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Key Points:

- The focus of climate mitigation policy on singular thresholds of global mean temperature conceals significant variability in regional impacts
- We propose a simple tool which maps how much warming is needed in one location to match the effects of reaching a specific warming threshold in another
- Expanding the "temperature of equivalence" framework could help with integrated adaptation planning in a warmer world

Supporting Information:

- Supporting Information S1

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How Uneven Are Changes to Impact-Relevant Climate Hazards in a 1.5 °C World and Beyond?

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Abstract In the last decade, climate mitigation policy has galvanized around staying below specified thresholds of global mean temperature, with an understanding that exceeding these thresholds may result in dangerous interference of the climate system. United Nations Framework Convention on Climate Change texts have developed thresholds in which the aim is to limit warming to well below 2 °C of warming above preindustrial levels, with an additional aspirational target of 1.5 °C. However, denoting a specific threshold of global mean temperatures as a target for avoiding damaging climate impacts implicitly obscures potentially significant regional variations in the magnitude of these projected impacts. This study introduces a simple framework to quantify the magnitude of this heterogeneity in changing climate hazards at 1.5 °C of warming, using case studies of emergent increases in temperature and rainfall extremes. For example, we find that up to double the amount of global warming (3.0 °C) is needed before people in high-income countries experience the same relative changes in extreme heat that low-income nations should anticipate after only 1.5 °C of warming. By mapping how much warming is needed in one location to match the impacts of a fixed temperature threshold in another location, this "temperature of equivalence" index is a flexible and easy-to-understand communication tool, with the potential to inform where targeted support for adaptation projects should be prioritized in a warming world.

Plain Language Summary While the threshold of global mean warming which results in damaging climate impacts is thought to differ significantly between different locations, quantifying these differences has proven difficult for the scientific community. This paper introduces a simple tool, called the "temperature of equivalence" index, which maps how much global warming is needed for one location to match the effects of reaching a specific warming threshold in another. As an illustration of the framework, we find changes to the severity of extreme heat events for low-income nations after 1.5 °C of warming would not be seen for other regions of the world until after a global temperature rise twice as high. By aggregating the temperature of equivalence index for previously incompatible measures of the impacts of climate change, future work could enable a more holistic understanding of which nations will have shared experiences in a warmer world, with potential benefits for adaptation planning as a consequence.

1. Introduction

There is significant societal interest in understanding how climate change impacts will manifest themselves in response to continued increases in global mean temperature (Seneviratne et al., 2016; Stott, 2016; Stott et al., 2016). In the context of the development of future mitigation targets (Schleussner, Rogelj, et al., 2016), there is also an enhanced need to more specifically understand how regional changes to weather extremes and other climate-related hazards will manifest themselves in response to specific thresholds of global mean warming (Hawkins et al., 2017; King et al., 2017; Mitchell et al., 2016). Following the signing of the Paris Agreement in December 2015, there has been a new focus on the regional impacts associated with "1.5° of warming above preindustrial levels," not previously the focus of targeted scientific research (Mitchell et al., 2016; Rogelj & Knutti, 2016; Schleussner, Lissner, et al., 2016). Of course, the question of whether the exceedance of any specific threshold of global-mean warming translates to "dangerous interference" of the climate system inherently simplifies potentially significant regional differences in the severity of such impacts—or more precisely, the threshold of warming which would result in damaging local impacts may differ significantly between different locations. However, resolving how different these "thresholds" are remains poorly constrained and is thus the focus of this analysis.

One method which has proven useful to characterize relative changes to future climate between different locations around the world has been that of "spatial climate analogues." Primarily used as a communication tool (for example, http://bit.ly/2n1ubbF), this approach commonly considers what regions of the world might today exhibit climatic conditions comparable to the projections expected for a different location under a future warming scenario. Many papers have presented variations on this theme (Brown & Katz, 1995; Hallegatte et al., 2007; Kalkstein & Greene, 1997; Pugh et al., 2016; Williams et al., 2007), each with different caveats: The most recent example from Dahinden et al. (2017) found that up to 20% of today's local climates, when characterized based on seasonal cycles of average temperature and precipitation over land regions, would disappear following an additional 2.0 °C rise in global temperatures.

