A simple framework for likely climate projections applied to tropical width

A Simple Framework for Likely Climate Projections Applied to Tropical Width

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Abstract

The increasing use of climate projections in adaptation necessitates a consistent method for producing estimates of likely future conditions from available climate model data. Many climate projections are produced using high emission scenarios and an evenly weighted ensemble of all available climate models despite substantial evidence that the continuously rising emissions in high emission scenarios are unrealistic, and that some models are more reliable than others. While high emission scenarios can be used to generate a more significant climate change signal and are often not intended to be interpreted as projections, a reader who is a non-expert on climate scenarios may not understand this nuance. As a result, unlikely climate projections could be inadvertently used to plan crucial adaptation efforts for future warming. Here, we present a simple and easy to use framework for creating projections of our likely future climate by combining existing methods. The framework involves three measures: selecting the most likely emission scenario, choosing the most reliable models, and debiasing against observational or reanalysis data. Each of these steps allows for a range of methods with varying complexity, precision, and utility. To demonstrate our framework and its components, we use the simplest applicable methods to estimate future changes in tropical width, a hydrologically important climate feature. Our projections show that the likely tropical expansion by the end of this century

is roughly half of some previously reported estimates, largely due to the selected emission scenario. This simple framework can be easily applied to other climate features, allowing for better estimates of likely future conditions.

Introduction

Adapting to our changing climate requires accurate information about the likely future. However, extracting estimates of probable future conditions from climate model simulations is challenging because the emissions scenarios and participating models of the Coupled Model Intercomparison Project (CMIP) differ so greatly. Simple variations in data processing methods such as model selection can produce a wide range of climate projections, complicating adaptation efforts. Recent estimates of future emissions and warming indicate that some simulations are more realistic than others, allowing for more precise estimates of probable future conditions. However, studies have often used implausibly high emission scenarios and included less-realistic models (Hausfather and Peters, 2020a), creating a situation where the prevalence of these simulations could cause improbable projections to be interpreted as our likely future. Here, we present a simple framework which uses probable estimates of future emissions, removes less realistic models, and debiases model outputs to create more realistic projections of the likely future climate.

In the last few years, substantial evidence has emerged that the high emission CMIP scenarios RCP 8.5 and SSP5-8.5 do not represent a plausible future (Hausfather and Peters, 2020b; Huard et al., 2022; Srikrishnan et al., 2022). Multiple recent reports suggest that global CO_2 emissions will peak before 2025 (Climate Analytics 2023, IEA 2023, BloombergNEF 2024), in disagreement with the continuously rising emissions in the high emission scenarios. This change in thought is further demonstrated by the recent interest by the ScenarioMIP working group in using a less intense high emission scenario than RCP 8.5 or SSP5-8.5 in CMIP7 due to these scenarios becoming increasingly unlikely (van Vuuren et al., 2023). While high emission scenarios should be considered as a low probability, high consequence potential future (Schwalm et al., 2020; Kemp et al., 2022), the implausibility of the current high emission scenarios limits their utility for planning purposes. Additionally, more realistic scenarios such as SSP2-4.5 have been less frequently studied than these high emission scenarios, creating a relative scarcity of more probable future climate projections (Pielke and Ritchie, 2020; Burgess et al., 2022). Although SSP2-4.5 is less extreme than SSP5-8.5, it still represents a substantially warmer future, with severe societal and ecological impacts necessitating strong adaptation and mitigation (Cook et al., 2020; Spinoni et al., 2021).

High emission scenarios are often chosen in theoretical studies to create larger signal-to-noise ratios, or due to data availability. Notably, many studies are explicit in describing these scenarios as a high-emission future or worst-case scenario. However, due to the prevalence of studies which have used this scenario, a reader who is not an expert in climate scenarios may assume that these studies are projections of a probable future. In addition, it may be interpreted that the frustratingly slow progress on decarbonization suggests that the high emission scenario is likely. Regardless, because of the focus on high emission scenarios, the estimates of probable future conditions necessary for adaptation are underreported for many parts of the climate system.

In addition to focusing on implausible scenarios, many projections have used ensembles which include less reliable models. A sizable portion of CMIP6 models have climate sensitivities which are improbable, primarily due to being too large, decreasing the representativeness of both the ensemble spread and mean (Sherwood et al., 2020; Liang et al., 2020; Tierney et al., 2020; Hausfather et al., 2022). One easily calculated climate sensitivity metric, the transient climate response (TCR), measures the relationship between temperature increase and carbon dioxide increase once carbon dioxide concentration has doubled. The International Panel on Climate

Change Sixth Assessment Report (IPCC-AR6) calculated TCR by combining multiple methods, resulting in the estimated likely (1σ) range of 1.4-2.2 K (Arias et al., 2021), which we also use in this study. Because climate models vary so greatly, as measured by TCR and other metrics, many techniques have been developed for creating weighted ensembles based on model skill (Brunner et al., 2020a). For example, by weighting models based on performance and independence, Brunner et al. (2020b) projected less intense warming from CMIP6 models. Here, we focus our model selection on TCR in an effort to present a simple version of this framework, though considering other metrics of model performance may also prove useful.

The final procedure in our framework is to debias the models. Biases in individual models and the ensemble mean have been well documented in CMIP6, with only modest improvements relative to CMIP5 (Kim et al., 2020). Because of this issue, a variety of methods for debiasing have been proposed, from simple mean subtraction to more advanced methods (Teutschbein and Seibert, 2012). In addition to discussion over the benefits of each method, the utility of debiasing has been debated for some applications (Laux et al., 2021), though some have argued that the negative effects of bias correction are not detectable (Maraun et al., 2017). To present a simple version of the debiasing without introducing large and potentially spurious changes to the tropical width projections, we focus on removing the minor circulation change biases associated with the present-day circulation, similar to those previously reported in Kidston and Gerber (2010), Simpson and Polvani (2016), Curtis et al. (2020), and Simpson et al. (2021).

We create projections of tropical width to showcase our proposed framework and the impact of each of its measures. Tropical width is a societally important feature of the climate system, as the poleward edge of the tropics is associated with sharp latitudinal gradients in precipitation (Lu et al., 2007; Schmidt and Grise, 2017). Over the satellite era (1979-present), the latitudinal width of the tropics has increased due to many factors including natural variability, global warming, and stratospheric ozone depletion (Grise et al., 2019; Waugh et al., 2015). While temperature is projected to increase in the 21st century under all CMIP6 scenarios, stratospheric ozone depletion peaked at the end of the 20th century and is projected to decline in the 21st century (WMO, 2022), countering the increase in tropical extent associated with warming (Perlwitz, 2011).

