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Polar ice sheets are decisive contributors to uncertainty in climate tipping projections

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The Earth's climate is a complex system including key components such as the Arctic Summer Sea Ice and the El Niño Southern Oscillation alongside climate tipping elements including polar ice sheets, the Atlantic Meridional Overturning Circulation, and the Amazon rainforest. Crossing thresholds of these elements can lead to a qualitatively different climate state, endangering human societies. The cryosphere elements are vulnerable at current levels of global warming (1.3 °C) while also having long response times and large uncertainties. We assess the impact of interacting Earth system components on tipping risks using an established conceptual network model of these components. Polar ice sheets (Greenland and West Antarctic ice sheets) are most decisive for tipping likelihoods and cascading effects within our model. At a global warming level of 1.5 °C, neglecting the polar ice sheets can alter the expected number of tipped elements by more than a factor of 2. This is concerning as overshooting 1.5 °C of global warming is becoming inevitable, while current state-of-the-art IPCC-type models do not (yet) include dynamic ice sheets. Our results suggest that polar ice sheets are critical to improving understanding of tipping risks and cascading effects. Therefore, improved observations and integrated model development are crucial.

The Earth system consists of a range of key components such as the Amazon rainforest, the Greenland ice sheet (GIS), the El Niño Southern Oscillation (ENSO) or the Atlantic Meridional Overturning Circulation (AMOC)[1,2]. Some of these critical components are suggested climate tipping elements, where beyond a critical threshold (tipping point), a small perturbation may qualitatively alter their state. The state change of any of these key Earth system components (whether tipping element or not) would have severe consequences for human societies through sea level rise, biome collapses, and further drastic environmental changes as recently reiterated by the Global Tipping Points Report[3]. While combinations of different drivers (rainfall, wind patterns, local temperatures) are decisive for the state of the key Earth system components, research has been able to trace many drivers back to the global mean surface temperature[2,4], revealing that some components may already lose stability between 1.5 and 2.0 °C above pre-industrial levels[2] until 2100. As updated during COP28, humanity is on track of at least temporarily overshooting 1.5 °C[5,6], and the most up-to-date projection of the *Climate Action Tracker* extrapolates global warming levels to 2.2–3.4 °C by 2100 under current policies and actions[7]. Furthermore, some tipping elements are starting to show signs of a potentially approaching instability[8–11]. In particular, as global warming levels are now reaching critical temperature ranges for climate tipping points (current level of global warming is at 1.3 °C and is very likely crossing 1.5 °C above pre-industrial)[5,6], we need to understand which uncertainties are decisive for whether we are at risk of tipping events and cascading effects.

Climate components also interact with each other, leading to the possibility of destabilising interactions and tipping element cascades[12–15]. These tipping cascades may occur when a climate component changes its state and influences other components. Such interactions can either increase or decrease the likelihood of other elements tipping depending on the interaction[15,16]. While it has been found that most interactions between the tipping elements tend to be destabilising[15,16], some interactions may stabilise parts of the climate system[17–19]. For example, a tipping of the Greenland Ice Sheet greatly increases the likelihood of the AMOC tipping through increased freshwater release reducing convection[20]. In return, the AMOC

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slowdown decreases the temperature in the North Atlantic around the GIS and could therefore reduce the likelihood of GIS tipping[15]. In a worst case scenario, these interactions between tipping elements could lead to tipping cascades that can propagate from one element to another. These links allow uncertainty in the threshold, tipping times or interactions of one element to strongly influence uncertainty in the behaviour of other elements. This makes it critical to assess the uncertainty in climate tipping elements as a whole system and consider the uncertainty propagation through it.

Although tipping points and large qualitative changes in key Earth system components pose large risks to human societies, we still have large uncertainties about their existence, interactions, and behaviour. Particularly, uncertainties with regard to critical thresholds, timescales for state change, and interactions are tremendous[2,21], frequently more than 100% of their mean value. The large uncertainties in these crucial values reveal that we have not yet sufficiently grasped the non-linear dynamics of the climate system and its subsystems, neither through measurements, observations nor modelling efforts. Concerningly, the uncertainty ranges of the tipping points have been adjusted and re-assessed downward since earlier assessments[11]. In particular, the polar ice sheets on Greenland and Antarctica have a threefold uncertainty: their timescales of tipping span magnitudes (centuries to millennia), their tipping points are partially at today's levels of global warming (between 1.0 and 3.0 °C above pre-industrial levels), and they have very large structural uncertainties regarding their impacts, in particular their contribution to sea level rise. This uncertainty is strongly influenced by MICI (Marine Ice Cliff Instability): estimates of sea level rise including MICI reach up to 16 m by 2300 (low confidence) compared to between 1.7 and 6.8 m without MICI[22]. Uncertainty arising from MICI thus dominates the uncertainty and modelling work to better understand MICI is currently ongoing. Thus, the significant change in our estimates for some tipping points and the remaining high uncertainty for most of these suggest that a great amount of progress still remains to be made. This study aims to help direct and focus future efforts on improving our understanding of climate tipping points and reducing uncertainties in risk assessments for tipping risks and cascading effects.

Coupled Model Intercomparison Project 6 (CMIP6) models are some of the most state-of-the-art and well-developed climate models currently in use, frequently consulted in the IPCC reports on climate change. They are used for a variety of simulations, including projections of future warming under different emissions scenarios, as well as reconstructing recent historical climate change. They also include many components, such as a coupled atmosphere and ocean, biosphere, and cryosphere. These complex models have enabled CMIP models to reconstruct past climate to within ±1 °C consistently throughout many iterations[23]. CMIP6 models are a significant improvement on previous iterations of CMIP, particularly in key metrics such as surface temperature and winds[23]. However, CMIP models are known to still be missing key elements of the climate dynamics, have common components (thus not representing a fully independent ensemble) and have large degrees of uncertainty, as shown for the CMIP5 ensemble[24].

State-of-the-art CMIP6 models do not include coupled dynamic ice sheets, which renders them unable to represent the tipping dynamics of these elements or their links and interactions with other elements[25,26] (although some modelling efforts have been performed on coupled ice sheet-climate models in ISMIP6[27]). This can cause significant issues in the behaviour of the ocean and the influence of varying ice sheet melt on the overturning ocean circulations[28]. CMIP6 models also do not include sea level rise and the impacts of this on the wider climate system, which has to be calculated separately[29], leading to a loss of any potential feedbacks or cascading impacts. The biosphere and the links between it and other parts of the climate system have also been shown to be critical for future tipping points and predictions of the climate[15,30], but many CMIP6 models do not feature key Earth System Components (such as a dynamically simulated biosphere) and those that do have important biases[31,32].

The stability of the AMOC has also been studied across a range of climate models[33–35] but, due to the aforementioned lack of freshwater forcing (e.g. from ice sheet melting) and issues with the dynamical representation (e.g. due to representation of deep water formation or convection), it has been suggested that the AMOC is over-stabilised in climate models[36]. This therefore has further impacts on the stability of the rest of the Earth system and the influence of the AMOC on the tipping of other elements.

This study aims to improve our understanding of the interactions between these climate-tipping elements and the key uncertainties associated with them. To do this we use (i) a Sobol variance analysis to understand which parts of the climate system are most impactful for future tipping probabilities and (ii) a leave one out analysis to understand the impact of key climate components being insufficiently represented or neglected in the analysis.

