

Global warming drives connectivity loss among climate tipping elements

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Tipping elements are large-scale components of the Earth system that may undergo abrupt and potentially irreversible transitions once critical thresholds are crossed. How these elements interact and coevolve under anthropogenic forcing remains poorly understood. Here, we introduce a Bayesian framework to quantify interdependence among tipping element regions based on lagged correlations, yielding a probabilistic measure of their connectivity that rigorously accounts for observational and sampling uncertainty. Using the preindustrial period as a baseline, we show that connectivity patterns among tipping elements are substantially weakened under high anthropogenic forcing, whereas the loss of coherence remains comparatively limited under low-forcing scenarios. This decorrelation is particularly pronounced in the Northern Hemisphere. We further identify the Atlantic meridional overturning circulation as a key contributor to the observed loss of connectivity, in line with recent evidence that it may be approaching a tipping point. In addition, we propose a simple toy model where tipping elements are seen as an adaptive dynamical system, losing coherence as a reaction to external perturbations. The results are robust across past decades and across different climate models, with deviations from the baseline strengthening into the future, especially under high-emission pathways.

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I. INTRODUCTION

Earth's climate is an intricate system, characterized by multiple dynamical equilibria and complex dynamics, and it can be highly sensitive to external or internal influences such as changes in atmospheric composition, in the input of solar radiation, and in the properties of the Earth's surface. On top of natural variability, in the last few decades an enormous amount of evidence highlighted the impact of human activities on Earth's climate [1,2], with already visible effects in the rate of extreme events [3] and in mean sea-level rise [4,5]. The increasing evidence of human impact on climate, generated by greenhouse gas emissions and land surface changes, underscores the urgency of properly understanding the complexities of climate dynamics [6].

An especially important aspect of climate variability is the existence of possible dynamical instabilities in some of its components, known as “tipping points” [7]. When a climatic element crosses a tipping point, its behavior can drastically change, for example, passing from one dynamical equilibrium

to another. Climatic components that are prone to such transitions are called “tipping elements,” usually associated with localized regions that can experience sudden and often irreversible changes in their climatic characteristics. In particular, warming exceeding 1.5 °C above preindustrial temperature could trigger the tipping of multiple elements [8].

At the global scale, the dynamics of some of the tipping elements are linked to each other. For instance, the study of teleconnections between tipping elements has revealed that the climatic variability of the Amazon rainforest exhibits strong correlations with the Tibetan Plateau and the West Antarctic Ice Sheet [9], suggesting deep and complex climatic interactions between these distant systems [10]. Moreover, climatological projections show a decline in overturning strength of the Atlantic meridional overturning circulation (AMOC) [11], which is possibly heading toward a tipping point, with potentially dramatic changes in the global climate system [12–14]. Other possible tipping points triggered by global warming include the ice sheet collapse [15–18], the Sahara greening [19], the boreal permafrost collapse [20], the boreal forest dieback [15,21], and low-latitude coral reefs die-off [22].

In this work, we consider a climate network approach to the study of tipping elements, with the dual aim of inferring their connectivity patterns and assessing how these patterns evolve under different forcing scenarios. Previous studies have shown that key aspects of the climate system can be effectively represented as complex networks [23–27].

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In these approaches, the strength of the links between nodes is typically quantified using statistical measures such as cross-correlation [28], Granger causality [29,30], or event synchronization [31]. These link weights are then converted into an adjacency matrix, often after applying some filtering or thresholding rule.

Within this context, the contribution of the present work is twofold. First, we study the time evolution of the connectivity of the tipping elements in both historical and future scenarios. We use climatological projections to assess the impact of human activities on the network of tipping elements under high- and low-emission scenarios. In the analysis, we consider a list of 13 potential tipping elements (see Fig. 1), which are both selected based on their ecological and climatic significance and, at the same time, identified as critical large components that could experience significant state changes due to anthropogenic forcing [7]. We quantify the shift of these connectivity patterns from the preindustrial baseline period (1850–1900), as in the latest Intergovernmental Panel on Climate Change reports [32], and how this change is projected to continue in the future under different emission scenarios.

Second, we contribute methodologically by addressing limitations of standard network-construction techniques. Conventional approaches that derive an adjacency matrix directly from a chosen statistic (e.g., cross-correlation) rely on filtering procedures, such as hard thresholding, which inevitably discard information and can distort the underlying network topology [33]. Moreover, as shown in Ref. [34], thresholding may obscure relevant dynamical features and lead to misleading interpretations of connectivity.

To mitigate the arbitrariness of these procedures and their associated biases, we formulate network reconstruction as a Bayesian inference problem, leading to a probabilistic, or “fuzzy,” network representation. This probabilistic framework yields an ensemble of networks consistent with the observed coactivation patterns, from which we can robustly estimate network descriptors that characterize interdependence among tipping elements.

A detailed description of the dataset and the construction of the coactivation matrix of near-surface temperature anomalies is provided in Sec. V. There, we also describe the mapping from the coactivation matrix to a probabilistic representation, where the entries correspond to the maximum posterior probabilities that a connection exists between two nodes. Finally, we describe how we aggregate the node-level results to obtain connectivity at the level of tipping elements. In the following, we present the temporal evolution of these probabilistic networks for past and future periods, compare the Bayesian approach with existing network-filtering methodologies, and discuss the implications of our findings for the broader literature on climatic tipping elements.

II. RESULTS

A. Tipping elements’ connectivity

We first investigate the connectivity between tipping elements using the Coupled Model Intercomparison Project

Phase 6 (CMIP6) under three different emission scenarios, namely, RCP2.6, RCP4.5, and RCP8.5, for a period of 80 years, from 2021 to 2100. In addition, we also analyze the historical run of the CMIP6 for the same three models, from 1970 to 2014.

We consider 2-m surface temperature anomalies as an observable proxy of the internal state dynamics of the considered tipping elements, which are shown in Fig. 1. Our working assumption is that, for most tipping elements, large-scale anomalies in near-surface temperature over the relevant domain are dynamically coupled to, and therefore statistically informative about, the state of the element itself.

We compute the connectivity between tipping elements on an annual basis and compare each yearly network with the mean connectivity over the preindustrial baseline period (1850–1900), in order to quantify deviations from the baseline. To synthesize these results, in Fig. 2 we aggregate the annual connectivity matrices into 30-year windows and average the resulting variations across the three climate models considered. Connectivity changes are represented using a color scale: Blue denotes a negative variation with respect to the baseline, indicating a decrease in connectivity, whereas red denotes positive changes, marking an increase.

In the low-emission scenario, where the multimodel mean global surface temperature increase remains below 2.0°C relative to the baseline, the connectivity patterns are remarkably stable. Absolute connectivity changes do not exceed about 0.02, even in the final 30-year period of the 21st century. In the middle-emission scenario, connectivity variations are still modest in 2041–2070, with notable exceptions including a more pronounced decrease in connectivity between permafrost and boreal forest, and between boreal forest and the Arctic sea-ice region. In 2071–2100, these deviations become larger and increasingly involve links associated with the permafrost region. Under the high-emission scenario, in which the mean global temperature increase exceeds 5°C, we observe a substantial reduction in connectivity for a much larger set of links, already evident in 2041–2070, particularly those connecting permafrost with the AMOC, coral reef, and boreal forest. These pronounced departures from the baseline connectivity indicate a profound reorganization of the internal dynamics of these regions and of their functional interactions, tightly coupled to the magnitude of global warming.