This study presents a new framework motivated by the concept of spatial climate analogues, but with a focus on assessing the level of *dissimilarity* in regional climate hazards following a given rise in global mean temperatures. Specifically, a climate model-based framework is used to identify how many degrees of global warming would be required for each individual grid cell around the world to reach the same threshold of emergent climate change as those experienced at 1.5 °C of warming for a specific location of interest. While nearly all previous approaches to spatial climate analogues keep the present-day climate fixed as a frame of reference, this paper's approach focuses on future warming thresholds as the target reference frame, thereby enabling a clearer demonstration of regional variability in *future* climate change and related policy implications.

Using emergent increases in the frequency of heat and precipitation extremes as examples (sections 2 and 3), section 4 will then discuss how an extended framework of comparing the emergence of climate change impacts above background variability across regions can have clear benefits for decision makers worldwide. Such benefits include (1) demonstrating that the emergent changes expected at some point in the future with continued carbon emissions in one part of the world are in fact closely related to the changes being felt in other regions of the world today (with the potential to then learn from the experiences of those places) and (2) highlighting which regions should be the focus of more targeted support for adaptation planning, given the severity of some changes which are projected to occur even if ambitious mitigation scenarios are successfully achieved.

2. Data and Methods

For illustrative purposes, this study utilizes two extreme temperature and precipitation metrics from the Expert Team on Climate Change Detection Indices (ETCCDIs, Sillmann et al., 2013): for temperature, we analyze the annual maxima of all daily maximum temperatures (hereafter TXx); for precipitation, we identify annual maximum 1-day precipitation accumulations at each location (Rx1day).

To facilitate a like-for-like comparison of the changes expected in a multitude of different climatic variables with continued warming, we focus on signal-to-noise (S/N) ratios for each individual variable. This normalizes the magnitude of climate changes with respect to the amount of natural variability expected at a certain location in the reference climate and thereby provides a method of circumventing some difficulties that otherwise arise when comparing metrics with different definitions and different units of measurement. However, the underlying premise of identifying "temperatures of equivalence" could equally be applied for absolute changes in TXx, and the importance of examining a variety of indices is discussed further in section 4.2.

For 23 models contributing to the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) which provided sufficient data for the calculation of TXx and Rx1day (Table S1 in the supporting information), time series of S/N ratios are calculated for each metric over the period 1861–2100, using "Historical" and "RCP8.5" simulations concatenated together. Only a single ensemble member (r1i1p1) is selected from each model. Following previously published methods (King et al., 2015, 2016), the signal of each variable at each grid cell is calculated as the mean over a running 21-year time window, relative to the mean over the period 1861–1880. The noise of each variable is calculated for each grid cell within each model as the standard deviation over 1901–2000, using Historical model simulations detrended with a simple linear fit. The S/N ratios are calculated for each model at their native resolution first, before being interpolated to a common 2.5° × 2.5° grid to facilitate comparative analysis later.

The corresponding estimate of global mean temperature anomalies for each model is also calculated using a 21-year running mean, and with respect to an 1861–1880 baseline. It is noted here that global-mean

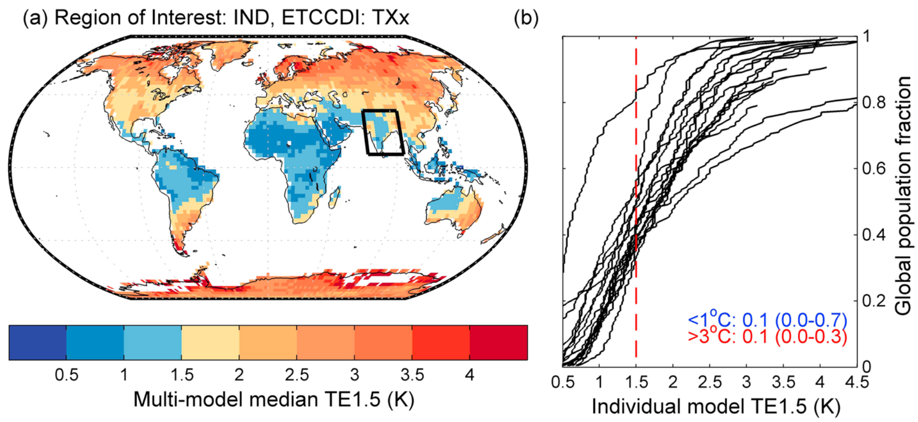

Figure 1. (a) Multimodel median temperature of equivalence (TE) with respect to changes in TXx signal-to-noise ratios over land regions in India at the 21-year period corresponding to 1.5 °C of global mean warming (with respect to 1861–1880). (b) TE1.5 within each CMIP5 model, expressed as a cumulative distribution function for the global population, using high-resolution gridded data for the year 2015. The dashed red line shows 1.5 °C of warming, which is the benchmark for the changes considered in the region of interest. Inset statistics in (b) show the fraction of people which have a TE1.5 of less than 1.0 °C or more than 3.0 °C (with best-guess estimates and a full model range presented respectively).

temperatures are calculated simply as the area-weighted average of near-surface air temperatures over all land and ocean regions in each model (that is, with no masking to specific regions with high observational coverage).

