Focus Article

Characterizing half-a-degree difference: a review of methods for identifying regional climate responses to global warming targets

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The Paris Agreement long-term global temperature goal refers to two global warming levels: well below 2°C and 1.5°C above preindustrial. Regional climate signals at specific global warming levels, and especially the differences between 1.5°C and 2°C, are not well constrained, however. In particular, methodological challenges related to the assessment of such differences have received limited attention. This article reviews alternative approaches for identifying regional climate signals associated with global temperature limits, and evaluates the extent to which they constitute a sound basis for impacts analysis. Four methods are outlined, including comparing data from different greenhouse gas scenarios, sub-selecting climate models based on global temperature response, pattern scaling, and extracting anomalies at the time of each global temperature increment. These methods have rarely been applied to compare 2°C with 1.5°C, but some demonstrate potential avenues for useful research. Nevertheless, there are methodological challenges associated with the use of existing climate model experiments, which are generally designed to model responses to different levels of greenhouse gas forcing, rather than to model climate responses to a specific level of forcing that targets a given level of global temperature change. Novel approaches may be required to address policy questions, in particular: to differentiate between half degree warming increments while accounting for different sources of uncertainty; to examine mechanisms of regional climate change including the potential for nonlinear responses; and to explore the relevance of time-lagged processes in the climate system and declining emissions, and the resulting sensitivity to alternative mitigation pathways.

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INTRODUCTION

The Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC)[1] aims to hold the increase in global mean surface air temperature to well below 2°C relative to preindustrial levels and to pursue efforts to limit it to 1.5°C (Box 1). Yet there is no clear picture of how a 1.5°C or 2°C world might look; or how these might compare to worlds with significantly higher levels of warming.[2] The distinction between increments of global mean temperature increase (ΔT_g) has received limited scientific attention, especially in terms of regional and local impacts. Literature on the implications of 2°C and other ΔT_g levels is growing, but with little discussion of methodological considerations. In particular, there has been limited discussion of how regional climate signals can be estimated at specific ΔT_g increments.

Climate change impacts assessment, for health, ecosystems, food, energy, and other key systems and sectors, represents a huge interdisciplinary challenge.[3,4] The identification of anticipated climate changes in a region is a key step of most impacts analyses. This article focuses on methods of identifying regional climate signals associated with global mean temperature changes. These 'signals' might comprise changes in temperature, precipitation, winds, humidity, evaporation, or any other climatic variable of relevance for impacts, on a continental, regional, or local scale.

The tools climate scientists most commonly use to explore future changes in regional climates are General Circulation Models (GCMs) run in transient experiments through the 21st century, and forced by changing emissions or concentrations of greenhouse gases (GHGs) and anthropogenic aerosols. The majority of the GHG scenarios applied in GCM simulations have rising GHGs which provide strong anthropogenic forcing: there are few scenarios which simulate substantial mitigation efforts.[5,6] To investigate future change in regional climate, many studies then examine time periods from these simulations, such as the mid or late 21st century. For example, the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) chapter on

BOX 1

THE LONG-TERM GLOBAL GOAL: SCIENCE AND POLICY

Since the establishment of the UNFCCC in 1992,[26] policy-makers have been debating what level of climate change constitutes dangerous anthropogenic interference with the climate system. Over time, a 2°C increase in global mean annual surface temperature relative to preindustrial emerged as a benchmark for dangerous interference. This was adopted by the EU in 1996 and the UNFCCC in 2010.[27–29] However, many countries, including the most vulnerable small island developing states and the least developed countries, assessed risks at 2°C of warming to be too high and demanded a goal below 1.5°C instead.[30]

In response, a dedicated process within the UNFCCC was established to review the adequacy of 2°C.[31] Running from 2013 to 2015, this process involved consultations with scientists and experts through a 'Structured Expert Dialogue' (SED). Findings of the IPCC were key inputs to the SED, including its expert assessment of climate change risks for five main 'Reasons for Concern' as a function of global temperature.[32,33] Based on all evidence provided, the final report of the SED concluded that 2°C should not be considered safe: it is not a 'guardrail' which guarantees full protection from anthropogenic interference, but an upper limit to be stringently defended.[34]