To further elucidate the spatial structure of these changes, Fig. 3 displays the global network of tipping elements, in which edge thickness represents the baseline connectivity and edge color represents the deviation from the preindustrial baseline. This spatial representation highlights that most connectivity changes are concentrated in the Northern Hemisphere and often involve teleconnections between geographically distant regions, such as permafrost and coral reef.

To quantify the role of each tipping element in shaping network reconfigurations across global warming levels, Fig. 4 ranks elements by their total change in connectivity. This metric is computed by summing the connectivity variations over all incident links for each region, evaluated over the periods 2041–2070 and 2071–2100. In the scenario where the global mean temperature increase does not exceed 2°C, the connectivity pattern is essentially stable in both the considered periods. In contrast, in the medium-emission

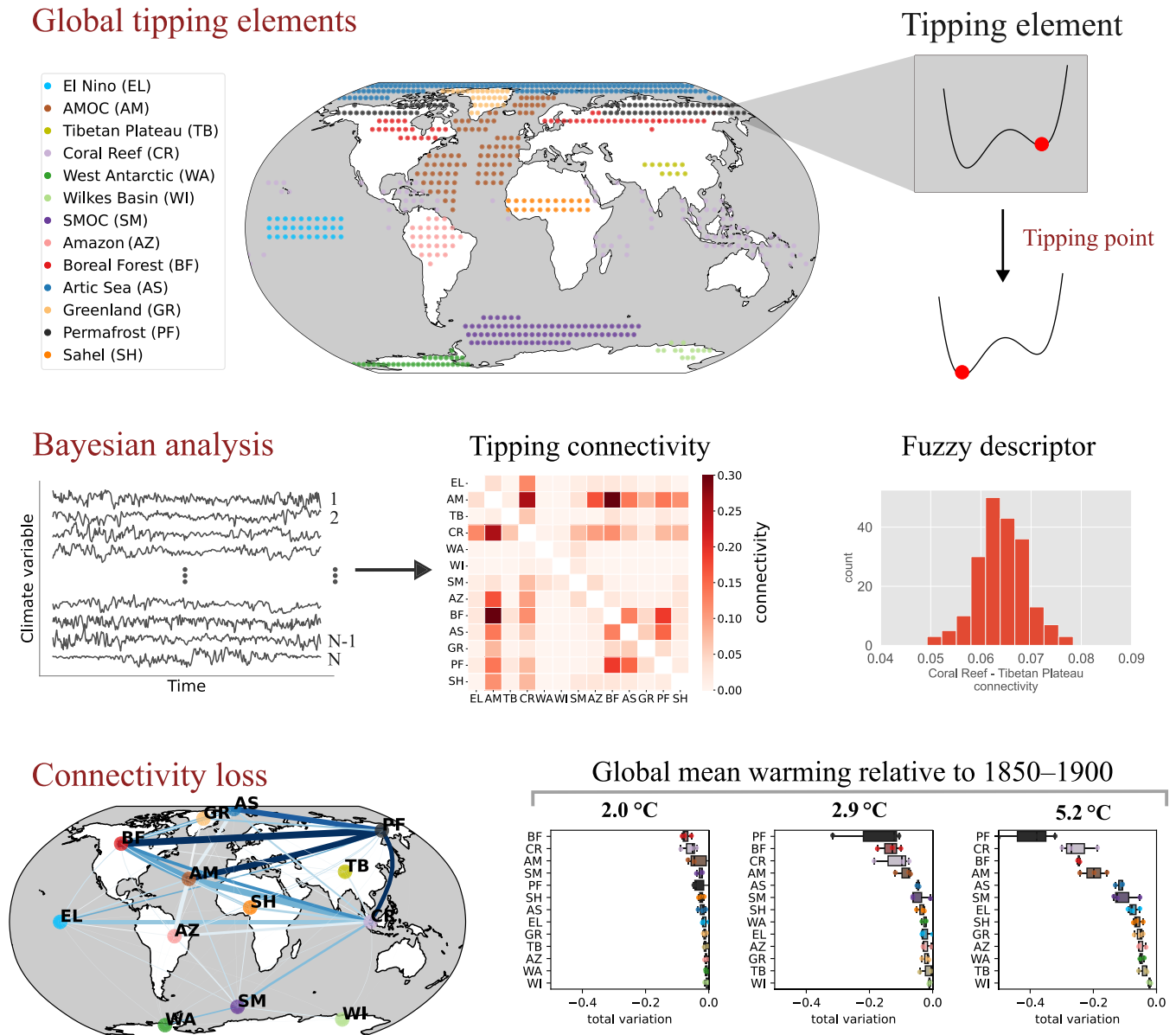


FIG. 1. Assessing the connectivity loss between tipping elements. Top panel shows the geographical locations of the 13 tipping elements considered in this work, with each region depicted in a unique color. External perturbations, such as anthropogenic forcing, may drive a tipping element toward a new equilibrium state, here represented by a red dot in a double-well potential, a phenomenon known as *tipping point*. Middle panel shows how to obtain the tipping connectivity matrix from the daily surface temperature anomalies: We compute the node-level fuzzy adjacency matrix π_{ij} , as in Eq. (4), representing the probability of existence of a link between two nodes and then we aggregate these results at the level of tipping elements. A key advantage of this approach is that each network descriptor becomes a fuzzy quantity: From the fuzzy adjacency matrix, we can generate an ensemble of networks and thereby obtain a full distribution for any descriptor. As an example, the histogram illustrates the distribution of the connectivity between the coral reef and the Tibetan Plateau, estimated from an ensemble of 100 networks sampled from the original fuzzy matrix. Bottom panel shows the network of connectivity loss (represented by the blue edges) between tipping elements with respect to the preindustrial baseline (1850–1900), while the boxplots represent the total variation computed in the last three decades of the 21st century with respect to the baseline, for three different SSP (Shared Socioeconomic Pathways)-RCP (Representative Concentration Pathways) climatic scenarios.

scenario (central column), the connectivity remains stable during 2041–2070 and then sharply decreases for many regions in the second period, for a global warming level of about 2.9°C. This pattern highlights the strongly nonlinear nature of this phenomenon in its response to temperature increase. Finally, we observe that in the high-emission scenario, an initial significant response can be already observed in the

years 2041–2070 and strongly increases in the last decades of the 21st century. Importantly, we find that these pronounced changes are predominantly associated with a small subset of tipping elements, involving only four regions to a significant extent, namely, permafrost, coral reefs, boreal forests, and AMOC. We also notice that the ranking of these top four regions with highest connectivity loss does not change across