Since information about climate change impacts associated with exceeding a specific threshold of global mean warming will be more desirable for decision makers (Knutti et al., 2016; Rogelj & Knutti, 2016), we next identify the 21-year period for which a global mean warming anomaly of 1.5 °C is exceeded within each individual model and remains exceeded until the end of the time series (2100). The corresponding S/N ratio for each of the two ETCCDIs is then extracted for this same 21-year period.

2.1. Defining the Temperature of Equivalence Index

To illustrate the "temperature of equivalence" (hereafter TE) index as a concept, we begin with a simple demonstration using TXx and a region roughly encompassing India as a case study. Aggregating across all land grid cells in the black rectangular box (8°N–35°N, 70°E–95°E) in Figure 1a, the S/N ratio of TXx changes is found for each individual climate model at the point of 1.5 °C of warming. We then look at all other grid cells worldwide separately and assess how much warming is required within that same model to produce the same emergent increases in TXx as was found for India after 1.5 °C of warming. The map in Figure 1 demonstrates the multimodel median amount of warming required for each grid cell to experience the same changes in TXx as for India—that is, the TE with respect to changes at 1.5 °C (or TE1.5). As expected, one can see that there are equal fractions of land with a TE1.5 just below (light blue) or above (yellow) 1.5 °C within the black rectangle itself.

The right-hand panel presents another way of interpreting the spatial patterns TE1.5 for TXx relative to the region of interest, showing the cumulative distribution of TE exposure for the global population. Population data for both this and all subsequent figures have been taken for the year 2015 from the Center for International Earth Science Information Network database (CIESIN, 2016). The population data were first aggregated from the 0.25° × 0.25° spatial resolution provided, to the 2.5° × 2.5° resolution of the climate model output. As can be seen by the individual lines shown for each CMIP5 model in Figure 1b, as much as 20% of the global population experiences the same *emergent* changes in TXx after less than 1.0 °C of warming as is found in India after 1.5 °C, while all models show at least 65% of the global population to have experienced the same changes after 3.0 °C of warming.

The remaining examples in this study do not consider the TE index with respect to a simple rectangular box as the location of interest, but instead with respect to the aggregation of S/N ratios from all low-income countries together, using classifications taken from the World Bank (2016, http://bit.ly/2bBWnzX; Figure S10 in the supporting information). Similarly, instead of considering population exposure for the *entire globe*

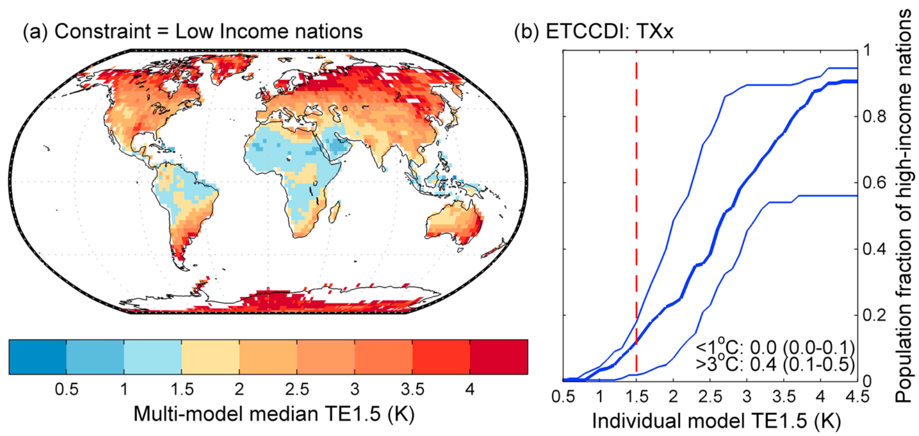

Figure 2. (a) Map of the multimodel median temperature of equivalence (TE) index, when comparing against the signal-to-noise ratio of TXx expected for the average citizen of a low-income nation after 1.5 °C of warming. (b) TE1.5 for the population of all high-income nation aggregated together, expressed as a cumulative distribution function using high-resolution gridded data for the year 2015. The dashed red line shows 1.5 °C of warming; the white land regions show where no "equivalent" emergence occurs by 2100 under RCP8.5; the thick blue line shows the multimodel median response; the thin blue lines indicate the 16th–84th percent model spread. Inset statistics in (b) show the fraction of people which have a TE1.5 of less than 1.0 °C or more than 3.0 °C.