Recent tropical width modeling studies either focused primarily on the high emission scenarios or included multiple scenarios with no emphasis on which projections are most probable. For example, Staten et al. (2018) and Grise and Davis (2020) only considered the high emission scenarios RCP 8.5 and SSP5-8.5 respectively. Tao et al. (2016), Allen and Ajoku (2016), and Xia et al. (2020) analyzed several scenarios, showing that tropical widening trends increase with emission intensity. Of these five studies, none considered model sensitivity, resulting in models with TCR outside of the likely range being included in the analyses. Using our simple framework, we attempt to project the most probable future tropical edge latitude and compare our results against those derived from methods such as those from Grise and Davis (2020). As we will show, our framework leads to a substantial reduction in estimated tropical expansion compared to these methods.

Data and Methods

We used CMIP6 (Eyring et al., 2016) zonal surface-wind and 2m air temperature data for the historical period 1850-2014 and for three forcing levels from 2015-2099: SSP1-2.6, SSP2-4.5, and SSP5-8.5. Zonal surface-wind and temperature data were acquired for all available CMIP6 models (Table 1). We selected 28 models based on the availability of data for both variables across all three forcings. TCR values were acquired from Hausfather et al. (2022) and checked against Njisse et al. (2020). Of the 28 models, 1 has a TCR of less than 1.4 K, 19 have TCR values in the likely range of 1.4-2.2 K calculated in IPCC-AR6 (Arias et al., 2021), and 8 have TCR values greater than 2.2 K. To provide observation-based estimates of the present-day tropical width, we used monthly averaged ERA5 (Hersbach et al., 2020) reanalysis data for zonal surface-wind from the satellite era (1979-2014). This period was chosen as a compromise between length and quality as there are fewer remote observations before 1979.

ERA5 is chosen as it is the successor to ERA-Interim, which is shown in Davis and Davis (2018) and Chemke and Polvani (2019) to be physically reasonable for phenomena associated with Hadley cell width and circulation strength. ERA5 is chosen over ERA-Interim due to the improved resolution and accuracy (Hersbach et al., 2020), and a recent study demonstrating that ERA5 produces internally consistent estimates of Hadley cell width using the chosen metric (Baldassare et al., 2023).

Zonal surface-wind data from both ERA5 and CMIP6 were zonally and annually averaged and then used to compute the latitudes of the tropical edge over the two hemispheres using the zonal surface-wind zero crossing method in the software package PyTropD (Adam et al., 2018). PyTropD uses spline interpolation to determine the tropical edge latitude, decreasing the impact of resolution differences between models. The zonal surface-wind zero crossing method is chosen over other methods such as the meridional stream function due to the consistency in estimates from ERA5 (Baldassare et al., 2023), though similar results were obtained using the meridional stream function (not shown). Annual mean global averages of 2-meter temperature were computed from CMIP6.

For both ERA5 and CMIP6, uncertainties are calculated through bootstrapping, using 10,000 samples with replacement. To focus on the likely changes to tropical width, we use the 1σ uncertainty range throughout, consistent with the likely range from IPCC-AR6 (Arias et al., 2021). For the final projections shown in Figure 6, the uncertainty range is calculated by summing the bootstrapped uncertainties of the 30-year mean of the model projected tropical edge latitude, present-day ERA5 tropical edge latitude, and the uncertainty of the ensemble mean.

Table 1: CMIP6 models used in this study with associated TCR values. Models with TCR below likely range of 1.4-2.2 K are marked in green, while those with TCR values greater than this range are in red.

Number	Model	TCR (K)
1	ACCESS-CM2	1.96
2	ACCESS-ESM1-5	1.97
3	AWI-CM-1-1-MR	2.03
4	BCC-CSM2-MR	1.55
5	CAMS-CSM1-0	1.73
6	CMCC-CM2-SR5	2.14
7	CMCC-ESM2	1.92
8	CNRM-CM6-1	2.22
9	CNRM-CM6-1-HR	2.46
10	CNRM-ESM2-1	1.83
11	CanESM5	2.71
12	CanESM5-CanOE	2.71
13	FGOALS-g3	1.50
14	GFDL-ESM4	1.63
15	HadGEM3-GC31-LL	2.49
16	IITM-ESM	1.66
17	INM-CM4-8	1.30
18	INM-CM5-0	1.41
19	IPSL-CM6A-LR	2.35
20	KACE-1-0-G	2.04
21	MCM-UA-1-0	1.90
22	MIROC-ES2L	1.49
23	MIROC6	1.55
24	MPI-ESM1-2-HR	1.64
25	MPI-ESM1-2-LR	1.82
26	MRI-ESM2-0	1.67
27	NESM3	2.72
28	UKESM1-0-LL	2.77
	Average for All Models	1.97
	Average for Likely TCR Models	1.76

Forcing Selection

Choosing the most representative emission scenario is the most critical step in producing a likely climate projection. To select the forcing scenario, we suggest comparing the emissions from each scenario to trustworthy emissions projections and probabilistic emissions models. This flexible method allows for potential refinements in climate projections following the anticipated emergence of additional emission scenarios and improved emission projections. For this study, we begin by comparing the emissions from the three SSP scenarios to the "Policies and Action", "2030 Targets Only", and "Pledges & Targets" projections from the Climate Action Tracker (Climate Action Tracker, 2022). These three projections represent 21st century emissions resulting from different assumptions in the implementation of national emission reduction pledges. All three projections most closely match SSP2-4.5 while also projecting emissions which are less than 1/3 of SSP5-8.5 emissions by the end of the century (Figure 1). None of the projections match SSP1-2.6 as the negative emissions needed for this scenario do not exist in the Climate Action Tracker projections. Next, we consider recent studies comparing each scenario to probabilistic integrated assessment models (Srikrishnan et al., 2022; Huard et al., 2022), both of which indicate that SSP2-4.5 is the most likely scenario in the late 21st century. Following these comparisons, we conclude that SSP2-4.5 is currently the most likely scenario, while the frequently used SSP5-8.5 is very unlikely.

