RESPONSES TO REVIEWER COMMENTS

We thank the reviewer for their constructive comments which helped us to substantially improve the manuscript. We have fully addressed the comments of the reviewer. For your convenience, we now provide below a point-by-point response to all the comments of the reviewers. Note that the reviewer' comments are indicated using blue Italian font, whereas our reply is indicated using black and regular fonts. The corrections in the revised manuscript (and quoted here) are indicated using red color.

Cheng et al. discuss the community structure of functional climate networks based on correlations among daily near-surface air temperature variations around the globe. They report systematic changes in the statistical properties of the network communities since the early 1980s and attempt to uncover the backbone of those changes in terms of a changing abundance of "isolated nodes". With its topical scope, the manuscript adds to a growing body of research utilizing network methods for studying the spatial organization of strong correlations in the global temperature field, as well as other climate variables at global and regional scales. The reported findings could be interesting, but are in my opinion not well enough explained, reflected regarding, and embedded into the context of existing knowledge on both climate variability and change and the methodological potentials and limitations of the employed type of network approach.

Response: We thank the reviewer for the positive remarks regarding our results. We have tried to address the reviewer's comments. See our response below.

In more detail, I have the following remarks that the authors should take into consideration when revising their presented work:

Line 18: It appears physically implausible, at least questionable, to speak of "nodes [grid points] experiencing amplified insolation". The insolation (i.e. amount of solar radiation directly reaching the Earth's surface) has not changed markedly over the period under study (except for changes in solar activity and maybe different atmospheric absorption by different types of aerosols). What likely has gradually changed is the amount of backscattered radiation that is kept within the atmosphere due to changing concentration and distribution of greenhouse gases and thereby contributes to warming the planet.

Response: We appreciate the reviewer's comment. To clarify, the term used in the text is "isolation," not "insolation." Our current study does not delve into aspects related to sunlight exposure.

Correction: (Lines 18, Par 1, Page 1) Additionally, we demonstrate that nodes experiencing amplified isolation.

Lines 21-22: It is not clear how the authors reach the conclusion that weakening ocean current *interactions may be responsible for the observed findings. The presented manuscript does not study oceanic variables, but only near-surface atmospheric conditions, and hence allows at most for very indirect inference of possible links with changes in ocean circulation. Moreover, it is not clear what kind of "interactions" the authors may have in mind. (Do they mean tropical basin interactions via atmospheric pathways?)*

Response: We sincerely appreciate the reviewer for providing the insightful comment. In the manuscript, our primary focus is on investigating near-surface air temperatures rather than oceanic variables. Given that the majority of nodes exhibiting heightened isolation are located in equatorial ocean regions, we deduce that the mechanism driving amplified isolation in the climate network may be comprehended through weakened interactions within tropical basins, linked to atmospheric pathways under global warming. We have addressed and clarified this aspect in the revised manuscript.

Correction: (Lines 20-23, Par 1, Page 1-2) We deduce that the mechanism driving amplified isolation in the climate network may be comprehended through the weakening of tropical circulations such as the Hadley cell and the Walker circulation in response to increasing greenhouse gases.

Line 27: Ocean acidification and glacier melting are not extreme events and hence referred to here out of context.

Response: Thanks for points the misleading text. In the revised manuscript, we have addressed the raised issues and included pertinent references to support the modifications.

Correction: (Lines 28-30, Par 2, Page 2) Global warming has led to a significant increase in various extreme weather events, encompassing extreme heatwaves, cold spells, heavy precipitation, droughts, and severe hurricanes etc. (Doney et al., 2009, Mondal et al., 2021, Komapala et al,. 2020, Mukherjee et al., 2020).

Scott C Doney , Victoria J Fabry, Richard A Feely and Joan A Kleypas: Ocean Acidification: The other CO2 problem, Annu. Rev. Mar. Sci. 1, 169-192 ,https://doi.org/10.1146/annurev.marine.010908.163834, 2009.

Mondal, S. and Mishra, A. K. : Complex networks reveal heatwave patterns and propagations over the USA, Geophys. Res. Lett., 48, e2020GL090411 , https://doi.org/10.1029/2020GL090411, 2021.

Konapala, G., Mishra, A. K., Wada, Y. et al.: Climate change will affect global water availability through compounding changes in seasonal precipitation and evaporation, Nat Commun 11, 3044 , https://doi.org/10.1038/s41467-020-16757-w, 2020.

Mukherjee, S., Mishra, A. K. : Increase in compound drought and heatwaves in a Warming World, Geophys. Res. Lett., 48(1), e2020GL090617, https://doi.org/10.1029/2020GL090617, 2020.

Lines 31-41: The authors cite here three recent, apparently randomly selected studies, the relationship of which with the topic and/or methodology of the present paper is not really clear to me. I would expect a more careful selection and discussion of relevant references at this prominent place of the Introduction.

Response: Thank you. In response to your comments. In our revised introduction, we have ensured a more discerning choice of studies that are directly relevant to the topic and methodology at hand as follows.

Correction: (Lines 33-49, Par 1, Page 2-3) Global warming has triggered significant transformations in atmospheric circulation and ocean circulation patterns, impacting the dynamics of the Earth's climate system (Shepherd, T., 2014; Vecchi, Gabriel A. and Brian J. Soden, 2007). The rise in global temperatures is a key driver of alterations in atmospheric circulation patterns, especially in the tropical belt, influencing phenomena such as the Hadley Cell, Walker Circulation, and the Madden-Julian oscillation (Lu et al., 2007; Tokinaga et al., 2012; Hu et al., 2021; Chang et al., 2015). The expansion of the tropics and changes in the distribution of sea surface temperatures contribute to shifts in the intensity and frequency of tropical cyclones and the behavior of the El Niño-Southern Oscillation (ENSO) (Emanuel et al., 2005; Kossin et al., 2020; Cai et al.,2021). These modifications in tropical circulations have widespread implications for precipitation patterns, extreme weather events, and regional climate variability. Additionally, the Atlantic Meridional Overturning Circulation (AMOC) may undergo a transition, with potential collapse having severe impacts on the climate in the North Atlantic and European regions (Rahmstorf et al. 2015; Boers, 2021). Previous studies have argued that the global climate experienced a shift in the 1970s (Graham, 1994; Tsonis et al., 2007; Swanson, 2009). Understanding these systematic changes is imperative for predicting future climate scenarios (e.g., precipitation, temperature, wind) and formulating effective adaptation and mitigation strategies.

Shepherd, T.: Atmospheric circulation as a source of uncertainty in climate change projections. Nature Geosci 7, 703 – 708 , https://doi.org/10.1038/ngeo2253, 2014.

Vecchi, Gabriel A., and Brian J. Soden: Global warming and the weakening of the tropical circulation, J. Climate 20(17) : 4316-4340, doi: https://doi.org/10.1175/JCLI4258.1, 2007.

Lu, J., G. A. Vecchi, and T. Reichler: Expansion of the Hadley cell under global warming, Geophys. Res. Lett., 34, L06805, doi:10.1029/2006GL028443, 2007.

Tokinaga, H., Xie, SP., Deser, C. et al.: Slowdown of the Walker circulation driven by tropical Indo-Pacific warming, Nature 491, 439 – 443, https://doi.org/10.1038/nature11576, 2012.

Hu K., Huang, G., Huang, P. et al.: Intensification of El Niño-induced atmospheric anomalies under greenhouse warming, Nat. Geosci. 14, 377 – 382, https://doi.org/10.1038/s41561-021-00730-3, 2021.

Chang, C.-W. J., W.-L. Tseng, H.-H. Hsu, N. Keenlyside, and B.-J. Tsuang: The Madden-Julian Oscillation in a warmer world, Geophys. Res. Lett., 42, 6034 – 6042, https://doi.org/10.1002/2015GL065095, 2015.

Emanuel, K.: Increasing destructiveness of tropical cyclones over the past 30 years, Nature 436, 686 – 688, https://doi.org/10.1038/nature03906, 2005.

Kossin J P, Knapp K R, Olander T L, et al.: Global increase in major tropical cyclone exceedance probability over the past four decades. Proceedings of the National Academy of Sciences, 117(22): 11975-11980, https://doi.org/10.1073/pnas.1920849117, 2020.

Cai, W., Santoso, A., Collins, M. et al.: Changing El Niño – Southern Oscillation in a warming climate, Nat Rev Earth Environ 2, 628 – 644, https://doi.org/10.1038/s43017-021-00199-z, 2021.

