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Title: Reversal of the impact chain for actionable climate information

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Abstract
Escalating impacts of climate change underscore the risks posed by crossing potentially irreversible thresholds for parts of the Earth system, socio-ecological systems, and adaptation limits. However, limitations in the provision of actionable climate information may hinder an adequate response. Here, we suggest a reversal of the traditional impact chain methodology as an end-user focused approach linking specific climate risk thresholds, including at the local level, to emission pathways. We outline the socio-economic and value judgment dimensions that can inform the identification of such risk thresholds. We apply this approach to heat-mortality risks in the city of Berlin. To limit the likely maximum increase in the occurrence of heat days with expected health impacts to less than 50% compared to today, the remaining global carbon budget in 2020 is 700 Gt CO2. We argue that linking risk threshold exceedance

directly to global emission benchmarks can aid the understanding of the benefits of stringent emission reductions for societies and local decision-makers.

Introduction

As climate change progresses with unprecedented local impacts emerging around the globe (Satoh et al. 2022; Robinson et al. 2021; King et al. 2016; Ranasinghe et al. 2021; Frölicher et al. 2016), local decision makers need targeted information to make evidence based decisions on adaptation planning (Hemmati, Kornhuber, and Kruczkiewicz 2022; Theokritoff et al. 2023; Theokritoff and Lise D'haen 2022). There is an ever-increasing availability of climate change information and, although some regions are systemically understudied (Otto et al. 2020; Callaghan et al. 2021), it is often not the lack of research that limits evidence based decision making (Goosen et al. 2014). In fact, recent studies indicate that access to climate services and information was one of the most important factors that enabled the adoption of different adaptation strategies (Obsi Gemeda, Korecha, and Garedew 2023). This apparent contradiction underlines that research does not systematically generate information in a format that makes it directly actionable, hence qualifying its provision as a climate service as per the WMO definition.

A key challenge to engage with climate information actually lies in the fact that it requires substantial domain knowledge (Weichselgartner and Arheimer 2019). Traditionally -- what we here call the *forward impact modeling chain* -- local impacts are estimated from simulations forced by a small set of predefined global emission scenarios or concentration pathways. This typically results in a wide uncertainty range of potential local impacts, which often leaves planners without actionable climate information (Capela Lourenço et al. 2019). Despite progress in moving adaptation governance away from 'predict, plan, act' and toward adaptive governance (Lempert et al. 2004), a large uncertainty range of potential future impacts can be difficult to take up in local planning processes.

Global emission or concentration scenarios are often based on the ScenarioMIP framework that also provides the basis for the presentation of scenario dependent emergence of climate impacts drivers in the 6th Assessment Report (AR6) of the Working Group 1 (WG1) of the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2021b). These pathways are motivated by a range of scientific considerations, but are not easily accessible for a non-expert audience. For example, it is not easy to deduce the warming outcomes from the set of pathways, or select the pathway that most closely resembles the best estimate of what a 'current policy' scenario would look like. One common way to address the challenge of scenario selection for adaptation planning is to focus on 'worst outcome' high or very high warming pathways (O'Neill et al. 2020; Hausfather and Peters 2020). While taking the strongest forcing seems like a reasonable choice to ensure the inclusion of high risk outcomes, it might actually only be partly the case. On adaptation relevant timescales, i.e. up to 2050, model uncertainty and natural variability often dominate over scenario uncertainty on the regional to local level (Lehner et al. 2020; Hawkins and Sutton 2009). A large ensemble size as well as model diversity are thus key to estimate high-end climate risks on the local level (Sippel et al. 2015; Kim et al. 2020). Ultimately, comparing the evolution in climatic impact-drivers between emission scenarios does not necessarily align with the questions asked by practitioners and thus might limit the usability of the research.

Here we introduce a novel approach for intuitively linking projected impacts at the local scale with associated global mitigation trajectories. Using a *reversed impact chain*, we take an innovative perspective on uncertainty propagation, taking the local climatic impact-driver as a starting point (see figure 1 - physical reversal). Climatic impact-drivers (CIDs) as defined in IPCC (2021a) are physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems. We then estimate uncertainties in the required emission reductions that would be needed to avoid global temperature trajectories that lead to that particular change in a climatic impact-driver of interest. This way we provide the required information to link relevant changes in climatic impact-drivers to implied global warming levels and the required emission reductions that would avoid these changes. We argue that this approach would also help to directly compare local impacts with mitigation efforts, leading to potential significant gains in the monitoring and evaluation (M&E) of adaptation efforts (Leitner et al. 2020) and their success (Dilling et al. 2019).

Different perspectives on the impact chain

State of the art climate research is based on observations and process based Earth System Models (ESM) that simulate changes in the Earth system assuming different anthropogenic emission and land-use change scenarios. These models are based on physical laws of fluid dynamics, thermodynamics and radiative transfer as well as parametrizations of complex and small-scale processes such as chemical processes in cloud formation or biological processes in the ocean or on land. The usual forward modeling is well justified as it follows our physical understanding of the problem from an earth science and causal perspective.

Alternative perspectives on changes in the climate system have been used in the literature. Most prominently, a focus on global warming levels above pre-industrial levels (Figure 1 - “Focus on global warming levels”) has emerged to inform climate policy under the Paris Agreement long-term temperature goal (Schleussner, Lissner, et al. 2016; Schleussner, Rogelj, et al. 2016). Other scholars have suggested extending such approaches to more regional and impact related climate targets (Seneviratne et al. 2016; Cheung, Reygondeau, and Frölicher 2016; Frölicher, Fischer, and Gruber 2018; Fischer and Knutti 2015).