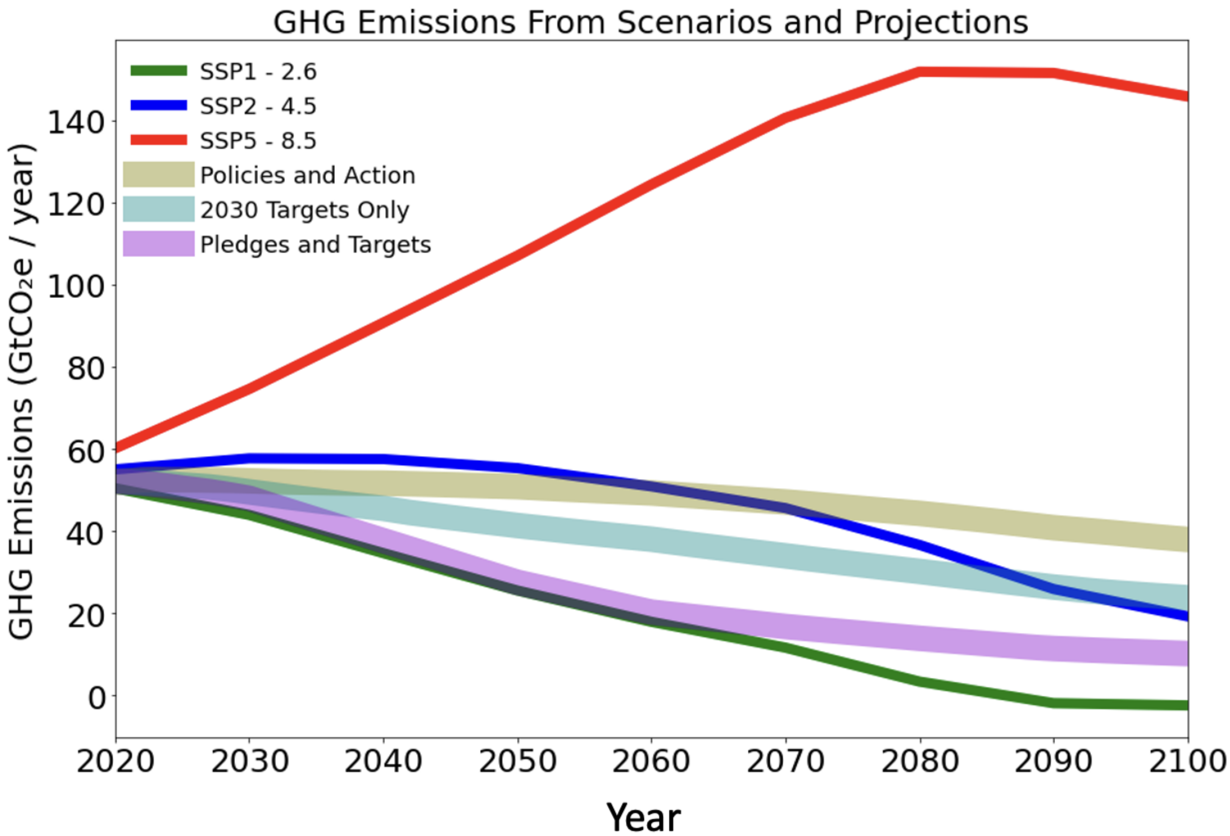

Figure 1: Greenhouse gas emissions from CO_2, CH_4, and N_2O in gigaton of CO_2 equivalent per year for three SSP scenarios and three Climate Action Tracker projections. Equivalent CO_2 emissions are calculated by multiplying the CH_4 and N_2O emissions by their respective global warming potentials and adding these values to CO_2 emissions. Climate Action Tracker data is from the Climate Action Tracker (Climate Action Tracker, 2022), and SSP scenario data is from Riahi et al. (2017).

The importance of forcing selection is shown by the substantial differences in projected tropical expansion between emission scenarios (Figure 2). The three scenarios shown are SSP1-2.6, an improbable low-emission scenario which limits warming to around 1.5 °C; SSP2-4.5, the most likely scenario with moderate emission reductions; and SSP5-8.5, an unlikely high-emission scenario with continuously rising emissions. In the Southern Hemisphere (SH), tropical expansion begins in the early 20th century and accelerates after 1960, coinciding with the start of ozone depletion (Polvani et al., 2011; Solomon et al., 2005), while the weaker Northern Hemisphere (NH) expansion only becomes noticeable after 1990. Because CMIP6 models project ozone recovery by the late 21st century (Revell et al., 2022), the larger SH expansion compared to the NH is unrelated to changes in ozone and indicates that the SH tropical width is more sensitive to the warming from increased greenhouse gases, in agreement with previous studies (Watt-Meyer et al., 2019). In addition, the greater sensitivity in the SH results in forcing differences which are larger than intermodel differences, in contrast to the NH where intermodel differences are greater (Fig. S1). As shown in Figure 2, by the end of the 21st century, the projected SH expansion under the low and high emission scenarios differs by a factor of three, and the expansion from SSP5-8.5 is roughly twice that of SSP2-4.5.