Rahmstorf, S., Box, J., Feulner, G. et al.: Exceptional twentieth-century slowdown in Atlantic Ocean overturning circulation, Nature Clim Change 5, 475 – 480, https://doi.org/10.1038/nclimate2554, 2015.

Boers, N. Observation-based early-warning signals for a collapse of the Atlantic Meridional Overturning Circulation. Nat. Clim. Chang. 11, 680 – 688, https://doi.org/10.1038/s41558-021-01097-4, 2021.

Graham, N. E.: Decadal-scale climate variability in the tropical and North Pacific during the 1970s and 1980s: observations and model results, Clim. Dyn., 10, 135 – 162, https://doi.org/10.1007/BF00210626, 1994.

A. A. Tsonis, K. Swanson, and S. Kravtsov: A new dynamical mechanism for major climate shifts, Geophys, Res. Lett., 34, L13705, doi:10.1029/2007GL030288, 2007.

Swanson, K. L., and A. A. Tsonis: Has the climate recently shifted? Geophys. Res. Lett., 36, L06711, doi:10.1029/2008GL037022, 2009.

Line 42: What do the authors mean by "diversity"? Diversity of what?

Response: We have revised the unclear sentence as follow.
Correction: (Lines 51-52, Par 2, Page 3) The climate system is intricately complex, marked by multivariable and multiscale nonlinear dynamics.

Lines 45-63: Similar as in the first paragraph of the Introduction, the selection of references on climate network analysis presented here appears not very systematic and concentrated on studies topically relevant to the presented work.

Response: Thank you for the comments. In our revised manuscript, we have carefully reviewed and refined the selection of references to enhance the coherence and topical relevance of our cited studies as follows.

Correction:(Lines 53-80, Par 2, Page 3-4) Complex network analysis emerges as a potent tool for investigating the nonlinear dynamics and structural characteristics of complex systems (Newman, 2018; Zou et al., 2019). Over the past several years, complex network methodologies have gained widespread application in the realm of climate science. In the climate network, nodes represent geographical locations where time series data for temperature (or other climate variables) are accessible. Links are established through bivariate similarity measures such as correlation, mutual information, or event synchronization between these time series (Tsonis et al., 2004; Donges et al., 2009; Quiroga et al., 2002). Climate network techniques have proven effective in enhancing our understanding of various climate and weather phenomena, including ENSO, teleconnection patterns of weather, and atmospheric pollution (Tsonis et al., 2008; Yamasaki et al., 2008; Fan et al., 2017; Kittel et al., 2021; Zhou et al., 2015; Boers et al., 2019; Di Capua et al., 2020; Zhang et al., 2019). Notably, complex network analysis has unveiled the weakening of tropical circulation under global warming (Geng et al., 2021; Fan et al., 2018). Furthermore, these techniques have demonstrated utility in forecasting climate events (Boers et al., 2014; Ludescher et al., 2014; Meng et al., 2018; Ludescher et al., 2021).

Complex systems naturally exhibit partitioning into multiple modules or communities, a significant feature of complex networks (Palla et al., 2005). In the context of climate networks, each community serves as a representation of a climate subsystem, shedding light on the interrelationships between different components (Tsonis et al., 2011). Community detection algorithms, rooted in modularity maximization (Newman, 2006; Cherifi et al., 2019), have been pivotal in unveiling structures within climate networks. These algorithms have successfully identified community structures in diverse contexts, including rainfall networks (Agarwal et al., 2018), interaction networks of sea surface temperature observations (Tantet et al., 2014), global climate responses to ENSO phases (Kittel et al., 2021) and the quantification of climate indices . Yet, scant attention has been given to the impact of global warming on the community structure of climate networks, particularly those with small sizes. This research endeavors to employ network analysis and community detection to investigate how global warming is reshaping the structure of the global temperature network. The ultimate goal is to deepen our understanding of climate change and inform strategies for addressing its impacts.

M. E. J. Newman: Networks. Oxford university press, 2018.

Zou, Y., Donner, R. V., Marwan, N., Donges, J. F. and Kurths, J.: Complex network approaches to nonlinear time series analysis, Phys. Rep., 787, 1-97.https://doi.org/10.1016/j.physrep.2018.10.005, 2019.

A. A. Tsonis, and Paul J. Roebber.: The architecture of the climate network, Physica A, 333: 497-504. https://doi.org/10.1016/j.physa.2003.10.045, 2004.

J. F. Donges, Y. Zou, N. Marwan and J. Kurths: Complex networks in climate dynamics, Eur. Phys. J. Spec. Top. 174, 157 – 179, https://doi.org/10.1140/epjst/e2009-01098-2, 2009.

R. Quian Quiroga, T. Kreuz, and P. Grassberge: Event synchronization: A simple and fast method to measure synchronicity and time delay patterns, Phys. Rev. E 66, 041904, https://doi.org/10.1103/PhysRevE.66.041904, 2002.

A. A. Tsonis and Kyle L. Swanson: Topology and Predictability of El Niño and La Niña Networks, Phys. Rev. Lett. 100, 228502, https://doi.org/10.1103/PhysRevLett.100.228502, 2008.

L.Yamasaki, A. Gozolchiani, and S. Havlin: Climate networks around the globe are significantly affected by El Niño, Phys. Rev. Lett. 100, 228501, https://doi.org/10.1103/PhysRevLett.100.228501, 2008.

J. Fan, J. Meng, Y. Ashkenazy, S. Havlin and H. J. Schellnhuber: Network analysis reveals strongly localized impacts of El Niño, Proc. Natl. Acad. Sci. U.S.A. 114, 7543 – 7548, https://doi.org/10.1073/pnas.1701214114, 2017.

Kittel, T., Ciemer, C., Lotfi, N. et al.: Evolving climate network perspectives on global surface air temperature effects of ENSO and strong volcanic eruptions, Eur. Phys. J. Spec. Top. 230, 3075 – 3100 , https://doi.org/10.1140/epjs/s11734-021-00269-9, 2021.

Zhou, Dong, et al.: Teleconnection paths via climate network direct link detection, Phys. Rev. Lett. 115, 268501, https://doi.org/10.1103/PhysRevLett.115.268501, 2015.

Niklas Boers, Bedartha Goswami, Aljoscha Rheinwalt, Bodo Bookhagen, Brian Hoskins and Jürgen Kurthsl: Complex networks reveal global pattern of extreme-rainfall teleconnections, Nature 566, 373 – 377, https://doi.org/10.1038/s41586-018-0872-x, 2019.

Di Capua, G., Kretschmer, M., Donner, R. V., van den Hurk, B., Vellore, R., Krishnan, R., and Coumou, D.: Tropical and mid-latitude teleconnections interacting with the Indian summer monsoon rainfall: a theory-guided causal effect network approach, Earth Syst. Dynam., 11, 17 – 34, https://doi.org/10.5194/esd-11-17-2020, 2020.

Zhang, Y., J. Fan., Chen, X., Ashkenazy, Y., and Havlin, S.: Significant impact of Rossby waves on air pollution detected by network analysis, Geophys. Res. Lett., 46, 12476 – 12485, https://doi.org/10.1029/2019GL084649, 2019.

Z. Geng, Y. Zhang, B. Lu, J. Fan, Z. Zhao and X. Chen: Network-Synchronization analysis reveals the weakening tropical circulations, Geophys. Res. Lett. 48, e2021GL093582, https://doi.org/10.1029/2021GL093582, 2021.

J. Fan, Meng, J., Ashkenazy, Y., Havlin, S., Schellnhuber and H.J.: Climate network percolation reveals the expansion and weakeningof the tropical component under global warming, Proc. Natl. Acad. Sci. USA , 115, E12128 – E12134, https://doi.org/10.1073/pnas.1811068115, 2018.

Boers, N., Bookhagen, B., Barbosa, H. et al.: Prediction of extreme floods in the eastern Central

Andes based on a complex networks approach. Nat Commun 5, 5199, https://doi.org/10.1038/ncomms6199, 2014.

J. Ludescher, A. Gozolchiani, M. I. Bogachev, A. Bunde, S. Havlin and H. J. Schellnhuber: Very early warning of next El Niño, Proc. Natl. Acad. Sci. U.S.A. 111, 2064 – 2066, https://doi.org/10.1073/pnas.1323058111, 2014.

J Meng, J. Fan, Y. Ashkenazy, A. Bunde and S. Havlin: Forecasting the magnitude and onset of El Niño based on climate network, New J. Phys. 20, 043036, https://doi.org/10.1088/1367-2630/aabb25, 2018.