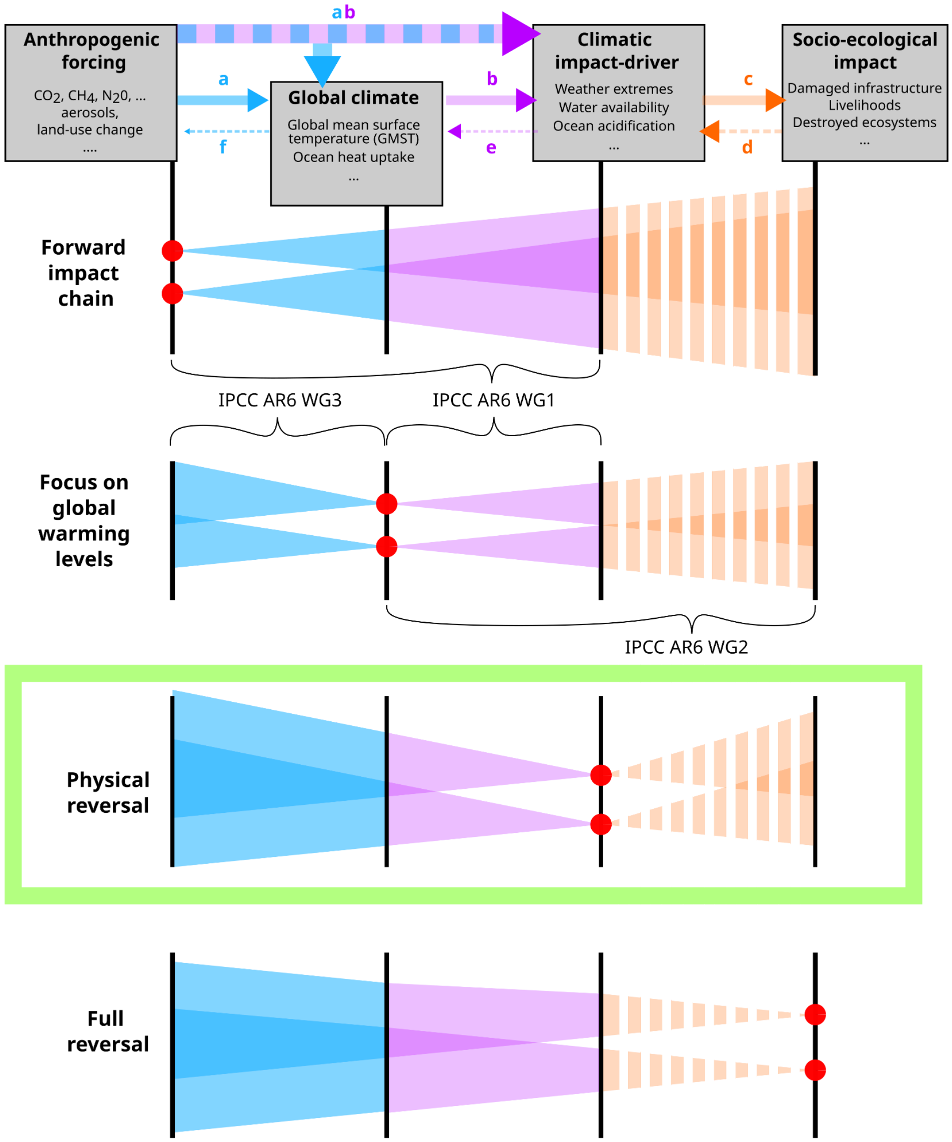

Fig. 1: Schematic of the impact chain from anthropogenic forcing through global climate and climatic impact-drivers towards socio-ecological impacts (from left to right). The width of arrows between parts of the chain (gray squares) indicate the degree to which research has focused on modeling the relationship between each of them, for both directions. Table 1 lists some available tools for each of the steps (letters and arrows). Below, the uncertainty propagation is schematically represented for different starting points (red dots) in the modeling chain. Forward impact chain: starting from a clearly defined emission scenario (upper left). Focus on global warming levels: partitioning the impact chain at global mean surface temperatures (lower left). Physical reversal: starting from a climatic impact-driver (upper right). Full reversal: starting from a socio-economic impact (lower right). Socio-ecological impacts depend on the climatic impact-driver but also on exposure and vulnerability which includes uncertainties of a different nature, indicated by dashed orange uncertainty propagation from climatic impact-driver to socio-economic impacts.

The Sixth IPCC Assessment Report (AR6) Working Group 1 (WGI) utilizes the forward impact chain to assess the evolution of the global climate system as well as climatic impact-drivers for different representative greenhouse gas concentration pathways (RCPs) coupled with shared socio-economic pathway combinations (SSPs) (IPCC 2021c). The SSPs represent socio-economic storylines that Integrated Assessment Models (IAMs) transform into emission scenarios with a RCP (or an equivalent forcing or warming level) as climate target. Additionally, global warming levels were chosen to present selected climatic impact-drivers in WGI, and to address some of the challenges that have emerged with the forward modeling chain such as the "hot model" problem - a sizeable number of CMIP6 climate models having higher climate sensitivity than is supported by observational constraints or process-based understanding, leading to raw projections being potentially biased warm (Tokarska et al. 2020; Hausfather et al. 2022). Global warming levels were also the main reference for presenting climate risks in the Working Group II, including as part of the iconic Reasons for Concern framework (B. O'Neill et al. 2022). Working Group III then assesses the required reduction in greenhouse gas emissions to avoid exceedance of such warming levels with a certain probability (IPCC 2022b). This approach to classify emission pathways according to their likelihood of avoiding certain warming levels already represents a limited reversal of the impact chain from global warming levels back into emission space.

Here we propose to extend this concept further to the local level by estimating emission reductions that are required to avoid specific climatic impact-drivers ("Physical reversal" in Figure 1).

A local risk perspective

Adaptation practitioners and policy-makers need to use climate information for their work. However, they are often lacking access to robust local-scale information, or may lack the scientific expertise to draw adequate conclusions from the information already available (Sultan et al. 2020; Weichselgartner and Arheimer 2019). It is therefore crucial to make climate change information available in a format that can be easily integrated into local planning and policy work. Precise information on future high impact events such as weather extremes would be most relevant for local adaptation planning (Kropf et al. 2022), however, these can only be estimated within the limits of uncertainties in global climate models representing local conditions and require sufficient ensemble sizes in order to resolve tail risks (Beusch et al. 2022). In addition, even though we are capable of predicting climate impacts from future emission pathways with their uncertainties, the future global societal changes determining these pathways are only a subset of all potential futures.