In Paris, countries agreed to pursue efforts to restrict warming to 1.5°C, but the limited availability of information was also recognized, and the IPCC was invited to produce a special report in 2018 on the impacts of global warming of 1.5°C above preindustrial levels, and related global GHG emission pathways.[1] The IPCC has now accepted this invitation.[25] In terms of impacts, the strongest evidence available is arguably for temperature-sensitive biophysical systems including sea ice, coral reefs, and global sea levels,[33,35–37] and changes in extreme temperature events;[38] but overall there has been relatively limited research targeting 2°C, much less 1.5°C, resulting in little information to assess the relative risks for human systems. Scientists have therefore highlighted the challenges of generating a Special Report on this timescale.[39] In 2018 there will be a 'facilitative dialogue' among Parties to 'take stock of the collective efforts' toward the long-term goal, 'to inform the preparation of nationally determined contributions.'[40] Research conducted in time for the Special Report might therefore inform these mitigation pledges, and ambition to meet them.[41]

long-term climate change presents many results for 2081–2100.[7] This approach is motivated by assessment of impacts, and may be suitable for adaptation planning, providing an estimate of climate change for a given time period, assuming a certain GHG forcing pathway. The aim is not to identify the response to a specified degree of global temperature increase, and it is challenging to extract information from these results about temperature limits, such as 1.5°C or 2°C. Figure 1 illustrates the difficulty of comparing ΔT_g increments using transient scenarios with increasing GHGs:[8] for 2075–2100 (illustrated by the thick black lines) the models have ΔT_g ranging from <2 to >4°C, despite being driven by the same GHG concentrations; therefore providing little information about regional climate changes associated with 2°C or any other degree of warming.

In recent years, however, there has been increasing emphasis on investigating the implications at a specific level of ΔT_g. Several research projects have produced projections in line with 2°C[9,10] and other degrees of global mean temperature increase,[11,12] with more currently in progress;[13–15] and conferences in Oxford and Melbourne encouraging research into 4°C and beyond.[16,17] Reports,[18–21] web interfaces,[22,23] and a Google Earth layer[24] have also been developed to disseminate scientific findings about climate signals at certain warming levels.

This article will interrogate the approaches used to estimate regional climate signals associated with ΔT_g increments in climate projections and climate impact studies, and critically evaluate the extent to which they deliver a sound basis for distinguishing between half degree ΔT_g increments, and thus whether they are suitable for impacts assessment to inform policy decisions. The IPCC has accepted an invitation from the UNFCCC to produce a Special Report on 1.5°C.[25] It is hoped that this article will provide a useful overview for those intending to contribute research to the report. The emphasis of this article will be on 2°C and 1.5°C, but approaches to estimate changes at other degrees of warming are equally relevant, since the costs and benefits of mitigating to 1.5°C or 2°C can be better evaluated in comparison with higher levels of anthropogenic forcing. Four main approaches will be outlined in *Review of Methods*, followed by a brief overview of some of the *Common Methodological Concerns*, including the selection of appropriate baselines, the influence of the warming pathway, and the representation of uncertainty. *Emerging Issues* will discuss important matters to be addressed in future research, followed by a *Conclusion*.

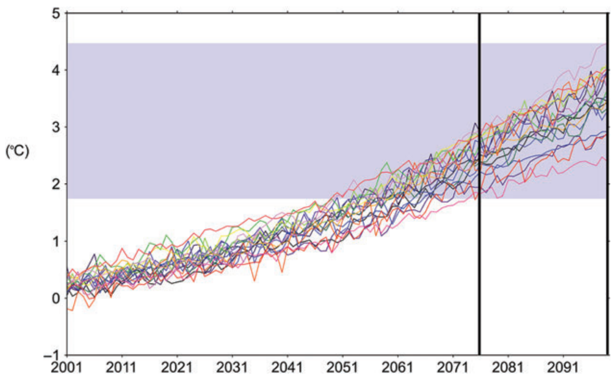

FIGURE 1 | Global mean surface temperature anomaly time series relative to 1985–1999 for 19 Coupled Model Intercomparison Project 3 models run in Special Report for Emissions Scenario A2. Thick black lines illustrate a typical time slice used to analyze regional projections (2075–2100), and the blue shading approximates the range of global temperature anomalies in this time slice. (Source: James, 2013)[8]