J. Ludescher, Martin, M., Boers, N., Bunde, A., Ciemer, C., J.Fan, Havlin, S., Kretschmer, M., Kurths, J., Runge, J.; et al.: Network-based forecasting of climate phenomena, Proc. Natl. Acad. Sci. USA , 118, e1922872118, https://doi.org/10.1073/pnas.1922872118, 2021.

Palla, G., Derényi, I., Farkas, I. et al.: Uncovering the overlapping community structure of complex networks in nature and society, Nature 435, 814 – 818, https://doi.org/10.1038/nature03607, 2005.

A. A. Tsonis, Wang, G., Swanson, K.L. et al.: Community structure and dynamics in climate networks, Clim Dyn 37, 933 – 940, https://doi.org/10.1007/s00382-010-0874-3, 2011.

M. E. J. Newman: Modularity and community structure in networks, Proc. Natl. Acad. Sci. 103, 8577 – 8582, https://doi.org/10.1073/pnas.0601602103, 2006.

Cherifi, H., Palla, G., Szymanski, B.K. et al.: On community structure in complex networks: challenges and opportunities. Appl Netw Sci 4, 117, https://doi.org/10.1007/s41109-019-0238-9, 2019.

A. Agarwal, N. Marwan and R. Maheswaran: Quantifying the roles of single stations within homogeneous regions using complex network analysis, J. Hydrol. 563, S0022169418304724-, https://doi.org/10.1016/j.jhydrol.2018.06.050, 2018.

Tantet, A. and Dijkstra, H. A.: An interaction network perspective on the relation between patterns of sea surface temperature variability and global mean surface temperature, Earth Syst. Dynam., 5, 1 – 14, https://doi.org/10.5194/esd-5-1-2014, 2014.

Kittel, T., Ciemer, C., Lotfi, N. et al.: Evolving climate network perspectives on global surface air temperature effects of ENSO and strong volcanic eruptions, Eur. Phys. J. Spec. Top. 230, 3075 – 3100 , https://doi.org/10.1140/epjs/s11734-021-00269-9, 2021.

Line 48: The statement "variables such as temperature or geographical location are used as network nodes" is nonsense. Nodes in a climate network are identified with geographical locations at which temperature (or any other climate) time series are available for analyzing their *bivariate similarity (e.g. correlation). In this regard, it is quite uncommon to use covariance instead of correlation (as suggested in line 49), since absence of normalization would lead to regions with high variance of temperature would then dominate the network connectivity.*

Response: Thanks. In the revised manuscript, we have modified the statement to avoid misleading as follows.

Correction:(Lines 56-60, Par 1, Page 3) In the climate network, nodes represent geographical locations where time series data for temperature (or other climate variables) are accessible. Links are established through bivariate similarity measures such as correlation, mutual information, or event synchronization between these time series (Tsonis et al., 2004; Donges et al., 2009; Quiroga et al., 2002).

A. A. Tsonis, and Paul J. Roebber.: The architecture of the climate network, Physica A, 333: 497-504. https://doi.org/10.1016/j.physa.2003.10.045, 2004.

J. F. Donges, Y. Zou, N. Marwan and J. Kurths: Complex networks in climate dynamics, Eur. Phys. J. Spec. Top. 174, 157 – 179, https://doi.org/10.1140/epjst/e2009-01098-2, 2009.

R. Quian Quiroga, T. Kreuz, and P. Grassberge: Event synchronization: A simple and fast method to measure synchronicity and time delay patterns, Phys. Rev. E 66, 041904, https://doi.org/10.1103/PhysRevE.66.041904, 2002.

Lines 73-79: The authors state that "there are many researches on the internal dynamics mechanisms of [the] climate system based on community structure", but cite just two of them. The second part of this block of sentences, "some studies have identified novel dynamical mechanisms of climate systems through the characteristics of community structures in networks", however cites a few studies, but all of them entirely out of context. Tsonis et al. (2007) is wrongly referenced to have appeared in Chaos (correct would have been Geophysical Research Letters) and just uses five climate indices, for which a consideration of network communities does not make any sense. Gozolchiani et al. (2008) is also falsely attributed to the journal Chaos instead of EPL and does not discuss climate network communities either. Swanson and Tsonis (2009) does not make use of any community or network concept, too. Finally, Elsner et al. (2009) uses visibility graphs, a concept entirely different from that used in the present work, without any referencing to community detection. Hence, I have to conclude that all four references to this sentence have nothing to do with the suggested statement.

Response: Thanks. We have improved the references in the revised manuscript as follows.

Correction: (Lines 68-76, Par 1, Page 4) Complex systems naturally exhibit partitioning into multiple modules or communities, a significant feature of complex networks (Palla et al., 2005). In the context of climate networks, each community serves as a representation of a climate subsystem, shedding light on the interrelationships between different components (Tsonis et al. 2011). Community detection algorithms, rooted in modularity maximization (Newman, 2006;

Cherifi et al., 2019), have been pivotal in unveiling structures within climate networks. These algorithms have successfully identified community structures in diverse contexts, including rainfall networks (Agarwal et al., 2018), interaction networks of sea surface temperature observations (Tantet et al., 2014), global climate responses to ENSO phases (Kittel et al., 2021) and the quantification of climate indices.

Palla, G., Derényi, I., Farkas, I. et al.: Uncovering the overlapping community structure of complex networks in nature and society, Nature 435, 814 – 818, https://doi.org/10.1038/nature03607, 2005.

A. A. Tsonis., Wang, G., Swanson, K.L. et al.: Community structure and dynamics in climate networks, Clim Dyn 37, 933 – 940, https://doi.org/10.1007/s00382-010-0874-3, 2011.

M. E. J. Newman: Modularity and community structure in networks, Proc. Natl. Acad. Sci. 103, 8577 – 8582, https://doi.org/10.1073/pnas.0601602103, 2006.

Cherifi, H., Palla, G., Szymanski, B.K. et al.: On community structure in complex networks: challenges and opportunities. Appl Netw Sci 4, 117, https://doi.org/10.1007/s41109-019-0238-9, 2019.

A. Agarwal, N. Marwan and R. Maheswaran: Quantifying the roles of single stations within homogeneous regions using complex network analysis, J. Hydrol. 563, S0022169418304724-, https://doi.org/10.1016/j.jhydrol.2018.06.050, 2018.

Tantet, A. and Dijkstra, H. A.: An interaction network perspective on the relation between patterns of sea surface temperature variability and global mean surface temperature, Earth Syst. Dynam., 5, 1 – 14, https://doi.org/10.5194/esd-5-1-2014, 2014.

Kittel, T., Ciemer, C., Lotfi, N. et al.: Evolving climate network perspectives on global surface air temperature effects of ENSO and strong volcanic eruptions, Eur. Phys. J. Spec. Top. 230, 3075 – 3100 , https://doi.org/10.1140/epjs/s11734-021-00269-9, 2021.

For community detection in their near-surface temperature network, the authors use the Louvain algorithm; however, this choice is neither explained nor justified. I would like to draw the authors' attention to Fig. 8 of Kittel et al. (Eur. Phys. J. ST, 2021). This figure compares the year-by-year variability of modularity for a (full-resolution) evolving climate network of surface air temperature anomalies (similar to that studied in the present work) obtained by different community detection algorithms, demonstrating that the choice of methodology may be crucial for the outcomes of community detection and may lack robustness.

Response: We thank the reviewer for the insightful comments. We have employed four different algorithms to detect community structures based on Ref (Kittel et al., 2021). Figure S3 below illustrates the modularity values obtained. The results highlight the robustness of the modularity transition around 1982 across different algorithms. Notably, the Louvain algorithm produces the highest modularity values, indicating its superior effectiveness in identifying community structures.

Correction:(Lines 141-144, Par 2,Page 7)Supplementary Figure S3 illustrates the modularity values obtained by four distinct algorithms, as outlined in Ref (Kittel et al., 2021). The results highlight the robustness of the modularity transition around 1982 across different algorithms. Notably, the Louvain algorithm produces the highest modularity values, indicating its superior effectiveness in identifying community structures.

(Lines 194-197, Par 1,Page 10)To establish robustness, we conduct the analysis using different community detection algorithms, the maximum time lag of 365 days, the shuffled nodes and a 6-month shift for the time window. The obtained results are consistent, as illustrated in Supplementary Figures. S3-S12.

Kittel, T., Ciemer, C., Lotfi, N. et al.: Evolving climate network perspectives on global surface air temperature effects of ENSO and strong volcanic eruptions, Eur. Phys. J. Spec. Top. 230, 3075–3100, https://doi.org/10.1140/epjs/s11734-021-00269-9, 2021.