Reversing the impact chain does not reduce the uncertainties along the impact chain, but reframes the problem in a way that can be useful for local decision-making. This framing starts from a relatable entry point for local decision-makers -- local climatic impact -- and redirects uncertainties as the envelope of global emissions quantities that would be consistent with the impact tolerance. In that way, the reversed impact chain can be an effective point of engagement between climate impact modeling and local adaptation planning. It further draws attention to global emissions and actions to reduce them, as higher emission scenarios most probably will see a greater increase in the chance of an unwanted local impact and therefore this framing offers potential to become an important science communication tool.

Towards identifying critical risk levels

The reversal of the impact chain builds on and extends approaches that focus on emission pathway classification following their global mean temperature outcome (Harrington, Schleussner, and Otto 2021; IPCC 2022a). The choice of a global temperature threshold and the associated avoidance probability is supported by a comprehensive risk assessment that has informed policy choices reflected in the long-term temperature goal of the Paris Agreement (UNFCCC 2015).

In the case of tipping points and irreversible changes in the climate system the identification of critical risk levels is rather straightforward (Armstrong McKay et al. 2022): the disappearance of cryospheric systems such as permafrost, peatlands, glacier, or parts of ice sheets, or unique ecosystems such as coral reefs or primary forests is clearly a risk to avoid (Kloenne et al. 2023). In such cases the main challenge is to characterize the geophysical conditions that would lead to such irreversible changes.

For societal impacts, the identification of critical risk thresholds is more challenging. Risks and impacts of climate change emerge from the interplay of climate hazards with vulnerability and exposure of human and natural systems, and future risks profoundly depend on assumptions about the evolution of these factors even on the global level (H.-O. Pörtner et al. 2022; Harrington, Schleussner, and Otto 2021). On the local level, assumptions on the evolution of vulnerability and exposure are even more dominant (Kropf et al. 2022).

The evolution of socio-economic factors, such as population growth and economic development, is largely independent of the future emission trajectories (Riahi et al. 2017). The evolution of different climate and socio-economic futures is therefore commonly explored in a matrix approach, based on the Shared Socioeconomic Pathways concept (B. C. O'Neill et al. 2016). Similarly, the evolution of different socio-economic futures cannot be meaningfully included in an approach that reverses the impact chain in the emission space. However, the socio-economic context provides the basis to identify critical risk levels that allow for the reversal of the impact chain (based on locally determined climatic impact-drivers). For example, heat related mortality strongly varies between cities around the world, with significant increases in mortality emerging for temperatures above 20°C for the city of Oslo, and only well above 30°C for Manila (Vicedo-Cabrera et al. 2021). Similarly, regional impacts of flooding very strongly depend on the exposure as well as the adaptation measures in place (Dottori et al. 2018).

Limits to adaptation are particularly relevant for identifying critical risk levels (B. O'Neill et al. 2022). The most recent IPCC AR6 WGII distinguishes between hard limits, where no further adaptation is possible (often linked to biophysical properties of systems such as thermal tolerance windows of species), and soft limits, where adaptation options are currently not available but may become in the future (such as lack of finance or weak governance hindering the implementation of an adaptation project) (A. Thomas et al. 2021). In the urban context, for example, a hard adaptation limit could occur if the thermal tolerance window of urban tree species is exceeded, one of the most prominent options for ecosystem based urban adaptation (Esperon-Rodriguez et al. 2022). Identification of such limits to adaptation can provide a very concrete starting point for the reversal of the impact chain approach.

The identification of critical risk levels for the reversal of the impact chain is thus informed by a number of considerations, going well beyond the climatic description of the hazard and the impacts it may produce (see Figure 2). Both the socio-economic context and respective system thresholds as well as limits to specific adaptation options need to inform the identification of critical risk levels. This may not always be possible based on quantitative data alone, in which case expert elicitation methods need to be deployed. Beyond that, certain value judgements about acceptable risk levels and time horizons of interest for specific impacts are required. Critical attention is needed on inequalities in climate impacts -- that the poor are disproportionately affected by climate change, and that climate change can exacerbate poverty (Hallegatte et al. 2016).

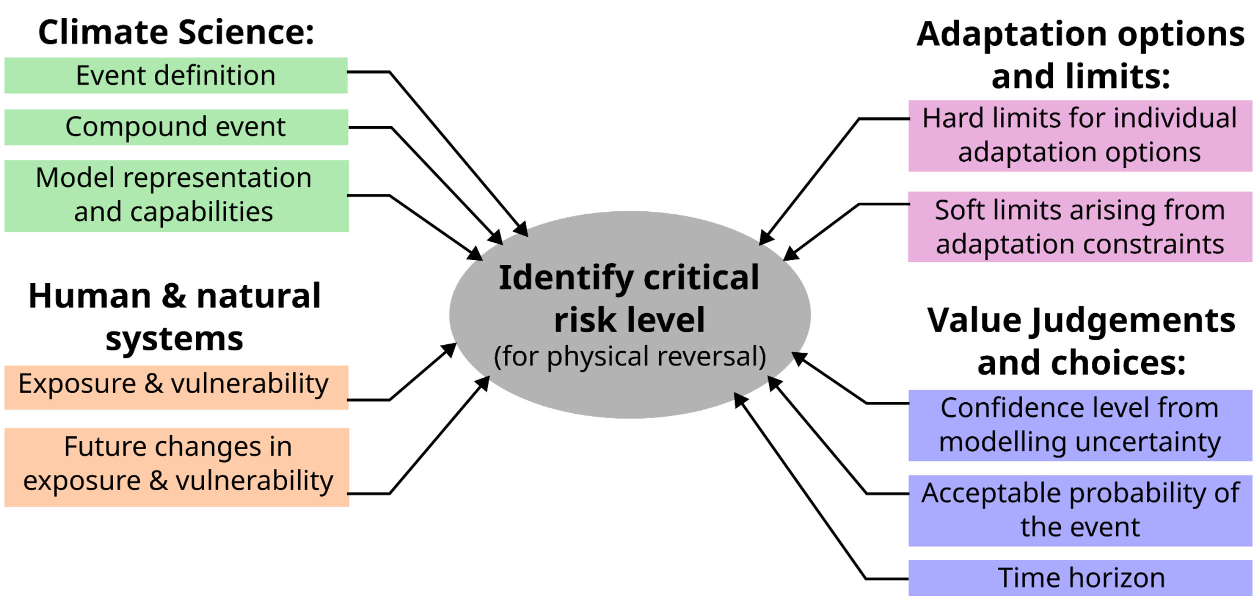

Figure 2: Considerations to take into account when defining a critical risk level for climatic impact-drivers.