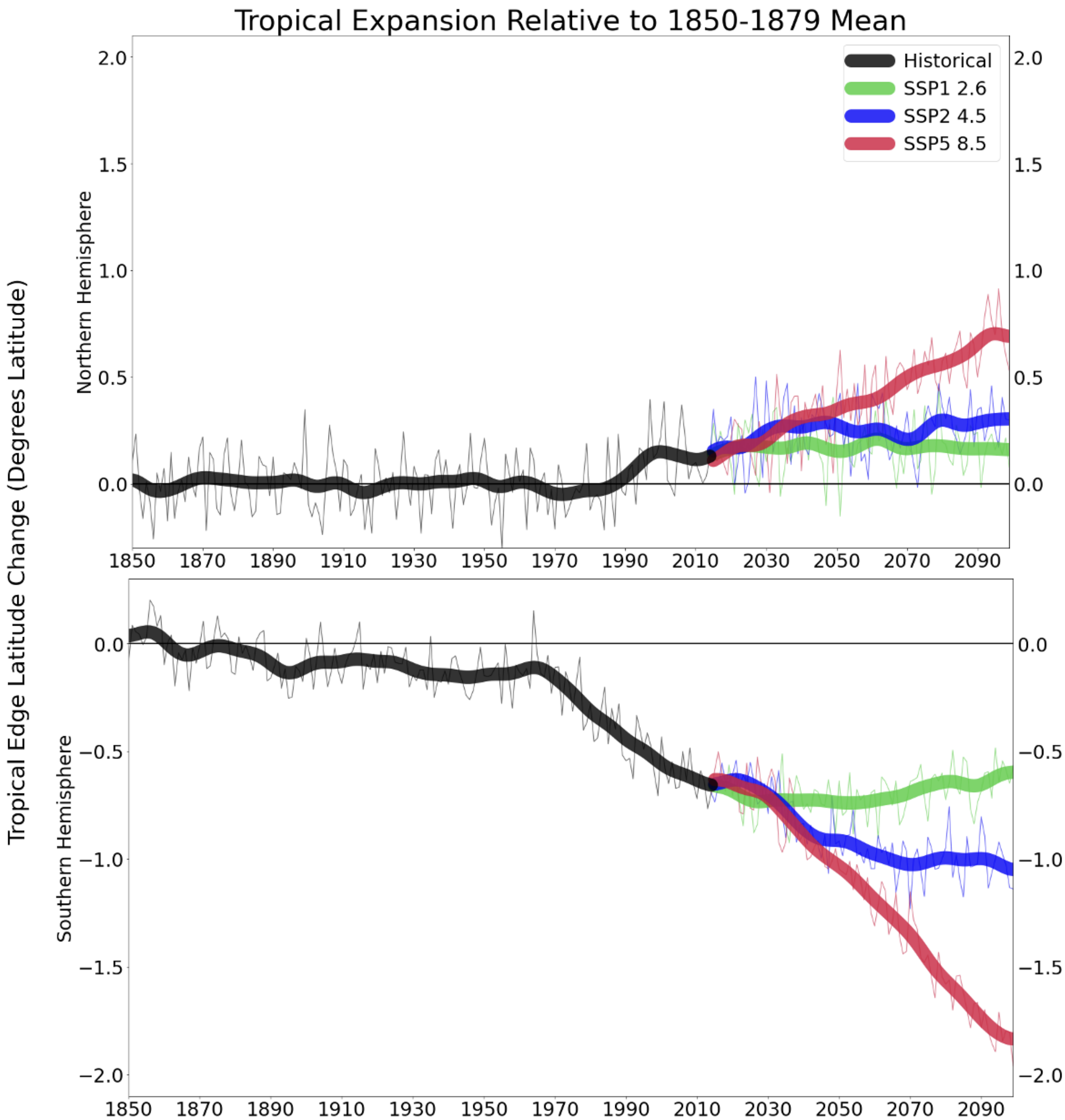

Figure 2: Ensemble mean tropical edge latitude change relative to 1850-1879 for 28 CMIP6 models from three forcing scenarios. Thin lines represent the raw ensemble mean while thick lines result from a Gaussian smoothing.

Model Selection

While selecting the most likely emission scenario SSP2-4.5 has a large impact on the tropical width projections, the full ensemble is still composed of models with implausible rates of future warming. We attempt to correct this issue by focusing on models with reasonable TCR values, discarding models outside of the likely climate sensitivity range of 1.4-2.2 K from IPCC-AR6 (Arias et al., 2021). Because more CMIP6 models have high TCR than low TCR values, our moderate ensemble has an average TCR of 1.76 K compared to the full ensemble average of 1.97 K (Table 1).

For SSP2-4.5, the moderate TCR ensemble projects less warming and less tropical expansion than the full ensemble as shown by the difference between the ensemble averages (Figure 3). There is an approximately linear relationship between warming and tropical expansion, with a greater slope in the SH and for higher forcing simulations. Although the slopes of the regression lines for all three scenarios are positive, they are significantly different from zero at the two-sided 95% confidence level only for the high forcing simulations in both hemispheres. For all scenarios in both hemispheres, the larger temperature increase projected by the full ensemble results in more expansion than the moderate TCR ensemble. Because of the greater sensitivity, the TCR filtering is more impactful in the SH, similar to the forcing selection shown previously.

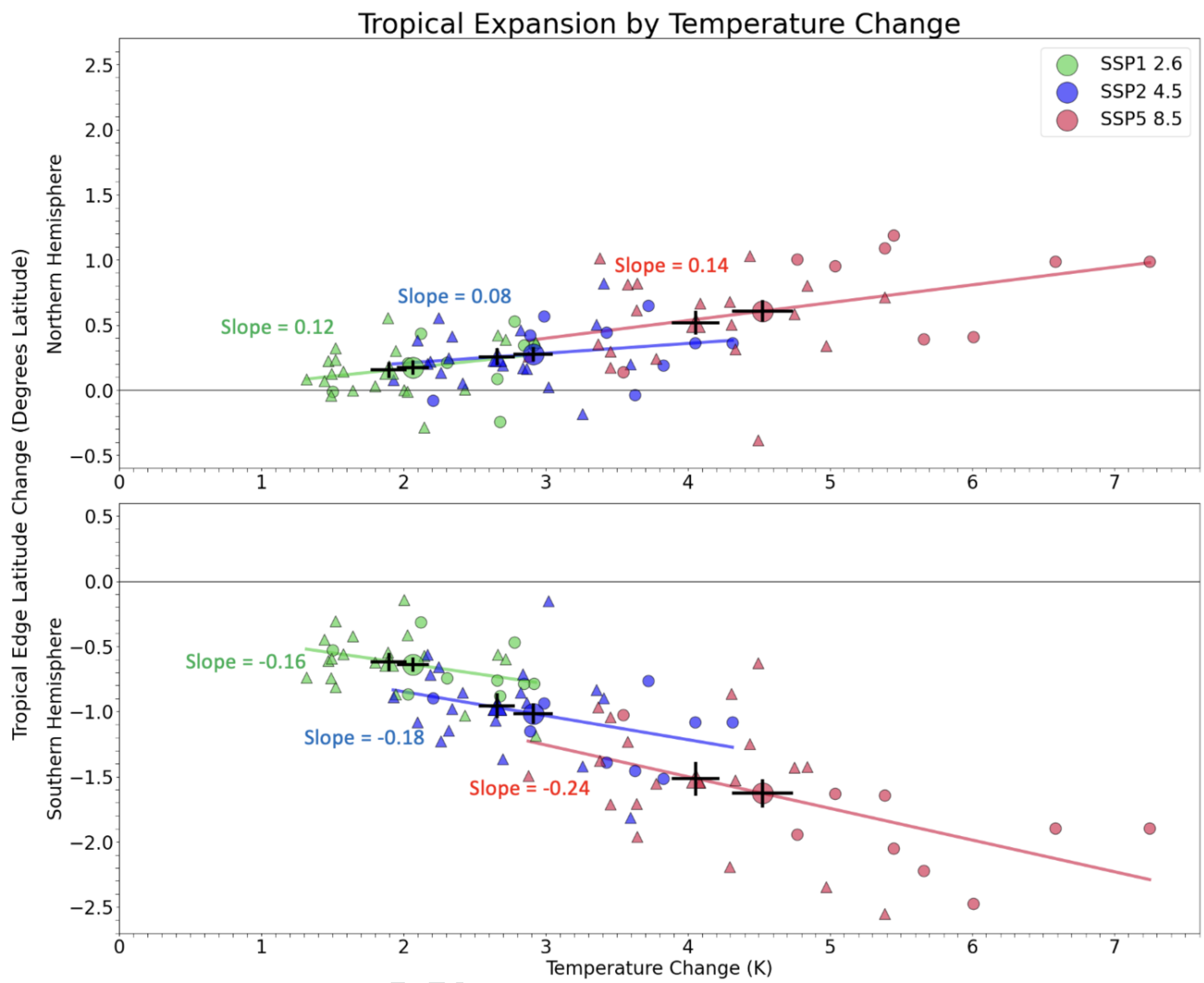

Figure 3: Changes in tropical edge and temperature from 1850-1879 to 2070-2099. Models with TCR values between 1.4 and 2.2 K are denoted by triangles, and models with TCR outside of this likely range are marked as circles. Large symbols denote ensemble means with their 1σ range, with the large circle representing the ensemble mean of all models, and the large triangle representing the mean of moderate TCR models. For each forcing level, a linear best fit from all 28 models is displayed in the corresponding color.