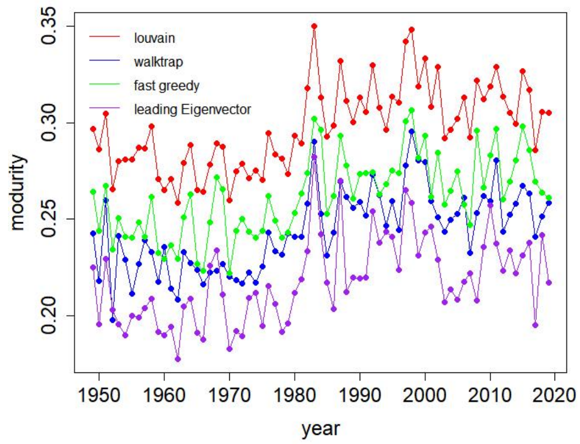

Figure S3: Time evolution of modularity for different algorithms, with red representing the Louvain algorithm, blue representing the Walktrap algorithm, green representing the Fast Greedy algorithm, and purple representing the Leading Eigenvector algorithm.

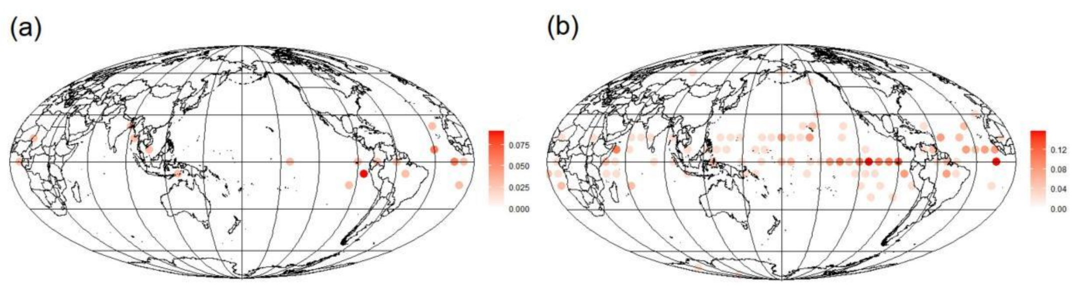

Figure S4: Probability graph of global isolated nodes using the Leading eigenvector algorithm for (a)

1949-1981 and (b) 1982-2019.

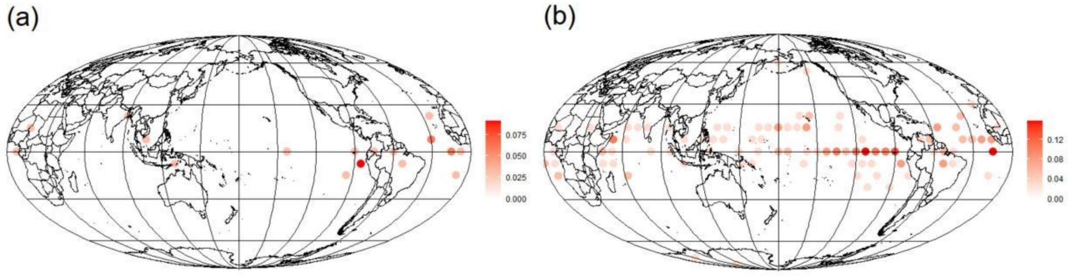

Figure S5: Probability graph of global isolated nodes using the Fast greedy algorithm for (a) 1949-1981 and (b) 1982-2019.

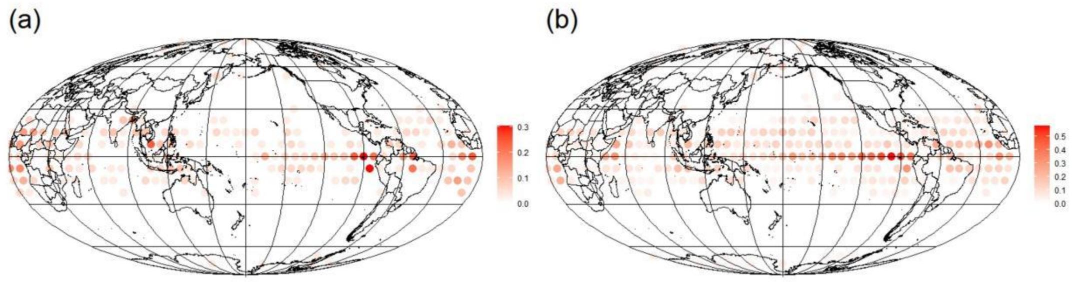

Figure S6: Probability graph of global isolated nodes using the Walktrap algorithm for (a) 1949-1981 and (b) 1982-2019.

Lines 94-96: The authors report that they "strategically select" 726 out of 10,512 grid points, but they do not describe how and why. With the information given in the Data section, the presented analysis is not reproducible. In fact, the heterogeneity or homogeneity of the spatial density of the considered nodes has a crucial effect on any network properties in climate networks, since nearby nodes are likely to have larger statistical similarity of climate variability (and, hence, a higher likelihood of being connected in the network). Possible solutions include consideration of area-weighted network measures (Heitzig et al., Eur. Phys. J. B, 2012) or specific selections of nodes when subsampling original fixed latitude-longitude grids in climate records (Radebach et al., Phys. Rev. E, 2013). I am afraid that without such consideration (that I do not see reported in the paper), the inter-node distance in high latitudes is much smaller than close to the equator, and accordingly the spatial placement of network connectivity is heavily biased towards the polar regions. Under such circumstances, it would be highly questionable to what extent the reported findings of the present work can actually be interpreted meaningfully.

Response: Thanks. The homogeneity of the spatial density of the considered nodes within the sphere has been a deliberate focus in our study. This rationale guides our selection of 726 nodes, strategically spaced to ensure uniform coverage of the Earth in Euclidean space, as depicted in the below Figure S1(a). The nodes are equally distributed in Euclidean space with distances between any two neighboring nodes approximately 850 km, as illustrated in Figure S1(b). This configuration eliminates the issue of "node spacing at high latitudes being much smaller than that near the equator." It's worth noting that these 726 nodes have been consistently utilized in previous studies for constructing climate networks (Guez et al., 2014).

Correction: (Lines 91-96, Par 1, Page 5) We select 726 nodes to construct the network and maintain the spatial density homogeneity within the climate network nodes in the sphere as suggested in previous studies (Zhou et al., 2015; Guez et al., 2014). These nodes are strategically spaced to ensure uniform coverage of the Earth in Euclidean space, as depicted in Supplementary Figure S1(a). The nodes are equally distributed, with distances between any two neighboring nodes approximately 850 km, as illustrated in Supplementary Figure S1(b).

Guez, O. C., Gozolchiani, A. and Havlin, S.: Influence of autocorrelation on the topology of the climate network, Phys. Rev. E, 90(6), 062814, https://doi.org/10.1103/PhysRevE.90.062814, 2014.

Zhou, Dong, et al.: Teleconnection paths via climate network direct link detection, Phys. Rev. Lett. 115, 268501, https://doi.org/10.1103/PhysRevLett.115.268501, 2015.

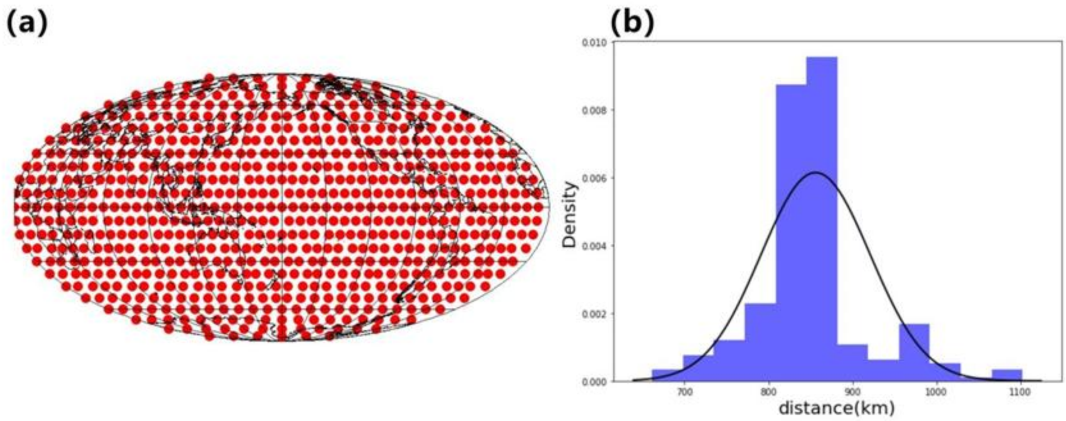

Figure S1: (a) Spatial distribution of 726 network nodes in Earth and (b) the PDF of distances between neighboring nodes.