Modelling approach

In this study, we use variance sensitivity methods to assess which key Earth system components and interactions are the most important to understand in order to limit uncertainties in cascading tipping risks assessments. Based on our assessment, we then suggest where further analysis, Earth observation and modelling may be most valuable.

We use the conceptual climate tipping element model *Pycascades*[37] to represent six important climate components and the interactions between them. The *Pycascades* model has been used to represent climate tipping point interactions and cascades to analyse the impact of interactions between tipping elements[16], under potential global warming pathways[12,38]. This study aims to build on this previous work by assessing the relative importance of different uncertainties to the overall behaviour of the system.

The six components analysed in this study are: the Greenland Ice Sheet (GIS), the West Antarctic Ice Sheet (WAIS), the Atlantic Meridional Overturning Circulation (AMOC), the Amazon Rainforest (AMAZ), the Arctic Summer Sea Ice (ASSI), and the El Niño Southern Oscillation (ENSO). The first four elements (GIS, WAIS, AMOC, AMAZ) are well-described tipping elements. The status of the ENSO as a tipping element is still under debate[39] although in some studies ENSO has been assessed unlikely to be a tipping element[2]. However, it is a key climate component with relevant changes under future climate forcing and strong links to the other elements analysed in this study[15]. The ASSI is likely not a tipping element[2] but does show qualitative changes in behaviour once the Arctic sea ice consistently disappears during the summer, and also shows relevant links to other elements. The reasoning behind choosing these six climate components in this study is due to their importance for their potential cascading interactions or their importance for Earth's climate system stability[2,3]. Although the ENSO and ASSI are not classified as clear tipping elements, they both undergo large qualitative changes in behaviour under climate forcing, transitioning to new states and producing impacts on other elements in this study. Due to this, they have been included in the study and will be described similarly to the other climate components with 'tipping thresholds', 'tipping timescales', and calculating the 'fraction tipped'. In these cases, if the components such as ASSI and ENSO are not considered as tipping elements then these values can be taken to refer to the transition of the component from its current state to a qualitatively altered one under climate forcing. More details on each of the six components, their stability under ongoing global warming and feedbacks are described in the supplement (see Sections 1 and 2). The respective critical thresholds (tipping point), tipping timescales as well as interaction strengths and directions are detailed in Supplementary Tables 1 and 2.

Using the *Pycascades* software, each component is represented by a differential equation where the dynamics are determined by the increase of the global mean temperature above pre-industrial levels and the interactions from other components. The well-described tipping elements are modelled using a differential equation with a fold-like tipping point as previously used in ref. 37. The ASSI and ENSO components respond linearly to forcing to reflect their nature as threshold-free feedbacks or unlikely tipping points[2]. The interactions between the components are represented as linear forcings. For more details on the equations used for the climate components or the impact of choosing linear or tipping functions for the ASSI/ENSO components, see the 'Methods'. Since there are considerable uncertainties in the

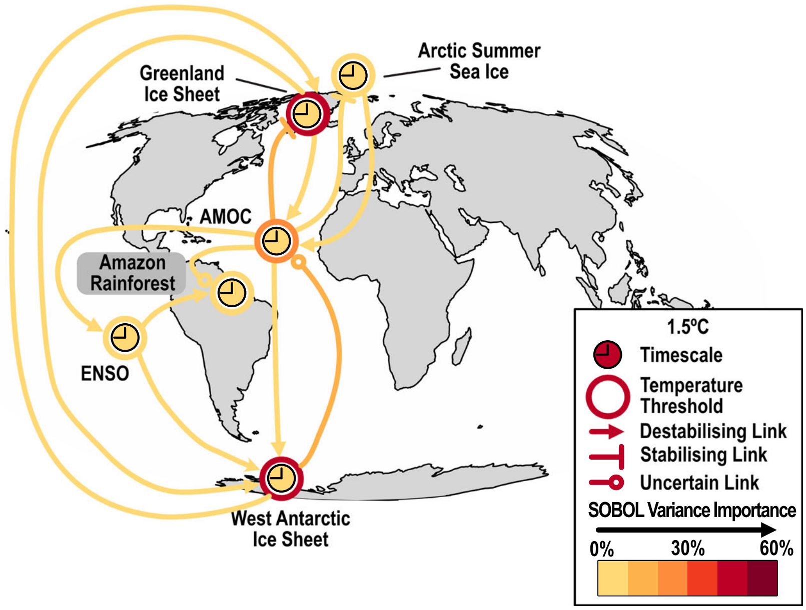

Fig. 1 | Sobol variance analysis at 1.5 °C. Sobol Total Effect Indices (measure of fraction of overall variance influenced for the total number of elements tipped and components transitioned) of the links, thresholds and tipping timescales of different components in the system, assessed at 1.5 °C global warming. The colour of the inner clock shape demonstrates the variance importance of the uncertainty of the tipping timescale for that component, while the colour of the outer ring shows the importance of the uncertainty in the threshold temperature. The links can be classified as destabilising (arrow), stabilising (bar) or uncertain (circle) based on their end-shape (in brackets). The colour of each of these links again gives the variance importance of their uncertainties. In this plot, the temperature threshold of Greenland and West Antarctic Ice Sheets show the darkest colours and the greatest Sobol variance importance.

tipping point, interaction strengths and timescales of tipping of the elements, we employed a large scale Monte Carlo ensemble of ~15,000 ensemble members to carefully propagate these uncertainties in our input parameters on to our results. For more details on our modelling approach, see Methods.

We analyse this model system to determine the key contributing factors to the uncertainty of the final tipping state of the key climate components. This analysis is done at two chosen levels of global warming, for 1.5 °C and 4.0 °C above pre-industrial temperatures. Each model is run for 100,000 years, which should allow sufficient time for all components to adjust to an equilibrium state. While 1.5 °C was chosen for its relevance to global climate goals, 4.0 °C was chosen as a representative upper limit of global warming. This analysis is initially carried out using a Sobol Sensitivity analysis[40], an established statistical method to determine the importance of *input* uncertainties (e.g. parameter uncertainties or initial values of a model) explaining the *output* uncertainty (e.g. in number of tipped elements and transitioned climate components). Therefore, we can understand how uncertainties in interactions between components, critical temperatures, and timescales of tipping could impact the tipping behaviour, measured by the number of tipped elements and transitioned climate components. The key parameter from this analysis is the Total Effect Index, which is calculated for each parameter in the model. It calculates the contribution of the variance in the chosen input parameter to the output variance, taking into account all of the impacts through interactions with other components and other variation in factors such as tipping thresholds and timescales. The Total Effect Index is effective at capturing non-linear effects, which is why we have chosen it for analysis. However, it can lead to double-counting of variations caused by multiple components and so the indices will sum to more than one. This allows for the qualitative significance of climate components to be assessed and is robust to variations but also means that estimates of exact values may be overestimates, which must be considered during interpretation. This overcounting is because, in a complex non-linear system, some effects may require multiple factors to occur. For example, in a particular scenario the AMOC might not tip if either of the GIS or WAIS tipped but would tip if both elements tipped. In this case, the change and uncertainty due to this tipping but would be completely assigned to both the GIS and WAIS as it would not have happened without both of them tipping. This leads to overcounting as a single effect is counted towards the Total Effect Index for both elements. However, despite this overcounting, relative magnitudes can still be informative, especially with the order of magnitude differences seen in this analysis. We then extended this work by a Leave One Out analysis, where one component or interaction is removed and the system response analysed to understand the importance of the removed component for overall system behaviour. For more detail on the statistical analysis techniques, see 'Methods'.