Multi-hazard risks, so-called compound events, are significant drivers of climate risks (Zscheischler et al. 2018). Capturing them in local risk assessments is therefore of critical importance. The reversal of the impact chain approach allows for a multi-dimensional event definition thereby directly catering to the need of identifying the most impact relevant climate risks. This allows for applying stress testing approaches to identify climate risks and develop scenarios of local adaptation planning (Albano et al. 2021).

Implementing impact chain reversal

In the *reversed impact chain,* we model from the effect (climatic impact-drivers, such as daily temperatures) to the cause (emissions). This can be achieved by using innovative ESM experiment designs or relying on indirect approaches making use of simplifications, statistical models and machine learning approaches. Innovative climate modeling frameworks have emerged over recent years, such as Adaptive emission reduction approach AERA (Terhaar et al. 2022), Adjusting Mitigation Pathways (AMP) (Goodwin et al. 2018) and Pathfinder (Bossy, Gasser, and Ciais 2022), but they do not yet complete the full modeling chain from climatic impact-drivers to emissions.

There are two overarching approaches to the problem:
1) Implement a simplified and efficient forward modeling chain to create a lookup table with impact probabilities for a comprehensive set of possible emission scenarios.
2) Combine tools that allow to reverse parts of the impact chain.

For both options, one can build on existing tools that have been developed to model individual steps of the impact chain in the forward as well as in the backward direction (Table 1). Modeling physical consequences of increased greenhouse gas concentrations (line ab in Table 1) has been a main focus of the climate science community and a number of ESMs exist and are further developed. Furthermore, Earth system models of lower complexity have also been developed to allow longer simulations or more ensemble members. When partitioning the impact chain, global mean temperature (GMT) levels are a commonly used divider and Simple Climate Models (SCMs) that mainly simulate GMT for given emissions (line a in Table 1) as well as ESM emulators that model local climate signals for a given GMT level (line b) have been developed. Finally, there are a number of models that allow us to assess the societal as well as ecological impacts for given climatic impact-drivers (line c). In these models, the climatic impact-driver is only one input besides exposure and vulnerability (Warszawski et al. 2014).

For the first approach, existing tools (Table 1) can be combined to efficiently simulate changes in climatic impact-drivers for a large number of emission scenarios. For instance, coupling a simple climate model (SCM) with Earth system model emulators allows to create climate projections orders of magnitudes faster than ESMs (Beusch et al. 2022). In the example box (figure 3) we use the SCM FaIRv1.6 (C. J. Smith et al. 2018) to simulate GMT for given emissions and a conditional normal distribution to estimate the probability of exceeding a daily temperature threshold in Berlin (see Methods). Depending on the climatic impact-drivers such methods can work well and can be implemented relatively easily.

Different approaches have been developed to create emission scenarios that stabilize global mean temperatures at a desired level (e.g. Adaptive emission reduction approach (AERA), Adjusting Mitigation Pathways (AMP), Pathfinder see table 1 row f). These methods can estimate emission pathways that eventually stabilize GMT at a chosen level and thereby help to reverse the first part of the impact chain going from emissions to GMT.

Combining these methods with an estimate of GMT levels for which a change in climatic impact-driver could be avoided would be an option for implementing approach 2). So far, little effort has been put in estimating emission limits that would avoid a local climatic impact-driver but we expect that with, for example, developments in new emulators, potentially including machine learning techniques, the implementation of a *reversed impact chain* could become a practicable framework for analyzing local climate impacts.

Table 1: Available tools to estimate parts of the impact chain. Each line corresponds to one modeling step following the labeling and color coding of figure 1. The first 4 lines represent forward modeling steps and the last 3 lines represent inverse modeling steps.

Approach		**Modeling step**	**Available methods and tools**
Forward modelling approaches	**a** **b**	Climate forcing -> climatic impact-drivers	Earth System Models - ESM (Tebaldi et al. 2021) Earth System Models of Intermediate Complexity - EMIC (Eby et al. 2012; Zickfeld et al. 2013)
Forward modelling approaches	**a**	Climate forcing -> global climate	Simple Climate Models - SCM (Z. R. J. Nicholls et al. 2020; Z. Nicholls et al. 2021)
Forward modelling approaches	**b**	Global climate -> climatic impact-drivers	Regional climate emulators (Beusch et al. 2021; Nath et al. 2022; Quilcaille et al. 2022; Liu et al. 2023; Tebaldi, Snyder, and Dorheim 2022; Quilcaille, Gudmundsson, and Seneviratne 2023) Time sampling (James et al. 2017) Conditional distribution
Forward modelling approaches	**c**	climatic impact-drivers -> socio-ecological impacts	General purpose climate impact/risk models: CLIMADA (Aznar-Siguan and Bresch 2019; Bresch and Aznar-Siguan 2021) Financial risk models: OasisLMF (“OasisLMF” [2018] 2023) Econometric and epidemiological approaches (Vicedo-Cabrera et al. 2021; Hsiang 2016; Hsiang et al. 2017) Sectoral impact models: see ISIMIP (“The Inter-Sectoral Impact Model Intercomparison Project” n.d.) Ecosystem services: InVEST (Zaks 2019) Humanitarian impacts: INFORM Climate change Climate Impact Chains (Estoque et al. 2022; GIZ 2014)
	d	Socio-ecological impacts -> climatic impact-drivers	Expert-based judgments Econometric and epidemiological approaches (Vicedo-Cabrera et al. 2021; Hsiang et al. 2017; Hsiang 2016) Evaluation of what is “socially” acceptable to policy-makers, for example using multi-criteria analysis
	e	climatic impact-driver -> global	Conditional distribution

		climate	
Inverse modelling approaches	**f**	Global climate -> anthropogenic forcing	Adaptive emission reduction approach (AERA) (Terhaar et al. 2022) Adjusting Mitigation Pathways (AMP) (Goodwin et al. 2018) Temperature tracking approach (Zickfeld et al. 2013; 2009) Pathfinder (Bossy, Gasser, and Ciais 2022)

Box: example - What emission reductions are required to avoid a 50% increase in summer days with expected important health impacts in Berlin?