REVIEW OF METHODS

Many alternative approaches have been used to assess the regional implications of 2°C and other degrees of warming, including comparison to analogs in warmer historical periods[42] and warmer locations.[43] This review will focus on the dominant paradigm in regional climate change and impacts research, which is to use data from GCM experiments run through the 21st century. Four main methods have been applied to extract responses from these model runs to represent ΔT_g increments. Each will be discussed below, with an explanation, examples of relevant academic and non-academic studies, and an evaluation of how much evidence they provide to compare degrees of warming, particularly 1.5°C and 2°C. Figure 2 illustrates the differences between the four methods,[44,45] and Table 1 provides a summary of their advantages and disadvantages relating to their scientific accuracy and treatment of different elements contributing to uncertainty.

Emission or Concentration Scenario Approach

Under the Coupled Model Intercomparison Project (CMIP), hundreds of 21st century climate model experiments have become publicly available. The most widely used scenarios are from the Special Report for Emissions Scenarios (SRES) used for CMIP3,[5] and the Representative Concentration Pathways (RCPs) used for CMIP5[46] (see Figure 2(a)). These experiments allow assessment of future climate changes associated with certain emissions or

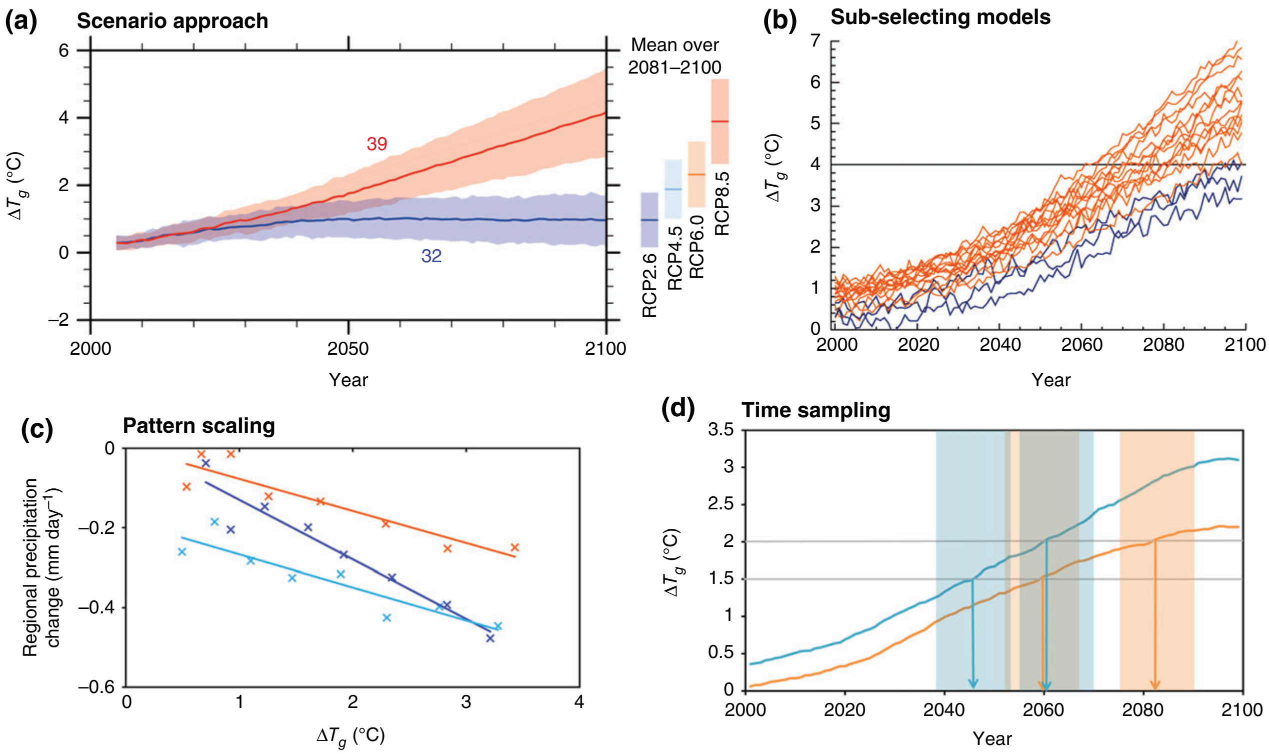

FIGURE 2 | Four methods for identifying regional climate signals at ΔT_g increments. (a) Uncertainty ranges in ΔT_g (relative to 1986–2005) for each Representative Concentration Pathway (RCP), from Intergovernmental Panel on Climate Change Fifth Assessment Report SPM6(a).[45] (b) ΔT_g time series (relative to 1861–1890) for different model runs, from Betts et al.[44] Model runs which exceed 4°C are highlighted in orange. (c) Schematic illustration of pattern scaling: for each model (shown by different colors), regional climate anomalies are regressed against global temperature, and the gradient used to compute changes per °C (here the example used is regional mean precipitation change over southern Africa, relative to 1980–1999). (d) Schematic illustration of how samples could be extracted at the time each model's smoothed ΔT_g time series exceeds 1.5 and 2°C. Two model runs are shown in orange and blue, with ΔT_g relative to 1985–1999. The gray lines indicate 1.5 and 2°C, the arrows indicate the year at which these ΔT_g increments are exceeded, and the orange and blue shaded areas illustrate the time periods to be sampled, centered around the date that 1.5 and 2°C are exceeded.

concentration scenarios. Often future change is analyzed for a specific time period from these simulations, such as 2081–2100,[7] enabling analysis of multiple modeled responses to a consistent GHG forcing.

For any given emissions, concentrations, or radiative forcing scenario, different climate models generate different global temperature responses due to variation in climate sensitivity[47] and aerosol forcing.[48,49] As shown in Figure 1, a time slice taken from one scenario, here SRES A2, is associated with a range of ΔT_g anomalies, making it difficult to infer implications for regional climate at any specific ΔT_g increment, or to compare ΔT_g increments. There is potential to make some inferences about the differences between ΔT_g increments by comparing output from different scenarios (e.g., RCP6 and RCP8.5). Although the ranges of global temperature projections from the scenarios often overlap (as in Figure 2 (a)), comparisons can be made based on the average or most likely global temperature response across the models in each scenario.