Results

Parameter uncertainty (Sobol Analysis)

Many parameters and dynamics in the climate system have significant uncertainty associated with them as our knowledge on tipping times and critical warming levels is far from perfect, but some uncertainties cross magnitudes (see Supplementary Table 1 for the large parameter ranges used in this study). To assess the key contributors to the tipping behaviour, we use a Sobol Variance analysis to quantify the contribution of different component to the overall variation in the mean number of elements tipped and components transitioned.

We find that the polar ice sheets dominate the variation, and reducing uncertainty in these key parameters can reduce the overall variation by far more than some of the less crucial components, see Figs. 1, 2.

Figure 1 shows the Sobol variance contributions of components at 1.5 °C global warming. Here we find that most of the variation is driven by nodes with low-temperature thresholds (i.e. low tipping points), these are the GIS and WAIS. Although ASSI and AMOC also have low temperature thresholds, they have a lower overlap with the 1.5 °C level of warming (AMOC tipping point between 1.4 and 8.0 °C, ASSI tipping point between 1.3 and 2.9 °C). Additionally, ASSI has fewer, weaker links to other nodes (see Supplementary Tables 1 and 2). Consequently, the links from them are less important, which is compounded by the fact that the elements which could be influenced by these links are also harder to tip at this temperature. This again reinforces the importance of the temperature thresholds for uncertainty at global warming levels of 1.5 °C, and confirms earlier results that the polar ice sheets act as initiators of tipping cascades due to their lower tipping points[16]. However, the ASSI is not a strong initiator of cascading effects because physically it is unclear whether the interaction with AMOC is strong enough to tip over the AMOC. The impact of the ASSI is also reduced because the probability of tipping at 1.5 °C is relatively low for ASSI given its temperature threshold range of 1.3–2.9 °C. At 1.5 °C it can also be seen that timescales for the tipping of the elements do not have a large impact. This is because the system is run to equilibrium and so if an element would tip then it has enough time to do so. The timescales could still have an impact by affecting the ordering of tipping and so the impact of potential stabilising or destabilising links, but this impact seems to be much less significant than the

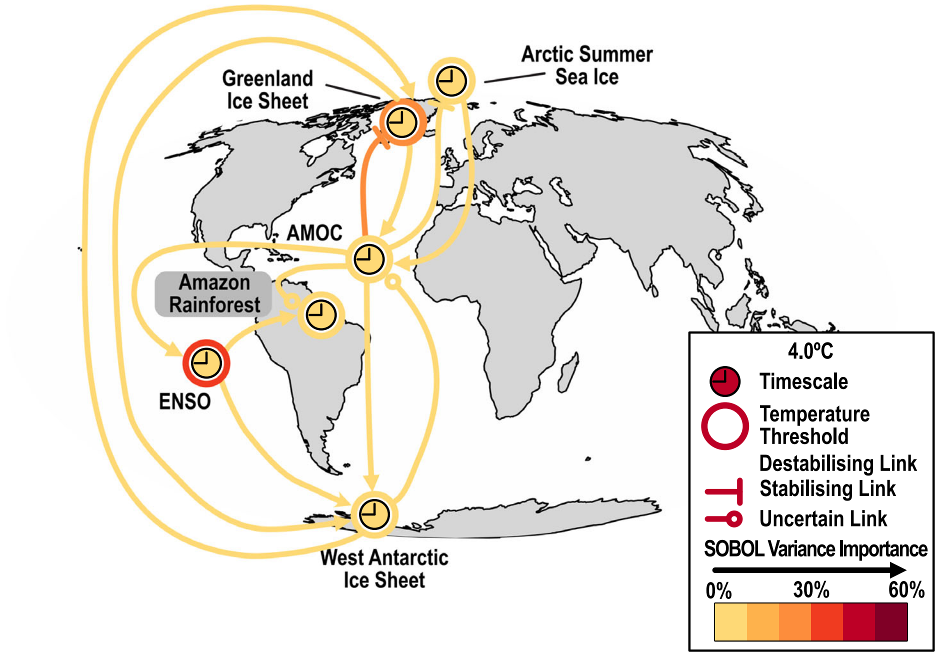

Fig. 2 | Sobol variance analysis at 4.0 °C. Sobol Total Effect Indices (measure of fraction of overall variance influenced for the total number of elements tipped or components transitioned) of the links, thresholds and tipping timescales of different components in the system, assessed at 4.0 °C global warming. The colour of the inner clock shape demonstrates the variance importance of the uncertainty of the tipping timescale for that component, while the colour of the outer ring shows the importance of the uncertainty in the threshold temperature. The links can be classified as destabilising (arrow), stabilising (bar) or uncertain (circle) based on their end-shape (in brackets). The colour of each of these links again gives the variance importance of their uncertainties. In this plot, the temperature thresholds of the Greenland Ice Sheet and the AMOC → GIS link show the darkest colours and strongest variance importance.

thresholds and links between elements. Thus, we conclude that the threshold temperature and the interactions of the polar ice sheets are most important for climate tipping events at 1.5 °C of global warming.

At higher temperatures of 4.0 °C above pre-industrial levels, Fig. 2 shows the Sobol variance contributions. This shows a very different structure to that at 1.5 °C because many critical thresholds of tipping elements/key Earth system components are crossed and, therefore, the tipping probabilities become very large beyond 1.5–2.0 °C[12,38]. The decisive factor is instead which components do *not* tip or transition to a new state. Therefore, the most important components at higher temperatures are those with high temperature thresholds (in particular ENSO), and the links to them. Alongside this, the elements with strong stabilising links that prevent them from tipping are also critical, such as the Greenland Ice Sheet and the strong stabilising link to it from the AMOC. Similarly to 1.5 °C, the timescales of tipping do not appear to be significant. This is again due to running our experiments to equilibrium and the lower impact compared to key parameters such as the thresholds and the links.

Across the range of temperature levels, we can draw some overarching patterns. Tipping risks are dominated by a few key uncertainties, which are: (i) The temperature thresholds of the Greenland and West Antarctic Ice Sheets at temperatures around 1.5 °C above pre-industrial as well as the interactions from them towards further tipping elements, and (ii) by the temperature thresholds of the Greenland Ice Sheet as well by the stabilising link AMOC → GIS at temperature around 4.0 °C. These results suggest that constraining the uncertainties of the large polar ice sheets in their tipping points and interactions is critical to reducing uncertainty in the future climate state.

Leave one out analysis

Removing a node from our network of interacting Earth system components is analogous to an element of the climate system not being simulated or being neglected. This could be due to lack of knowledge, simplifying assumptions or resource constraints and is a very common issue in modern climate models. Climate models are often run without coupled components such as the polar ice sheets and state-of-the-art climate models run in this setup can give good predictions of the short-term climate while this component is relatively static and less impactful, but will begin to struggle over longer timescales when the behaviour of the polar ice sheets becomes critical[27,41]. Removing a section from the model is also a frequent experimental technique in climate models when trying to isolate the dynamics of a particular system. Models may be run with particular components (such as the ocean, atmosphere or biosphere) uncoupled from the other components to see how it behaves without these coupled feedbacks, or to prevent instabilities or unusual behaviour in one component affecting other key components[42,43].