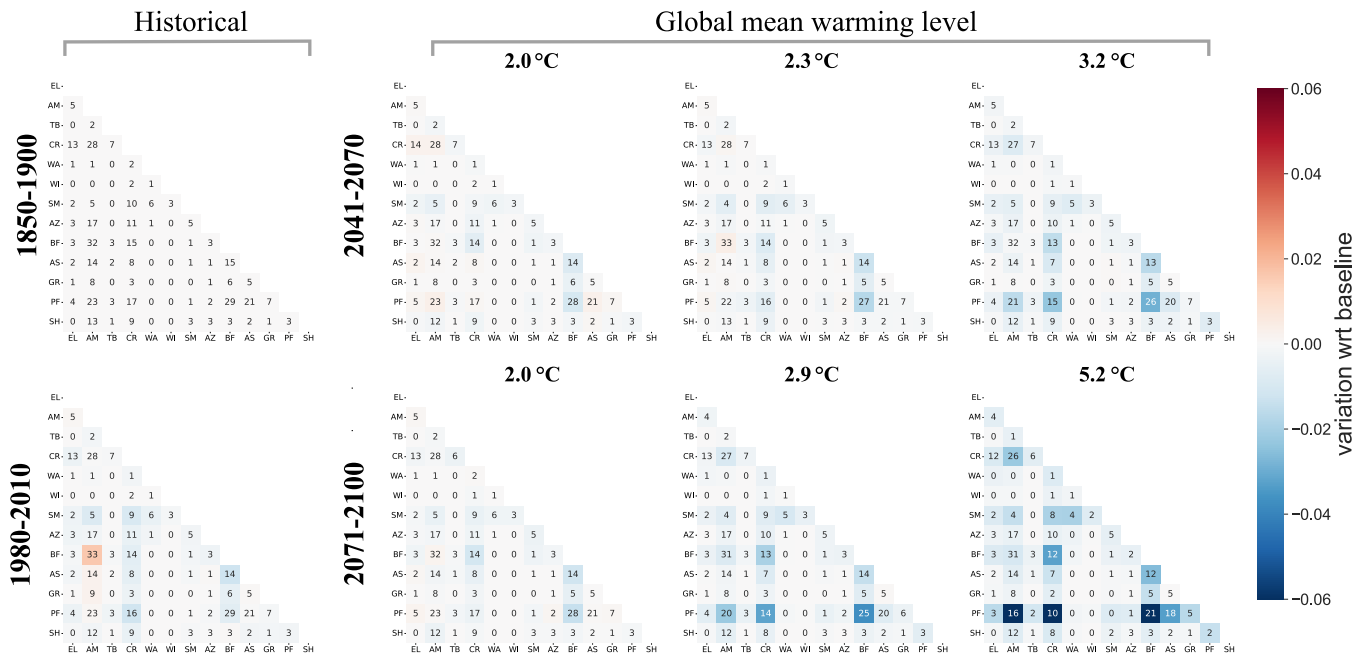


FIG. 2. Connectivity variations of climatic tipping elements relative to the preindustrial baseline (1850–1900). Entries show the connectivity between pairs of tipping elements, expressed in percentage points. Colors indicate the absolute change in connectivity with respect to the preindustrial baseline. The future global warming levels are computed as the increase of the mean surface temperature with respect to the baseline period. Results are averaged over the three climate models considered and the labels for the 13 tipping elements are defined in Fig. 1.

the three scenarios (with the only exception of AMOC in the low-emission scenario). It is worth noticing that, for most regions, the three models (represented by the dots within each bar) yield consistent estimates of the total variation,

which supports the robustness of our results. We additionally perform a 10-year window analysis, obtained by averaging the annual connectivity matrices over six consecutive decades between 2040 and 2100. The resulting connectivity variations

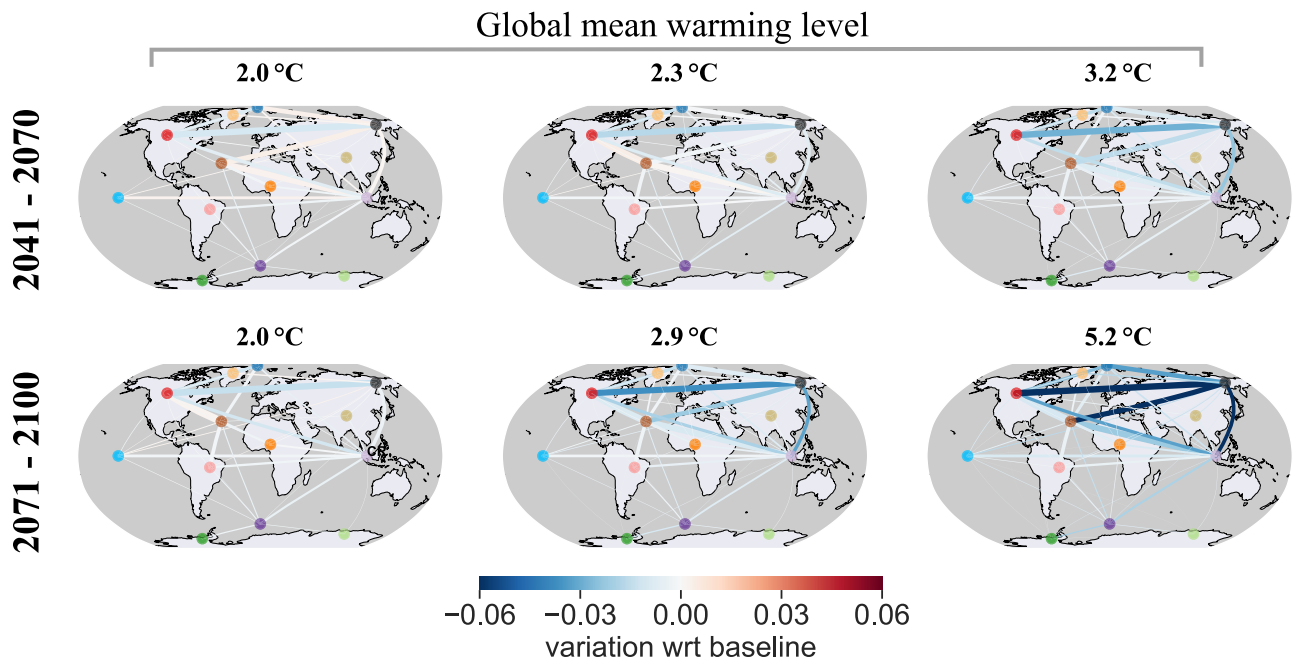


FIG. 3. Global network of connectivity variations relative to the preindustrial baseline (1850–1900). Blue edges indicate decreased connectivity and red edges indicate increased connectivity with respect to the baseline. Each column corresponds to a different emission scenario, ordered from left to right by increasing emissions. Results are averaged over the three climate models considered. Edge thickness is proportional to the baseline connectivity $\bar{C}_{AB}$ between tipping elements A and B, while edge color encodes the connectivity variation $\Delta C_{AB} = C_{AB} - \bar{C}_{AB}$ for the corresponding 30-year period.