An analysis of heat related mortality in Berlin suggests that a day with average temperatures above 28°C considerably increases heat mortality (Vicedo-Cabrera et al. 2021 figure 2c).

Over the period 1991-2018 (GMT level of 0.9°C above pre-industrial), 1% of all summer (June-August) days had an average temperature greater than 28°C and for the current climate (GMT level of 1.2°C above pre-industrial), 1.5% of all summer days exceed this threshold. For this example, we assess what emission reductions are needed to assure that in 2050 the relative increase in the frequency of such days with average temperatures above 28°C is limited to 50% compared to current climatic conditions.

In this impact chain, greenhouse gas emissions (left) lead to an increase in global mean temperature (global climate) (panel a). At higher global temperatures, the likelihood of hot days (climatic impact-driver) increases in Berlin which leads to an increase in heat related mortality (societal impact). Here we use the simple climate model FaIRv1.6 (C. J. Smith et al. 2018) to simulate GMT trajectories for a given greenhouse gas emission scenario (panel b) and conditional normal distributions with the location depending linearly on GMT to model daily averaged temperature distributions for a given GMT level (panel c). See methods for more details.

The orange cone (panel a) illustrates how uncertainties (66% confidence interval) propagate along this impact chain for the SSP1-26 scenario. Note that SSP1-26 is defined in terms of greenhouse gas concentrations and not emissions. The blue cone illustrates the range of GMT levels and cumulative CO2 emissions that are likely to lead to a relative increase in summer days with averaged temperatures above 28°C of 50% in 2050 relative to now (physical reversal).

Instead of showing a confidence interval (66%) for cumulative CO2 emissions we can also calculate the highest possible CO2 emissions for which we have a 66% chance of limiting the relative increase in summer days with expected health impacts in Berlin to 50% in 2050: 700 Gt (see first line in panel d). Note that this CO2 budget also depends on non-CO2 assumptions and that under high methane emissions this budget would be smaller.

As explained in Figure 2, value judgment, adaptation considerations and assumptions on future societal developments enter into consideration when defining a critical risk level. Panel (d) lists a few alternative choices for the daily average temperature threshold, increase in frequency and confidence level. For a higher confidence level, such as 90%, only 300 Gt of CO2 can be emitted to limit the relative increase in days with average temperatures of 28°C to 50%. Assuming that adaptation, such as greening of the city, could reduce the city-average temperature by 1°C, the acceptable CO2 budget to keep the same frequency of summer days with expected health impacts as today with a 90% confidence level would be 730 Gt (third line). Finally, if the relative increase in days with 28°C averaged temperatures in Berlin should be limited to 50% in 2100 a total of 880 Gt of CO2 can be emitted until 2100.