as a way of presenting how the changes at 1.5 °C for one location compares with others (as with Figure 1b), we will hereafter compare against those people who live in high-income nations (Figure S10). Not only does this framework illustrate the versatility of the TE concept, but aggregating regional groups according to shared socioeconomic characteristics helps to characterize similar levels of capability in addressing the impacts of climate change (Frame et al., 2017).

2.2. Methodological Considerations

While the intention is primarily to illustrate practical examples of the TE concept, the decision to examine S/N ratios for the chosen extreme climate indices is motivated by the multitude of studies which have placed an increasing emphasis on interpreting the signal of regional climate change in the context of existing variability over a given location (Diffenbaugh & Scherer, 2011; Fischer & Knutti, 2015; Frame et al., 2017; Harrington et al., 2016; Hawkins & Sutton, 2012; King et al., 2016; Lehner & Stocker, 2015; Mahlstein et al., 2011). It is further noted that this study only calculates S/N ratios at a given warming threshold from a high-carbon scenario of future climate change (RCP8.5): Such a scenario, which crosses a wide range of temperatures, is a necessary requirement for the framing of results presented in both sections 2.1 and 3. However, previous studies have shown that, for many ETCCDIs, the response to the same increase in global temperatures is largely similar across RCP scenarios—that is, scenario uncertainty across RCPs is significantly smaller than corresponding model uncertainty (Harrington et al., 2016; Seneviratne et al., 2016; Wartenburger et al., 2017).

Finally, it is important to acknowledge that this framework could be easily applied to a variety of other temperature thresholds—the 1.5 °C example has been simply chosen here to provide relevance for decision making about the ambitious targets of the 2015 Paris Agreement. Equivalent results for 2.0 and 2.5 °C of warming are presented in the supporting information.

3. Results

3.1. Example of Monotonic Climate Changes: Temperature Extremes

Figure 2 shows the patterns of TE when considering the multimodel median change in TXx S/N ratios following 1.5 °C of global warming for all low-income nations aggregated together. As the left-hand panel reveals, there is a notable latitudinal gradient in the amount of warming required to match this level of emergent increase in heat extremes. For some lower latitudes, such changes have already been reached before 1.0 °C of warming (a threshold thought to have been already exceeded in 2017; Haustein et al., 2017), while the vast majority of continental locations in midlatitudes require between 2 and 3.5 °C of warming to reach these levels.

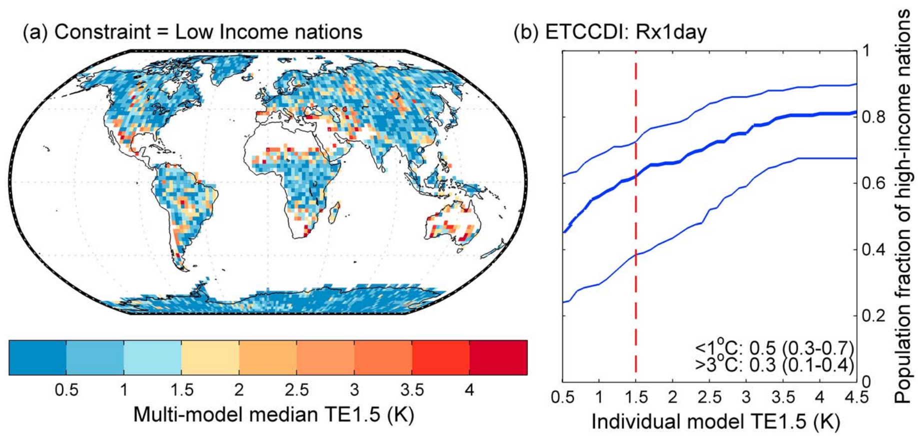

Figure 3. Same as for Figure 2, but showing the patterns of TE1.5 when focusing on the emergent changes in Rx1day for the average citizen of a low-income nation.