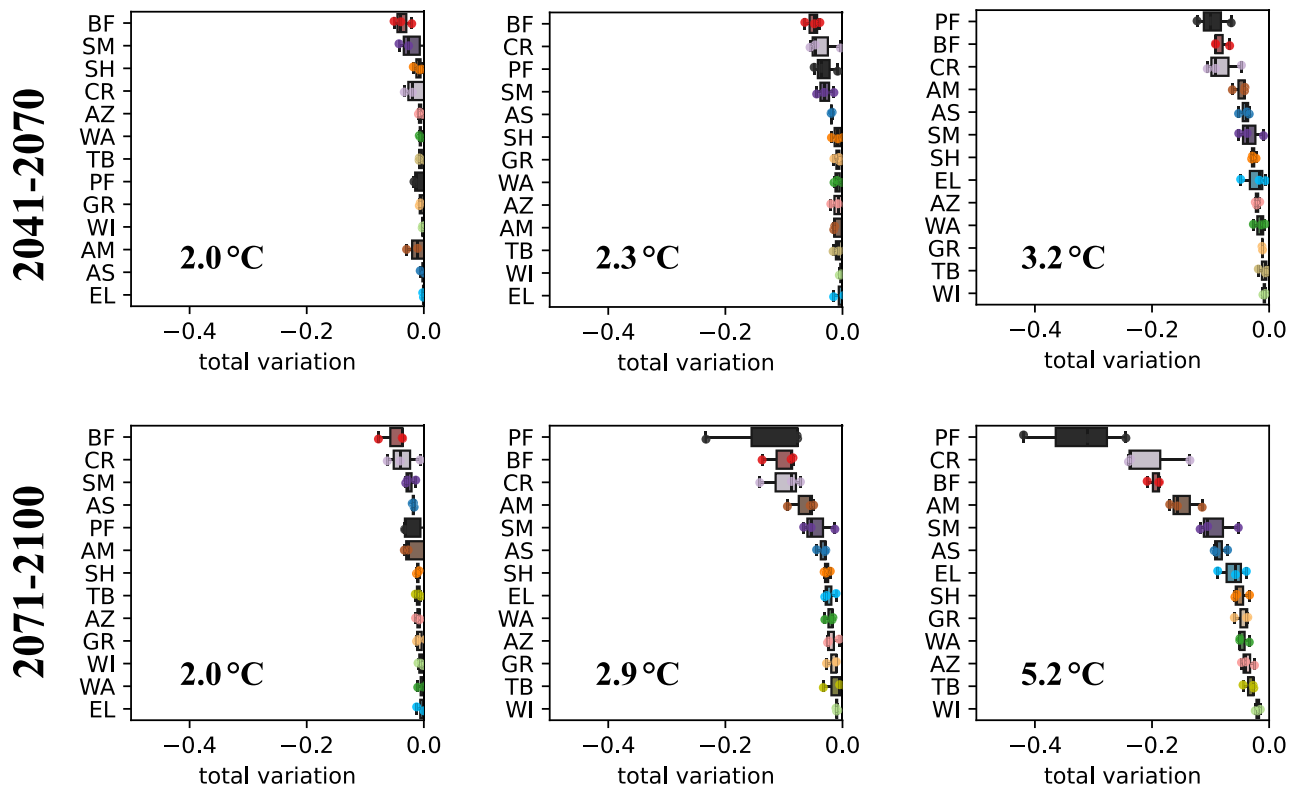


FIG. 4. Tipping elements' ranking according to their total connectivity variation with respect to the preindustrial baseline (1850–1900). Each panel shows the total connectivity variation of each tipping element as a function of global warming in the years 2041–2070 (top row) and in the years 2071–2100 (bottom row), while each dot within each bar represents a different climatic model. All tipping elements experience a degree of connectivity loss, but the effect is stronger in the medium-emission scenario during 2071–2100, and in both the considered time periods for the high-emission scenario.

are consistent with those from the 30-year window analysis (see Appendix E of the Supplemental Material [41]), indicating that the effect persists even when accounting for the greater variability inherent to decadal timescales.

B. Lag analysis

To further interpret the connectivity analysis, we consider the temporal structure of interactions between tipping elements by examining the lag at which the cross-correlations between nodes in different regions peak. In Fig. 5, each entry of the heatmaps represents the peak cross-correlation lag (including its sign) for a given pair of tipping elements. A positive lag indicates that variations in the anomalies of the first region systematically precede those in the second, whereas a negative lag implies that the activity of one region follows the other. As can be seen, the signs of the lags are predominantly positive, indicating that the activity in many tipping elements systematically precedes that in others, which we interpret as being consistent with the observation that sea surface temperature anomalies have been observed to propagate eastward in the middle latitudes [35], where most of the considered regions are located. It is also interesting to see that this pattern is rather stable across the considered scenarios, supporting the claim that global warming does not change qualitatively the direction of the propagation of energy fluxes in the atmosphere. It is also worth noting that the stability of these fluxes at midlatitudes may reflect underlying

mechanisms of atmospheric dynamics that are primarily driven by other factors, such as Earth's rotation and the distribution of land masses, which appear to be robust under the considered levels of climate change.

C. Network analysis

To investigate the evolution of the node-level network at a global scale, we consider the evolution of various global network metrics under different climatic scenarios. Specifically, in Fig. 6 we focus our analysis on edge density, global clustering coefficient, and modularity. The first quantity that we consider is the edge density (top row), which shows that the network is globally becoming more sparse over time under the high-emission scenario. This is also reflected in the loss of connectivity found in the tipping element analysis of Fig. 3. Another relevant feature is transitivity, quantified by the clustering coefficient (middle row). In a climatic context, this measures the likelihood that three regions form a triangular pattern of connections. For example, if temperature variability in the North Atlantic is connected to both Western Europe and the Arctic, and these two regions are also connected to each other, the three regions form a closed climatic triangle. Such patterns may reflect shared large-scale circulation processes or common climatic drivers. We observe a sharp loss of transitivity, which is particularly evident under the high-emission scenario. Finally, modularity score is increasing, which suggests stronger community structure, with relatively denser

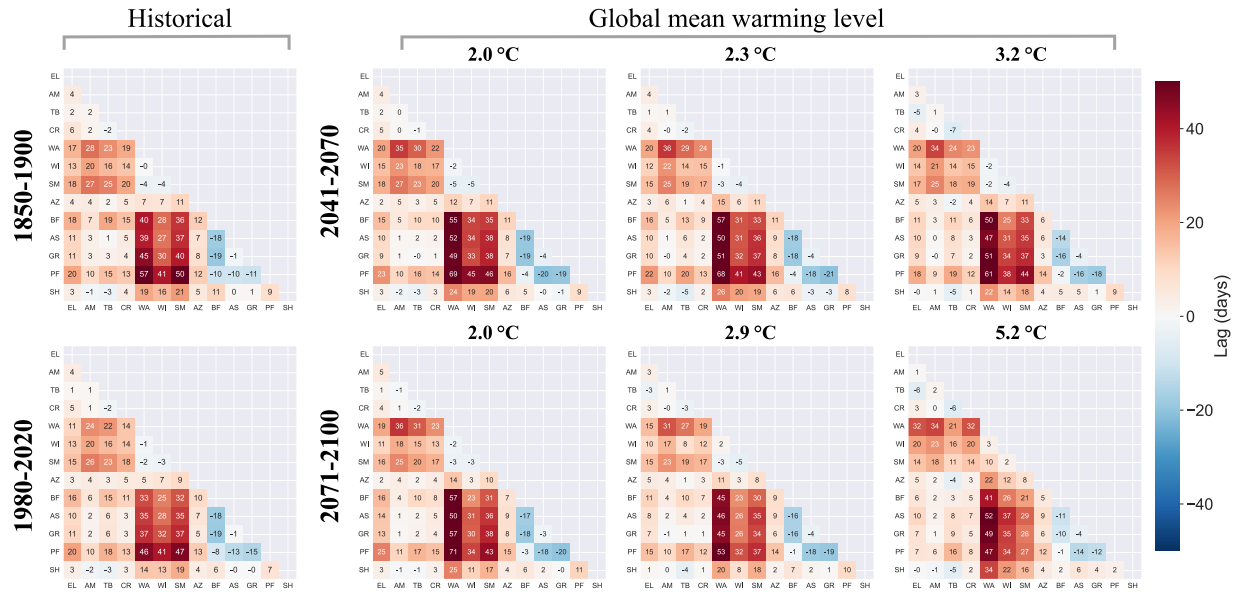


FIG. 5. Lag analysis. Heatmaps show the lag τ at which the cross-correlation peaks between each pair of tipping elements. Each entry represents the average lag across all possible links between two tipping elements. A positive lag indicates that the anomaly fluctuations of one tipping element precede the activity of another. For example, in the top-right panel, a time lag of 11 indicates that the covariability of the boreal forest precedes the activity of the Tibetan Plateau by 11 days. Results are also averaged over the CMIP6 simulation models considered in this study.