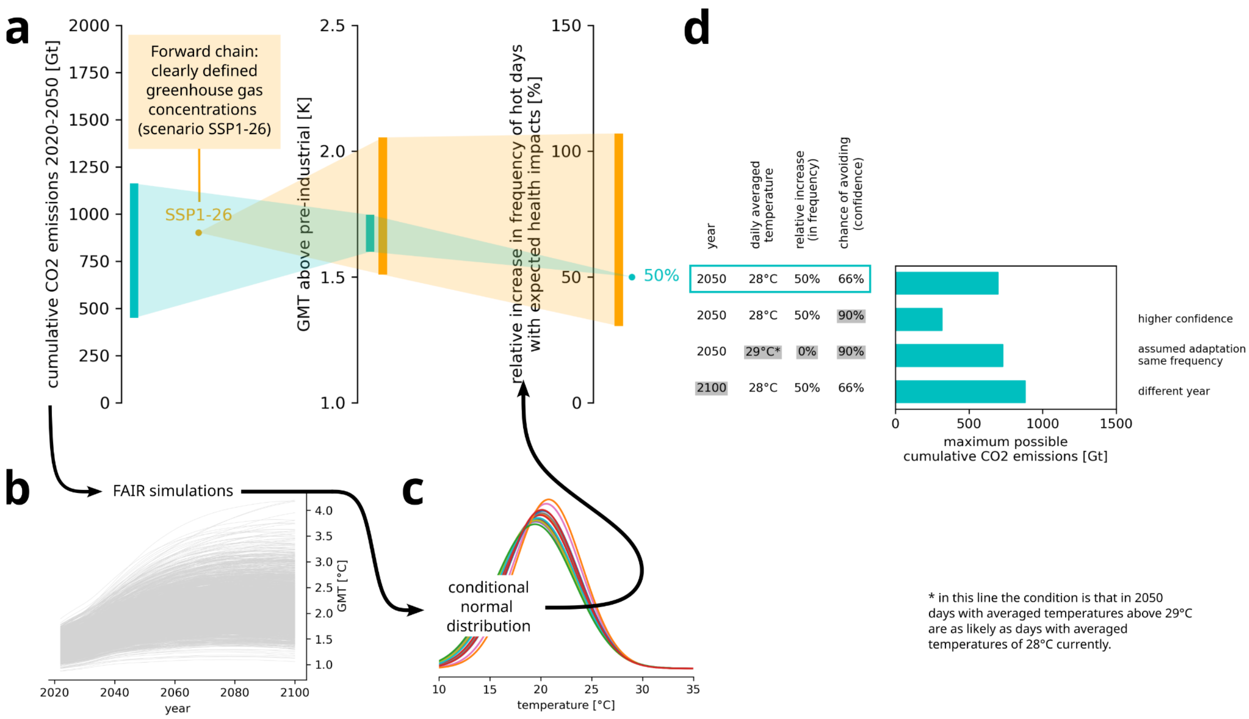

Figure 3: Increased frequency of hot days with expected important health impacts in Berlin. (a) Forward (orange) and physically reversed (blue) impact chain from emissions through GMT to the relative increase in summer (June-August) days in Berlin with daily averaged temperatures above 28°C. The orange cone represents the 66% uncertainty range for the SSP1-26 scenario. The blue cone shows the 66% confidence interval for a reversed impact chain where the relative increase in Berlin summer days with averaged temperatures above 28°C is limited to 50% (relative to current climate). (b) GMT trajectories from FaIR simulations of one exemplary emission scenario. (c) Conditional normal distributions of averaged daily summer temperatures in Berlin for current climate (GMT level of 1.2°C above pre-industrial). (d) Estimates of the maximal allowed CO2 budget for different levels of climatic impact-driver changes. First line: 66% chance to limit the relative increase in frequency of summer days with averaged temperatures above 28°C in Berlin to 50% in 2050. Second line: as the first line, but with a 90% confidence level. Third line: 90% chance of getting not more days with averaged temperatures above 29°C in 2050 than days with averaged temperatures above 28°C currently. Forth line: same as first line but for the year 2100.

Discussion and Outlook

The reversed impact chain provides an intuitive way to communicate climate science and its societal relevance: instead of comparing how impacts evolve in abstract emission scenarios into the future, the reversed impact chain allows to focus on a specific climatic impact-driver and to estimate what emission reductions (or GMT limit) would be required to avoid a critical local risk level. This way climatic impact-drivers (e.g. heat wave intensity, storm surge level) and their societal effects are put on the center stage of the discussion.

The usefulness of the reversed impact chain to inform policy-making depends on many factors and has yet to be assessed. One of these factors is the ability of defining a critical risk level that should be avoided. For some impacts, climatic impact-driver thresholds can be readily defined based on natural or structural tolerance levels or hard adaptation limits (e.g., flood level that a dam can withstand, heat that the human body can endure). In these cases, the confidence in avoiding the impact or the frequency at which the impact would still be acceptable has to be chosen. However, depending on the system or sector and region, the precise value of a climatic impact-driver threshold may depend strongly on local environmental and system characteristics (Ranasinghe et al. 2021). Identifying a critical risk level requires information or decisions about a range of factors outside the realm of physical climate science (compare Fig. 2). A lack of information on vulnerability and exposure of the affected system and potential limits to adaptation would render establishing a meaningful risk level very difficult. However, even in such cases, the reversed impact chain could still provide useful insights for stress-testing adaptation strategies based on illustrative thresholds or expert judgment. In addition, it can also be difficult for practitioners and policy-makers to pin down a specific number beyond which impacts are unacceptable as this comes with large ethical implications and responsibilities (e.g. amount of acceptable mortality during a heatwave, inequalities in climate impacts, etc.), and also depends on the diversity of values and objectives of the respective decision-makers (Reisinger et al. 2020). For some of these challenges, further research can improve the knowledge base and reduce uncertainties, while for others, research can help to clarify the consequences of societal choices.

Here we only illustrate a limited application of the reversed impact chain framework. The estimation of local climate impacts requires multivariate projections with high spatial and temporal resolution (Castaneda-Gonzalez et al. 2019). A promising avenue for extension are modular setups that play an increasingly important role in climate science with the developments of more and more Earth system and impact model emulators building on statistical (Beusch et al. 2021; Nath et al. 2022; Quilcaille et al. 2022; Liu et al. 2023; Tebaldi, Snyder, and Dorheim 2022) or machine learning approaches (Abramoff et al. 2023) allowing for down-scaling to very high local resolution (Quesada-Chacón, Barfus, and Bernhofer 2022).

Despite the convenience of this modular setup it has to be noted that climate impacts are subject to varying levels of time lag from forcing or global mean temperatures which may complicate the simple global mean temperature scaling approach explored here. However, as it is also possible to in principle explore time lagged impacts such as sea level rise or permafrost loss with simple modeling or emulator tools (Gasser et al. 2018; Nauels et al. 2019; Mengel et al. 2018), the reversal of the impact chain approach can in principle be well extended to also include time-lagged thresholds (such as for example avoiding 1m of sea level rise in a certain location over a certain time frame).

The consequences of sea level rise and the need for continuous coastal adaptation also provides for some concrete examples on how the identification of system thresholds or adaptation limits and their exceedance risk can be meaningfully integrated into adaptation planning. Specifically, the dynamic adaptation pathway approach (Haasnoot et al. 2013; Schlumberger et al. 2022) outlines how the understanding of limits to specific adaptation action, and the transgression of such thresholds, can be incorporated into decision making frameworks early on allowing for continuous build up of different adaptation options and strategies. While these approaches have been most commonly explored in coastal adaptation with very well defined physical thresholds and limited (near-term) scenario dependency, our reversal of the impact chain approach allows for an extension to other application areas such as urban adaptation planning or compound climate risks (Simpson et al. 2023).

Furthermore, the reversal of the impact chain approaches can enhance and support conducting system stress tests, commonly pursued for example in the financial sector (Battiston et al. 2017). Stress testing approaches can provide crucial insights into critical thresholds of vital societal support systems, including also health (Ebi et al. 2018) or critical infrastructure (Linkov et al. 2022). However, the bottom-up system perspective on physical climate risk stress testing does not provide for means to connect back to the emission scenario space per se - a gap that the reversal of the impact chain can close. Being able to assign physically grounded risks to stress testing can thereby enhance classical stress testing approaches and provide for more informed and sound decision making despite cascading uncertainties.

Lastly, being able to link back local climate change risks to global emission reduction efforts can greatly help to foster understanding about the benefits of stringent emission reductions for societies and local decision makers (Feygina et al. 2020). Providing relatable climate information can be a central educational element to gather public support for the far-reaching societal transitions (M. Thomas et al. 2022; Moore et al. 2022) required to achieve the goals of the Paris Agreement.

In times of accelerating climate impacts, providing actionable climate information becomes more relevant than ever. End-user and decision-making focussed approaches like the reversal of the impact can help to bridge the gap between science and implementation.