Line 101: Detrending and subtracting the average seasonal cycle are two entirely different things.

Response: We have modified the sentence in the revised manuscript as follows.

Correction: (Lines 100-1025, Par 2, Page 5) The time series of a node (denoted as i) undergoes deseasonalization by subtracting the average seasonal cycle and dividing by the standard deviation of the cycle, resulting in the temperature anomaly.

Line 108: Why do the authors use a maximum lag of 200 days for an analysis of time windows of just 365 days? How robust are the reported results regarding this choice?

Response: Upon comparing the results with a maximum time lag of 365 days, we observed similarities with those obtained using a maximum time lag of 200 days, as depicted in the below Figures S7 and S8. Therefore, the results demonstrate robustness across different time lag choices.

Correction:(Lines 193-197, Par 1, Page 10) To establish robustness, we conduct the analysis using different community detection algorithms, the maximum time lag of 365 days, the shuffled nodes and a 6-month shift for the time window. The obtained results are consistent, as illustrated in Supplementary Figures. S3-S12.

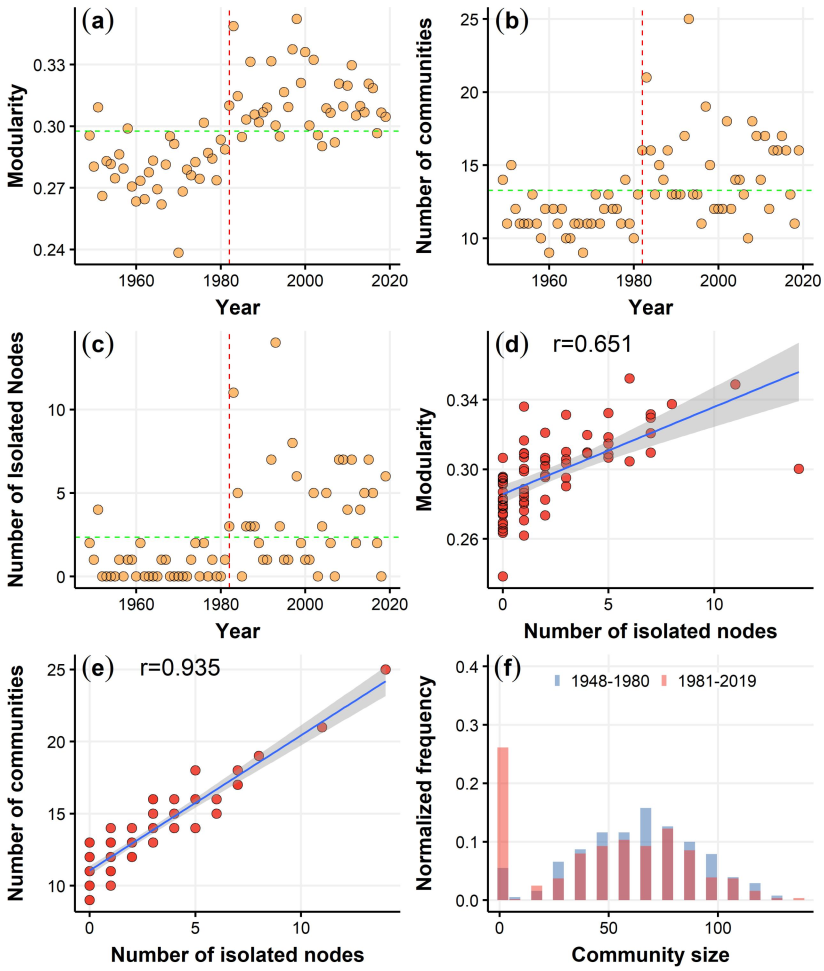

Figure S7: Same as Fig. 1 of the main text but for the maximum time lag of 365 days.

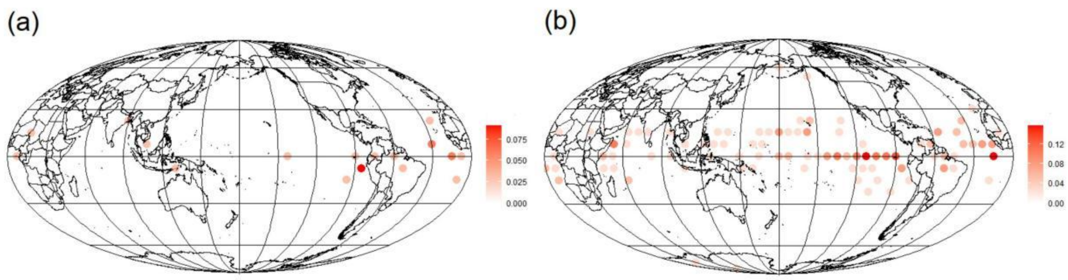

Figure S8: Same as Fig. 2 of the main text but for the maximum time lag of 365 days.

Line 111: Why do the authors list "minimum value" here when it is not made use of? What are maximum, (minimum,) mean and standard deviation taken from? In Equation (3), left and right-hand side have the same indices, so this description is mathematically inconsistent. Also the following text is quite problematic. It is correct that strong auto-correlation inflates the significance of the cross-correlation, but not the cross-correlation itself. It is not clear how the link strength can eliminate the effect of serial dependence. For the latter purpose, a better alternative might be the consideration of p-values, as originally suggested by Palus et al. (Nonlin. Proc. Geophys., 2011), which however have considered only lag-zero correlations.

Response: Thank you for the comment. We have modified the description of Eq. (3) in the revised manuscript. In Eq. (3), "max," "mean," and "std" denote the maximum value, mean, and standard deviation of the cross-correlation over all time lag days from -200 to 200 days between nodes i and j. Ref (Guez et al., 2014) have demonstrated that the link strength W can eliminate the effect of autocorrelation. Following the suggestion in Ref (Palus et al., 2011), we compared our results with those derived from a shuffled dataset, where the time series of each node was randomized without establishing any correlation between nodes. Specifically, we shuffled the time series of each node for all years while maintaining the order of 365 days per year. This process was repeated 100 times, and recalculations were performed for each shuffled dataset. The PDFs of the link strength W for both the real and shuffled data are illustrated in Figure S5 below. A threshold of theta=3.5 corresponds to a p-value of 0.03, signifying that 97% of the values in the shuffled data fall below this threshold (see the below Figure S2). Consequently, the identified links are considered significant.

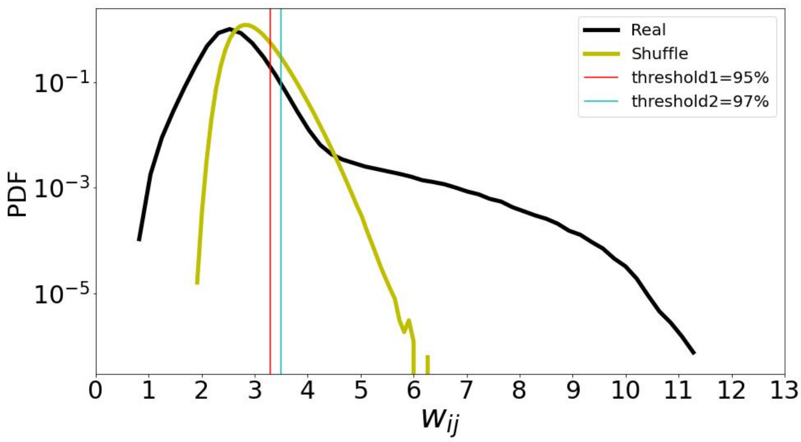

Figure S2: The probability density function (PDF) of W_{ij} for both the real and shuffled data. Red line represents the threshold value $W_{ij} = 3.3$ (signifying that 95% of the values in the shuffled data fall below this threshold), and blue line represents the threshold value $W_{ij} = 3.5$ (signifying that 97% of the values in the shuffled data fall below this threshold). Black line represents the real data, yellow line represents the shuffled data, where the time series of each node was randomized without establishing any correlation between nodes. Specifically, we shuffled the time series of each node for all years while maintaining the order of 365 days per year. This process was repeated 100 times, and recalculations were performed for each shuffled dataset.

