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Abstract

Climate projections typically treat anthropogenic greenhouse gas emissions as exogenous, overlooking feedbacks through which human behavioral responses to climate change reshape emission pathways. Here, we incorporate human behavioral responses into a reduced-complexity climate model to examine how behavioral feedbacks dynamically reshape future climate trajectories across multiple Shared Socioeconomic Pathway scenarios. We find that human behavioral responses can substantially alter projected warming, shifting end-of-century global mean temperature outcomes up to ± 1 °C relative to projections without human behavioral responses. These effects differ across emissions pathways, possibly amplifying warming under SSP1-2.6 while reducing warming under SSP5-8.5. Personal action confidence, collective action confidence, and sensitivity of climate anxiety emerge as the dominant behavioral processes, determining both the magnitude and direction of climate responses. Human behavioral responses accumulate over time, with sustained adaptive responses progressively enhancing cooling effects, whereas prolonged maladaptive responses increasingly amplify warming. Our findings demonstrate that human behavior is not merely a consequence of climate change, but an active component of the climate system capable of reshaping long-term climate projections and evaluating the effectiveness of mitigation responses. These findings highlight the importance of integrating behavioral dimensions into climate governance, as policies that promote adaptive responses may reinforce mitigation efforts, whereas maladaptive responses could lock societies into trajectories of greater climate risk.

Climate change is driving rapid and unprecedented transformations in Earth system¹. As anthropogenic greenhouse gas emissions remain the dominant driver of future warming², emission pathways fundamentally determine climate outcomes. Reliable climate projections are therefore essential for climate policy, mitigation planning and societal adaptation. However, most current climate projections rely on externally prescribed emission scenarios, implicitly treating human emission behaviors as exogenous to evolving climate conditions³. This static forcing assumption overlooks critical feedback involving human behaviors. Rising temperature and extreme climate events affect human response by risk perceptions, social priorities, policy instructions, thereby progressively altering future emission trajectories⁴, which could be a large uncertainty in long-term climate projections.

A critical but underrepresented interface in human-climate interactions lies in the process through which climate signals are perceived, evaluated, and translated into action. Human behavioral change rarely arises directly from temperature increases; instead, it emerges through a chain of cognitive and emotional pathways including perception, memory, and risk appraisal of climate change⁵⁻⁷. Personal experience of extreme climate events often plays a key role. Individuals exposed to floods, heatwaves, or droughts are more likely to perceive climate change as an immediate and serious threat^{8,9}, which in turn increases support for climate policies and motivates individual actions such as reducing residential energy consumption, purchasing energy-efficient appliances, or supporting carbon-reduction legislation^{10,11}. Emotional responses of climate change further shape these dynamics¹². Among them, climate anxiety, distress associated with perceived climate threats¹³, has been widely reported across countries¹⁴, and is associated with stronger engagement in mitigation behaviors and climate advocacy¹⁵. However, individuals differ in the extent to which perceived climate risks translate into emotional responses, here represented by the Sensitivity of Climate Anxiety (SCA). Higher SCA amplifies the behavioral impact of climate signals, particularly extreme events. Behavior responses also depend on perceived behavioral control at both personal and collective levels¹⁶. Personal Act Confidence (PAC), or self-

efficacy, reflects an individuals' belief in their ability to perform climate-related actions¹⁷, whereas Collective Act Confidence (CAC), captures the belief that collective actions can effectively mitigate climate risks¹⁸. PAC primarily influences engagement in individual mitigation behaviors, such as reducing household energy use, choosing low-carbon transport options, or changing consumption patterns, in ways that contribute to lowering emissions¹⁹, whereas CAC shapes support for collective responses including climate policies and coordinated societal actions²⁰. By contrast, when climate anxiety is not matched by perceived control, individuals may disengage, avoid climate information, or fail to act ²¹.

Recent efforts have increasingly sought to incorporate human dimensions into climate projections, particularly through integrated assessment models and socio-climate feedback frameworks²². These approaches typically attribute human behaviors to macro-structural drivers such as economic growth, technological diffusion, mitigation policies, or adaptive capacity²³. While capturing important systemic determinants, human responses are often parameterized in simplified or static forms, and behavioral adjustments are frequently instantaneous, or policy-driven²⁴. As a result, current models may fail to capture behaviorally driven feedbacks, in which human responses evolve over time and dynamically reshape emission pathways.

Here, by incorporating human behavioral responses into a reduced-complexity climate model, we show that human behavior is not merely a response to climate change, but a key driver of it, capable of shifting end-of-century warming by nearly ± 1 °C. Human behavioral responses systematically alter climate trajectories across emission scenarios, amplifying warming under low-emission pathways while reducing warming under high-emission pathways. This variation is largely governed by PAC, CAC, and SCA, whose impacts tend to intensify over time. Our results demonstrate that early and positive-guided behavioral responses can effectively mitigate warming, whereas maladaptive responses may instead exacerbate it, underscoring the critical role of human behavior in shaping future climate trajectories.

Human behavioral response reshapes future temperature projections

Incorporating human behavioral responses into the coupled climate system substantially alters future emission pathways and temperature projections across SSP scenarios (detail in Method “Model Specification”, Text S1, Fig. 1). To quantify these effects, we conducted 186,624 simulations with varied combinations of key human behavioral response parameters (detail in Text S1, Table S1) under SSP1-2.6, SSP2-4.5, SSP 5-8.5 scenario, using the median projection of emissions and temperature change compared with preindustrial level (circa 1850). Compared with simulations without human behavioral responses, the inclusion of human behavioral responses produces distinct climate trajectories under low-, intermediate-, and high-emission futures (Fig. 2). Under the low-emission scenarios (SSP1-2.6), median emissions and temperature consistently exceed the no-response baseline throughout 2010–2100 (Figure S1). By 2100, change in emissions relative to preindustrial level increase from $-5.72 \text{ GtCO}_2 \text{ yr}^{-1}$ (baseline) to over $10.75 \text{ GtCO}_2 \text{ yr}^{-1}$, resulting in an additional $0.55 \text{ }^\circ\text{C}$ of warming compared with no-response baseline (Figure S1, Fig. 2). This pattern is consistent with weak behavioral responses under relatively mild climate conditions, which reduce incentives for sustained mitigation and allow emissions to remain elevated over time^{16,25}. By contrast, under the high-emission scenario (SSP5-8.5), human behavioral responses produce sustained reductions in both emissions and temperature relative to no-response baseline. By 2100, median change in emissions relative to preindustrial level decline from $127.82 \text{ GtCO}_2 \text{ yr}^{-1}$ in the no-response baseline to $40.26 \text{ GtCO}_2 \text{ yr}^{-1}$ when behavioral responses are included (Figure S1). This reduction is accompanied by a $0.94 \text{ }^\circ\text{C}$ decrease in projected temperature relative to the no-response baseline of $4.18 \text{ }^\circ\text{C}$ (Fig. 2). These results suggest that strong climate warming signals under high-emission conditions promote persistent mitigation responses, leading to substantial reductions in emissions^{7,16}. Unlike the consistent trends observed in SSP1-2.6 and SSP5-8.5, the SSP2-4.5 scenario shows a distinct turning point around 2063. Emissions including human behavioral responses relative no-response baseline shift from $+11.61 \text{ GtCO}_2 \text{ yr}^{-1}$ in the preceding decade to $-8.71 \text{ GtCO}_2 \text{ yr}^{-1}$ in the following decade, and

continue declining to $-17.32 \text{ GtCO}_2 \text{ yr}^{-1}$ by 2100 (Figure S1). The temperature, correspondingly, shows a minor increase of 0.17°C in 2100 compared with no-response baseline (Fig. 2). This turning point implies the dynamic adjustment of behavioral responses as climate conditions intensifies, producing a balance between warming-amplifying and warming-mitigating behavioral effects.