We can relate the scenarios in Fig. 3 to climate models as follows. The Control runs (where no nodes were discounted or removed, zero percentage change in Fig. 3) can be considered to model the real-world climate, with complex tipping dynamics and all features fully represented. The 'Node Discounted' scenario (where the dynamics of all links and nodes are run as usual, but the climate component is removed from the final count of tipping events) represents a system where we are fully representing the important dynamics but not measuring or recording some components. This is what we hope our climate models should be doing, where we are neglecting some components but we capture the important ones and so broadly simulate correct dynamics. However, the 'Node Removed' scenario (where the model is run with the given climate node and all direct linked interactions removed) represents what our climate models actually do, including the knock-on impacts and incorrect dynamics due to removing an element from the system. We can observe the impact of complex dynamics even in this very simple model, removing a key component from the system has significant impacts on the wider dynamics, suggesting that in more complex climate models, this can still be a large issue.

Figure 3 demonstrates that removing a single node can have significant impacts beyond that of just neglecting the component as in 'Node Discounted' simulations. This can have impacts of up to 58% for the 'Node Removed' scenario rather than up to 40% for the 'Node Discounted' scenario (See Fig. 3a). Removing a component is thus damaging both for its own representation but also the wider system. This can lead to large errors in the tipping behaviour of other component through the dynamics of the system.

We can see in Fig. 3 that although the distributions for the 'Node Discounted' and 'Node Removed' scenarios do overlap, the distributions are significantly different. In the 1.5 °C scenario we can see that the entire distribution shifts to a significantly greater amount of tipping when we move from the 'Node Discounted' scenario to the 'Node Removed' scenario. This illustrates the knock-on impacts and interaction dynamics increasing the effect of removing a single node. At 4.0 °C we see that as most nodes tip in all scenarios, there is a very low interquartile range for the 'Node Discounted' scenario as discounting each component discounts a similar percentage of tipping. The 'Node Removed' scenario has a smaller difference at 4.0 °C than at 1.5 °C as the interactions are less critical at the higher temperature as

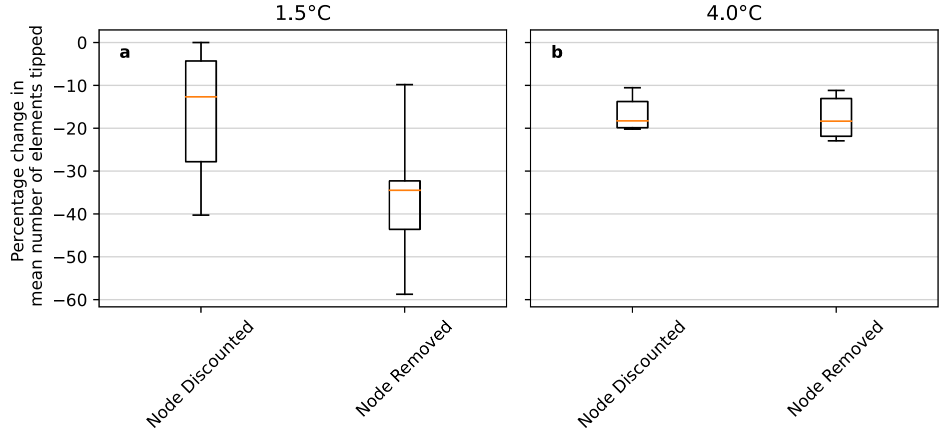

Fig. 3 | Impact of node removal on tipping distribution. Boxplot showing the distribution of the mean number of elements tipped and components transitioned at 1.5 °C (**a**) or 4.0 °C (**b**) for two different scenarios. The first scenario is the 'Node Discounted' scenario where the node in question still takes part in the dynamics of the system but is not included in our final sum. The 'Node Removed' scenario is where the node is entirely removed from the system and is unable to tip or interact with the other components. The analysis was repeated for each of the six nodes and the boxplots represent the distributions of outcomes produced. The orange bar on the boxplot gives the median value, while the box represents the interquartile range of the distribution and the tails show the full range.

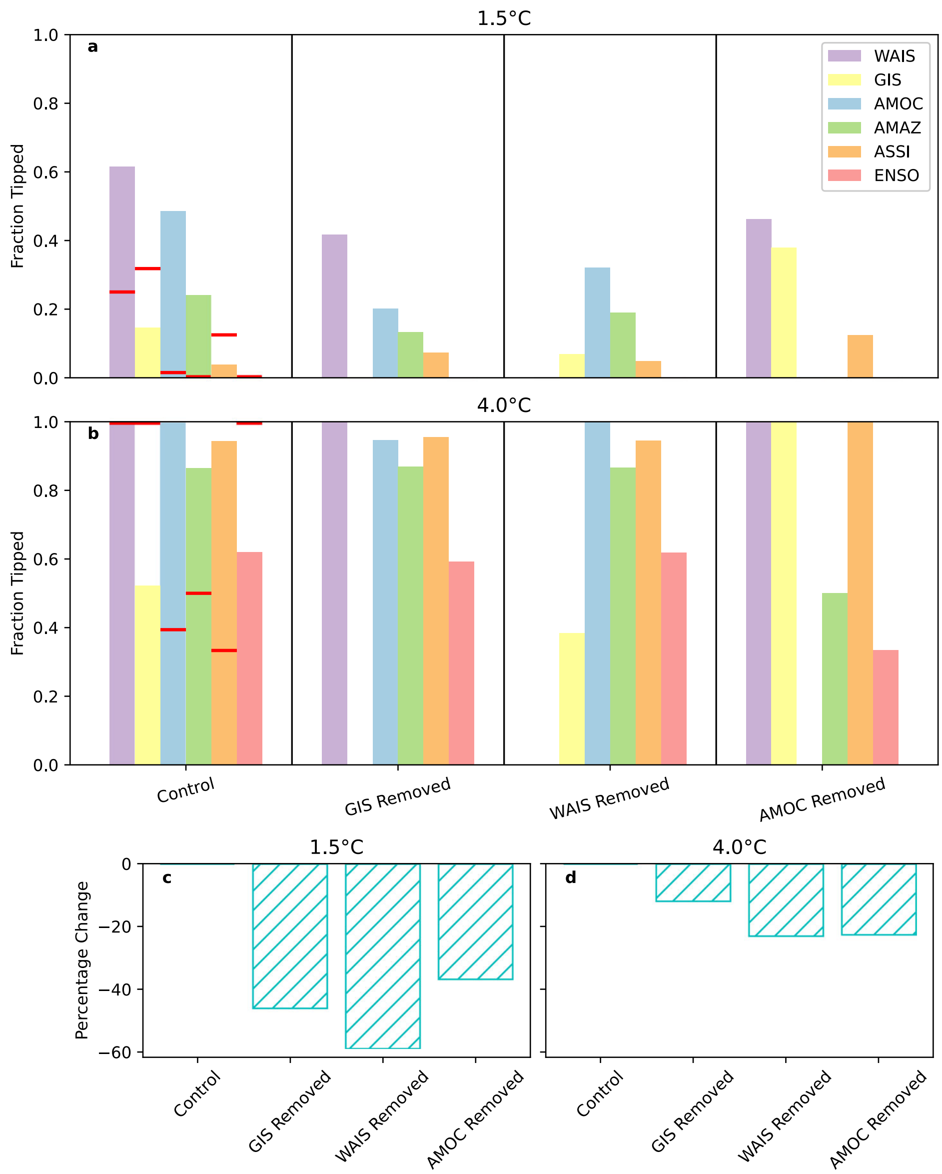

Fig. 4 | Impact of GIS/WAIS/AMOC removal on tipping. Fraction of runs in which each element tipped or component transitioned for four scenarios at both 1.5 °C (**a**) or 4.0 °C (**b**). These scenarios are: the control runs where all components are enabled, the scenario when the GIS is completely removed from the dynamics and counting of the system, the scenario where the WAIS is completely removed, and the scenario where the AMOC is completely removed. **a** and **b** show the changes in tipping or transitioning for each component in each scenario. **c**, **d** show the percentage change in overall tipping for each scenario. The red bars in the first chart in (**a**) and (**b**) give the fraction of runs in which the given component would tip or transition at this temperature in the absence of links (calculated based on the uniform distribution of thresholds used and the runs going to equilibrium).