Mitigation scenarios are particularly relevant for investigating global temperature targets such as 2°C, however there are very few available. None of the SRES scenarios were designed to simulate mitigation, and until recently investigation of mitigation scenarios was mainly based on efforts from individual modeling centers.[50–52] The ENSEMBLES project also ran a mitigation scenario with a number of GCMs.[53] Under CMIP5 there has been a more systematic initiative, through 'RCP3-PD' or 'RCP2.6,' which results in a likely chance (66%) of staying below 2°C relative to preindustrial.[54] Most modeling centers now have model runs for RCP2.6, projecting 0.3–1.7°C (5–95% range) by the end of the 21st century relative to 1986–2005,[7] or approximately 0.9–2.3°C relative to 1850–1900. Some studies have used RCP2.6 to represent 1.5°C or 2°C relative to the preindustrial;[55,56] in some cases comparing it to

TABLE 1 | Summary of Advantages and Disadvantages of each of the Four Methodologies

	Advantages	Disadvantages
A. Scenario Approach	Mitigation scenarios include the full response of the climate system, its time-lagged components as well as scenario dependent warming effects arising, for example, from aerosol emissions or land-use change, thereby providing the most comprehensive picture in relation to future warming projections	Few mitigation scenarios are available: not currently possible to compare 1.5 and 2°C Computationally expensive to run new experiments In practice difficult to run sufficient scenarios to test the sensitivity of the response to multiple pathways with different greenhouse gas (GHG) and aerosol profiles Models run with the same forcing scenario have different global temperature responses, which renders differentiation between small differences in ΔT_g difficult Model variability is due to temperature sensitivity to GHGs as well as other uncertainties
B. Sub-Selecting Models	Based on the assumption that the projected climate signal response is independent from the selection criterion based on climate sensitivity, this approach allows for analysis of one ΔT_g increment (rather than a comparison between them)	Difficult to assess the influence of anthropogenic warming on regional climate, as differences between ΔT_g increments may be due to model and parameter uncertainty as well as global temperature Model climate sensitivities and projected changes might not be independent, but potentially even closely related, particularly in relation to the hydrological cycle
C. Pattern Scaling	Computationally cheap Assuming relationship between global temperature and local change is linear, a useful way to isolate global warming signal from natural variability in a single model run A simple way to extract climate signals for impact assessments, assuming a linear climatic response Facilitates comparison of regional signals between emissions scenarios, including between SRES (CMIP3) and RCPs (CMIP5)	Assumed linear relationship between global temperature and local climate change does not hold in all cases and for all variables Assumes the implications of ΔT_g increments will be the same regardless of the emissions pathway Difficult to extract signals involving joint variables or time evolving changes Not suitable for not-time invariant impacts such as sea-level rise or glacier loss Not possible to investigate how model uncertainty changes with global warming
D.Time Sampling	Different models have the same global temperature Direct comparison of ΔT_g increments which does not assume linear relationship between global temperature and local change Computationally cheap Model variability due to temperature sensitivity to GHGs is removed, reducing the range of projections for some temperature-related variables	Assumes the implications of ΔT_g increments will be the same regardless of the emissions pathway Not suitable for not-time invariant impacts such as sea-level rise or glacier loss Sensitive to multi-decadal natural variability and localized aerosol forcing in particular for small model ensembles