The magnitude and direction of climate outcomes vary substantially with the strength of human behavioral responses, as indicated by the interquartile ranges (P25-P75) of emission and temperature deviations from the no-response baseline by 2100 under each SSP scenario (Fig. 2). Under SSP1-2.6, emissions change relative to no-response baseline ranges from $-11.75 \text{ GtCO}_2 \text{ yr}^{-1}$ to $+45.33 \text{ GtCO}_2 \text{ yr}^{-1}$ (Figure S2), corresponding to temperature changes relative to no-response baseline of -1.74°C to $+0.27^\circ\text{C}$, indicating that behavioral effects could shift the system from modest mitigation to slight warming amplification. This divergence becomes more pronounced in SSP2-4.5, where emission deviations widen to $-34.23 \text{ GtCO}_2 \text{ yr}^{-1}$ to $+113.04 \text{ GtCO}_2 \text{ yr}^{-1}$ and translate into broader temperature range of -2.04°C to $+0.92^\circ\text{C}$ (Figure S1, Fig. 2), suggesting increased sensitivity to behavioral heterogeneity under intermediate emission scenario. The largest variability emerges under SSP5-8.5, with emission deviations spanning $-98.15 \text{ GtCO}_2 \text{ yr}^{-1}$ to $+369.70 \text{ GtCO}_2 \text{ yr}^{-1}$ and corresponding temperature changes of -2.24°C to 2.31°C (Figure S1, Fig. 2). Under such high-forcing conditions, strong behavioral responses can substantially enhance mitigation, whereas weak or maladaptive responses can further amplify warming. Thus, across all projected SSP emissions scenarios, climate trajectories are highly sensitive to human behavioral responses strength, with both the magnitude and direction of change determined by the intensity and orientation of human responses.

Dominant drivers of human behavioral responses to climate change

To investigate how human behavioral responses shape climate outcomes, we first define the set of behavioral parameters included in the coupled system. The model includes 13 behavior-related parameters (details in Text S1, Table S1), which are grouped into four components of human-climate system: characteristics of extreme

events (extreme definition threshold, temperature scale factor), mechanisms of memory (memory threshold, memory duration, forgetting rate), processes of risk perception (extreme intensity, intensity sensitivity, norm events, severity weighting, perception delay), and cognitive adjustment and emotional responses (PAC, CAC, SCA) (Fig. 1). We then quantify the influence of these parameters using a global Sobol sensitivity analysis across scenario–time combinations (SSP1–2.6, SSP2–4.5 and SSP5–8.5 evaluated at 2050 and 2100). To disentangle their contributions, parameter effects are decomposed into independent effects, reflecting the influence of each parameter acting alone, and combined effects, which capture interaction effects among parameters²⁶. Across all scenario–time combinations, a consistent set of dominant parameters emerges, forming a leading group that is clearly separated from the remaining variables by a sharp decline in contribution (Fig. 3, Figure S2). This group comprises six parameters, including PAC, CAC, SCA, memory duration, forgetting rate and severity weighting. Collectively, these six parameters overwhelmingly determine how temperature responds to changes in the coupled system, contributing over 95% of the cumulative total influence across all parameters, while the remaining seven parameters contribute less than 5% (Figure S2, Table S2, S3). This concentration of influence suggests that the effects of human behavioral responses on climate outcomes are governed by a limited number of behavioral processes despite the broader complexity of the coupled system^{7,27}.

Under SSP5-8.5 scenario, PAC, CAC and SCA consistently rank as the top three parameters contributed to variation in temperature projection both in 2050 and 2100 (Fig. 3, Figure S2, Table S2, S3). In 2050, PAC and CAC each account for about 45% of the variation in projected temperature across simulations with different behavioral parameter combinations. Their influence is primarily driven by their independent effects (about 35%), with a small contribution arising from interactions with other behavioral parameters (around 10%). SCA explains a small proportion of the differences in projected temperature (approximately 12%) with only about 3% arising from its independent effect. This pattern suggests that near-term climate outcomes are

largely determined by perceived behavioral control, as both individual (PAC) and collective (CAC) play a decisive role in shaping mitigation responses^{28,29}. By 2100, the relative importance of these parameters shifts (Figure S2, Table S2, S3). The contributions of PAC and CAC decrease to around 37% each, whereas the contribution of SCA increases to 34%. This shift is primarily driven by an increase in the independent effect of SCA^{30,31}, which rises from about 3% in 2050 to approximately 22% in 2100, while interaction effects remain relatively stable (about 10%), suggesting that long-term climate outcomes become increasingly sensitive to variation in climate-anxiety sensitivity.

This temporal shift is observed not only under SSP5–8.5 but also under SSP1–2.6 and SSP2–4.5 (Fig. 3, Text S2), suggesting a general feature of the coupled human–climate system. Independent random forest analyses (Text S3) and alternative model structures (Text S6, S7) further support this conclusion (Figure S3, S9–S10).

Human behavioral responses accumulate over time

The influence of behavioral feedbacks strengthens progressively over time, producing increasingly large deviations in climate outcomes relative to simulations without behavioral responses^{32–34}. In SSP5–8.5, the effect of human behavioral responses evolves over time, with median change in temperature relative to no-response baseline shifting from a slight warming of +0.18 °C (P25:P75: -0.48 °C to +0.57 °C) in 2050 to a substantial cooling of -0.94 °C (P25–P75: -2.24 °C to +2.31 °C) by 2100 (Fig. 2, Figure S4). This transition indicates that the cooling benefits of adaptive behavioral responses emerge only after sustained accumulation over time, whereas short-term responses are insufficient to offset ongoing warming. This divergence is also supported by regression tree results (Text S4, Figure S5).

To quantify the role of timing, we conduct sensitivity simulations in which behavioral responses are introduced into the coupled system at different start years (2010, 2020 and 2030), with all simulations run to 2100. A later start year therefore corresponds to a shorter duration over which human behavioral responses operate. Temperature outcomes in 2100 are then partitioned relative to the no-response baseline (SSP5–8.5:

4.18 °C) into two components: values above the baseline, representing additional warming from cumulative maladaptive behavioral responses, and values below the baseline, representing cooling from cumulative adaptive behavioral responses. This decomposition therefore clarifies how the timing of behavioral intervention determines whether long-term feedbacks amplify mitigation or intensify warming trajectories. Under SSP-5.85 scenario, we find an amplified warming with early start times of maladaptive human behavioral responses, with temperature change relative to no-response baseline being +2.08 °C (P25:P75: +1.39°C to +2.67°C) start in 2030, +2.14°C in 2020 (P25:P75: +1.52°C to 3.00°C), +2.49°C (P25:P75: +1.59 °C to +3.21°C) in 2010 (Fig. 4). This indicates that initiating the maladaptive human behavioral responses in 2010 leads to an additionally warming of 0.35°C and 0.41°C compared to 2020 and 2030, respectively. The results suggest that earlier maladaptive responses accumulate and amplify long-term warming. A similar cumulative effect is observed for simulations with adaptive human behavioral responses producing net cooling relative to the baseline. The median cooling relative to no-response baseline increase from -1.99°C (2.19°C, P25-P75: -2.14 °C to -1.44 °C) for a 2030 start to -2.14°C (P25-P75: -2.32 °C to -1.47 °C) for 2020, and -2.24°C (P25-P75: -2.45°C to -1.41°C) for 2010 (Fig. 4). The greater cooling achieved under earlier intervention demonstrates that adaptive behavioral responses also accumulate through time, progressively enhancing mitigation benefits when initiated sooner. Moreover, the additional cooling gained between 2010 and 2020 (0.10 °C) exceeds that gained between 2020 and 2030 (0.05 °C) by 2100 under SSP5.8-5 scenario (Fig. 4), suggesting diminishing returns as behavioral interventions are delayed. The cumulative effect also observed under SSP1-2.6 and SSP2-4.5 scenarios (Figure S6-7, Text S5). Taken together, these results demonstrate that both adaptive and maladaptive behavioral responses exhibit strong cumulative dynamics. Early adaptive responses progressively enhance long-term cooling, whereas persistent maladaptive responses increasingly amplify warming. Future climate trajectories are therefore influenced not only by the nature of behavioral responses but also by when those responses emerge and how long

they persist within the coupled human–climate system.

Conclusion and discussion

Human behavioral responses to climate change are often treated as external drivers in climate projections, yet in reality they evolve dynamically as societies perceive, interpret, and emotionally respond to changing climate conditions. By explicitly embedding these human responses within coupled human-climate model, our study indicates human behavioral responses fundamentally alter both the magnitude and direction of future emission and temperature trajectories. Behavioral responses in our model function as a state-dependent and cumulative feedback that reshapes climate trajectories. Their effects vary systematically across scenarios, much possibly reducing it under high-emission pathways while amplifying warming under low-emission conditions with amplified effect over time no matter the scenarios. Under the same scenario, behavioral responses would either decrease or increase in temperature depending on the positive or negative behavioral responses, which dominated by perception-, cognition-, and action-related behavior (PAC, CAC, and SCA).

These findings have implications for climate mitigation strategies. While climate policy has traditionally emphasized technological transitions, economic incentives, and regulatory instruments, our results show that behavioral response can also possibly alter long-term emission and temperature trajectories and should therefore be treated as a component of mitigation frameworks. In particular, the dominance of a small set of behavioral parameters (PAC, CAC, and SCA) suggests that interventions targeting how individuals perceive risks, process information, and translate intention into action may have disproportionate effects on long-term climate outcomes. A key implication is that effective mitigation strategies should not only communicate climate risks but also strengthen individuals' perceived capacity to respond. When people recognize climate threats yet remain uncertain about how their actions contribute to collective outcomes, concern may fail to translate into sustained behavioral change^{35,36}. Policies that link climate awareness with clear and accessible action pathways may therefore be particularly effective. Examples include expanding opportunities for low-carbon

mobility, reducing barriers to household renewable energy adoption, and providing practical guidance on energy-saving behaviors^{37,38}. Such interventions can reinforce both personal and collective act confidence by making climate action more feasible and by clarifying how individual behaviors contribute to broader mitigation efforts. More broadly, the cumulative nature of behavioral effects further highlights the importance of the direction of early interventions^{34,39}. Initial tendencies toward either higher or lower emissions are progressively reinforced rather than corrected^{40,41}. As a result, early responses that contribute to high emissions tend to lock in long-term warming trajectories, whereas early responses that reduce emissions or promote mitigation accumulate over time and generate persistent cooling effects. This path-dependent dynamic implies that early action can either constrain or exacerbate future climate outcomes depending on whether it reinforces warming-inducing or cooling-inducing behavioral patterns.

Although our framework captures key features of behavioral–climate interactions, limitations should be acknowledged. The model simplifies complex behavioral response into a limited set of parameters and therefore cannot capture the full diversity of human responses to climate change. Factors such as cultural values, political identity, institutional trust, and social norms are known to influence climate perceptions and behaviors but are not explicitly represented in the current framework^{3,27,42}. Behavioral responses are modeled at a globally aggregated level, which may obscure important regional and cultural differences in how climate risks are perceived and acted upon. By considering both cognitive and emotional dimensions, this study illustrates the value of explicitly integrating comprehensive behavioral response into climate modelling, providing a blueprint for climate policies that not only reduce emissions but also enhance societal resilience and long-term engagement with climate action. Future research may extend this modelling framework by incorporating regional heterogeneity and refining behavioral representations to identify the most effective behaviors in shaping long-term climate outcomes. Improved empirical evidence on how individuals interpret climate experiences and translate them into sustained behavioral responses

291 would further enhance the realism, predictive capability, and policy relevance of
292 coupled human-climate models.
293

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Methods

Overview of coupled human-climate model. To investigate feedbacks between climate change and human behavioral responses, we developed a coupled human–climate model integrating the Extended Parallel Process Model (EPPM)⁴³ with the reduced-complexity climate model of the Climate Rapid Overview and Decision Support climate model (C-ROADS)⁴⁴. The human–climate model consists of four interconnected modules: the climate system, memory module, perception processes, and cognitive–emotional response module (Fig. 1). Climate change influences the occurrence of extreme weather events, which are encoded into memory and subsequently shape threat perception and climate anxiety. Together with perceived behavioral control (PBC, including PAC and CAC), these psychological responses determine behavioral change, which modifies anthropogenic emissions and feeds back to future temperature trajectories. The principal endogenous output of the model is behavior-modified global anthropogenic CO₂ emissions, which represent the mechanism through which human responses influence the climate system. The primary climate outcome is global mean temperature change relative to preindustrial conditions, evaluated throughout the simulation period and particularly at 2050 and 2100. All simulations run from 1850 to 2100 with a time step of 0.25 years under three Shared Socioeconomic Pathways (SSPs) scenarios: SSP1–2.6, SSP2–4.5, and SSP5–8.5. All climate variables are expressed relative to preindustrial conditions (1850). Each simulation is initialized with externally prescribed SSP trajectories of anthropogenic CO₂ emissions, land-use emissions, anthropogenic methane emissions, and non-CO₂ radiative forcing⁴⁵. Historical observations and forcing reconstructions drive the model before 2010, whereas scenario-specific SSP trajectories drive the model thereafter.

Climate system module. The climate system module provides the physical forcing that initiates the human–climate feedback loop (Fig. 1). Global mean temperature change relative to preindustrial conditions is simulated by C-ROADS as a function of greenhouse gas emissions, atmospheric concentrations, and radiative forcing. Temperature change subsequently influences the occurrence of extreme weather events,

which serve as the primary climate signal entering the human behavioral response system.

Following Beckage et al.³², extreme weather events are represented as changes in the upper tail of the global temperature distribution rather than as direct functions of mean temperature alone. The underlying assumption is that climate warming shifts the temperature distribution toward higher values, thereby increasing the probability that temperatures exceed a predefined extreme-event threshold.