many of the components will tip without interactions. However, there is an increase in variation between 'Node Discounted' and 'Node Removed', due to the influence of stabilising links being removed or changes to components with high-temperature thresholds.

It is important to note that the impact of removing a node can also vary strongly with the choice of node. As a specific case study, Fig. 4 shows the impact of removing the GIS from the system of interacting climate components. We initially focus on the GIS as it is consistently one of the most

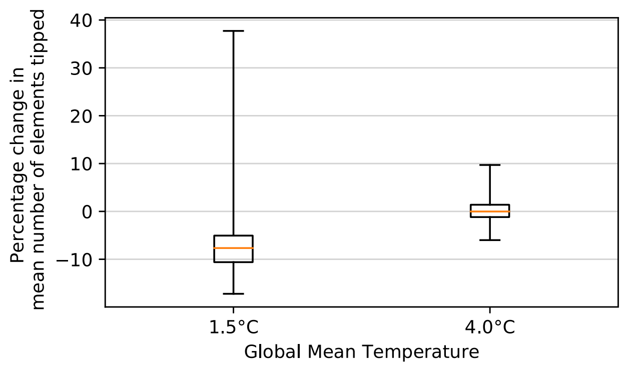

Fig. 5 | Impact of link removal on tipping distribution. Boxplots showing the impact of removing a single link on the mean number of elements tipped and components transitioned of the model. The impact is shown for both 1.5 °C and 4.0 °C, calculated for every link in the model, the boxplots show the distribution of these outcomes. The orange bar on the boxplot gives the median value, while the box represents the interquartile range of the distribution and the tails show the range.

important components in both the Sobol variance analysis (see Figs. 1 and 2) and the leave one out analysis (see Fig. 4), giving one of the biggest decreases in mean number of elements tipped when removed from the 1.5 °C scenario. At 1.5 °C, the impact of totally removing the GIS is a reduction of 46% in the mean number of elements tipped and components transitioned in the system, but it also has significant impacts on the qualitative behaviour of the system. As the GIS has a low tipping point (between 0.8 and 3.0 °C) and strong links to other tipping elements (AMOC, WAIS), it is a key initiator of cascades at low global warming levels. So, when it is removed, the amount of tipping events and cascading effects that we record in the other components is greatly reduced. Although these are the only elements with direct links to the GIS, there are cascading impacts through these links onto the entire system, so the outcome of removing the GIS is a significant reduction in tipping or transitioning for every investigated component. However, at higher temperatures (4.0 °C) the importance of the GIS as an initiator is much lower and has almost no impact on the wider dynamics when it is removed. This suggests that we must be careful to consider that although some dynamics appear negligible under certain conditions, they may be critical for the behaviour of a larger complex system at other conditions. Thus, neglecting them could lead to critical misrepresentations.

The WAIS is the element leading to the largest percentage change in the mean number of elements tipped and components transitioned at 1.5 °C (as shown in Fig. 4c). Similarly to the GIS, this is due to its low tipping point (between 1.0 and 3.0 °C) and potential cascading impacts onto the GIS and AMOC. It has a larger impact on overall tipping than the GIS because it tips more often as it does not have the stabilising link from the AMOC, which is why it shows up more strongly in the leave one out analysis. However, it has a weaker impact on the overall uncertainty as it has weaker links to other components, tips more consistently, and lacks the stabilising link from the AMOC seen for the GIS, and so it appears less strongly in the Sobol analysis.

Figure 4 also demonstrates the impact of removing the AMOC node from the system. This is qualitatively different to the impact of removing the GIS, suggesting that the removal of nodes can have a range of qualitatively different outcomes which are not always easy to predict, especially in more complex and realistic climate models. AMOC behaves very differently to the GIS in the model, acting as a mediator of cascades and also as a stabiliser of the GIS in the cases where the AMOC tips due to its strong stabilising link to the GIS. This makes its impact much more nuanced than the GIS as seen in Fig. 4. When the AMOC is removed entirely at 1.5 °C, the mean number of elements tipped and components transitioned is reduced by 37%, less than the 46% when the GIS term was removed. This is because the total removal of the AMOC tipping (and the subsequent loss of Amazon and ENSO tipping, which are only tipping at this temperature due to AMOC forcing) is significantly compensated by increases in the tipping of the GIS and ASSI, as they are no longer stabilised by the AMOC. Therefore, removing a component can have both a quantitative impact on the amount of tipping in a system but also a large qualitative impact on the behaviour of different elements and which elements tip. This suggests that if components are missing from an analysis or a climate model, even the broad behaviour of climate components may be incorrectly modelled, and the relative importance of components and regions of the climate system may be misjudged. At higher temperatures of 4.0 °C the AMOC still represents a powerful stabilising control on the tipping of the GIS and so removing it increases tipping of the GIS. At such high temperatures, the Earth system components which are least likely to tip or transition are the GIS, AMAZ and ENSO because these are the most resistant to temperature forcing (or have stabilising links in the case of the GIS). As most components tip or transition at this temperature forcing, factors which control these components are the most influential. As the AMOC exerts direct influence on all of these links, the AMOC retains its important role in the system at higher temperatures. This can be seen in Fig. 4 where the GIS tips more frequently when the AMOC is removed while the ENSO tipping is lower (in the 4.0 °C). We also see that the WAIS has a large impact when removed at this temperature partly due to its high probability of tipping but also because it is a key factor in determining the tipping of the GIS. When the WAIS is removed, it cannot destabilise the GIS and so the stabilising influence of the AMOC is more likely to prevail. This leads to a decrease in the number of GIS tipping events.

Another key measure for these systems is tipping risk, the likelihood that at least one component of the system is tipped or transitions during the simulation. This is the likelihood that we leave our current safer, more stable climate system and begin to enter one which is less stable and familiar, where elements have tipped or components have transitioned. We can see from Supplementary Table 3 that the tipping risk of a system can be decreased by up to 39% when nodes are removed from a system entirely (with this maximum value seen when the WAIS is removed). This leads to a significant underestimation of tipping risks.