the high forcing of RCP8.5[57] as a proxy for 4°C or unmitigated warming.[19,58]

RCP2.6 is a valuable addition for CMIP5, allowing examination of approximately 1.5°C or 2°C, but, crucially, it does not allow for differentiation between these two warming levels. For the next highest RCP, RCP4.5, CMIP5 models project 1.1–2.6°C (5–95% range) by the end of the 21st century relative to 1986–2005.[7] Recently, a review of 1.5°C-compatible emissions scenarios has been published,[30] and for CMIP6, an emissions scenario lower than RCP2.6 is being planned to investigate the implications of explicitly aiming to return warming well below 1.5°C by 2100. This additional RCP could facilitate comparison between 1.5°C and 2°C, although the scenario is not part of the prioritized set of experiments,[59] and so the number of GCM experiments will depend on the interest of the individual modeling centers.

The 'scenario approach' therefore currently provides limited information to compare 1.5°C and 2°C of warming. Additional mitigation scenarios could be useful in this regard, and are important to understand the regional implications of steep GHG emissions reductions, and possible negative emissions.[60,61] Scenarios allow exploration of climate change signals at low emission levels while taking into account the timescales of the Earth system, and the regional response to GHGs, anthropogenic aerosols, and land-use change.[61] However, the scenario approach is also computationally expensive, and the value of new experiments should be weighed against the strengths and weaknesses of other approaches that can be used to identify regional climate signals associated with ΔT_g increments.

Sub-Selecting Models Based on Global Temperature Response

Several studies have investigated ΔT_g increments by sub-selecting runs from a single scenario ensemble based on their global temperature response. For example, if the aim is to understand the implications of a 4°C warming, only those runs which exceed 4°C are used (Figure 2 (b)). This approach has been employed to research 4°C and beyond,[44,62] and a similar approach has been applied to analyze heatwave risk at 2, 3, and 4°C ΔT_g[63] (model runs from a large ensemble were grouped based on climate sensitivity). Many of these studies have been based on perturbed physics ensembles, with more model runs and greater ranges of climate sensitivity than multi-model ensembles,[44,64] allowing for larger samples at each ΔT_g increment than CMIP.

This method might be reasonable for exploring possible futures at one ΔT_g increment, for example, 2°C or 4°C, but is less useful for understanding the distinction between them. Using a sub-selection approach, samples at different warming levels have different underlying physics and can have arbitrarily different sample sizes. It is therefore difficult to determine which differences between ΔT_g increments are due to anthropogenic forcing, and which are due to model and parameter uncertainty and sampling. This is equally true for small ΔT_g increments, such as 1.5°C versus 2°C.

Pattern Scaling

Another way to investigate ΔT_g increments using existing climate model experiments is pattern scaling.[65,66] The relationship between global temperature and local climate is derived and then used as a factor to scale local responses by ΔT_g. A very simple approach to pattern scaling is to extract changes associated with one ΔT_g increment (e.g., 2°C) and multiply these to compute changes at other ΔT_g increments (such as 4°C). A more comprehensive technique uses data from the full length of a climate model experiment, and linearly regresses global temperature against local change (see Figure 2(c)).