Previous studies found an insignificant relationship in the NH between tropical widening and equilibrium climate sensitivity, which measures temperature change once climate has reached equilibrium following a pulse of carbon dioxide (Grise and Polvani, 2014; Grise and Polvani, 2016; De et al., 2021). However, we find that TCR is significantly correlated with tropical widening in both hemispheres, requiring the removal of overly sensitive models for realistic tropical width projections (Figure 4). The disagreement between our study and previous studies could be the result of different models or metrics, but may also be due to the fact that by 2100 the scenario simulations are not yet in equilibrium, causing TCR to be a better predictor of the projected 21st century warming and widening than equilibrium climate sensitivity.

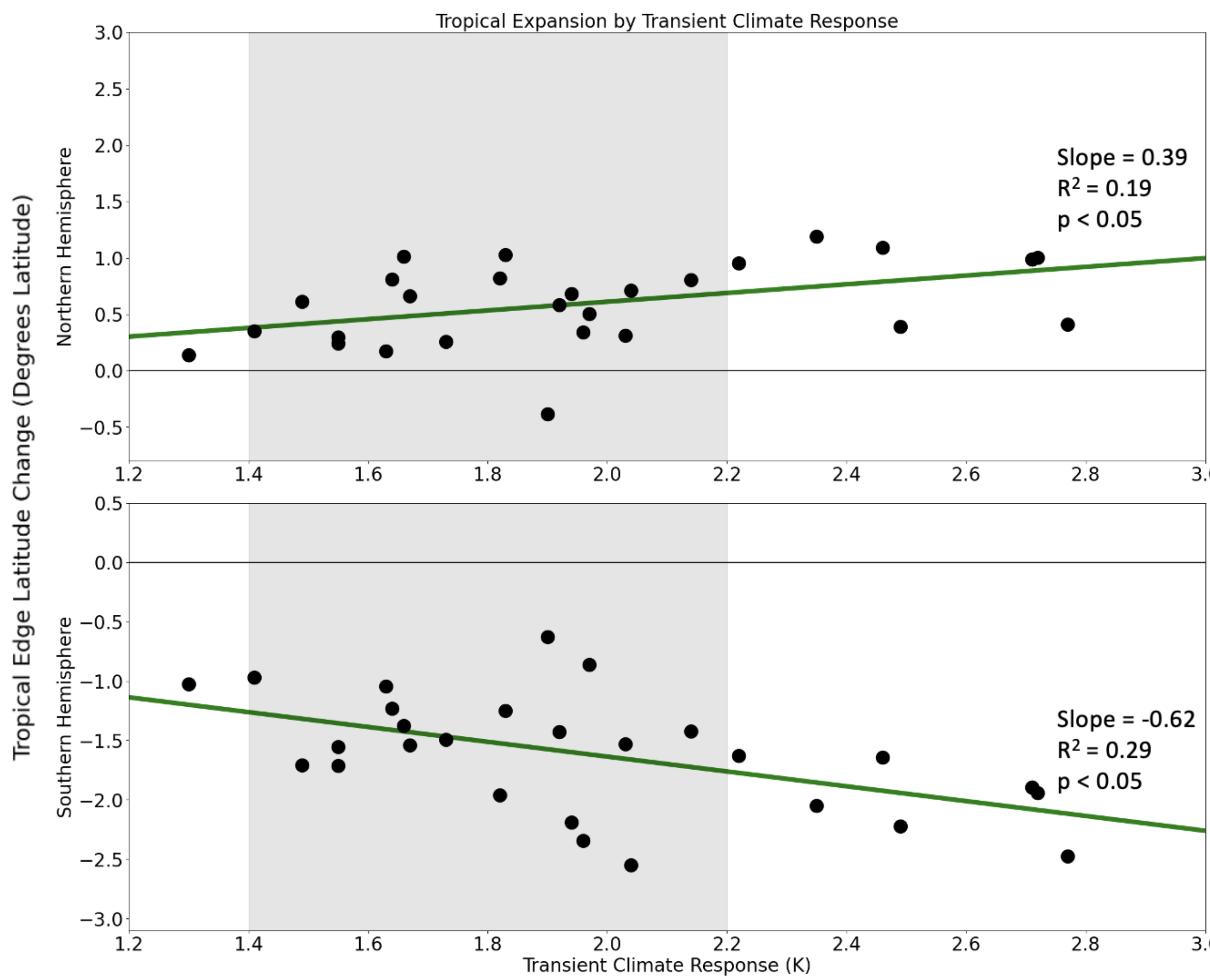

Figure 4: Projected tropical edge latitude change (2070-2099 – 1850-1869) by transient climate response for all CMIP6 models using SSP5-8.5. The shaded gray region denotes the likely TCR range of 1.4-2.2 K according to IPCC-AR6 (Arias et al., 2021).

Debiasing Model Outputs

Now that we have chosen the most likely emission scenario and constructed an ensemble of the most reasonable models, the final measure is to debias the models. Depending on the feature of interest, debiasing may be necessary due to limitations in climate simulations (Laux et al., 2021). For example, both individual models and ensembles have been shown to inaccurately represent satellite era precipitation in the tropics (Kim et al., 2020). These issues may become especially pronounced when focusing on a subset of precipitation or a more specific region or time period, an example being the large 95th percentile precipitation biases in October through December in East Africa shown in Ayugi et al. (2021). As here we are focusing on zonally averaged features of the annual mean Hadley cell, a climate feature which is generally well simulated (Chemke and Polvani, 2019), debiasing may not be as beneficial and could introduce spurious changes as observed from other debiasing methods (Cannon et al., 2015). To demonstrate this step in the framework without introducing large and questionable changes to the projections, we choose to perform a relatively simple debiasing, focusing on a minor and statistically insignificant tendency for models with equatorward biased jets tend to exhibit more widening than other models (Kidston and Gerber, 2010; Simpson and Polvani, 2016; Curtis et al., 2020; Simpson et al., 2021). To analyze whether present-day biases in the latitude of the Hadley cell edge exhibit a similar relationship in the chosen CMIP6 models, we calculate the corresponding statistics for each model (Figure 5). Similar to previous studies (Kidston and Gerber, 2010; Simpson and Polvani, 2016; Curtis et al., 2020; Simpson et al., 2021), we find that the models with equatorward biased present-day tropical width project more future widening in both hemispheres. While Figure 5 shows the results for 2070-2099, this feature is present throughout the 21st century, though it is not statistically significant. Because the ensemble mean present-day tropical edge is biased equatorwards relative to ERA5 in both hemispheres, roughly 0.3 degrees in the NH and 0.1 degrees in the SH, the tendency for equatorward biased models to project more expansion may result in an overestimation of future expansion.