To represent this process, annual maximum temperatures in simulation year t are assumed to follow a normal distribution:

$$X_t \sim N(\mu(t), \sigma^2) \quad (1)$$

where X_t denotes the distribution of annual maximum temperatures in simulation year t , t represents time measured in years, $\mu(t)$ is the global mean temperature anomaly simulated by C-ROADS. σ^2 is the variance of the reference temperature distribution with 16.763, based on global temperature variability reported by Donat and Alexander⁴⁶. The reference climate is defined by the global mean temperature change in 2010:

$$\mu_{ref} = 0.964 \text{ } ^\circ\text{C} \quad (2)$$

which serves as the baseline climate condition for identifying extreme events.

Extreme events are defined relative to a fixed threshold derived from the reference climate distribution. The corresponding threshold temperature is obtained as

$$X^* = F_{ref}^{-1}(\text{Extreme threshold}) \quad (3)$$

where *Extreme threshold* corresponds to the upper-tail percentile threshold (Text S1, Table S1), and the corresponding threshold temperature, denoted X^* , is obtained from the inverse cumulative distribution function (F_{ref}^{-1}) of the reference climate distribution.

For a given climate state, the standardized distance between the threshold temperature and the current mean temperature is

$$Z(t) = \frac{X^* - \mu(t)}{\sigma} \quad (4)$$

where $Z(t)$ measures how far the extreme-event threshold lies above the current

climate state in units of standard deviation. As global temperatures increase, the mean temperature distribution $\mu(t)$ shifts toward the threshold, which reduces $Z(t)$. Consequently, a larger proportion of the temperature distribution exceeds the temperature threshold (X^*).

The probability that annual maximum temperatures exceed the extreme-event threshold is then calculated as:

$$P(t) = 1 - \Phi(Z(t)) \quad (5)$$

Where $P(t)$ represents the exceedance probability under the current climate state and Φ denotes the cumulative standard normal distribution.

To quantify changes relative to the reference climate, a ratio is calculated as:

$$\text{Extreme event ratio}(t) = \frac{P(t)}{1 - \text{Extreme threshold}} \quad (6)$$

This *Extreme event ratio*(t) represents the relative change in extreme-event occurrence compared with the reference climate in year t . Values greater than 1 indicate that extreme events occur more frequently than baseline conditions, whereas values below 1 indicate fewer extreme events.

The expected annual number of extreme weather events is then determined as

$$\text{Extreme event mean}(t) = \text{Temperature scale factor} \times \text{Extreme event ratio}(t) \times \text{reference}$$

Here, *reference extreme event mean* represents the reference mean number of extreme events per year. To prevent unrealistically small event frequencies, a minimum event rate is imposed such that the expected annual frequency cannot fall below a predefined lower bound (20 events year⁻¹). *Temperature Scale Factor* controls the sensitivity of extreme-event occurrence to changes in temperature (Text S1, Table S1). By explicitly representing *Temperature Scale Factor* as an adjustable parameter, the model allows uncertainty in the relationship between climate warming and extreme-event occurrence to be explored through sensitivity analysis.

The realized annual number of extreme events is then generated from a Poisson distribution:

$$\text{Extreme Weather}(t) \sim \text{Poisson}(\text{Extreme Event Mean}(t)) \quad (8)$$

where $Extreme\ Weather(t)$ represents the observed number of extreme events in year t . This stochastic formulation captures interannual variability in extreme-event occurrence while preserving the long-term influence of climate warming on event frequency.

Unlike models that assume individuals respond directly to the absolute number of extreme events, we assume that climate experiences are evaluated relative to recent conditions. Individuals therefore respond primarily to anomalies in event occurrence rather than to absolute event counts⁴⁷. To represent this process, a moving experience window is applied to the generated event series.

The average number of extreme events over the preceding experience window is calculated as

$$Average\ Event(t) = \frac{1}{\tau} \int_{t-\tau}^t Extreme\ Weather(s) ds \quad (9)$$

where τ denotes the length of the memory window (Text S1, Table S1). The event signal entering the memory module is then defined as

$$Event\ series(t) = \max[0, Extreme\ weather(t) - Average\ Event(t)] \quad (10)$$

where $Event\ series(t)$ represents deviations between current and recently experienced climate conditions. Positive values indicate years with unusually high numbers of extreme events relative to recent experience, whereas values near zero imply little departure from expected conditions. Because negative anomalies are assumed to contribute little to increasing climate concern, only positive deviations are retained. The resulting $Event\ series(t)$ is subsequently passed to the memory module, where climate experiences are selectively encoded and accumulated over time.

Memory module. The climate anomaly signal, $Event\ series(t)$, represents experienced climate events. However, such experiences are assumed to influence future judgments only if they are encoded into memory. Events that are not encoded are rapidly forgotten and therefore do not contribute to the accumulation of remembered climate experiences⁴⁸. To represent this process, event anomalies are incorporated into memory only when their magnitude exceeds a predefined *Memory threshold* :

$$508 \quad \text{Memory encoding}(t) = \begin{cases} 0, & \text{Event series } (t) < \text{Memory threshold} \\ \text{Event series } (t), & \text{Event series } (t) \geq \text{Memory threshold} \end{cases} \quad (11)$$

509 where *Memory encoding*(*t*) represents the effective climate signal entering
 510 memory formation and *Memory threshold* determines the minimum event
 511 anomaly required for encoding (Text S1, Table S1). Larger threshold values imply that
 512 only more pronounced departures from recent experience contribute to remembered
 513 climate experiences.

514 Accumulated climate experiences are represented by the stock variable
 515 *Events in Memory*, which integrates newly perceived climate anomalies while
 516 simultaneously decaying through forgetting:

$$517 \quad \frac{d(\text{Events in Memory})}{dt} = \text{Memory encoding}(t) - \text{Forgetting of Events}(t) \quad (12)$$

518 This formulation reflects the assumption that climate memories are continuously
 519 updated as individuals encounter new climate experiences while gradually losing access
 520 to older experiences over time.

521 The rate at which remembered experiences decay is determined by:

$$522 \quad \text{Forgetting of Events}(t) = \frac{\text{Events in Memory}(t)}{\text{Time to Forget}} \quad (13)$$

523 where *Time to Forget* represents the characteristic retention time of climate
 524 memories. Following Beckage et al.³², memory persistence is linked to the temporal
 525 window over which individuals evaluate climate conditions:

$$526 \quad \text{Time to Forget} = \text{Memory window} \times \text{Memory retention factor} \quad (14)$$

527 where *Memory window* denotes the event-sensing window introduced above and
 528 *Memory retention factor* controls the persistence of remembered climate
 529 experiences (Text S1, Table S1). The model assumes that individuals who evaluate
 530 climate conditions over longer temporal windows also retain remembered climate
 531 experiences for longer durations. Similarly, larger values of
 532 *Memory retention factor* slow memory decay, whereas smaller values produce
 533 more rapid forgetting (Text S1, Table S1).

534 The resulting *Events in Memory*(*t*) represents accumulated remembered
 535 climate experiences through which climate conditions influence subsequent risk

perceptions.

Perception processes. Remembered climate experiences (*Events in Memory(t)*) provide the information individuals use to judge both the seriousness of climate impacts and the likelihood of being personally affected. Perceived climate risk is therefore assumed to arise from two complementary dimensions: perceived severity and perceived susceptibility^{25,49}. Perceived severity reflects the perceived magnitude of climate impacts, whereas perceived susceptibility reflects the perceived likelihood of being personally affected by those impacts. These dimensions determine overall perceived threat.