Removing a link from the model means that an element of the dynamics linking two components is missing but that all of the climate components in the model are still represented. This is somewhat less invasive and damaging to the model than removing a component altogether as we still have all of the key climate components and most of the dynamics are still represented. However, removing a link from the model can still lead to knock-on effects beyond the components which the link connects. Removing links can be analogous to missing key dynamics from a model, not resolving a key feature or running the models in an uncoupled fashion where feedbacks between components can be one-way or decoupled entirely. Figure 5 shows the average impact of removing links from the system, with some links having a 38% impact (i.e. increase, see Fig. 6c) on the mean number of tipped elements and transitioned components in the system. In Fig. 5, we also show the distribution of percentage change at 1.5 °C and the highly skewed distribution with most destabilising links producing a 5–10% reduction in the mean number of elements tipped and components transitioned while a long tail extends to 38% increase with the removal of the AMOC → GIS link.

Figure 6 shows the impact of removing the strong stabilising AMOC → GIS link. This link was chosen as a case study as it is the strongest stabilising link in the system and has the greatest destabilising impact of any link when removed. When this link is missed out, there is a strong increase in the mean number of tipped or transitioned components across the system (a 38% increase at 1.5 °C and a 10% increase at 4.0 °C). This reasserts that if we are missing even a single link we could be vastly overestimating the (in-)stability and tipping in the whole system as the link has a large impact on the node it directly affects (e.g. for the AMOC → GIS link this is the GIS node) as well as cascading impacts on the wider system. These cascading impacts affect many subsequent nodes which the GIS then links to, in this case particularly the WAIS. Therefore, analyses that miss even one (strongly) stabilising dynamic may be vastly overestimating the instability, suggesting we should remain cautious about our claims of instability or the probability of cascading risks as long as we are unsure about stabilising feedbacks and interactions as well as their strengths.

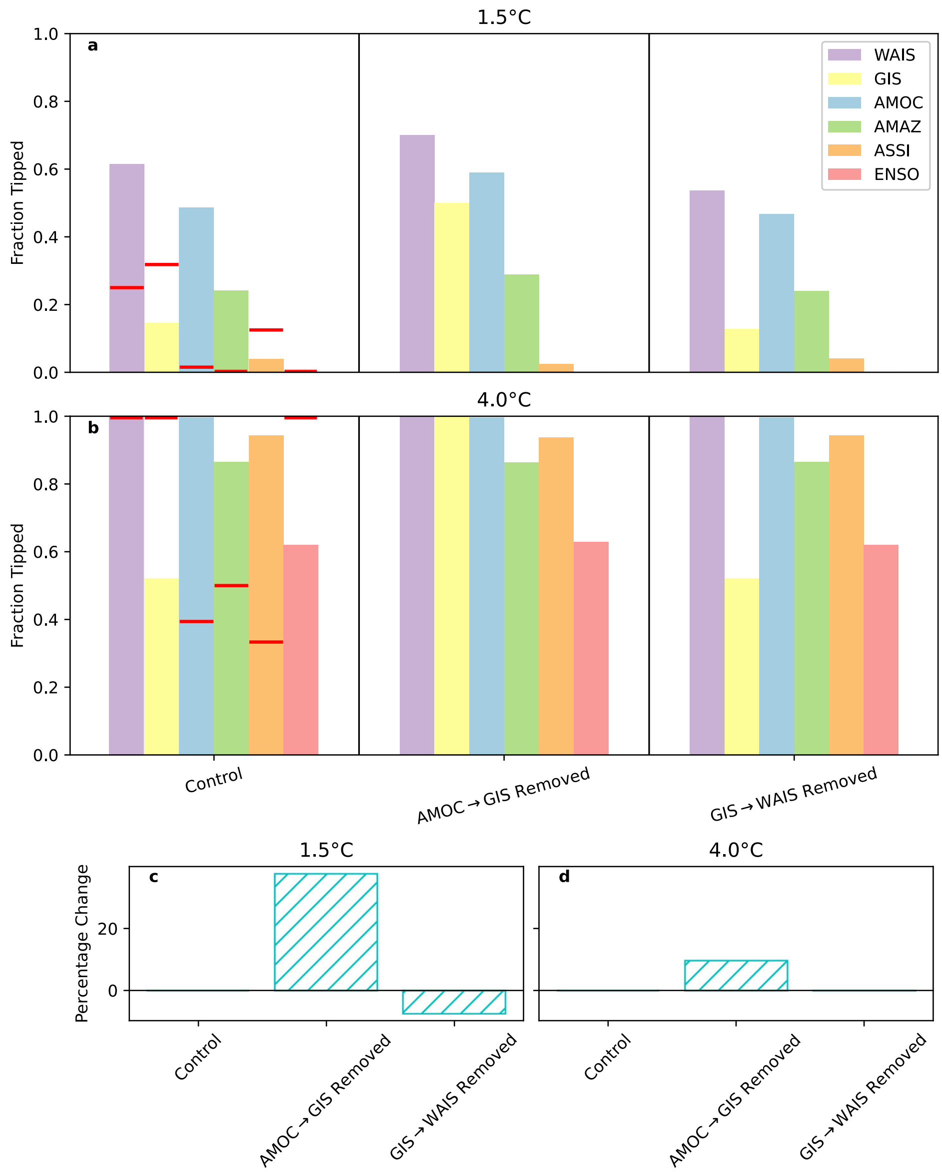

Fig. 6 | Impact of AMOC → GIS/GIS → WAIS removal on tipping. Fraction of runs in which each component tipped or transitioned for three scenarios at both 1.5 °C (**a**) or 4.0 °C (**b**). These scenarios are the control runs where all components are enabled, the scenario when the AMOC → GIS link is completely removed from the dynamics, and the scenario where the GIS → WAIS link is removed. **a** and **b** show the changes in tipping or transitioning for each component in each scenario. **c** and **d** show the percentage change in mean number of components tipped or transitioned for each scenario. The red bars in the first chart in (**a**) and (**b**) give the fraction of runs in which the given component would tip or transition at this temperature in the absence of links (calculated based on the uniform distribution of thresholds used and the runs going to equilibrium).

However, the opposite can also be true. If we miss a destabilising link, we underestimate tipping strongly (see Fig. 6c), e.g. if we miss the link GIS → WAIS. This shows that when the link is missed in the 1.5 °C scenario, the tipping of the system decreases by 7.5%, suggesting that missing a single destabilising link can lead to significant underestimation of the overall observed tipping events. This again has a large cascading impact, with the biggest impacts being seen on the WAIS but also cascading impacts on the AMOC and other components.

It is also important to note that at 4.0 °C the impacts of the removed links have changed. The AMOC → GIS link has a reduced but still destabilising impact when removed while the GIS → WAIS link has no impact when removed at 4.0 °C because the WAIS tips in every run without this additional forcing from the interaction.

These examples show that if we are missing a single link from our analysis, the results we obtain can differ from the control analysis by 20–40%. This means that missing key dynamics can significantly change our predictions of the future climate state and potential tipping risks.

Discussion

There is large uncertainty across all tipping elements in the climate system, from their mechanisms, over key thresholds and tipping timescales, to the dynamics and strengths of their interactions with other tipping elements and key Earth system components. All of these areas are critical and deserve further research as each individual element and dynamic process has the potential to critically impact their immediate area and often has significant impacts worldwide. However, some elements lead to a greater degree of uncertainty and impact than others when determining our future climate state. At the levels of global warming around 1.5 °C (that we are currently approaching and potentially crossing at least temporarily in the foreseeable future[5,6]), the most important elements are the large cryosphere elements: the Greenland and West Antarctic Ice sheets. The AMOC is also important (though to a lower degree than the polar ice sheets) due to its potential low critical temperature and its interactions with the ice sheets. These results are similar at the higher temperatures of the 4.0 °C runs, with the Greenland Ice Sheet remaining critical in the Sobol Variance analysis and the polar ice sheets and AMOC continuing to have large impacts when removed from the system. The key difference at 4.0 °C is that the nodes with higher temperature thresholds become more important and so ENSO becomes more important, as shown in Fig. 2. These results suggest that we can reduce our uncertainty most effectively by reducing our uncertainty in key elements of the system, such as the polar ice sheets.