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Code availability

The code to reproduce the example for heat extremes in Berlin and Figure 3 can be found here: https://gitlab.com/PeterPeter/reversed_impact_chain_heat_berlin

Statement of competing interests

The authors declare no competing interests.

Methods

For the example in figure 3 we construct a simplified impact chain based on GMT projections from FaIRv1.6 (C. J. Smith et al. 2018) and conditional normal distributions modeling daily temperatures in Berlin for any given GMT.

Emissions to global climate:
We use a comprehensive set of emission scenarios (1500) developed for the PROVIDE project (Lamboll, Rogelj, and Schleussner 2022). For each emission scenario 2237 FaIR simulations are used to represent the uncertainty in climate sensitivity (C. J. Smith et al. 2018; Lamboll, Rogelj, and Schleussner 2022). The 2237 ensemble members were selected to span the range of assessed physical climate uncertainty from the IPCC AR6 WGI including the distributions of equilibrium climate sensitivity, transient climate response and radiative forcing, and are constrained to reproduce hindcasts of observed GMT and ocean heat content change, including uncertainties (C. Smith et al. 2021).

Global climate to climatic impact-driver:
To model daily averaged temperatures in Berlin we use conditional normal distributions with location linearly depending on GMT.

For each ESM we select the grid-cell closest to Berlin and bias correct daily summer temperatures (June, July, August) to daily summer temperatures in ERA5 in the grid-cell covering Berlin using a quantile mapping approach (Cannon, Sobie, and Murdock 2015). ERA5 does not reproduce the urban heat island effect (UHI) over Berlin (Hooyberghs, H. et al. 2019).

Instead of incorporating the full UHI in our bias adjustment approach, we adjust the daily temperature distributions to the climate data used in (Vicedo-Cabrera et al. 2021) to allow comparability to this heat related mortality analysis. We estimate the 99th percentile of daily summer temperatures for the period 1991-2018, compare it to the respective value that is specified in (Vicedo-Cabrera et al. 2021) and shift the location of our fitted distributions accordingly.

For each ESM the slope and intercept of the location as well as the scale of the normal distribution are estimated by minimizing the negative log-likelihood function. In our training data, some GMT levels are more frequent than others. We bin GMT into 0.1K bins and weight data points in the fitting procedure by the inverse of the number of data points in the respective bin in the log-likelihood calculation. We exclude data points that correspond to GMT levels for which less than 10 years of projections are available (high GMT levels).

We only consider ESMs that have been selected as skillful for European climate by Palmer et al. (2022):
ACCESS-CM2, BCC-CSM2-MR, CESM2, CESM2-WACCM, CNRM-CM6-1, CNRM-ESM2-1, EC-Earth3, EC-Earth3-Veg, EC-Earth3-Veg-LR, GFDL-ESM4, HadGEM3-GC31-LL, HadGEM3-GC31-MM, MPI-ESM1-2-LR, MRI-ESM2-0

We also test alternative conditional distributions:

- Normal distributions with location and the scale depending on GMT
- Skew normal distribution with location depending on GMT
- Skew normal distribution with location and scale depending on GMT
- Skew normal distribution with location, scale and shape depending on GMT

Adding more parameters slightly improves the fit (figure 4a), but the Bayesian information criterion (BIC) suggests that the normal distribution with only the location depending on GMT is the most adequate model (figure 4b).

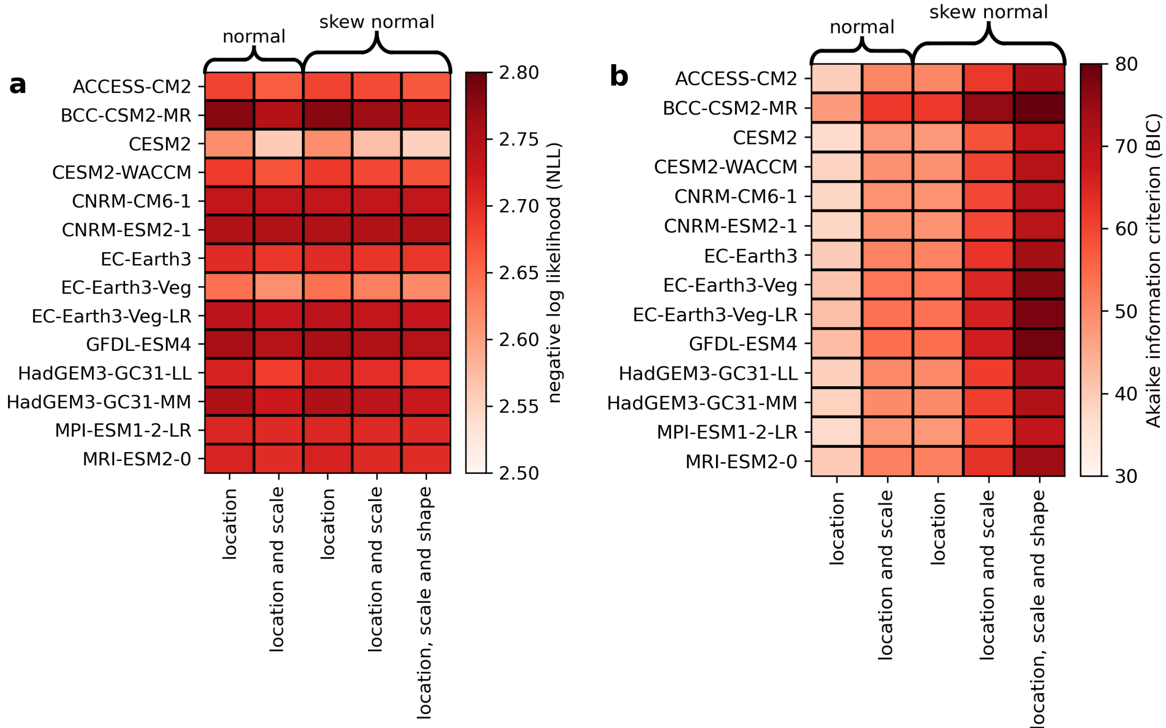

Figure 4: (a) negative log-likelihood function (NLL) for different ESMs and different conditional distributions of daily averaged summer temperatures in Berlin. Normal distribution with location depending on GMT (column 1), normal distribution with location and scale depending on GMT (column 2), skew normal distribution with location depending on GMT (column 3), as column 3 but with scale additionally depending on GMT (column 4), as column 4 but with shape additionally depending on GMT (column 5). (b) same as (a) but for the Bayesian information criterion (BIC).