Once the underlying model runs are available, pattern scaling is a relatively simple and computationally inexpensive approach to examine regional responses to ΔT_g, and can be used to quickly explore a wide array of alternative futures. It has frequently been used to compare 2°C and 4°C.[23,67,68] Using a Simple Climate Model (SCM) pattern scaling can also be applied to explore the influence of different emissions scenarios on global temperature, and the subsequent implications for regional climate.[9,69] This is one way to explore the benefits of mitigation in the absence of GCM experiments run using mitigation scenarios. The MAGICC/SCENGEN framework is an example of this, developed to facilitate the preparation of national climate scenarios for vulnerability and adaptation assessments in developing countries.[70]

Pattern scaling has become a popular tool to provide climate scenarios for the climate impacts community, for example, the availability of pattern scaled projections over Australia has promoted their use in impacts assessment nationally.[71] In addition, pattern scaling allows for comparison of regional signals from different emissions scenarios,[72,73] including comparison of results from SRES scenarios and RCPs, which do not correspond in terms of radiative forcing.[74] For example, in the most recent IPCC report, projections presented as a function of global temperature (per °C) were used to compare CMIP3 and CMIP5.[7,75,76] Of course, this comparison is based on the assumption that the dominant influence on future climate is global temperature increase. Projections from SRES and RCP scenarios might also differ due to localized climate forcings such as aerosols.

The standardization by global temperature is, moreover, only valid to the extent that the relationship between global temperature and regional climate is linear and independent of the type of forcing. That is, the rate of regional change with warming is constant (e.g., a 4°C change is double a 2°C change), and it is not dependent on the emissions scenario (e.g., a 2°C change is the same regardless of the pathway toward 2°C). Another potential problem is that each target variable is scaled separately, which may be problematic for impacts assessment where the interaction and combination of different variables is key, such as the interrelated role of temperature and precipitation in drought. It is also difficult to extract coherent signals in terms of time evolving changes, such as changes in the seasonal cycle.

Several studies have tested the validity of pattern scaling from scenarios with increasing GHGs: Mitchell[66] and Tebaldi and Arblaster[77] find that pattern scaling is a good approximation, while Lopez et al.[78] find that it obscures nonlinear change in some regions and for some variables. It is generally accepted that the method is more robust for seasonal means than extremes, and more appropriate for temperature than precipitation;[77] although Seneviratne et al.[79] demonstrate that CMIP5 mean responses scale with global temperature for maximum daytime temperatures and heavy precipitation events. There has been limited work to test pattern scaling for other impacts relevant variables such as radiation, humidity, evaporation, and wind speed. Research using idealized experiments indicates the potential for nonlinear responses to CO_2 forcing[80–82] and increasing sea surface temperatures (SSTs).[83]

Pattern scaling has rarely been used to directly examine 1.5°C and 2°C. The potential to provide useful information here hangs on the validity of the assumption of linearity. If linearity can be assumed, pattern scaling represents a useful method to isolate the influence of anthropogenic warming: a 1.5°C or 2°C world will feature natural variability as well as global temperature increase, and by deriving the relationship with ΔT_g from high emissions scenarios, the role of anthropogenic warming can be more clearly defined. If linearity in the climate signal can be assumed, pattern scaling is also a cheap and quick way to compute inputs for impact assessment to explore sensitivities (and potential nonlinearities) in, for example, ecosystems and food systems. However, evidence of nonlinearities in the climate system suggests that application of pattern scaling should be exercised with caution for some variables, and accompanied by explanation of the caveats.

Sampling at the Time of Global Temperature Increments

Another way to use existing climate model experiments to investigate ΔT_g increments is to identify the time that each degree of warming is reached and examine regional climate changes which occur at that date.[84–86] For example, global mean temperature time series can be extracted and smoothed for each member of a multi-model ensemble, and then, a 15°C or 30-year period centered around the date a particular ΔT_g increment is reached can be used for comparison with other increments or a historical baseline.[87]

This approach has most commonly been used to examine the change in climate signals and impacts at 2°C warming,[10,84,88–90] and sometimes to compare 1, 2, 3, and 4°C.[86,87,91] Direct comparisons of 1.5°Cand 2°C are rare, although there have been a few recent studies.[37,38,92,93] These studies have generally found progressive change with increased warming. Analysis of 2°C relative to 4°C and higher degrees of warming shows an expansion and intensification of regional climate changes with warming.[91] In terms of mean climate, few thresholds or trend reversals have been identified between ΔT_g increments.[87] Nevertheless, analysis using the time sampling approach also showed that the strengthening of anomalies may not be sufficiently linear to be captured by pattern scaling.[87] The few studies which have compared 1.5°C and 2°C find larger changes at the higher warming level, particularly for extreme events. Fischer and Knutti[38] find that the probability of a hot extreme occurrence at 2°C is almost double that at 1.5°C. For precipitation-related extremes, Schleussner et al.[37] highlight that the difference is regionally dependent, but can be large, for example, in the Mediterranean an increase from 1.5°C to 2°C amplifies the dry spell length by 50%.