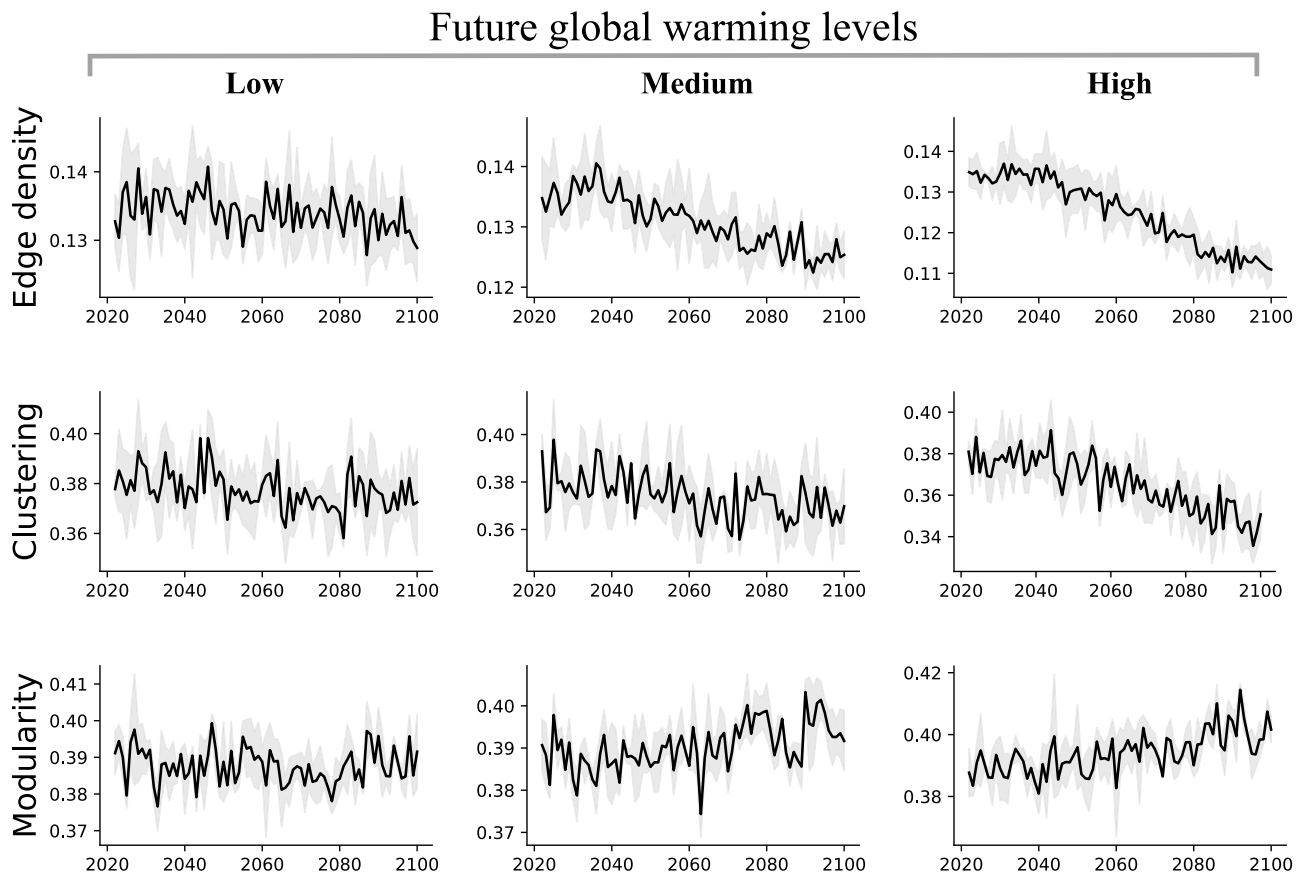


FIG. 6. Network analysis across climatic scenarios. We report edge density, global clustering coefficient, and modularity for node-level yearly fuzzy networks derived from the surface temperature analysis. The solid black line denotes the ensemble mean across the three climate models, while the gray band indicates the mean absolute error. Columns correspond to different warming pathways: Low, medium, and high global warming levels correspond to SSP1-RCP2.6, SSP2-RCP4.5, and SSP5-RCP8.5 scenarios, respectively.

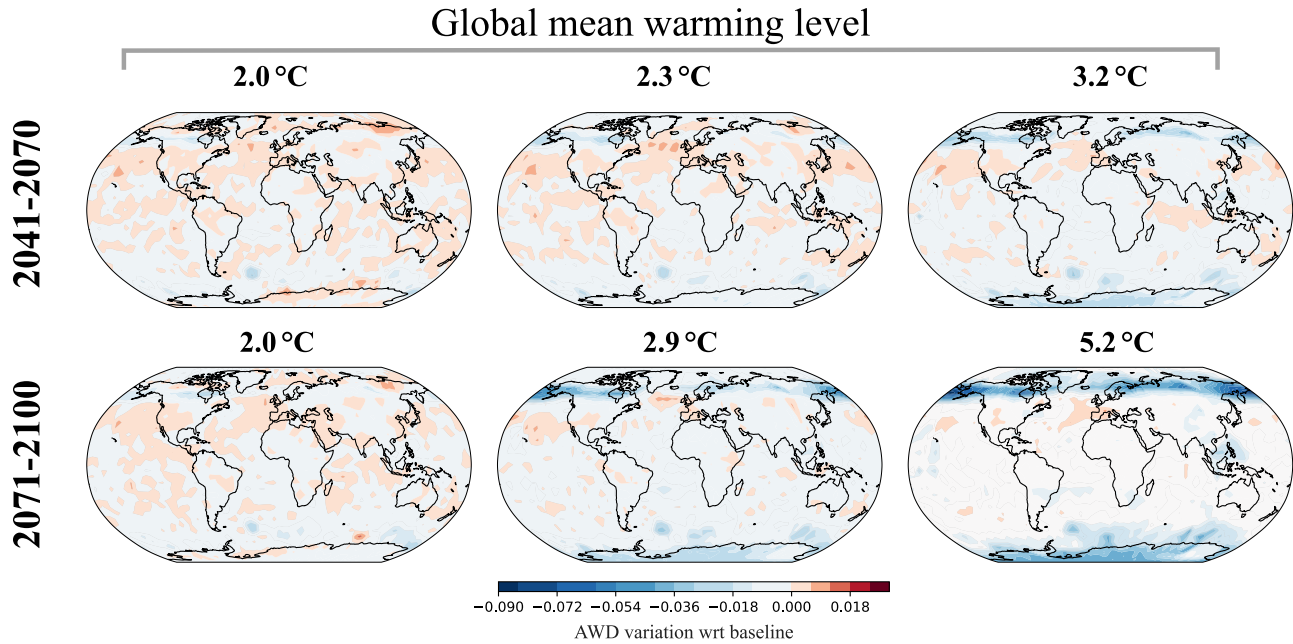


FIG. 7. Area-weighted degree (AWD) anomaly relative to the preindustrial baseline (1850–1900). The plot shows the node-level variations in AWD connectivity, as defined in Eq. (3), computed with respect to the baseline period. For each climate scenario, results are averaged across the three models considered.

intracommunity connectivity and weaker intercommunity connectivity, consistent with a more segregated (i.e., modular) network organization.