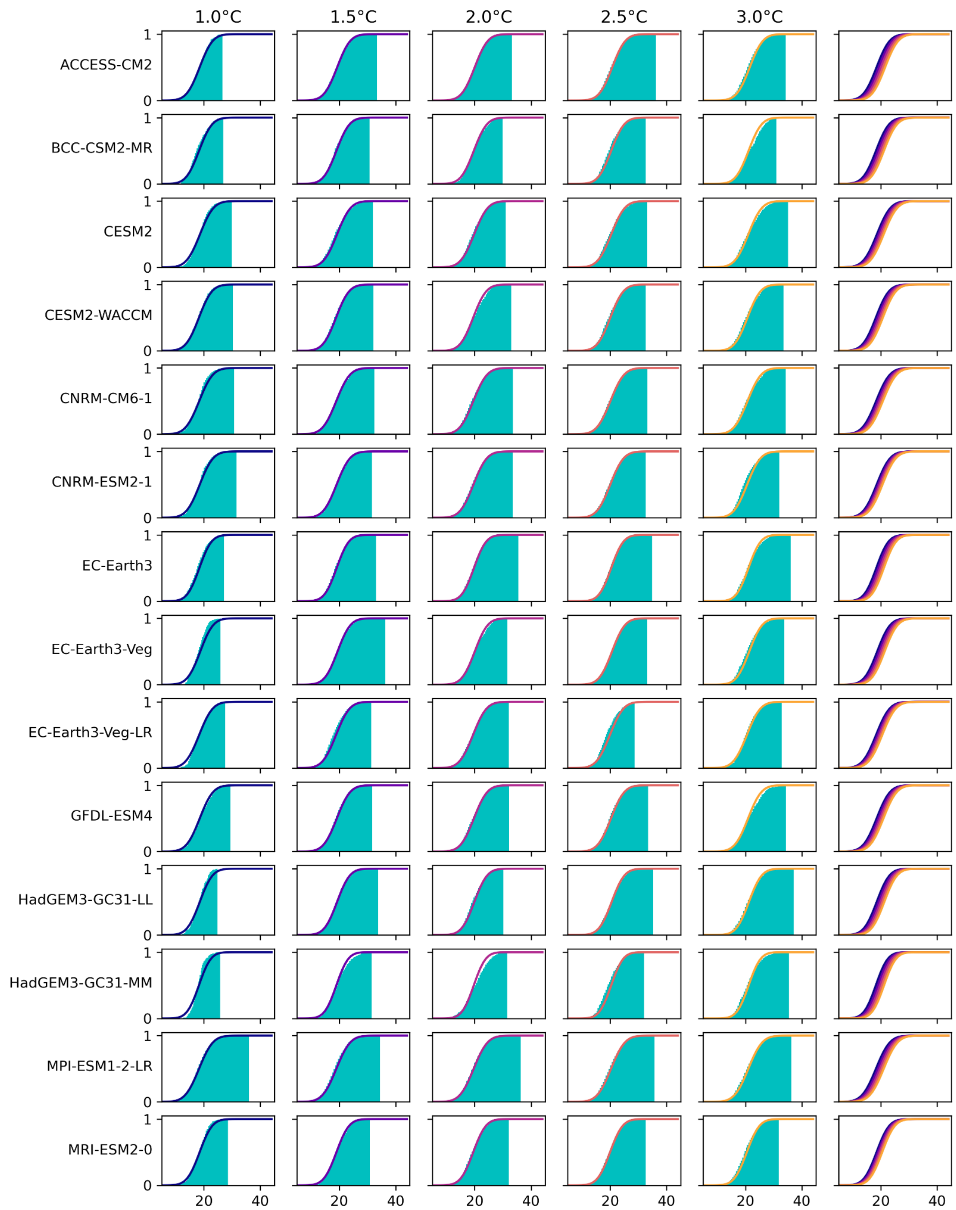

Figure 5: Cumulative distribution functions of daily averaged summer day temperatures in Berlin projected for different warming levels (different columns). The empirical CDFs (cyan bars) are merged projections of years where GMT deviates less than 0.05 K from the desired GMT level. The colored lines show a conditional normal distribution with the location depending on GMT.

Forward modeling:

In the forward impact chain the uncertainty range is limited by the 17th and the 83th percentile of all FaIR runs for GMT estimates and all combinations of FaIR runs and ESM-specific non-stationary distribution parameters for the climatic impact-driver.

Physical reversal:

After setting a climatic impact-driver threshold (50% increase in summer days with average temperatures above 28°C in Berlin), we estimate the 66% range of possible cumulative CO_2 emissions by evaluating the likelihood of getting this climatic impact-driver for a comprehensive set of emission scenarios:

1) We partition a wide range of possible cumulative CO_2 emissions in 100 equally spaced bins.

2) For each bin:

2a) We merge the estimated probability of exceeding the climatic impact-driver threshold (28°C) of all combinations of FaIR runs, all ESM-specific non-stationary distribution parameters and all scenarios falling into that bin.

2b) We estimate a kernel density estimate for the probabilities of 2a) and estimate the likelihood of getting the chosen climatic impact-driver at the specified probability (50% more likely than currently) for the bin by integrating the kernel density estimate over a small area around this probability threshold.

3) Using the center of the bins of 1) as values and the likelihood of getting the chosen climatic impact-driver of 2) at the specified probability as weights, we calculate weighted percentiles for the 17th and 83th percentile representing the 66% confidence range on the emission side.

A similar procedure is performed to estimate the GMT range that could lead to the chosen climatic impact-driver. Here the GMT axis is binned and the different ESMs are the only uncertainty.

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