Perceived severity is assumed to increase with the accumulation of remembered extreme-weather experiences. Individuals evaluate the seriousness of climate risks relative to their expectations of normal environmental conditions⁵⁰. The underlying severity signal is therefore defined as

$$Severity(t) = \frac{Events\ in\ memory(t)}{Norm\ events} \times (1 + SeverityPerception \times Extreme\ intensity)(15)$$

where *Norm events* represents the reference number of remembered events required to generate a substantial severity response, *Extreme intensity* denotes the perceived intensity of individual extreme-weather events, and *SeverityPerception* captures the extent to which individuals interpret high-intensity events as more damaging or consequential than low-intensity events, independent of the number of events experienced.

Larger values of *Events in memory(t)* increase perceived severity because individuals accumulate more evidence of climate-related disruption. Similarly, higher values of *Extreme intensity* increase the perceived consequences associated with each remembered event, thereby strengthening severity assessments.

To capture the nonlinear nature of climate-risk appraisal, perceived severity is represented using a logistic response function. Logistic functions provide a bounded representation of perception while capturing both threshold effects and diminishing marginal increases in perception at high experience levels. This formulation reflects empirical evidence that individuals often exhibit weak responses to small changes in

climate experience, followed by more rapid increases in perceived risk once accumulated experience exceeds a critical level⁵¹.

$$Severity\ Raw(t) = \frac{L}{[1 + \exp(-K(Severity(t) - X_0))]} \quad (16)$$

where L denotes the maximum attainable perception level, K controls the steepness of the response curve, and X_0 represents the midpoint at which severity perception increases most rapidly. $Severity\ Raw(t)$ captures the instantaneous cognitive evaluation of severity prior to temporal integration. $Perceived\ severity(t)$ is then obtained via exponential smoothing since perception is not updated instantaneously:

$$Perceived\ severity(t) = SMOOTH[Severity\ Raw(t), Perception\ delay] \quad (17)$$

where $Perception\ delay$ represents the time required for individuals to update their assessment of climate severity in response to changing environmental conditions. $SMOOTH[Severity\ Raw(t), Perception\ delay]$ is defined as a delayed adjustment process that updates the current value toward $Severity\ Raw(t)$ with time constant $Perception\ delay$, representing gradual cognitive updating over time (Text S1, Table S1).

Perceived susceptibility reflects the extent to which individuals perceive themselves as exposed to climate impacts. Exposure is assumed to depend on the proportion of the population affected by extreme-weather events. The annual affected population is calculated as:

$$AnnualAffectedPopulation(t) = \min[TotalPopulation, AverageAffectedPerEvent \times Extreme]$$

where

$$AverageAffectedPerEvent = BaseAffectedPerEvent \times (1 + Intensity\ Sensitivity \times Extreme)$$

where $Intensity\ Sensitivity$ captures the extent to which increasing event intensity expands the affected population and therefore increases perceived personal exposure (Text S1, Table S1). The corresponding $Exposure\ Share$ is then:

$$ExposureShare(t) = \frac{AnnualAffectedPopulation(t)}{TotalPopulation} \quad (20)$$

$Susceptibility\ Raw(t)$ is represented using a logistic response function to capture threshold and saturation effects in responses to increasing climate exposure. This

formulation reflects the assumption that perceived vulnerability responds weakly to low levels of exposure, increases more rapidly beyond a critical threshold, and gradually approaches saturation at high levels of exposure.:

$$Susceptibility\ Raw(t) = \frac{L}{[1 + \exp(-K(ExposureShare(t) - X^0))]} \quad (21)$$

where *Susceptibility Raw(t)* represents the immediate cognitive appraisal of personal vulnerability derived from population exposure to extreme-weather events while the parameters have analogous interpretations to those described in *Severity Raw(t)*.

As with perceived severity, susceptibility is assumed to adjust gradually rather than instantaneously. The *Perceived susceptibility* is therefore calculated as:

$$Perceived\ susceptibility(t) = SMOOTH[Susceptibility\ Raw(t), Perception\ delay] \quad (22)$$

Overall *Perceived Threat* is represented as a weighted combination of *Perceived severity* and *Perceived susceptibility*:

$$Perceived\ threat(t) = w * Perceived\ severity(t) + (1 - w) * Perceived\ susceptibility(t) \quad (23)$$

where parameter $w \in [0,1]$ captures the relative importance of severity over susceptibility in shaping threat appraisal (weighted severity, Text S1, Table S1).

Perceived threat not only reflects cognitive risk appraisal but also evokes emotional responses⁵². In the context of climate change, this emotional response is represented here as climate anxiety.

Cognitive and emotional response. Climate anxiety arises as the emotional response arising from perceived climate risk³¹, here reflecting individuals' emotional reaction to both the potential severity of climate impacts and their personal susceptibility to these impacts (*Perceived threat(t)*). Empirical studies have consistently shown that individuals who perceive climate change as more severe or personally threatening are more likely to experience elevated levels of climate-related anxiety⁵³. Consistent with EPPM, the relationship between perceived threat and anxiety is nonlinear: low perceived threat generates negligible emotional response, moderate threat triggers a rapid increase in anxiety, and very high threat leads to saturation^{43,54}. Based on the

theoretical and empirical evidence, climate anxiety is modeled as nonlinear saturating function of *Perceived threat*(*t*)³²:

$$ClimateAnxiety(t) = SCA * \frac{L}{1 + \exp[-k * (Perceived\ threat(t) - X_0)]} \quad (24)$$

where *L* denotes the maximum level of anxiety, *k* controls the steepness of the response curve, and *X*₀ represents the threshold at which climate anxiety begins to increase sharply. *SCA* scales affective responsiveness. This formulation captures the empirical observation that emotional responses to climate change do not increase linearly with perceived risk but instead exhibit threshold and saturation behavior.

While climate anxiety provides motivation for action, behavioral responses also depend on whether individuals believe that effective action is possible²¹. Here, efficacy is represented through perceived behavioral control (PBC), which combines perceptions of personal capability and perceived effectiveness of climate actions. Specifically, PBC is calculated using a harmonic mean of *PAC* and *CAC*:

$$Efficacy = \frac{2}{\frac{1}{PAC} + \frac{1}{CAC}} \quad (25)$$

The harmonic mean ensures that low values in either component constrain overall efficacy⁴³. Consequently, individuals are unlikely to feel capable of addressing climate change when either personal capability or confidence in collective action remains low.

Climate anxiety is generated from perceived threat, as described above, and combines with PBC to determine the probability of pro-environment or maladaptive behavior^{15,21}. Following EPPM⁴³, we distinguish four behavior states: high climate anxiety-high PBC (*HcaHpbc*), high climate anxiety-low PBC (*HcaLpbc*), low climate anxiety-high PBC (*LcaHpbc*), and low climate anxiety-low PBC (*LcaLpbc*). The weight of each state is computed using threshold-based multiplicative rules:

$$W_{HcaHpbc} = CA_{threshold} * PBC_{threshold} \quad (26)$$

$$W_{HcaLpbc} = CA_{threshold} * (1 - PBC_{threshold}) \quad (27)$$

$$W_{LcaHpbc} = (1 - CA_{threshold}) * PBC_{threshold} \quad (28)$$

$$W_{LcaLpbc} = (1 - CA_{threshold}) * (1 - PBC_{threshold}) \quad (29)$$

where *CA*_{threshold} and *PBC*_{threshold} denote the relatively high social climate anxiety

and PBC, respectively, with percentile-based and fixed forms (Text S8). These weights are subsequently normalized so that the four behavioral states collectively represent the entire population.