When aggregating these spatial results from Figure 2a according to where people in high-income countries live, clearer results begin to emerge. Specifically, we find in Figure 2b that the same amount of emergent changes in temperature extremes felt by low-income countries after 1.5 °C of warming would be reached instead for an equal fraction of high-income populations after 2.6 °C (1.9–3.0 °C) of warming. Another way of interpreting this result is that the changes in extreme heat felt by the average citizen of a low-income country after 1.5 °C of warming would not be felt by about 40% (16th–84th percentile range of 12%–51%) of people living in high-income nations until well after double the amount of global warming (3.0 °C) is reached. Such disparities are significant, and underscore how different the rates of emergent changes in extreme heat can be for different locations (Figure S1a). Further versions of Figure 2 can be found in supporting information for several other global temperature thresholds and using a different metric of extreme heat (TX90p)—all results show qualitatively comparable outcomes.

3.2. Impact-Relevant Climate Changes With Spatially Divergent Responses to Warming: High-Precipitation Extremes

For a climatic variable which experiences monotonic changes in response to greenhouse gas emissions, like extreme temperatures, the TE index can be well understood and interpreted in a relatively straightforward way. Some interpretation difficulties do, however, arise when applying the TE framework to a variable for which climate change may induce a decreasing or increasing signal of change, depending on the location considered. To illustrate such an example, we replicate the analysis of Figure 2, but this time using S/N ratios of annual-maximum 24-hr precipitation accumulations (hereafter Rx1day) at each grid point, instead of TXx.

First, it is important to highlight that for the majority of populated regions around the world, projections show an increase in the intensity of daily-scale rainfall extremes to emerge after 1.5 °C of warming (Figure S1b). When these changes for low-income countries are presented as a map of TE1.5 however (Figure 3a), it becomes clear that there are many locations which have already seen the same emergent changes in extreme rainfall (blue grid cells) as expected after 1.5 °C for the average citizen of a low-income country, while such changes will never occur for other locations (white land regions). These disparities are quantified more explicitly in Figure 3b: To a first-order approximation, half of all people in high-income countries experience the same amount of emergent increases in extreme rainfall after 1.0 °C as for inhabitants of low-income countries after 1.5 °C of warming, while some 20% (10%–30%) of people will never see such changes. This partly reflects the fact that several low-income countries span arid regions in Africa which show very small S/N ratios (Figures S2 and S10); hence, many Northern Hemisphere regions experience equivalent changes in extreme rainfall after much less warming.

These results are nevertheless still as informative as those for temperature extremes: People living in one location can identify other places around the world which will experience a comparable increase in the severity of rainfall extremes after some threshold of global mean warming—it just so happens that the differences in these projected signals of change are more geographically diverse than is the case for changes in extreme heat. For example, those places in the high northern latitudes with robust projected increases in extreme rainfall frequency (Figure S1b; Min et al., 2011) would not expect to find shared future experiences with those arid regions of the world which anticipate negligible or even opposing signals of extreme precipitation changes in the future (Pfahl et al., 2017).

4. Discussion

4.1. Potential Applications of the Temperature of Equivalence Framework

The examples provided in this study demonstrate two possible applications of the TE index: (1) providing a means of comparing between two countries (or groups of countries), to determine what locations will experience similar changes in response to some threshold of continued warming and thus have shared interests in developing adaptation frameworks and (2) demonstrating how anomalous the emergent hazards for a specific community may be after exceeding some threshold of global warming, especially when compared to projections for the global population as a whole.

The TE framework also represents a powerful tool to highlight how a large fraction of the many potential hazards anticipated with climate change are actually similar for many different regions around the world, but with the important caveat that the amount of warming required for these changes to emerge will be different in different locations. The TE concept could therefore provide an effective framework to facilitate integrated climate adaptation plans: For example, every individual country could calculate, for a range of future global temperature thresholds of interest to local planners (such as 1.5, 2, 2.5 °C, or beyond), which other countries (if they exist) best represent a similar level of emergent change in the present day. This would then incentivize collaborative efforts between the two nations to prepare adaptation plans for this fast emerging country, as it would also serve as a useful waypoint for the country which is anticipating similar changing hazards in the coming decades.

4.2. Considerations for Extending the TE Framework to Other Impact-Relevant Metrics of Climate Change

This approach to integrated adaptation planning could be examined for many metrics of a changing climate for which the TE framework could be implemented. However, for the TE framework to be most successful, scientists would need to provide calculations for a wide range of indices which characterize impact-relevant climate hazards—similar to the examples of section 3—but without making any assumptions a priori about what will be most useful for stakeholders, and instead leaving those choices to downstream decision makers (Hewitt et al., 2017).