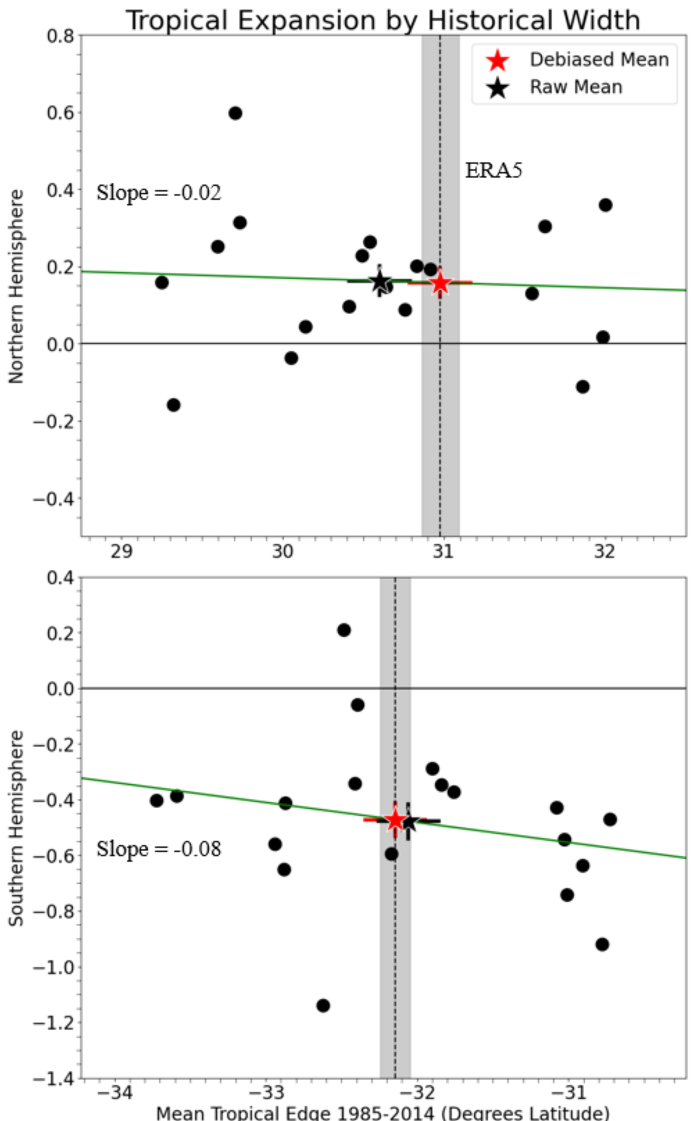

Figure 5: Tropical expansion between 1985-2014 and 2070-2099 by 1985-2014 tropical edge latitude for moderate TCR models using SSP2-4.5. The stars denote the raw (black) and debiased (red) ensemble means, with the 1σ range shown. The vertical dashed line marks the mean tropical edge in ERA5 from 1985-2014 with the gray shaded region depicting the 1σ range calculated from bootstrapping. The green line is a linear best fit of all models prior to debiasing. R^2 is nearly zero in both hemispheres.

To debias the projections, we remove this tendency from the models by the following process, which is performed in each year *j* and repeated for both hemispheres as demonstrated in Fig. S2. First, the present-day (1985-2014) tropical edge for each model ϕ_i and for ERA5 ϕ_{ERA5} is calculated, as well as the future tropical edge in each model, using 30-year mean data centered on the year of interest *j*. For each model *i* in each year *j,* the present-day tropical edge ϕ_i is subtracted from the future tropical edge, resulting in the change of tropical edge $\Delta\phi_{i,j}$. A linear best fit is calculated between the tropical edge changes and present-day tropical edges of all models in each year *j*, producing the intercept a_j and slope b_j. Next, from the linear best fit, each model's estimated expansion $\Delta\hat{\phi}_{i,j}$ is

$$\Delta\hat{\phi}_{i,j} = a_j + b_j\phi_i \, , \tag{1}$$

and the residual $\varepsilon_{i,j}$, which is the difference between the estimated and the actual expansion, is

$$\varepsilon_{i,j} = \Delta\phi_{i,j} - \Delta\hat{\phi}_{i,j} \, . \tag{2}$$

Finally, the debiased expansion $\Delta\tilde{\phi}_{i,j}$ is given by the sum of the expansion projected by the best fit line at the ERA5 present-day edge and the residual

$$\Delta\tilde{\phi}_{i,j} = a_j + b_j\phi_{ERA5} + \varepsilon_{i,j} = \Delta\phi_{i,j} + b_j(\phi_{ERA5} - \phi_i) \, . \tag{3}$$

This results in small reductions in projected expansion, which are not statistically significant in either hemisphere, and are larger in later years and in the NH. While in this example the debiasing has minor impacts, for climate features with large known biases such as extreme precipitation, debiasing may be useful for providing more realistic projections (Xu et al., 2021).

Likely Tropical Width Projections

In Figure 6, we compare the projections from our simple framework (blue) to those from a more "typical" methodology such as Grise and Davis (2020) (red), which uses an ensemble of all CMIP6 models with SSP5-8.5 as the forcing scenario. Compared to this methodology, our framework projects roughly half of the tropical expansion. The decrease is primarily the result of using the moderate emission scenario, though the TCR selection results in a further reduction in expansion. Our framework (Figure 6, blue) projects a 21st century tropical widening of 0.1 degrees in the NH, which is within the likely range of the late 20th century as measured by the 1σ range of the ERA5 mean (1985-2014). In contrast, the projected 21st century SH widening of 0.5 degrees is significant, further demonstrating the hemispheric differences in sensitivity. These results strongly differ from the projections of expansion from "typical" methods (Figure 6, red), which are significant at the 1σ level in both hemispheres. The "typical" methods (Figure 6, red) estimate roughly 0.5 degrees of expansion in the NH and 1.1 degrees in the SH. The differences between our framework and the previous approaches are larger in the SH due to the greater sensitivity, although by the end of the 21st century the difference is also significant in the NH. Following our methodology, the best estimate for the absolute position of the tropical edge at the end of the 21st century is 31.1 degrees in the NH and 32.6 degrees in the SH.