It is important to notice that the observed trends are consistent over the three considered models. Interestingly, in the low-emission scenario the situation is rather stable, with no significant trend over the considered period. This indicates that, with low anthropogenic forcing, the network does not undergo significant changes even at the level of single nodes, consistent with the results obtained with the tipping element network. Conversely, under the high-emission scenario, the global climate system appears to move toward a qualitative transition, as reflected by changes in the network topology. It is also informative to examine the evolution of the area-weighted degree connectivity, as defined in Eq. (3), which acts as the analog of node degree for nodes representing different areas. In Fig. 7, we present the change in this measure for the two 30-year windows compared to the baseline preindustrial period, across the different climate scenarios. The figure indicates that increases (dark red regions) remain modest in all scenarios, whereas the most substantial changes emerge under the high-emission scenario, with pronounced decreases (blue regions) concentrated in the Arctic, primarily associated with the permafrost and boreal forest tipping elements.

D. Comparison against thresholding

An advantage of our Bayesian approach is that it does not require selecting a fixed threshold to filter the results. Instead, a network ensemble is sampled from a probabilistic (fuzzy) network, preserving potentially important information that might otherwise be lost in threshold-based methods. To compare our Bayesian method with traditional threshold-based approaches for constructing climate networks, we applied

different thresholds, specifically selecting the top 1%, 5%, and 50% percentiles of the Z-scores.

The heatmaps in Fig. 8 illustrate the difference between the values C_i , representing the area-weighted degree of each node, obtained with thresholding and those obtained with the Bayesian approach, for different threshold levels. The impact of the chosen threshold on the obtained results is clearly evident. Additionally, we note that it is not straightforward to select a threshold that produces a network density comparable to that achieved with our Bayesian approach. This is because varying the threshold leads to nontrivial and uncontrollable changes in the resulting network structure.

III. DISCUSSION

In this work, we analyzed the evolution of climatic networks built on the functional lagged covariability of surface air temperature under different levels of anthropogenic forcing. We focused on the connections between large-scale components known as tipping elements, revealing that the connectivity pattern between these components has been rather stable in the past, but shows significant changes in the connectivity of several regions under medium- and high-emission scenarios. In particular, our analysis indicates that in these scenarios the pattern of connectivity between the tipping elements changes significantly from 2041 to 2100. This effect sharply increases in the last 30 years of the 21st century, showing an acceleration of the deviation from the baseline condition and a generalized decrease of the connectivity among different tipping elements. Interestingly, it appears that four regions are more affected than others, namely, permafrost, boreal forest, coral reef, and AMOC. Permafrost appears to play a pivotal role in the pattern of changing connectivity, especially in the last decades of the

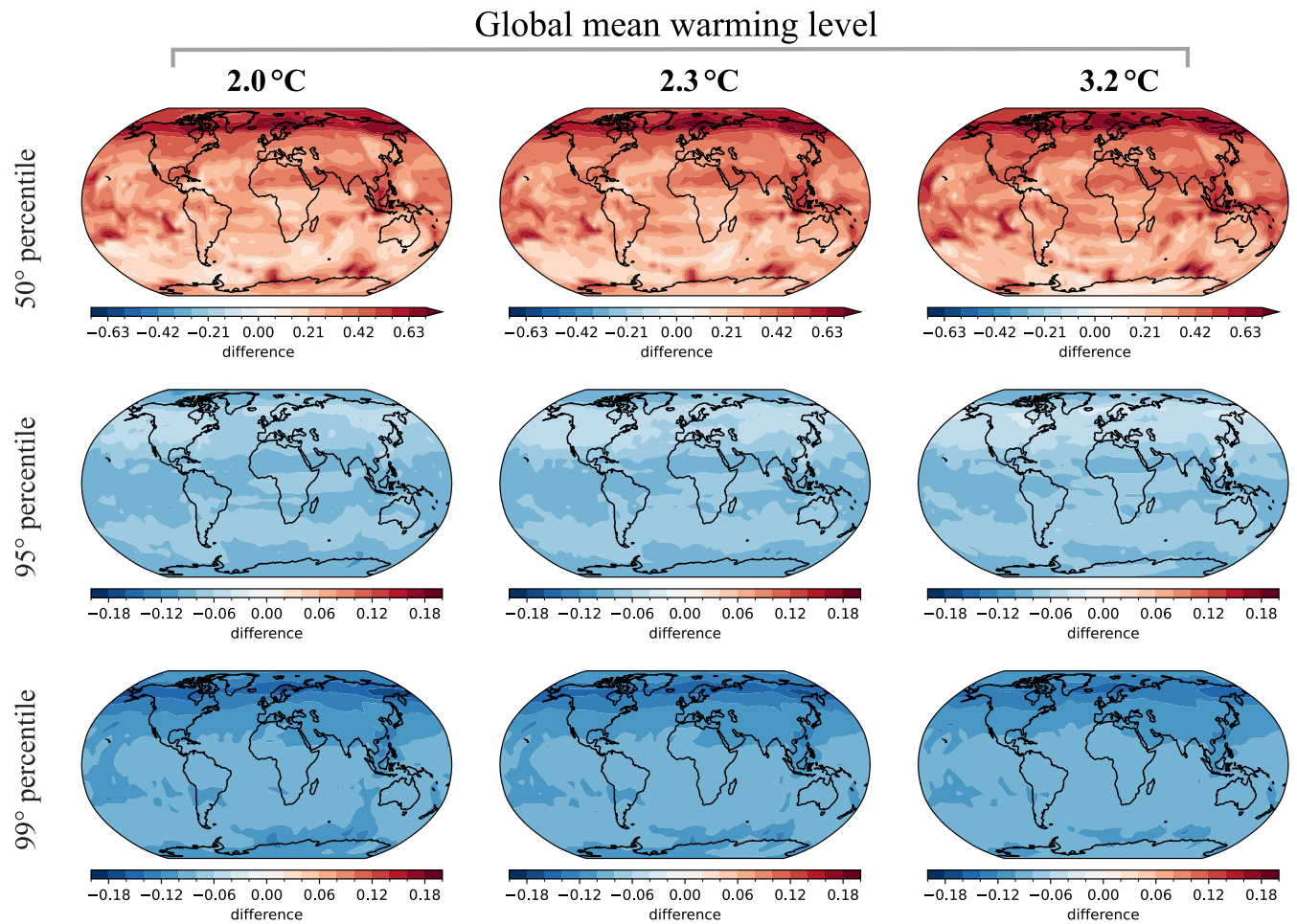


FIG. 8. Comparison between thresholding and Bayesian approach. Each map depicts the difference in area-weighted node degree [defined in Eq. (3)] between networks obtained via thresholding and those derived from the fuzzy Bayesian matrices. Rows correspond to increasing threshold values, and columns to distinct climate scenarios. Values are averaged across the three models considered.