Correction: (Lines 109-120, Par 2, Page 6) Therefore, the link strength between each pair of nodes in the network is denoted as follows:

$$W_{i,j}^{y} = \frac{\max\left(C_{i,j}^{y}(\tau)\right) - mean\left(C_{i,j}^{y}(\tau)\right)}{std\left(C_{i,j}^{y}(\tau)\right)}, \qquad (3)$$

in this context, "max","$mean$" and "std" denote the maximum value, mean, and standard deviation of the cross-correlation over all time lags from -200 to 200 days between nodes i and j. Strong autocorrelation can inflate the significance of cross-correlation. In contrast, the link strength $W_{i,j}^{y}$ is more effective in mitigating the effects of autocorrelation, offering a more reasonable reflection of the relationship between two nodes (Guez et al., 2014). This approach has proven valuable in predicting climate phenomena (Ludescher et al., 2021). To select meaningful links in the network and eliminate false association. A threshold of $\theta = 3.5$ (corresponding to a p-value of 0.03 (Palus et al., 2011) signifying that 97% of the values in the shuffled data fall below this threshold in Supplementary Figure S2) is applied to obtain an adjacency matrix A (when $W_{i,j}^{y} \geq \theta$, the element $A_{ij} = 1$, otherwise, the element $A_{ij} = 0$).

Guez, O. C., Gozolchiani, A. and Havlin, S.: Influence of autocorrelation on the topology of the climate network, Phys. Rev. E, 90(6), 062814, https://doi.org/10.1103/PhysRevE.90.062814, 2014.

Paluš, M. and Novotná, D.: Northern Hemisphere patterns of phase coherence between solar/geomagnetic activity and NCEP/NCAR and ERA40 near-surface air temperature in period 7 – 8 years oscillatory modes, Nonlin. Processes Geophys., 18, 251 – 260, https://doi.org/10.5194/npg-18-251-2011, 2011.

J. Ludescher, Martin, M., Boers, N., Bunde, A., Ciemer, C., J.Fan., Havlin, S., Kretschmer, M., Kurths, J., Runge, J.; et al.: Network-based forecasting of climate phenomena, Proc. Natl. Acad. Sci. USA , 118, e1922872118, https://doi.org/10.1073/pnas.1922872118, 2021.

Lines 120-122: Does the outcome of the Louvain algorithm depend on the order with which the different nodes are considered in the algorithm? I would also recommend some brief discussion on the convergence of the method to some global modularity optimum (respectively, the risk to approach some local optimum by following this iterative methodology).

Response: Upon comparing the results with those derived after shuffling the order of nodes, we noted consistent patterns in key outcomes such as modularity and the spatial distribution of isolated nodes, as illustrated in Figures S9 and S10 below. Therefore, our main findings in this study appear independent of the algorithm employed. The robustness of these results is further affirmed by additional algorithms, as highlighted in the preceding response.

Correction:(Lines 193-197, Par 1, Page 10) To establish robustness, we conduct the analysis using different community detection algorithms, the maximum time lag of 365 days, the shuffled nodes and a 6-month shift for the time window. The obtained results are consistent, as illustrated in

Supplementary Figures. S3-S12.

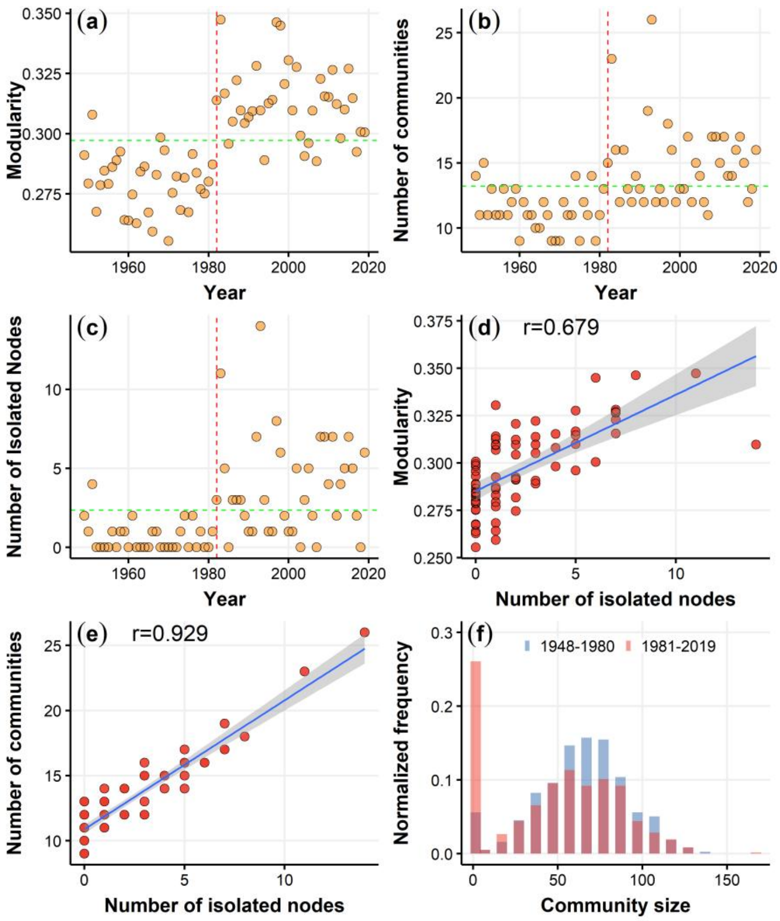

Figure S9: Same as Fig. 1 of the main text but for after shuffling the order of nodes.

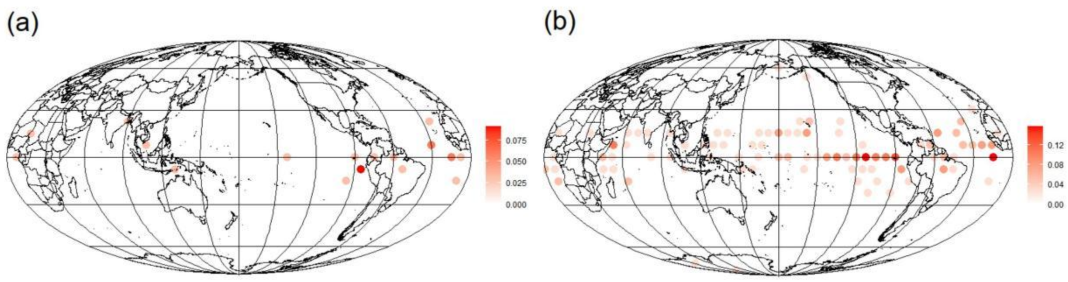

Figure S10: Same as Fig. 2 of the main text but for after shuffling the order of nodes.

Line 127: k_i and k_j are the degrees of the nodes i and j - not the sums of the link weights (which would be the node strengths). The formula for modularity given in Eq. (4) applies to unweighted networks.

Response: Thanks. We have modified "k_i" and "k_j".

Correction:(Lines 130, Par 3, Page 6) Where $k_i = \sum_j A_{ij}$ and $k_j = \sum_i A_{ij}$ $(i \neq j)$ are the number of links connected to vertex (node) i and j.

The authors choose their running time windows to coincide with the calendar years. This may bear the risk of mixing months affected by a declining El Nino (winter/spring) with those of an approaching La Nina (fall/winter) – or vice versa - during the same year. From numerous previous works, we know that El Nino and La Nina prominently affect global surface air temperature anomaly based networks (see works by Gozolchiani et al. (2008), Yamasaki et al. (Phys. Rev. Lett., 2008), Tsonis et al. (Phys. Rev. Lett., 2008), Ludescher et al. (PNAS, 2013), Radebach et al. (Phys. Rev. E, 2013), and many others). Mixing the effects of opposite ENSO phases might blur the analysis results (especially since the statistics of El Nino and La Nina episodes has changed over the last decades). I would suggest repeating the presented analysis with time windows shifted by 6 months to check for the robustness of the reported findings.

Response: We appreciate the reviewer for the comment. We have repeated our analysis with time windows shifted by 6 months as shown in Figure S8 and S9 below. We also found consistent patterns in key outcomes such as modularity and the spatial distribution of isolated nodes, as illustrated in Figures S11 and S12 below.

Correction:(Lines 193-197, Par 1, Page 10) To establish robustness, we conduct the analysis using different community detection algorithms, the maximum time lag of 365 days, the shuffled nodes and a 6-month shift for the time window. The obtained results are consistent, as illustrated in Supplementary Figures. S3-S12.