:

$$TotalW = \sum W_i \quad (30)$$

$$Wn_i = \frac{W_i}{TotalW} \quad (31)$$

Adaptive behavior is most likely when individuals simultaneously perceive substantial threat and believe effective action is possible according to empirical evidence^{21,43,55}. Accordingly, the HcaHpbc group is assumed to generate pro-environmental responses. The probability of pro-environmental behavior (*ProHH*) is represented by

$$ProHH(t) = \frac{L}{1 + \exp[-K(ProCAHH * ClimateAnxiety(t) + (1 - ProCAHH) * PBC) - X_0]} \quad (32)$$

where ProCAHH controls the relative influence of SCA compared with PBC.

In contrast, individuals experiencing high anxiety but low efficacy are expected to exhibit fear-control responses, including avoidance, fatalism, or maladaptive behavior⁵⁶. The probability of maladaptive behavior (*MalHL*) is therefore calculated for the HcaLpbc group as.

$$MalHL(t) = \frac{L}{1 + \exp[-K(MalCAHL * ClimateAnxiety(t) + (1 - MalCAHL) * PBC) - X_0]} \quad (33)$$

where *MalCAHL* determines the relative contribution of climate anxiety.

The remaining behavioral states are assumed to contribute minimally to environmental action because either motivation (climate anxiety) or efficacy is insufficient. Individuals with high anxiety but low PBC (HcaLpbc) experience learned helplessness, limiting proactive action; low-anxiety individuals (LcaHpbc, LcaLpbc) lack sufficient motivation to change behavior⁵⁷. Therefore, their probabilities are set to small fixed values (0.01–0.05), effectively negligible in the net pro-environmental response.

Aggregating across all behavioral states yields the population-level probabilities of pro-environmental (P_{pro}) and maladaptive behavior (P_{Mal}):

$$P_{pro}(t) = ProHH(t) * Wn_{HcaHpbc} + \text{small fixed contributions from other states} \quad (35)$$

$$P_{Mal}(t) = MalHL(t) * Wn_{HcaLpbc} + \text{small fixed contributions from other states} \quad (36)$$

The net behavioral outcome is then defined as:

$$BehaviorChange(t) = P_{pro}(t) - P_{mal}(t) \quad (37)$$

Positive values of $BehaviorChange(t)$ indicate a predominance of pro-environmental responses, whereas negative values indicate that maladaptive responses dominate.

$BehaviorChange(t)$ is endogenously translated into emissions dynamics by modulating the rate of anthropogenic CO₂ emissions. Specifically, the net behavioral outcome ($BehaviorChange(t)$)—defined as the difference between pro-environmental and maladaptive actions—enters the climate system as an emissions intensity factor with an inverse sign:

$$Emissions\ Intensity\ Factor(t) = -BehaviorChange(t) \quad (38)$$

This formulation ensures that increases in pro-environmental behavior reduce emissions, whereas maladaptive responses amplify them. Rather than directly altering emissions levels, $Emissions\ Intensity\ Factor(t)$ operates on the rate of emissions change, allowing behavioral influences to unfold gradually over time. After a specified coupling start time, the annual rate of CO₂ emissions change is given by

$$\frac{dE}{dt} = \begin{cases} 0, & t < t_{start} \\ \alpha * Emissions\ Intensity\ Factor(t) * (E - E_{min}), & t \geq t_{start} \end{cases} \quad (39)$$

Where α represents the maximum annual emissions adjustment rate. This parameter is introduced to capture the limited speed at which behavioral changes can be translated into real-world emissions reductions, reflecting infrastructural inertia, technological lock-in, and policy implementation delays. The value of $\alpha=0.5\ yr^{-1}$ implies that, at most, 50% of the remaining emissions gap relative to the minimum emissions level can be adjusted within one year under strong behavioral pressure. This choice reflects a moderate-to-high responsiveness regime, consistent with empirical observations that rapid emissions reductions are possible under strong societal and policy mobilization, yet remain bounded by physical and institutional constraints⁵⁸.

E_{min} denotes the minimum achievable emission level, the inclusion of which reflects

the fact that a fraction of emissions is structurally difficult to eliminate due to hard-to-abate sectors, such as heavy industry, aviation, agriculture, and legacy infrastructure. The value of $E_{min} = 5 \text{ GtCO}_2 \text{ yr}^{-1}$ chosen to represent a lower-bound residual emissions level consistent with mitigation pathway literature⁵⁸. Scenario assessments indicate that only a small fraction of pathways achieve residual emissions below 5 GtCO₂ at the net-zero stage, corresponding to more than 10% of current global CO₂ emissions⁵⁸. In addition, a moderate value is adopted to ensure comparability across scenarios, as excessively high values would cause emissions trajectories under SSP1-2.6 to converge prematurely toward the lower bound, thereby suppressing behavioral effects and reducing the contrast with higher-emission pathways (e.g., SSP2-4.5 and SSP5-8.5). This choice therefore balances empirical realism with the need to preserve meaningful differentiation in system dynamics across scenarios. E denotes baseline fossil fuel and industrial CO₂ emissions obtained from the IIASA SSP Database for SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios⁵⁹. The term $(E - E_{min})$ therefore captures the remaining reducible emissions space, ensuring that the effect of behavioral change diminishes as emissions approach structural limits.

The behavioral influence accumulates over time through integration of the emissions change rate:

$$\Delta E_{cum} = \int \frac{dE}{dt} dt \quad (40)$$

This cumulative modification is then added to baseline emissions trajectories under each SSP scenario to produce behavior-adjusted emissions pathways:

$$EmissionChange = E + \Delta E_{cum} \quad (41)$$

This formulation enables emissions to evolve as a function of both exogenous SSP trajectories and endogenous behavioral feedbacks, yielding bounded, path-dependent, and temporally lagged emissions dynamics that link psychological processes to long-term climate outcomes.

Simulation scenario design. To systematically evaluate the influence of behavioral responses on climate outcomes and to identify the mechanisms driving uncertainty in future projections, three groups of simulation experiments are conducted using the

coupled human–climate model.

The first experiment (Experiment I) quantifies the range of climate outcomes that emerge from uncertainty in behavioral responses under three SSPs (SSP1-2.6, SSP2-4.5, SSP5-8.5) and two evaluation horizons (2050, 2100). For each scenario, key behavioral parameters are systematically varied across the uncertainty ranges (Text S1, Table S1, Figure S2). A full-factorial experimental design is adopted, generating 186,624 parameter combinations for each SSP scenario. Model outputs are subsequently evaluated at both 2050 and 2100. In total, Experiment I comprises 559,872 simulations ($186,624 \times 3$), yielding six scenario–time ensembles for subsequent analysis. These ensembles characterize the uncertainty envelope of future temperature outcomes arising from variation in behavioral-response mechanisms.

The second experiment (Experiment II) evaluates the relative contribution of uncertain model parameters to variability in projected temperature outcomes. A variance-based global sensitivity analysis is performed using Sobol decomposition²⁶. The base sample size is set to $N = 1500$. With $P = 13$ uncertain parameters, the total number of model evaluations for each scenario–time combination is $N(2P + 2)$, resulting in 42,000 simulations⁶⁰. Sensitivity analysis is then conducted for the same six scenario–time combinations for a total of 252,000 simulations ($42,000 \times 6$). Random forest regression and regression tree analyses^{61,62} are further performed using the complete simulation ensembles generated in Experiment I. For each scenario–time combination, all 186,624 simulations are used as the analysis dataset.