One potential limitation of the method is that each GCM will reach a different maximum ΔT_g during an experiment of future warming; therefore a different number of models may be available at 1, 2, 3°C, etc. This can however be largely circumvented by using a high forcing scenario and excluding any models which do not reach the maximum level of warming of interest. A further potential limitation is that the method is sensitive to multi-decadal variations which are not related to global temperature: most importantly localized aerosol forcing and multidecadal natural variability. By taking samples in time windows, these variations could be falsely attributed to differences in global temperature. Finally, the time sampling approach shares a limitation with pattern scaling in that it assumes the climate response to a specific ΔT_g increment is path independent. Results obtained by time sampling have been shown to be quite robust to the rate of anthropogenic forcing while GHGs are still rising.[87] However, any lag in the response to anthropogenic forcing, or changes due to emissions reductions, would not be captured.

COMMON METHODOLOGICAL CONCERNS

The methods outlined in above share some challenges in their application to provide useful messages for impact assessments and policy. The first concern is the choice of a suitable reference period. The second is path dependency: would the regional climate signal at 1.5°C or 2°C vary depending on the pathway toward that level? And how can this be explored? Further challenges arise from the fact that, for any pathway, there is uncertainty (originating from several sources) in the global temperature response, and in regional climate signals.

Reference Period

The 1.5°C and 2°C limits in the UNFCCC Paris Agreement refer to global mean temperature increase relative to preindustrial levels. Studies of ΔT_g increments vary in their choice of baseline, and in this article 'ΔT_g' is used to refer to increments of global mean surface temperature increase without reference to baseline. A great deal of climate research compares changes to a reference period in the recent past (e.g., 1986–2005 in many IPCC figures, which is 0.61 ± 0.06°C above the 1850–1900 reference period).[94] Expressing results additionally relative to an earlier reference period can significantly improve the usefulness and accessibility of studies which explore the difference between half-a-degree temperature increments, allowing the reader to put projected changes in the context of the UNFCCC global temperature goals. For example, the IPCC 'Reasons for Concern' figure is displayed with two reference periods, to show risks relative to 1850–1900 as well as 1986–2005.[32]

Switching between reference periods does not come without complications. Several studies adopt the 'time sampling' approach and show anomalies at the time of 1.2 or 1.4°C warming relative to the recent past.[10,37] These temperature increments represent a 2°C warmer world relative to preindustrial, when taking into account the global warming which has already been experienced in the past.[10,37] However, the results of these studies do not show the regional climate change *induced by* 2°C of warming (i.e., a 2°C anomaly), but rather the change from a recent period (e.g., 1986–2005) *at the time of* a 2°C warming (e.g., a 1.4°C anomaly). They can thus inform what difference half a degree makes, but are less useful to assess the full extent of anthropogenic interference at 2°C. For the latter, climate projections have to be combined with observations of the recent past, which is not straightforward. Unfortunately, there is no optimal preindustrial reference period, given limited observations and availability of model runs for the period prior to the industrial revolution. Research to investigate ΔT_g increments can therefore best support policy by clearly communicating the choice of reference periods and the distinction from preindustrial levels.