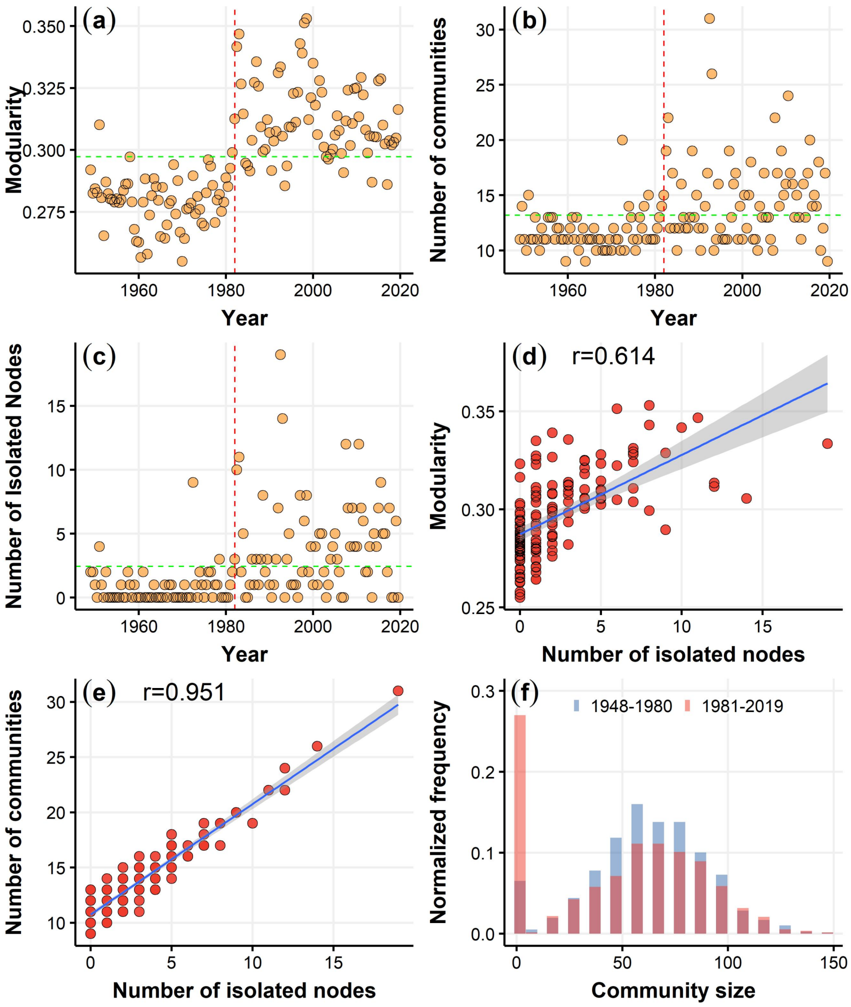

Figure S11: Same as Fig. 1 of the main text but for a 6-month shift for the time window.

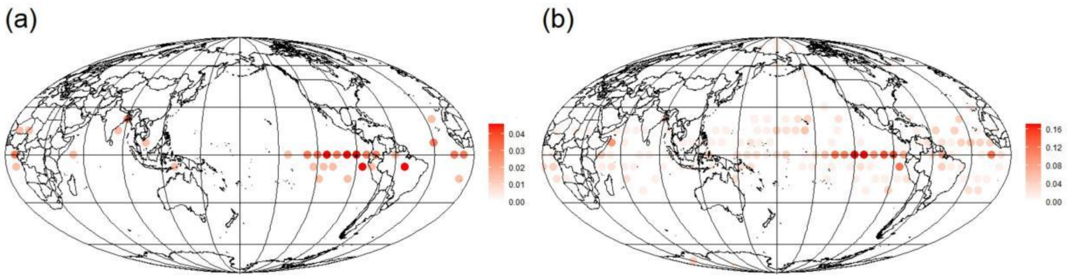

Figure S12: Same as Fig. 2 of the main text but for a 6-month shift for the time window.

Lines 142-143: It is trivial that average community size and number of communities display opposite trends, since both characteristics exhibit a trivial inverse proportionality: <s>=N/N_c. So discussing both characteristics appears somewhat pointless to me.

Response: We are grateful for the valuable suggestion. We have modified the average community size in Fig. 1c to now represent number of isolated nodes as a function of year. There is a non-trivial relationship between number of communities and number of isolated nodes as shown in Fig. 1e.

Correction: (Lines 149-151, Par 2, Page 7) Figure 1(c) also shows the escalating count of isolated nodes since 1982. The isolated node is identified by the Louvain algorithm with a community size of 1 (equivalent to a degree of zero, $k_i = 0$).

The authors attribute the timing of the identified changes in community statistics around the year 1982 to the 1982/83 El Nino episode. I am wondering if there are any other findings demonstrating a similarly long-lasting effect of this particular El Nino event on the global climate system. Besides overall global temperature rise (being heterogeneously distributed in space and time), other potential reasons for the reported marked shift in community properties have not been discussed (including multidecadal variability). Tsonis et al. (2007) and Swanson and Tsonis (2009) – two references cited in the present manuscript – have partly discussed a late-1970s climate shift, and could serve as an initial source of inspiration for identifying further potential origins (but there is far more, also more recent, literature). In terms of the used dataset, one should also not forget that the availability of satellite data assimilated into the reanalysis products has started only in the late 1970s, so that the observed changes could also be affected by underlying heterogeneities in the considered data. I do not claim that this is the case, but this possibility cannot be simply ruled out by the present analysis.

Response: We appreciate the reviewer's suggestions. The observed systematic change in community structure since the early 1980s could be linked to the reported climate shift, as indicated by Refs (Graham, N.E., 1994; Tsonis et al., 2007; Swanson, 2009) utilizing both reanalysis data and climate simulations. The substantial increase in greenhouse gas emissions has contributed to a shift in the mean climate state since the 1980s in the tropical belt (Cai et al., 2021). This shift is further evident in the altered properties of El Niño since the early 1980s (Gan et al., 2023).

Correction: (Lines 151-156, Par 2, Page 7-8) The observed systematic change in community structure in since the early 1980s could be linked to the reported climate shift, as indicated by Refs (Graham, 1994; Tsonis et al., 2007; Swanson, 2009) utilizing both reanalysis data and climate simulations. The substantial increase in greenhouse gas emissions has contributed to a shift in the mean climate state since the 1980s in the tropical belt (Cai et al., 2021). This shift is further evident in the altered properties of El Niño since the early 1980s (Gan et al., 2023).

Graham, N.E.: Decadal-scale climate variability in the tropical and North Pacific during the 1970s and 1980s: observations and model results, Clim. Dyn. 10, 135 – 162, https://doi.org/10.1007/BF00210626, 1994.

A. A. Tsonis, K. Swanson, and S. Kravtsov: A new dynamical mechanism for major climate shifts, Geophys. Res. Lett., 34, L13705, doi:10.1029/2007GL030288, 2007.

Swanson, K. L., and A. A. Tsonis: Has the climate recently shifted? Geophys. Res. Lett., 36, L06711, doi:10.1029/2008GL037022, 2009.

Cai, W., Santoso, A., Collins, M. et al.: Changing El Niño – Southern Oscillation in a warming climate, Nat Rev Earth Environ 2, 628 – 644, https://doi.org/10.1038/s43017-021-00199-z, 2021.

Gan, R., Liu, Q., Huang, G. et al.: Greenhouse warming and internal variability increase extreme and central Pacific El Niño frequency since 1980, Nat. Commun. 14, 394, https://doi.org/10.1038/s41467-023-36053-7, 2023.

Figure 1f: Since the community sizes have been binned for showing the relative frequencies (likely a more suitable term than "probability"), I would recommend showing them as a histogram with bars instead of a line plot. Alternatively, a cumulative distribution plot taking all explicit values of community sizes into account might be a reasonable alternative.

Response: Thanks for the comment. We have modified Fig. 1f in the revised manuscript as follows to the histogram with the normalized frequencies (normalized by the total number of communities for each period).

