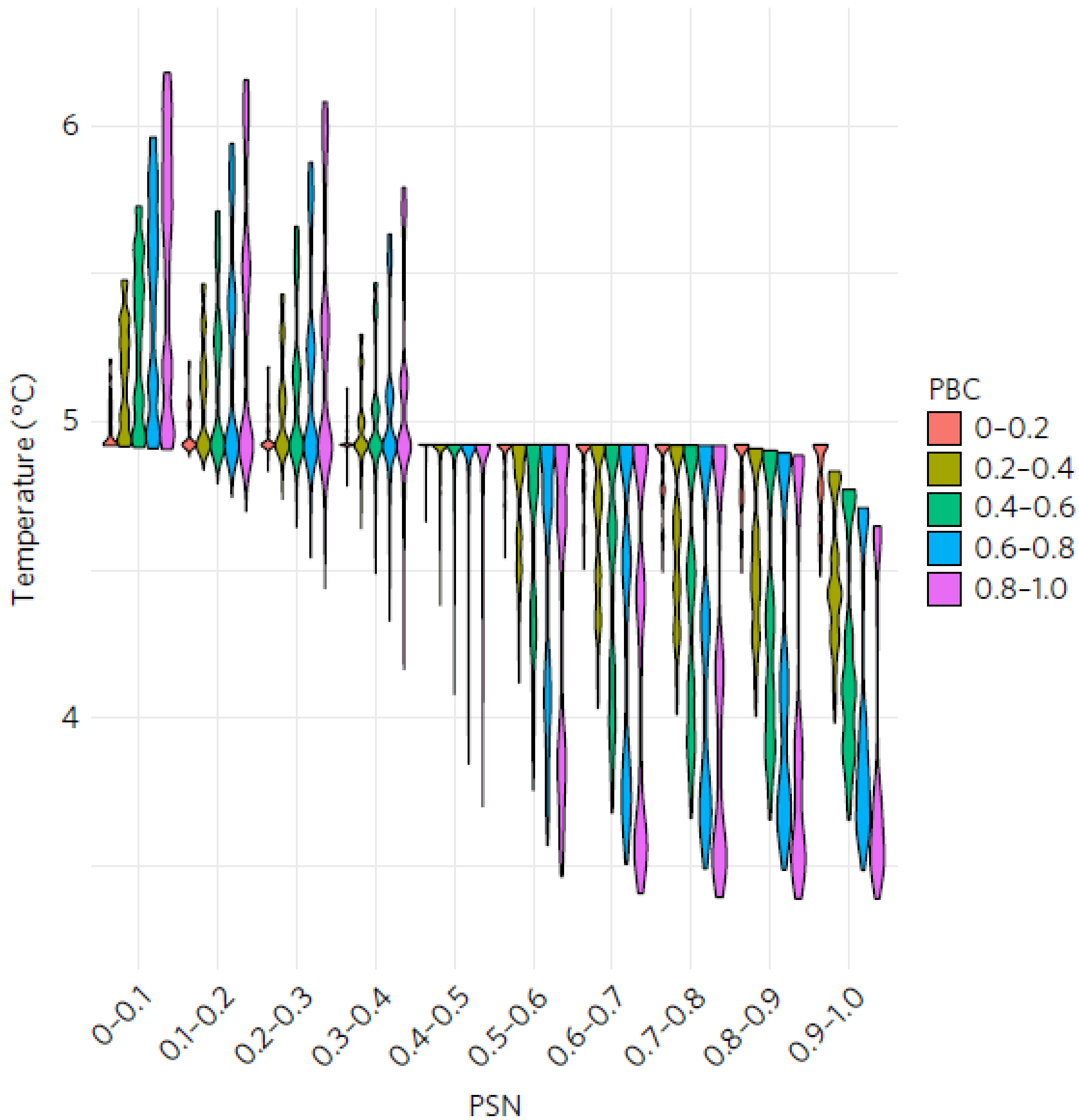

Figure 4. Effect of PSN and PBC on mean global temperature in 2100 for simulations with a cumulative mitigation response in carbon emissions. PSN and PBC both range from 0–1.0 and have been split into 0.1 bin widths for PSN and 0.2 bin widths for PBC. All functional forms (logistic, linear and cubic) are aggregated. See Supplementary Figs. 5–7 for similar plots conditioned on functional form.