21st century, reducing its connection strength with other tipping elements, most notably AMOC, boreal forest, and coral reef. In contrast, the connectivity pattern under the low-emission scenario remains relatively stable within the levels of statistical significance. Although there is a general decrease in connectivity, the changes are much less pronounced. Extending the same investigation up to the year 2100, we observe a crucial difference between the low-emission scenario and the high-emission case. For the high-emission scenarios, the changes are dramatic. In particular, we observe slow changes with respect to the present day until the middle of this century, after which alterations become more abrupt. In the scientific literature, the impact of temperature increase on permafrost, boreal forest, coral reef, and AMOC has been studied [15,20–22,36,37]. Moreover, AMOC region is considered susceptible to approaching a tipping point in some of the future scenarios [12]. These decorrelations indicate a general loss of functional coherence between the temperature variability of some climatic regions and may suggest a progressive shift of climatic state toward a new regime where climate dynamics are more chaotic and thus the observables are less predictable. This interpretation is consistent with a previous study [38], which showed that the proximity to a climatic

critical transition may be accompanied by critical slowing down, including a slower decay of correlations and an increase in decorrelation times. Such changes could also affect short-term weather forecasting and our ability to predict extreme events. This hypothesis is consistent with a recent study [39] showing that the projected dynamical predictability of agricultural droughts is expected to decrease significantly under warming scenarios.

We remark that near-surface temperature is among the most reliably observed and simulated climate variables. It integrates the net effect of multiple interacting processes across the Earth system and therefore provides a robust observational proxy for the underlying dynamics of its components [40]. However, considering surface temperature alone may be limiting for a complete description of the state of many tipping elements. For example, the state of the Amazon rainforest is also determined by precipitation, which is, in turn, influenced in a nontrivial way by the state of the atmosphere. For this reason, a possible extension of this work could consider additional climatological variables or adopt a multivariate approach.

In the Supplemental Material [41], we provide a mechanistic interpretation of the decorrelation between tipping

elements identified in this study. Specifically, we consider a synthetic network of interacting tipping elements, each represented by a double-well potential, where interactions are mediated by a global coupling strength σ . Crucially, we introduce a global adaptive mechanism in the node states: The units respond to state perturbations through a feedback loop, such that the effective coupling σ becomes time dependent and evolves according to a prescribed dynamical rule. By simulating the resulting trajectories and computing correlations between anomalies using the same procedure as in the main analysis, we recover a progressive decorrelation over time (see Fig. S3 in Appendix A of the Supplemental Material [41]), qualitatively consistent with our empirical findings. While this model is intentionally simplified and cannot reproduce the full complexity of the Earth system, it offers a plausible mechanism underlying the observed behavior.

Previous climate-network studies have only considered few tipping elements and have not systematically compared multiple climate scenarios [28]. A similar analysis on connectivity pattern between tipping elements has been performed in Ref. [9], where they explored the teleconnections between Amazon rainforest, Tibetan Plateau, and West Antarctic Ice Sheet. For the projection data, they only considered the RCP8.5 emission scenario. In contrast, our work considers a comprehensive network of individual tipping elements and examines how their connectivity reorganizes under different levels of global warming, thereby clarifying their role in the evolving structure of the climate system.

In Appendix H of the Supplemental Material [41], we also examine the historical evolution of tipping element connectivity using the historical runs (1970–2014) of the CMIP6 models. Following the procedure adopted in the main text, we computed the connectivity variation with respect to the preindustrial baseline, and then mapped the connectivity changes of each tipping region with respect to all others and reported results over two successive 30-year time windows. Overall, the pattern of connectivity changes remains remarkably stable over the 40-year period considered, showing no initial signs of the decorrelation observed under the future high-emission scenario. This result suggests that, although anthropogenic forcing was already present during the historical period, substantial changes in connectivity may emerge only after a certain threshold is crossed.

A limitation of the present analysis is that pairwise correlations do not distinguish direct interactions from statistical dependencies induced by common drivers or other confounding variables. In principle, conditional or partial correlation methods could help disentangle these effects. However, applying such approaches at the scale considered here would require conditioning on a very large number of variables, making the analysis computationally unfeasible. Restricting the conditioning set would alleviate the computational burden, but would introduce an additional model-selection problem, since the relevant confounders may include not only temperatures at other locations but also other atmospheric variables, such as temperature at different pressure levels. We therefore adopt a pairwise functional approach and interpret the inferred links as statistical dependencies rather than direct causal interactions. Accordingly, our results are intended to characterize the large-scale decorrelation among climatic regions and tipping

elements, rather than to identify the specific physical mechanisms responsible for these changes.

IV. CONCLUSION

The main goal of this work is to assess how the interdependencies among tipping elements evolve under different anthropogenic forcing and to highlight the impact of human activities in Earth's dynamics. The analysis of surface temperature anomalies under high-emission scenarios reveals a troubling trend of decreased connectivity and less coherent climate dynamics across several tipping elements. Regions in the Northern Hemisphere are particularly vulnerable, exhibiting substantial connectivity changes when the global mean temperature anomaly exceeds 2°C relative to the preindustrial baseline.

These results highlight the complex, scenario-dependent nature of climatic interactions and further emphasize the influence of anthropogenic forcing on large-scale climate dynamics. The comparison across time windows clarifies how connectivity among tipping elements evolves under sustained high emissions, revealing a strongly nonlinear response to increasing global warming.

Overall, the high-emission scenario suggests that continued greenhouse gas emissions may substantially reorganize interdependencies among tipping elements, potentially facilitating cascading responses as components approach critical thresholds where irreversible transitions become more likely. Taken together, these findings reinforce the importance of maintaining a low-emission trajectory to limit abrupt and potentially disruptive reconfigurations of the global climate system.

Our findings underline the unpredictable nature of climate dynamics and raise concerns about the possible decrease of large-scale connectivity and mutual interactions between the planetary tipping elements, pushing the climate system toward a spatially less coherent dynamics under climate change stress. These results thus confirm, from a different perspective, the urgent need for global efforts to reduce emissions and maintain the stability of the Earth's climate system, preventing a cascade of irreversible changes that could disrupt ecological and human systems worldwide. This analysis also underscores the urgency of devising and implementing effective mitigation strategies: Reducing greenhouse gas emissions may limit the most pronounced reconfigurations in interdependence among tipping elements, thereby helping to preserve key aspects of the current climate-system organization.

In conclusion, our study reveals how the network of functional interdependencies between tipping elements changes over time and highlights the potentially severe consequences of sustained high-emission trajectories.

V. METHODS

A. Data

We considered daily 2-m surface temperature on a spatial global grid between the years 2021 and 2100 for three models from the Coupled Model Intercomparison Project Phase 6: AWI-CM-1-1-MR, MRI-ESM2-0, and CESM2. We also considered the historical run of the same models, from 1970 to

2014. Since each model is defined on a different spatial grid, we have down-sampled each dataset to a 5×5 degree resolution global grid, resulting in $N = 2664$ time series, one for each grid point. These models have been chosen because they have been extensively analyzed in the literature, and some of them are known to exhibit pronounced responses to RCP forcings in specific contexts, including for certain tipping element dynamics. For instance, CESM2 has been used in a detailed investigation of AMOC behavior under strong forcing [12], while MRI-ESM2-0 shows signs of AMOC collapse even in a low-forcing scenario [42,43]. To assess the impact of human activities, we considered the high (SSP5-RCP8.5), medium (SSP2-RCP4.5), and low (SSP1-RCP2.6) future scenarios. The Shared Socioeconomic Pathways outline different future policy scenarios regarding demographics, economics, and technology, while the Representative Concentration Pathways are climate change scenarios to project future greenhouse gas concentrations [44].