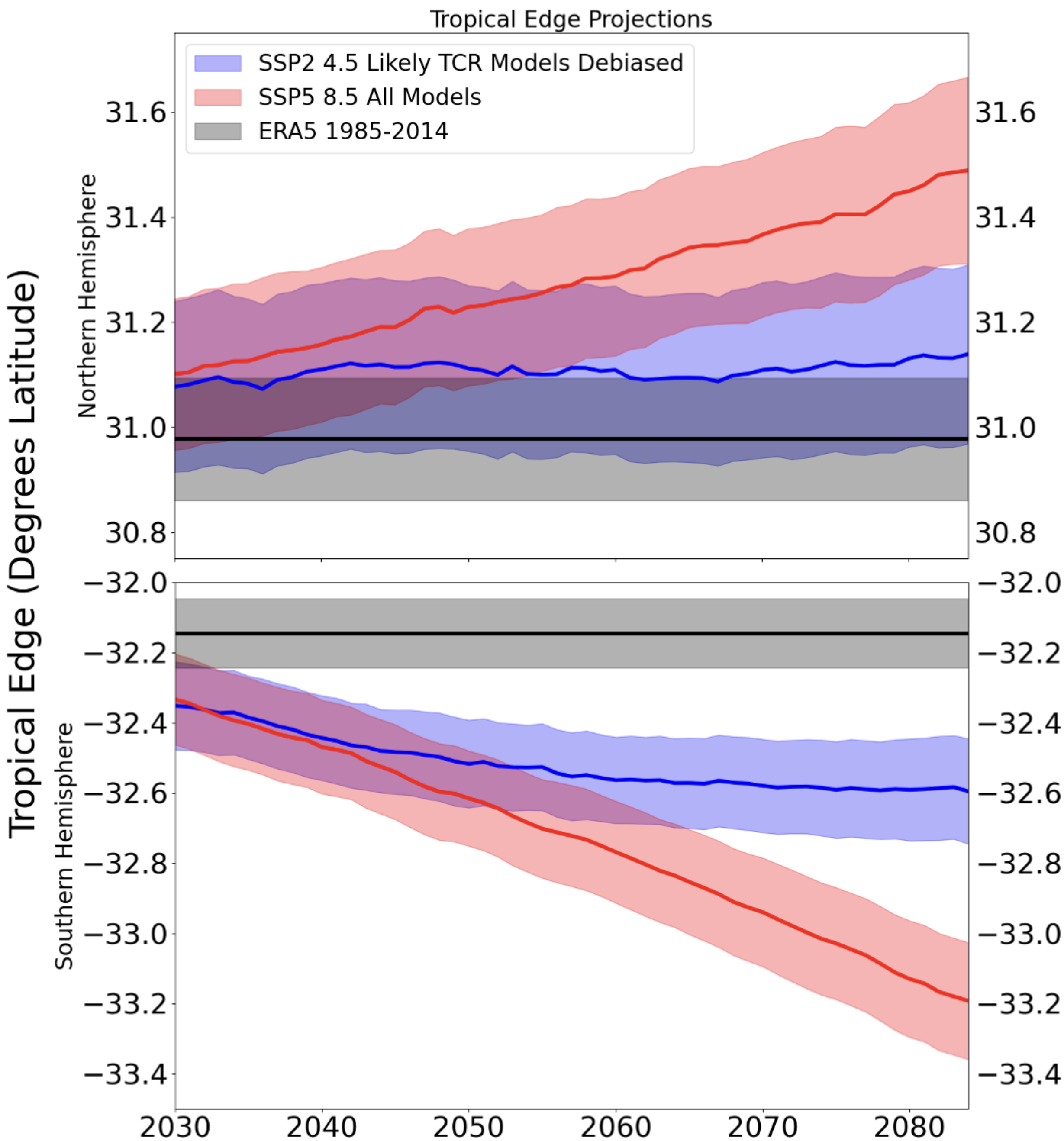

Figure 6: Tropical edge latitude following "typical" approaches (red) and the proposed framework (blue). The value presented for each year is the 30-year mean centered on the year of interest. The "typical" approach described here uses the mean of all CMIP6 models under SSP5-8.5. Our framework includes only the models with moderate TCR values, uses SSP2-4.5 as

forcing, and debiases the relationship between present-day tropical edge bias and future expansion. In addition, for both methods we subtract the ERA5 present-day mean to remove mean biases. The thick areas in each color represent the 1σ range from bootstrapping.

Summary and Discussion

Following our methodology, the likely end of century NH expansion relative to present is about 0.1 degrees while the SH expansion is roughly 0.5 degrees, both of which are considerably smaller than the estimates from methods used in some previous studies, for example Grise and Davis (2020) (Figure 6). Each measure of our proposed framework has distinct impacts on the projected tropical expansion. Focusing on the more likely moderate emission scenario roughly halves the expansion in both hemispheres. Excluding models with TCR values outside of a likely range decreases projected warming, causing a further reduction in expansion of roughly 0.1 degrees globally, primarily due to reduced expansion in the Southern Hemisphere. The removal of model biases similar to Kidston and Gerber (2010), Simpson and Polvani (2016), Curtis et al. (2020), and Simpson et al. (2021) further decreases projected expansion in both hemispheres.

The framework we have described creates probable projections of future climate using available climate model data. The measures in this framework are adaptable for different applications and can be modified as better information or methods become available. The emission scenario selection will likely change due to revised estimates of future emissions and the creation of new scenarios. Additionally, the emission selection could be improved through the consideration of other relevant factors such as aerosols, which have spatially heterogenous impacts and may be especially impactful for certain regions (Persad et al., 2023) or climate features (Zhao et al., 2020). The model selection could be refined by considering multiple measures of skill based on historical observations or theoretical arguments, or by using a more sophisticated weighting method. For some climate features the debiasing step could be ignored, while for other features, debiasing could be modified by utilizing methods tailored to the system of interest. As it stands, the simple methods presented here produce improved climate projections with minimal effort.

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Declarations

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Competing Interests

The authors have no competing interests.

Author Contributions

DB performed the numerical analysis and wrote the initial draft of the manuscript. Both authors were equally involved in the design of the study, the interpretation of the results, and the review of the manuscript.

Ethics Approval

Not applicable

Consent to Participate

Not applicable

Consent for Publication

Not applicable

Code and Data Availability

CMIP6 data was acquired from the CEDA Archive https://catalogue.ceda.ac.uk. ERA5 data can be downloaded at https://cds.climate.copernicus.eu (Hersbach et al., 2020).

Supplement

A Simple Framework for Likely Climate Projections Applied to Tropical Width

Text S1: Tropical edge latitude change for all simulations

Tropical edge latitude change for all models using all forcing levels. In the NH the intermodel differences are larger than the inter-forcing differences. In the SH the inter-forcing differences are greater than the intermodel differences. Overall, the intermodel spread is similar in both hemispheres, so this difference is a result of hemispheric differences in sensitivity.