Further temperature scenarios or specific overshoot pathways would be an interesting extension of this study, the 1.5 °C and 4.0 °C runs were chosen here as two important cases of possible future global warming. More detailed analysis between these temperatures could determine the range of temperatures for which a given node is important for the variability, and also which temperatures give the greatest uncertainty in final tipping state.

Although the network model used in this study is a strongly simplified and non-process-based model, it has common features with more advanced models (in particular, relevant for this study, its ability to represent known unknowns and unknown unknowns such as missing components etc.). However, the simplifications of climate components in this model due to representing complex components as simple fold-tipping points or linear responses, assuming single timescale responses to forcings, or linear forcings between components are limitations of this study. Results from this model can therefore not be taken as climate projections nor can the results be trivially transferred from this simple model to more complex models. This model also suffers from limitations around representation of timescales in the model, with some elements (such as the critical polar ice sheets) known to respond on multiple timescales[44,45]. These systems may begin melting more rapidly and influencing other elements on short timescales of years and decades, but take centuries to millennia to reach their fully melted state. This leads to significant uncertainty in which timescales to use in this model and whether a single bifurcation tipping point is sufficient to represent these elements. In this study, we used the newest literature values for these timescales and thresholds from Armstrong Mckay et al., Kriegler et al., and Wunderling et al.[2,16,21]. Another key source of uncertainty in this model is that it only allows for pairwise linear interactions between components even though some of these interactions are potentially non-linear and may involve multiple components. This non-linearity may be critical for the complete representation of dynamics. However, because the model emulates key behaviours of tipping elements (non-linear behaviour, interactions between tipping points), it is able to explore some of the space of potential transitions and interactions. As the key results in this study relate to missing components and their interaction with the complex dynamics of the model, it is possible that similarly significant effects may be observed in more complex climate models if known components are not represented.

State-of-the-art GCMs such as those used in the CMIP6 project are one of the best ways for us to understand the future climate and rightly form a key component of our toolbox to inform IPCC reports and key decision-makers about climate change. However, climate models will always have components missing or poorly represented due to resource limitation and incomplete knowledge of the systems involved. These key components currently include the cryosphere and biosphere but constraints on grid resolution and parameterisation of key processes are predicted to continue into the foreseeable future[46]. This study shows that missing out even one component of the system can lead to significant first-order errors in the predictions for the system. This leads to two key messages.

First, missing components in a climate model can have as great an impact on the uncertainty as uncertainty in the temperature threshold of a given climate component. Comprehensive climate models should therefore aim to include as many components as possible and represent the interactions between them. Although this is almost trivially true, this is a tremendously challenging task. This is critical because even if many components are simulated accurately, missing even one component can have a large impact on the behaviour of the model, as shown in this study. Thus even if a model simulates a particular feature (such as the AMOC or ENSO) very accurately, if it is missing a key component such as the polar ice sheets, the forcing on the AMOC or ENSO can be wrong and so the overall model behaviour may lack key climate dynamics (at least on timescales relevant to the large ice sheets). Therefore, it seems helpful that climate model development may want to prioritise the inclusion of currently missing components in the system (in a reasonably faithful way) rather than improving the representation of components that are already included. For example, many climate models do not include a coupled ice sheet and although these are fundamentally very difficult to couple to a climate model, even a simplified ice sheet component coupled to the climate model may provide a very fruitful way forward[47].

Second, as we know that we cannot include all components even at the highest complexity in our climate models, we must be careful with the interpretation of our climate models, their limitations, and the impact of unknown missing components. Ensembles of climate models can be good for dealing with known unknowns and uncertainty in parameters across models. However, although ensembles of climate models benefit from having a range of techniques and modelling setups they often incorporate common structures, modelling techniques and parameter choices. This means that they cannot resolve errors/uncertainties introduced by missing Earth system model components or by common modelling choices[41,48,49]. In this study, we outlined the impact of missing a single component or interaction, which can contribute significant uncertainty to climate projections from our models. This uncertainty will remain even as climate models improve and include more components. This is because some components will remain unresolvable despite improvements in model resolution. We may also miss components, interactions or behaviours because the climate problem is an extrapolation problem and we may not have experienced novel behaviours in new states of the climate that we are moving into. This uncertainty should encourage us to be careful with our future projections and maintain significant uncertainty around them due to the assumptions and missing components in our model design.

In conclusion, the uncertainties in climate models and our epistemic uncertainty should encourage us to focus our energies on the most productive ways to reduce our uncertainties, but also to develop better decision-making under high uncertainty (as for instance discussed in Katzav et al.[50]). As our climate model output is inherently uncertain, we need to evolve our decision-making to view these climate models not as the only decision-support tool, but also have a range of different predictive and projective methods. We should then plan and consider a wider range of possible futures and aim for a precautionary-principle approach which is robust to the worst-case scenarios that we cannot rule out[51]. We should also aim to consider a broader range of predictive climate methods beyond conceptual but also complex coupled climate models to get the best range of predictions from improved (Earth observation and satellite) observations, reanalysis, paleoclimate records but also including expert knowledge[52,53]. This is particularly important for climate tipping elements, given that we are on track of (and at least temporarily) overshooting 1.5 °C of global warming[5,6], a temperature where tipping risks strongly increase[2,3].

Methods

Interacting tipping element model

This study focuses on a simple six component climate network model where each of the considered components in the system is represented by a stylised equation. The four elements (AMAZ, AMOC, GIS, WAIS) which are clear tipping points are represented by a double-fold bifurcation for simplicity and consistency among the Earth system components. See Supplementary Sections 1 and 2 for a discussion on all six considered Earth system components and how they should be represented. The key equation governing the behaviour of the system is expressed as follows:

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = \left[-x_i^3 + x_i + \sqrt{\frac{4}{27}} \cdot \frac{\Delta\,\mathrm{GMT}}{T_{\mathrm{crit,i}}} + \frac{1}{2}\sum_{j,j\neq i} d_{ij}(x_j + 1)\right]\frac{1}{\tau_i} \qquad (1)$$

Where x_i gives the state of the element, ΔGMT is the global mean temperature change from pre-industrial conditions, $T_{\mathrm{crit,i}}$ is the critical temperature (temperature threshold/tipping point) of the element i in question, and τ_i is the tipping timescale for the given element. d_{ij} gives the strength and sign of the interaction between element i and j. The first three terms in this equation govern the dynamics and tipping behaviour for a single element while the final terms in the sum represent the interaction from all other elements. If there are no interaction terms, then the critical threshold values where the tipping occurs are when the global mean temperature change ΔGMT exceeds the critical temperature $T_{\mathrm{crit,i}}$.