The third experiment (Experiment III) examines the consequences of delayed behavioral responses for long-term climate outcomes. Human–climate feedbacks are activated at three alternative intervention years (2010, 2020, 2030). For each intervention year, simulations are performed under the three SSP pathways. The same factorial parameter design used in Experiment I is applied to each intervention-year–scenario combination, generating 186,624 simulations per experiment. Consequently, Experiment III produces 1,679,616 simulations ($186,624 \times 9$). Comparisons across intervention years isolate the climatic consequences of delayed behavioral engagement

and quantify how postponing collective responses influences future emissions trajectories and temperature outcomes under different socioeconomic futures.

Across all experiments, a total of 2,491,488 model simulations are conducted (559,872 scenario ensemble simulations, 252,000 sensitivity-analysis simulations, and 1,679,616 intervention-timing simulations), providing a comprehensive assessment of uncertainty, parameter importance, and behavioral intervention timing within the coupled human–climate system.

Sobol Analysis.

We conduct a variance-based global sensitivity analysis using Sobol decomposition to quantify how uncertainty in model parameters contributes to the variance in projected temperature outcomes²⁶. Sobol methods are widely used in nonlinear, high-dimensional systems because they decompose output variance into contributions from individual parameters and their interactions²⁶. Within this framework, we compute two key sensitivity measures: first-order Sobol indices (S1), which represent the independent contribution of each parameter to output variance, and total-order Sobol indices (ST), which represent the combined contribution of each parameter including all interaction effects with other parameters²⁶ (Text S2). An S1 value close to zero indicates negligible direct influence, while ST captures the overall importance of a parameter in driving output variability through both direct and interaction effects. Second-order interaction indices are not estimated due to computational constraints and the dimensionality of the parameter space; instead, interaction effects are further explored using a complementary machine learning approach described below.

We apply the Sobol framework across all scenario–time combinations to identify parameters that contribute most to uncertainty in temperature change relative to pre-industrial level, which is used as the primary outcome variable because it integrates cumulative emissions over time and avoids boundary effects that emerge when emissions trajectories approach lower constraints. For each parameter, we estimate both independent effect (S1) and combined effect (ST) under each scenario. To support

interpretation and screening of influential parameters, we use commonly adopted heuristic thresholds from the literature, where S1 values above approximately 0.02 indicate non-negligible direct effects and ST values above approximately 0.1 indicate substantial overall influence including interactions (Figure S2). These thresholds are used as descriptive guidelines rather than strict decision rules, helping to identify parameters with consistent influence across scenarios. Across the six scenario–time combinations, a subset of behavior-related parameters consistently exhibits non-negligible sensitivity indices, including PAC, CAC, SCA, weighted severity, memory retention factor, and memory window.

To further explore interaction structures among these influential parameters, we construct a full factorial combination of the selected parameters to generate a comprehensive scenario grid. This grid is implemented through batch sensitivity simulations using Vensim software, with emissions and transformation switches configured according to each SSP scenario specification. Model outputs, specifically temperature change relative to preindustrial levels, are extracted and processed for subsequent analysis of patterns and interactions among key behavioral drivers.

Random forest and regression tree. To further quantify the relative importance of parameters and to characterize nonlinear interaction structures affecting temperature change, we apply both Random Forest regression and regression tree analysis^{61,62}. These methods provide a complementary, data-driven extension to the variance-based Sobol framework by capturing complex nonlinear relationships and higher-order interactions without requiring explicit model specification.

Random Forest regression is used as an ensemble learning approach that aggregates predictions from multiple decision trees to estimate the influence of each parameter on temperature outcomes. Within this framework, parameter importance is quantified using the %IncMSE metric, which measures the increase in prediction error when a given variable is permuted⁶¹. Higher values indicate stronger contributions to predictive accuracy and therefore greater influence on temperature variability. In parallel, regression tree analysis is used to provide an interpretable, hierarchical

representation of parameter interactions. The tree structure recursively partitions the data based on parameter thresholds that minimize within-node variance in temperature outcomes, thereby revealing dominant splitting variables and interaction pathways. For each scenario–time combination, analyses are conducted using the complete simulation ensemble generated in Experiment I.

Regression trees are visualized using customized node coloring to distinguish high versus low temperature outcomes⁶². Each node is annotated with the mean temperature response, the number of samples, and the proportion of observations contained within that node. This visualization supports direct interpretation of how combinations of parameters partition the outcome space and where nonlinear thresholds or interaction effects emerge.

These methods provide a complementary analytical layer to the Sobol-based global sensitivity analysis by identifying dominant predictors and revealing structured interaction pathways that shape temperature responses under different behavioral and scenario assumptions.

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Declaration of competing interest

The authors declare no conflicts of interest relevant to this study.

Data and code availability:

All data and codes used in this study are available at <https://doi.org/10.5281/zenodo.20795755>.

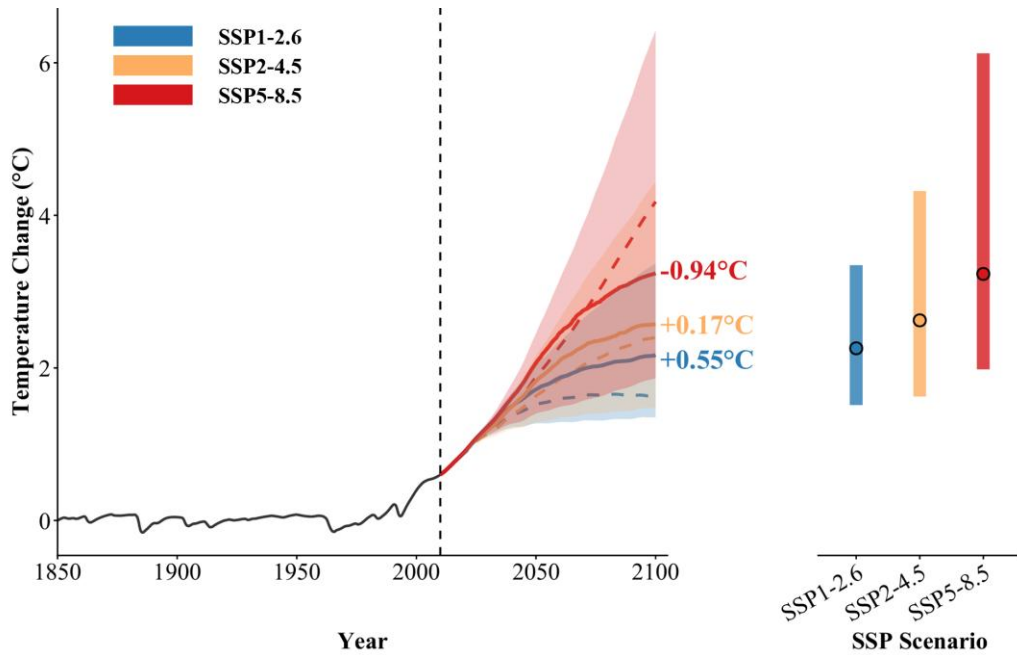


Fig. 2 Temperature trajectories under gradual adjustment of emissions by human behavior across SSP scenarios. The left panel illustrates global mean temperature change relative to the 1850 baseline. The black line represents the no-response baseline prior to 2010. Colored dashed lines indicate the continuation of the no-response baseline after 2010, while colored solid lines show the median (P50) temperature trajectories incorporating human behavioral responses under SSP1-2.6 (blue), SSP2-4.5 (orange), and SSP5-8.5 (red). Shaded areas represent the interquartile range (25th - 75th percentiles). Annotated values indicate the differences between the median simulated temperatures and the corresponding baseline. The right panel summarizes temperature outcomes in 2100 across scenarios. Black circled markers denote median temperatures, while colored bars indicate the interquartile range (5th - 75th percentiles) for each scenario. The figure shows human behavior introduces scenario-dependent deviations in temperature trajectories, highlighting that future warming is shaped by both physical processes and socio-psychological feedbacks.