Even for the case of multiple temperature-related hazards in a warming world, the TE index for a 1.5 °C world should be calculated for a range of metrics which capture both absolute and normalized changes for both direct and wet-bulb temperatures, as each of these metrics is specifically relevant to different types of heat-related hazards. For the case of direct heat stress, Im et al. (2018) demonstrate that the fraction of time exceeding specific wet-bulb temperature thresholds of 28, 31, and 35 °C are important indices to consider, as such levels constitute upper bounds of heat-regulating capabilities for the human body (Sherwood & Huber, 2010). Equally, multiple studies of nonambient temperature mortality rates show that individual cities have optimal temperature bounds which are specific to their historical climate (Gasparrini et al., 2015; Tobías et al., 2017), thus suggesting that deviations beyond historical familiarity (or S/N ratios in temperature) will also be important indices for local stakeholders and health practitioners.

Impacts specifically assessed by the ISI-MIP project (Warszawski et al., 2014) or more targeted regional modeling projects (Giorgi & Gutowski, 2015) are also possible candidates, with examples including hydrological drought severity, how often growing season temperatures exceed optimum thresholds for specific crop types, or even changes to freshwater availability. If specifically assessed using these fit-for-purpose modeling frameworks, the potential to aggregate multiple climate change impacts under the banner of the TE index could also help to alleviate difficulties in interpreting nonlinear or sigmoidal patterns of change which might emerge with further warming (Ricke et al., 2016). By providing a method which equates the relative speed of changes to this myriad of impact-relevant hazards in a warming world under a consistent metric, the TE index could be used as a way to more accurately resolve which countries will in fact experience the fastest and most severe effects from a specific *N*-degree rise in global mean temperatures and thus warrant targeted support from those countries which may experience relatively less severe changes.

Other types of important physical climate changes are more difficult candidates to be assessed under the TE framework: One such example is sea level rise. While Lyu et al. (2014) presented a useful "time of emergence" analysis (Hawkins & Sutton, 2012) for regional sea level changes in the future, this approach may not be the most informative in terms of comparing the relative impacts of changing coastlines in a future climate. A more appropriate metric for a TE-based analysis might instead be what fraction of a country's gross domestic product or population (Hallegatte et al., 2013) are directly exposed to a 1-in-N-year coastal inundation event with continuing warming—that way, the TE framework could then be easily used to show a like-for-like comparison between different locations worldwide.

For all of the above examples, we continue to emphasize that the specific and often value-laden (O'Brien & Wolf, 2010) selection of which metrics of climate change are most relevant for use in a TE framework should remain for local and regional decision makers to independently determine. However, by providing a broad range of metrics (which is the subject of ongoing work), each of which are directly relevant to multiple climate change impacts, we argue the TE index represents a potentially powerful tool for stakeholders.

4.3. Limitations

The framework proposed in this study has some methodological limitations which need to be carefully considered—these primarily relate to whether the transient climate change scenarios currently available to characterize TE1.5 are fit-for-purpose. Our analysis has made use of the high-emissions RCP8.5 scenario as there is a necessary requirement for the future climate trajectory to span as wide a range of temperature thresholds as possible. However, there are open questions about (1) how the impacts of an *N*-degree increase in global mean temperatures are influenced by the emissions pathway taken to reach that threshold, such as regional changes to aerosol emissions (Samset et al., 2018; Wang et al., 2017), as well as (2) whether reaching a global temperature threshold in a transient scenario will generate the same climate impacts as for a case where temperatures stabilize at that threshold (James et al., 2017). These remain open questions which could influence the TE index for some individual locations and for some types of impacts and should thus be a priority for future research.

5. Summary

The TE framework is a relatively simple and easy-to-understand method to characterize the dramatic differences in regional climate hazards projected for future increases in global temperatures. This has been applied to two examples of precipitation and temperature extremes, but we emphasize the potential value of extending this framework to a range of climate change indices of interest to regional decision makers. For our illustrative results using only one specific metric of characterizing heat extremes, even the most aggressive mitigation scenarios can result in changes to the severity of extreme heat events for low-income populations which would not be seen for other regions of the world until after a global temperature rise twice as high. By aggregating the TE index for previously incompatible measures of the impacts of climate change, future work could enable a more holistic characterization of how different regions of the world will experience the impacts of a 1.5 °C warmer world and beyond. With an improved understanding of which nations will share common experiences under future climate change, the TE framework may also help to facilitate the prospect of joint adaptation plans for different countries worldwide.

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