Correction: (Fig. 1(f))

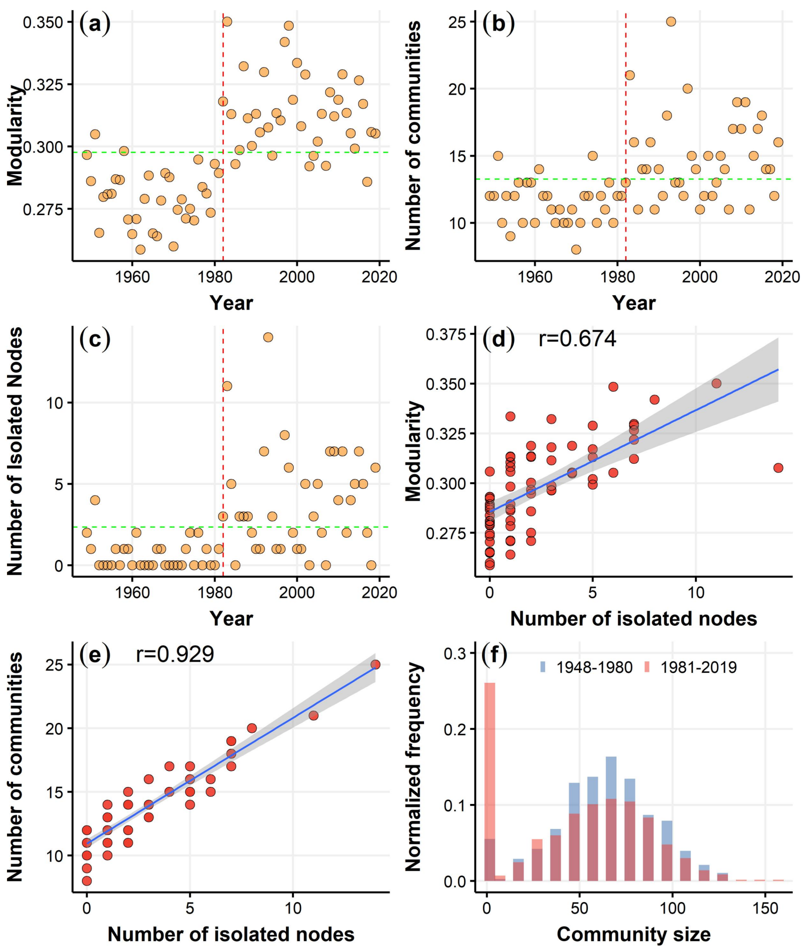

Figure 1: Temporal evolution of (a) network modularity, (b) the number of communities and (c) the number of isolated nodes from 1949 to 2019, illustrated by the green dashed line denoting the average level, and the red dashed line represents the transition around 1982. Scatter plot of (d) the network modularity, (e) the number of communities versus the number of isolated nodes during the period 1949-2019. (f) The normalized frequencies of community size for 1949-1981 and 1982-2019 respectively (normalized by the total number of communities for each period), where the first bar represents the normalized frequency of the community with a node.

Line 158: Nodes are commonly called isolated when their degree is zero (i.e., there do not exist any links to other nodes). It is not clear if the definition of community size 1 considered here is equivalent, or if nodes can also form a community of size 1 under the Louvain algorithm if there exist such connections (and if so, why such nodes are not attributed to any community). This should be clarified. In any case, I would recommend using the more standard definition of degree k_i=0 for isolated nodes to avoid confusion. Note that the fact that "isolated nodes" are commonly restricted to the tropical belt (Fig. 2, ll. 181-184) is compatible with my aforementioned concern regarding a connectivity bias towards the poles due to the heterogeneous spatial density of nodes.

Response: We have addressed this point in the revised manuscript. Specifically, the isolated node identified by the Louvain algorithm with a community size of 1 is equivalent to having a degree of zero (k_i=0).

The presence of isolated nodes in the tropical belt cannot be attributed to the heterogeneous spatial density of nodes since the nodes are strategically spaced to ensure uniform coverage of the Earth in Euclidean space. Notably, utilizing the Pearson correlation coefficient instead of the strength W for network construction yields very different results. When employing the Pearson correlation coefficient, nodes in the tropical belt exhibit high connectivity. The distinctions between these two types of network links have been extensively discussed by Ref (Guez et al., 2014). The lower frequency of time series in the tropical belt, coupled with strong autocorrelation, results in an overestimation of the cross-correlation by calculating the Pearson correlation coefficient between two nodes. Guez et al. has also demonstrated that link strength W is more effective in mitigating the effects of autocorrelation, providing a more reasonable reflection of the relationship between two nodes. This approach has proven valuable in predicting climate phenomena (Ludescher et al., 2021).

Correction: (Lines 150-151, Par 2, Page 7) The isolated node is identified by the Louvain algorithm with a community size of 1 (equivalent to a degree of zero, $k_i = 0$).

Guez, O. C., Gozolchiani, A. and Havlin, S.: Influence of autocorrelation on the topology of the climate network, Phys. Rev. E, 90(6), 062814, https://doi.org/10.1103/PhysRevE.90.062814, 2014.

J. Ludescher, Martin, M., Boers, N., Bunde, A., Ciemer, C., J.Fan, Havlin, S., Kretschmer, M., Kurths, J., Runge, J.; et al.: Network-based forecasting of climate phenomena, Proc. Natl. Acad. Sci. USA , 118, e1922872118, https://doi.org/10.1073/pnas.1922872118, 2021.

A non-mandatory suggestion: The authors study the number of communities (which, when viewed from a statistical perspective as a clustering problem, is a matter of statistical model selection that is not clearly described in the manuscript) – along with the equivalent information on average community size – along with the corresponding modularity. In network theory, there is the more fundamental concept of components (if the network is split into disconnected subgraphs), which are less ambiguous than communities. (Besides both depending on the threshold for distinguishing links from non-links.) I wonder if statistics used in the analysis based on network components could be adapted to communities as well (e.g., the size of the largest group of nodes, the number of groups with two elements, or others, which are often considered for network components in the study of percolation processes). Maybe such measures might provide any useful additional information beyond the two characteristics studied in the present manuscript.

Response: Thank you very much to the reviewer for the intriguing suggestion. The network component indeed offers valuable information, such as the percolation threshold. In this study, our emphasis lies in exploring the characteristics of amplified isolation in climate networks. This trait should remain consistent for both components and communities due to the shared definition of isolated nodes. Nevertheless, we anticipate that exploring various characteristics related to the giant component and subgraphs, especially under global warming, could yield interesting results. We plan to undertake this research in our future work.

Lines 186-188: Attributing the changes in community structure (especially increasing frequency of isolated nodes) to global warming (i.e., the average temperature at all considered nodes) could be merely a coincidence; a direct statistical link between these properties (which all change gradually with time) has not been demonstrated nor discussed in a plausible manner. Especially, lines 217-219 suggest increase ice melt as one reason for the reorganization of network connectivity, which however hardly explains the changes reported by the authors, which are most dominant in the tropics where there is hardly any ice to melt. Lines 221-224 appear as an attempt to put the reported findings into a broader context, but any details are unfortunately missing. What are specific processes, and could the authors support their corresponding claims by appropriate references?

Response: Thank you for your valuable comments. We have made corresponding revisions to these statements and have included appropriate references to support our claims.

Correction: (Lines 193-194, Par 1, Page 10) Hence, isolated nodes in the equatorial region have been systematically increasing since the early 1980s, resulting in changes to the climate network structure.

(Lines 222-229, Par 1, Page 11)Previous studies have suggested the weakening of tropical circulations such as the Hadley cell and the Walker circulation, in response to increasing greenhouse gases (Lu et al., 2007; Tokinaga et al., 2012; Cai et al., 2021). This weakening may contribute to the amplified isolation of nodes in tropical oceans. Additionally, the weakened tropical circulation could potentially trigger extreme climate phenomena, such as the intensification of El Niño, with more pronounced teleconnection impacts on distant regions (Fan et al., 2017; Hu et al., 2021). This could, in turn, strengthen the linkage between equatorial regions and continents in climate networks.

Lu, J., G. A. Vecchi, and T. Reichler: Expansion of the Hadley cell under global warming, Geophys. Res. Lett., 34, L06805, doi:10.1029/2006GL028443, 2007.

Tokinaga, H., Xie, SP., Deser, C. et al.: Slowdown of the Walker circulation driven by tropical Indo-Pacific warming, Nature 491, 439 – 443, https://doi.org/10.1038/nature11576, 2012.

Cai, W., Santoso, A., Collins, M. et al.: Changing El Niño – Southern Oscillation in a warming climate, Nat Rev Earth Environ 2, 628 – 644, https://doi.org/10.1038/s43017-021-00199-z, 2021.

J. Fan, Meng, J., Ashkenazy, Y., Havlin, S., and Schellnhuber, H. J.: Network analysis reveals strongly localized impacts of El Niño. Proceedings of the National Academy of Sciences, 114(29), 7543-7548, https://doi.org/10.1073/pnas.1701214114, 2017.

Hu K., Huang, G., Huang, P. et al.: Intensification of El Niño-induced atmospheric anomalies under greenhouse warming, Nat. Geosci. 14, 377 – 382, https://doi.org/10.1038/s41561-021-00730-3, 2021.