To remove any seasonal effect, we computed the daily temperature anomalies, subtracting the average for each specific day (calculated over a baseline period) from the daily observations. This step eliminates spurious correlations due to seasonal effects, as temperatures are anticorrelated between opposite hemispheres. During the preprocessing, we did not remove the linear trend from the temperature data, as analysis indicates that detrending has a minimal impact on the correlations between anomaly series (see Appendix G of the Supplemental Material [41] for a detailed discussion).

B. Correlation analysis

We computed the cross-correlation ρ_{ij}^{τ} between locations i and j for all lags $\tau \in [-150, 150]$ and for all possible pairs of locations. As a proxy for the connectivity measure, we considered the Z score of the maximum of this statistics with respect to a null model:

$$Z_{ij} = \frac{|\rho_{ij}^{\tau^*} - \frac{1}{n} \sum_s \tilde{\rho}_{ij}^{\tau^*}|}{\sqrt{\frac{1}{n} \sum_s (\rho_{ij}^{\tau^*} - \frac{1}{n} \sum_s \tilde{\rho}_{ij}^{\tau^*})^2}}, \quad (1)$$

where $\rho_{ij}^{\tau^*} = \max_{\tau} \rho_{ij}^{\tau}$, while $\tilde{\rho}_{ij}^{\tau^*}$ denotes the corresponding quantity obtained from surrogate time series. Importantly, for each surrogate realization, the maximum cross-correlation was independently computed over all considered time lags. As a null model, we generated $n = 100$ time series using the iterative amplitude adjusted Fourier transform algorithm [45]. This quantity indicates how extreme the observed maximum correlation compared to a random noise that preserves the autocorrelation of the original series while eliminating any interseries correlations. Due to this property, the analysis is robust against spurious links generated by residual autocorrelations [46].

We performed the historical analysis for each calendar year from 1970 to 2020, totaling 50 windows, and from 2021 to 2100, totaling 80 windows, using CMIP6 climatic projections.

C. Tipping elements' connectivity

To quantify the connectivity between tipping elements, we aggregate the node-level adjacency matrix by summing

the connections within the domains of each pair of tipping elements. To this end, we introduce a measure of intercluster link density that also accounts for the Earth's spherical geometry: Since nodes located at higher latitudes represent smaller surface areas, each connection is weighted by the cosine of the latitude of the corresponding nodes. The total is then normalized by an appropriate geometric factor to ensure comparability across regions. Quantitatively, the connectivity between two tipping elements A and B is defined as

$$\mathcal{C}_{AB} = \frac{1}{\mathcal{Z}} \sum_{i \in A, j \in B} A_{ij} \cos \theta_i \cos \theta_j, \quad (2)$$

where A_{ij} is the adjacency matrix, θ_i is the latitude of the node i , and $\mathcal{Z} = \sum_i \cos \theta_i$. Note that, with the given normalization, even when the two regions are fully connected $\mathcal{C}_{AB} \neq 1$, while $\mathcal{C}_{AB} = 0$ when they are completely disconnected. A similar approach to correct for the spherical geometry of the Earth's surface was used in Refs. [25,47].

For the node's connectivity $\mathcal{C}_i$, we adopt the area-weighted degree [47], which quantifies the fraction of Earth's surface a node is connected to. Specifically, for node i , the AWD connectivity measure $\mathcal{C}_i$ is defined as

$$\mathcal{C}_i = \frac{1}{\mathcal{Z}} \sum_{j=1}^N A_{ij} \cos \theta_j, \quad (3)$$

where θ_i denotes the latitude of the node i and $\mathcal{Z} = \sum_j \cos(\theta_j)$. By weighting each connection by $\cos \theta_j$, this measure accounts for the Earth's spherical geometry, ensuring that the spatial extent associated with each node is properly represented.

D. Bayesian analysis of the coactivation patterns

In this study, we use Bayesian reasoning to estimate the probability of existence π_{ij} of a functional interdependence between two nodes starting from the connectivity measure Z_{ij} , following the framework introduced in Ref. [48]. This approach accounts for the uncertainty in observational data and sidesteps the pitfalls of thresholding and hypothesis testing, offering a more robust and reliable approach for network reconstruction [49]. First, we note that the p value of the observed statistic Z_{ij} does not provide information on the probability of existence of the alternative hypothesis $P(H_{ij}^1)$, which is precisely what we want to estimate through a Bayesian approach. When the null hypothesis is true, the p values are uniformly distributed between 0 and 1, as a consequence of the probability integral transform [50]. On the other hand, if the alternative hypothesis is true, it is more likely to obtain extreme values of the test statistic and, as a consequence, the distribution of the p values will be skewed toward zero. We denote with $P(H_{ij}^0)$ the prior probability that a link exists between two geographical nodes i and j . We want to compute $\pi_{ij} \equiv P(H_{ij}^1)$, which is the probability of existence of a link.

Here, we use a Bayesian calibration of the p-value [50,51] to obtain the minimum posterior probability for the alternative

hypothesis:

$$\pi_{ij} = 1 - \left[1 + \left(\frac{B_{ij}P(H_{ij}^0)}{1 - P(H_{ij}^0)} \right)^{-1} \right]^{-1}, \quad (4)$$

where $B_{ij} = -ep \ln p$ if $p < e^{-1}$ and $B_{ij} = 1$ if $p > e^{-1}$ is the inferior Bayes factor.

From a Bayesian perspective, the Bayes factor represents how much more likely is the alternative hypothesis compared to the null hypothesis. This means that the distinction between a physically meaningful weak connection and statistical noise is encoded in the posterior probability π_{ij} of link existence. A weak observed correlation provides only limited evidence in favor of the alternative hypothesis and therefore results in a low or intermediate posterior probability, depending on how compatible the observation is with the null hypothesis.

For the prior probability, the simplest and most conservative choice is an uninformative prior, setting $P(H_{ij}^0) = 0.5$ for all links. However, due to spatial correlations, close points are more likely to be connected. To capture this, we use

$$P(H_{ij}^0) = 1 - \exp\left(-\frac{d_{ij}}{k}\right),$$

where k is a spatial scale empirically set to 2000 km, as detailed in the Supplemental Material [41], and d_{ij} is the great-circle distance between two points. It is worth noting that the value of $k = 2000$ km aligns with findings from other climatological studies, where spatial correlations become negligible beyond this distance [28]. Moreover, in Appendix F of the Supplemental Material [41] (see Figs. S8 and S9), we tested that the choice of the parameter k does not affect significantly the main results of the analysis. From the link

probabilities, we can define the fuzzy matrix W as

$$W = \begin{pmatrix} 0 & \pi_{12} & \cdots & \pi_{1N} \\ \pi_{21} & 0 & \cdots & \pi_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{N1} & \pi_{N2} & \cdots & 0 \end{pmatrix},$$

which is symmetric and fully connected. Starting from W , for each year we sample 100 adjacency matrices of the same size by generating a random number η for each link, and assigning an edge if $\eta < \pi_{i,j}$. Each year is represented by an ensemble of climate networks that can be used to incorporate a confidence interval for each network feature used in the analysis [49]. More precisely, in a fuzzy network, all topological features (e.g., node degree and clustering coefficient) are random variables sampled from a network ensemble. This allows us to compute the mean and standard deviation of these descriptors, thereby quantifying a proper confidence interval. Consequently, the analysis of the temporal evolution of these network features can be performed with appropriate statistical tests to determine the significance of changes over time.

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DATA AVAILABILITY

The code is available in Ref. [52]. The data that support the findings of this article are openly available from the Copernicus repository in Ref. [53].

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