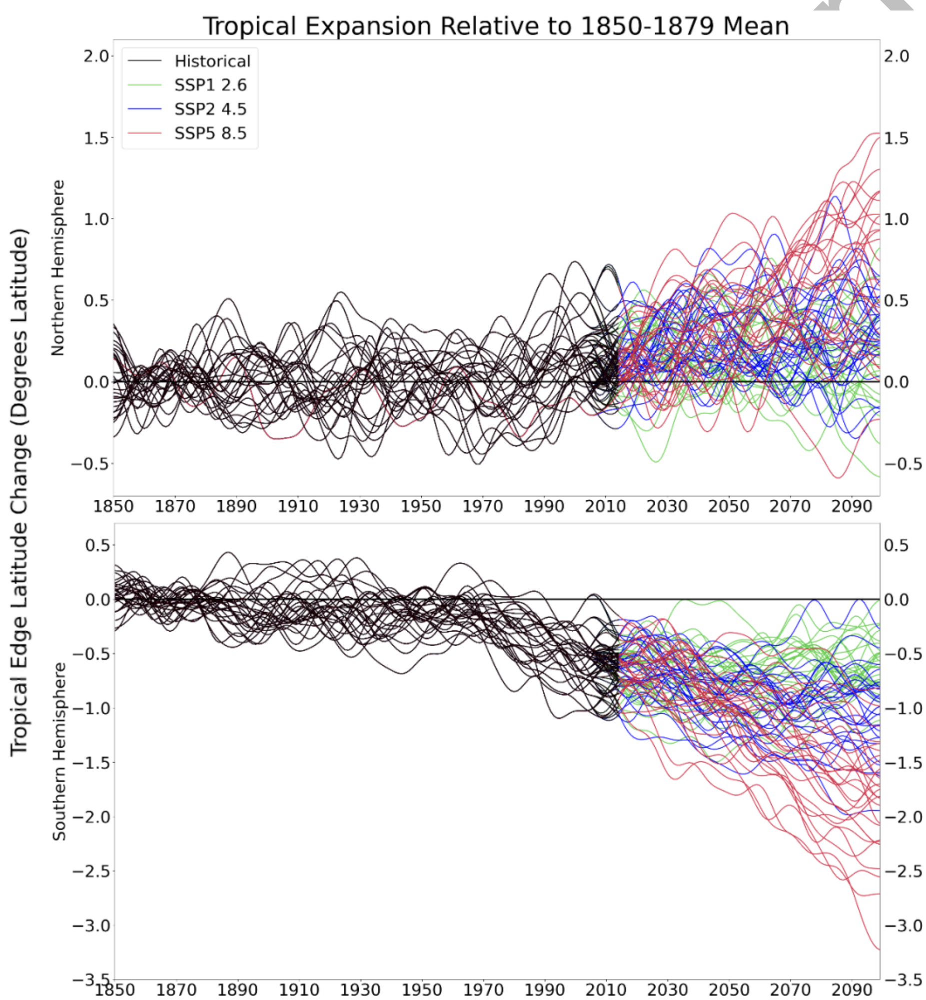

Fig. S1: Tropical edge latitude change for all simulations grouped by forcing level (color) in both hemispheres. All changes are relative to the 1850-1879 mean.

Text S2: Annotated tropical expansion by historical tropical width showing debiasing methods

Tropical expansion in year j (2084) by 1985-2014 tropical width in the Southern Hemisphere showing variables and methods included in the debiasing for an individual model i. The debiasing results in a slight increase in projected expansion for this model.

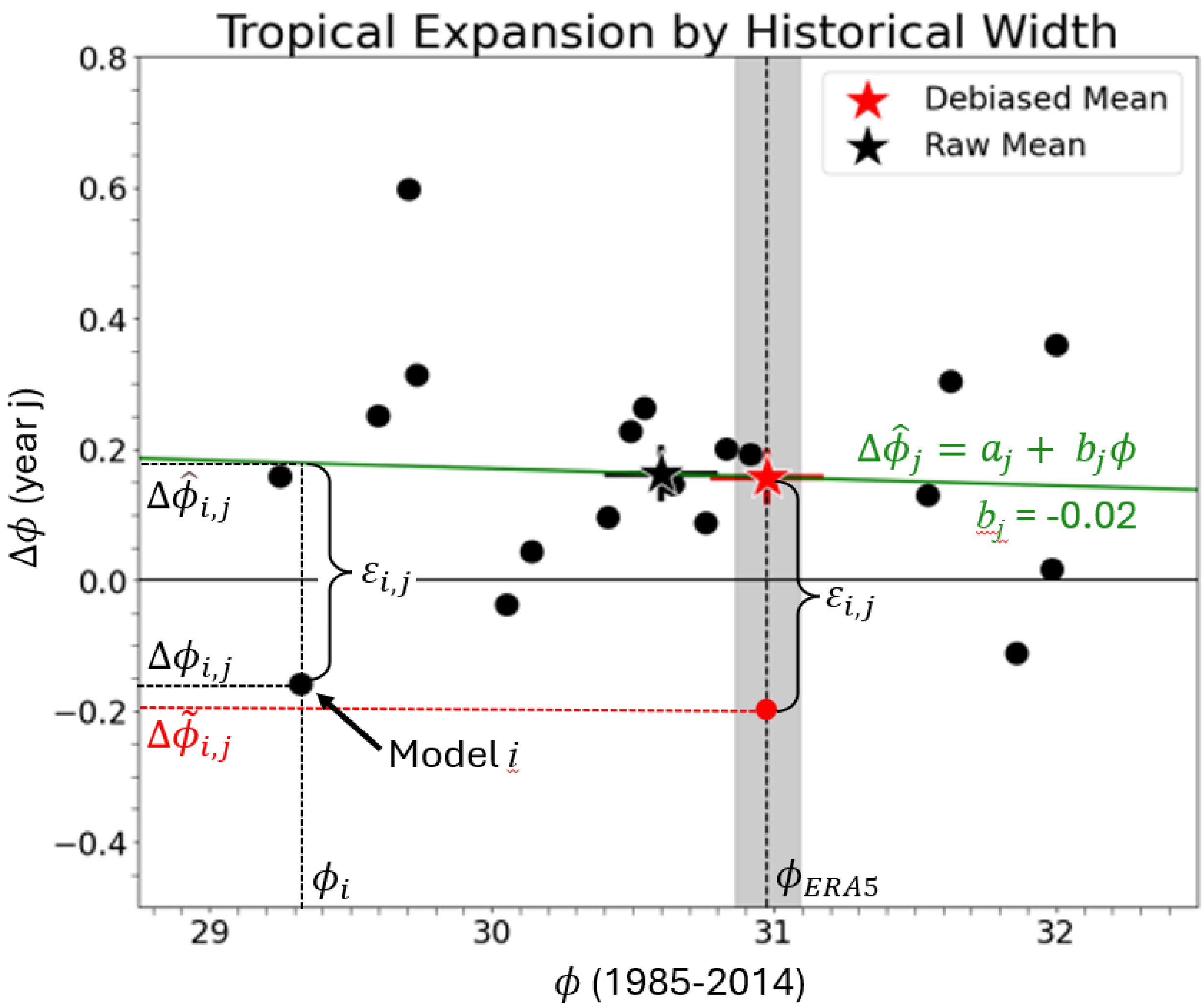

Fig. S2: Tropical widening in 2070-2099 relative to 1985-2014 by tropical width in 1985-2014 for SSP2-4.5 models with likely TCR. The debiasing is demonstrated for a single model.