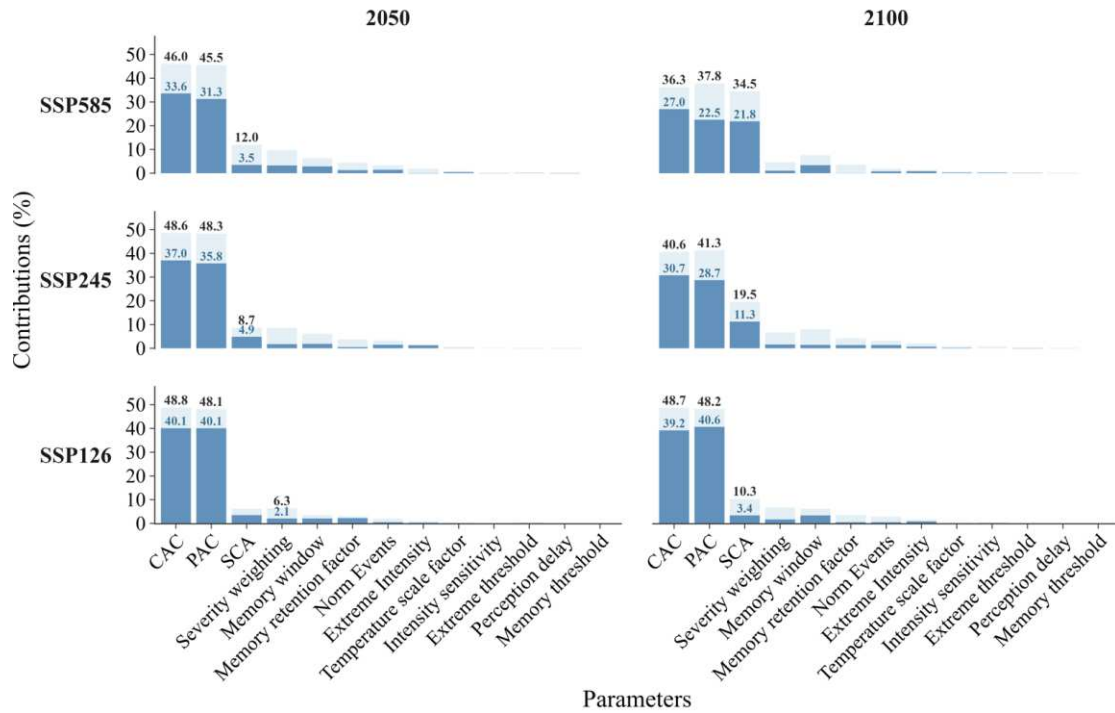


Fig. 3 Sensitivity of projected temperature to human behavioral parameters across SSP scenarios. Contributions of 13 behavioral parameters to temperature variability are quantified using Sobol global sensitivity analysis under SSP5–8.5, SSP2–4.5, and SSP1–2.6 for 2050 and 2100. Light blue bars denote combined effects (ST), while dark blue segments indicate independent effects (S1). Across all scenarios and time horizons, PAC, CAC, and SCA dominate the variance contribution, with memory window, memory retention factor, and severity weighting also playing significant roles.

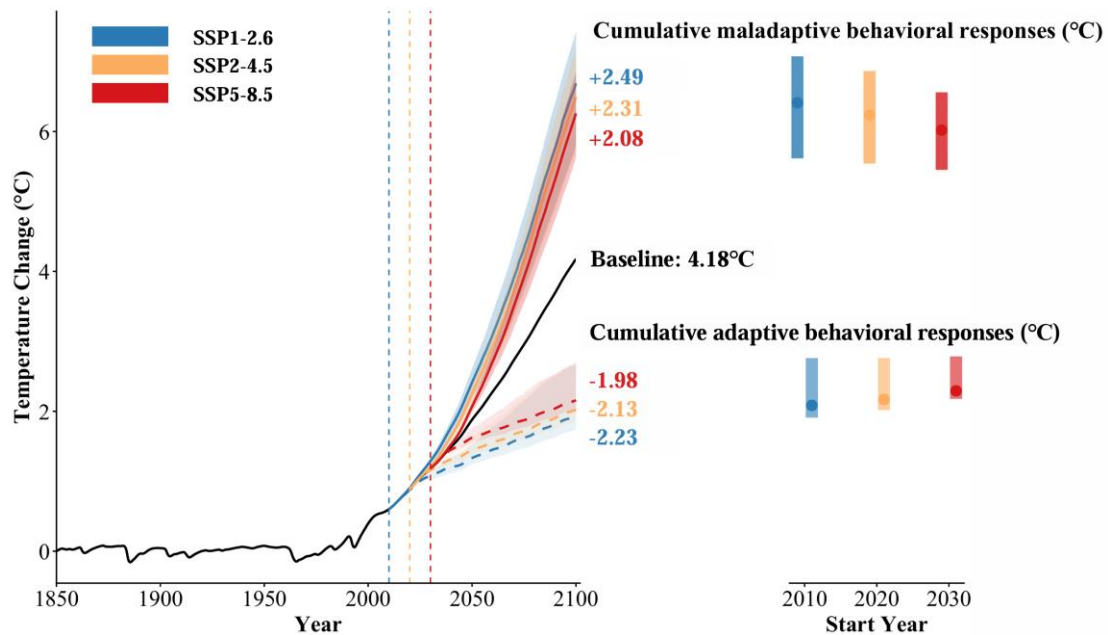


Fig. 4 Warming and cooling trajectories under different behavioral coupling start year (2010, 2020, 2030) in the SSP5-8.5 scenario. Behavioral responses are introduced into the coupled system at different start years (2010, 2020, and 2030), with all simulations run to 2100. In the left panel, the black line before 2010 represents the no-response baseline temperature change from preindustrial. Projected temperature changes are decomposed relative to no-response baseline into two components: values above the baseline (solid lines), representing additional warming driven by cumulative maladaptive behavioral responses, and values below the baseline (dashed lines), representing cooling driven by cumulative adaptive behavioral responses. Colors indicate the coupling start year (blue: 2010; orange: 2020; red: 2030), and vertical dashed lines mark the corresponding initiation times. Bars in the right panel summarize temperature deviations from the baseline in 2100, separating warming and cooling contributions for each start year. The figure demonstrates that the timing of behavioral responses critically shapes long-term climate outcomes, with earlier responses amplifying both warming from maladaptive behaviors and cooling from adaptive behaviors through cumulative feedbacks.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [20260707SIHumanbehavioralresponsestoclimatechangereshapeclimateprojections.pdf](#)