For ENSO and ASSI these components are threshold-free feedbacks or lack persistent self-amplifying feedback and so are represented using a monotonic linear response function[2]. The equation governing this behaviour is shown below:

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = \left[-1 - x_i + \frac{\Delta\,\mathrm{GMT}}{T_{\mathrm{crit,i}}} + \frac{1}{2}\sum_{j,j\neq i} d_{ij}(x_j + 1)\right]\frac{1}{\tau_i} \quad (2)$$

This equation structure was chosen for the linear response to ensure that the initial state with no warming was at -1 and that as the temperature and forcing increase the equilibrium increases with the state of $x = 0$ being chosen to represent the component having reached the new qualitative state, as in other components with the non-linear behaviour.

Values for the critical temperature ($T_{\mathrm{crit,i}}$) and the characteristic timescale (τ_i) of each Earth system component are given in Supplementary Table 1, while the values for the interaction parameters (d_{ij}, values following Wunderling et al.[16]) are given in Supplementary Table 2 (with some link strengths guided by the wider literature[2,15,21], as described in the supplement, Section 2).

Pycascades package

The Pycascades python package (as described in Wunderling et al.[37]) is designed to investigate tipping elements and interactions between them, for instance in ecology, economy, or climate. Pycascades is an established tool for interaction climate tipping elements to investigate under which global warming trajectories tipping points are crossed and potentially irreversible changes are caused[12,16,38].

Similar differential equation approaches have been used widely across many fields like ecology, complex networks, and climate to qualitatively describe tipping dynamics[14, 54–58]. In this particular case, the model is an extension of the four tipping element model described in Wunderling et al.[16] by adding two further important Earth system elements. In this study, the key climate elements included are: the Greenland Ice Sheet (GIS), the West Antarctic Ice Sheet (WAIS), the Atlantic Meridional Overturning Circulation (AMOC), the Amazon Rainforest (AMAZ), the Arctic Summer Sea Ice (ASSI), and the El Niño Southern Oscillation (ENSO). The first four elements (GIS, WAIS, AMOC, AMAZ) are well-described tipping elements while the ASSI is not a tipping element and ENSO is likely not a tipping element. These six elements were chosen for their potential cascading interactions based on recent literature[2,15]. We expand our reasoning as to why their dynamics are acceptably well represented by our simplified equation in the supplement (see supplement sections 1 and 2).

Sobol analysis

A Sobol Sensitivity Analysis is an established statistical method to assess the importance of uncertainty in the inputs to a model in the uncertainty of the outputs from a model[40]. In other words: A Sobol analysis explains from which input parameters the output uncertainty arises. In this study we use it to assess the relative importance of uncertainties in model parameters. In particular, we take the critical temperatures (tipping points), tipping timescales and interaction strengths into account and quantify how their uncertainties explain key model outputs such as the number of tipped elements.

The Sobol Method[40] decomposes the total variance in an output into fractions attributable to different components, allowing to determine the relative importance of inputs. The method works in a number of stages as described below:

For a model with d input dimensions and using N samples

- Sampling: Generate two $N \times d$ sample matrices (matrix A and matrix B) where the elements in the matrices are random samples from the probability distributions for each parameter of the model. These two matrices are used to generate independent samples for the parameters which are directly comparable (i.e. rather than samples being completely random, their values are taken from either matrix A or matrix B so that the effect when everything else is held constant can be easily determined).
- Matrix generation: Create a new matrix for each dimension by replacing the corresponding column in matrix A with the equivalent values for the dimension from matrix B. These new matrices can be labelled $\boldsymbol{A}_{\boldsymbol{B}}^{i}$.
- Calculation: Run the model to generate outputs from each sample for the $N(d+2)$ samples which are now created across the initial A and B matrices and the additional d-altered matrices.
- Evaluation: Calculate the indices of interest. The relevant expectation and variance parameters for the calculation of the *total-effect indices* can be calculated from the matrix outputs:

$$\mathrm{Var}_{X_i}(E_{\boldsymbol{X}_i}(Y|X_i)) \approx \frac{1}{N}\sum_{j=1}^{N} f(\boldsymbol{B})_j(f(\boldsymbol{A}_B^i)_j - f(\boldsymbol{A})_j) \quad (3)$$

$$E_{\boldsymbol{X}i}(\mathrm{Var}_{X_i}(Y|\boldsymbol{X}_i)) \approx \frac{1}{2N}\sum_{j=1}^{N}(f(\boldsymbol{A})_j - f(\boldsymbol{A}_B^i)_j)^2 \quad (4)$$

These terms can then be used to calculate indices for the variance associated with each parameter. In this analysis, we primarily use the *total-effect index*. This is a measure of the total variation caused by a single parameter. As some factors in the model are highly non-linear and depend on a combination of variables, it is possible for multiple variables to be responsible for a particular amount of variation. In the total-effect index all variation which can be attributed to a parameter is attributed, which is a crude but effective measure of the overall impact of a parameter but does lead to double-counting when interaction effects are present so the sum of the total-effect indices will be greater than 1.

$$S_{Ti} = \frac{E_{\boldsymbol{X}i}(\mathrm{Var}_{X_i}(Y|\boldsymbol{X}_i))}{\mathrm{Var}(Y)} = 1 - \frac{\mathrm{Var}_{\boldsymbol{X}i}(E_{Xi}(Y|\boldsymbol{X}_i))}{\mathrm{Var}\,(Y)} \quad (5)$$

24 parameters (Critical temperatures, tipping timescales, and interaction strengths) were varied with 13,312 samples to perform this analysis. The analysis was performed using the SALib python package (as described in Iwanaga et al.[59] and Herman and Usher[60]), which is able to execute an efficient implementation of the Sobol method.

Leave one out analysis

The impact of particular components or links in the model can also be assessed through the method of removing it from the system and comparing the outputs to the outputs of the unperturbed system. We performed the following steps:

- Generate: Generate two sets of samples using latin hypercube sampling (in this work using the PyDOE package taken from Baudin[61]): (i) The first set of the two samples is the control run without any changes. (ii) The second set of samples is the perturbed run, where the respective component (node, for instance GIS is deleted) or interaction (link, for instance the link GIS → AMOC is deleted) is removed. For links in the system, this is simple and the link strength value can be set to zero. To remove a node from the system, tipping is prevented by setting the critical temperature to a very high value and all links into and out of the node are set to zero.
- Calculate: Run the model on both sets of samples to generate outputs.
- Compare: For each link or node, compare the outcomes between the control run and the sample when this component is removed. This returns a first-order assessment of the importance of the given component and its role in the system.

Data availability

Input samples and output data are available at https://github.com/JonathanRosser/Cryosphere-tipping-elements-decisive-for-tipping-risks-and-cascading-effects-in-the-Earth-system.

Code availability

In this study, we have used the Pycascades package. The usage can be found in Wunderling et al.[37] and on the associated webpage at: https://zenodo.org/record/4153102. The most up-to-date version of Pycascades can be accessed at https://github.com/pik-copan/pycascades. The specific code used in this analysis is available at https://github.com/JonathanRosser/Cryosphere-tipping-elements-decisive-for-tipping-risks-and-cascading-effects-in-the-Earth-system.

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Author contributions
N.W. conceived the study. J.R. and N.W. designed the study. J.R. performed the simulations and prepared the figures. J.R. and N.W. equally led the writing of the original paper draft with input from R.W. The internal review and editing process was performed by all authors. N.W. supervised the study.

Competing interests
The authors declare no competing interests.

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