Path Dependency

The emission pathway which eventually leads to, for example, an increase of 2°C, can influence the signals identified at that warming level. This challenge of path dependency is illustrated conceptually in Figure 3. Alternative warming pathways are shown for reaching 2°C after (1) a rapid global warming over several decades (shown in purple), (2) a period with a slower rate of warming (shown in orange), (3) a rapid increase followed by a fairly constant temperature over a century (shown in red), or (4) a peak warming of >2°C followed by a decline in global temperature (shown in blue). The regional response associated with 2°C in each of these pathways might be different, if regional change is sensitive to the rate of warming, lags in the climate system, emissions reductions, or temperature overshoot. The forcings which contribute to the pathway toward 2°C could also influence the regional response: for example, a 2°C climate forced only by CO_2 emissions would likely be different to a 2°C climate additionally driven by localized aerosol forcings[61] and changes in land use.[95]

There has been little research to explore the implications of path dependency on regional climate at specific ΔT_g increments. The scenario approach is the only one of the four methods which can explore different pathways. Comparisons between RCP2.6 and other RCPs has provided some insights here,[96,97] however, as noted above, the availability of mitigation scenarios is a limitation. The other three

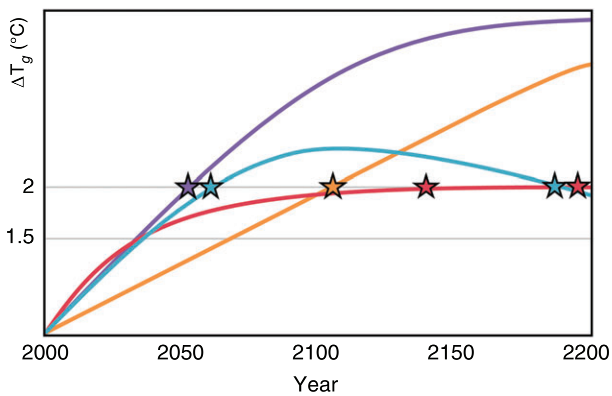

FIGURE 3 | Schematic representation of alternative pathways toward a specified global temperature interval (here 2°C). Each of the stars indicates a 2°C anomaly, but the pathways toward 2°C differ in terms of the rate of warming.

approaches (*Sub-Selecting Models Based on Global Temperature Response*, *Pattern Scaling*, and *Sampling at the Time of Global Temperature Increments*) assume the response to ΔT_g is path independent. So how important is this gap for understanding 1.5°C and 2°C?

Lags in the climate system are likely to be more important for some variables than others. In this article we focus on atmospheric responses, but for some geophysical impacts, for example, glacial retreat, changes in ice sheets, and sea-level rise, adjustments in response to global temperature could take decades or centuries.[7,98,99] For these impacts, approaches like pattern scaling and time sampling are inappropriate. Their feedback effects on the atmosphere could also lead to long-term changes in regional temperature, precipitation, or atmospheric circulation, which would call into question the use of pattern scaling or time sampling for these variables too. This appears plausible as, for example, some large-scale circulation patterns may exhibit recovery dynamics as soon as global temperature stops increasing. The patterns of temperature and precipitation changes per °C ΔT_g derived from CMIP5 are different for 2081–2100 compared to 2181–2200,[7] possibly suggesting some distinction between 'transient' and 'stabilized' warming patterns.

Emissions reductions may further complicate the regional response: in idealized experiments, CO_2 rampdown is associated with an acceleration of the global hydrological cycle.[100] Experiments with declining CO_2 and global temperature show different climate states during CO_2 increase relative to CO_2 decrease.[81,101] These asymmetries occur partly due to the direct effect of CO_2, but also long-term effects of warming such as ocean memory. Another consideration is the potential for hysteresis effects: if there is a temperature overshoot (e.g., the blue pathway in Figure 3), this could have distinct effects from a gradual temperature increase (analogous to the red pathway), as the short period with higher global temperatures might force changes which are irreversible.[99,102]

Research comparing RCP2.6 with other RCPs also points to the importance of further work to explore path dependency. The rate of global mean precipitation change per °C ΔT_g is different for RCP2.6 relative to other RCPs,[96] and by 2300, there are notable differences in the pattern of precipitation change per °C ΔT_g between RCP2.6 and RCP8.5.[97]

Uncertainty in Global Temperature

For any future anthropogenic forcing pathway, there is uncertainty in the global temperature response. Each of the schematic pathways shown in Figure 3 represents a response to hypothetical GHG forcing, and if uncertainty in global temperature were represented, these projections would not be neat lines, but plumes, as in Figure 2(a). Sources of uncertainty in ΔT_g projections include the proportion of GHG emissions which are absorbed by the terrestrial biosphere and oceans;[103] the sensitivity of the global climate system to radiative forcing;[104] and modes of multidecadal variability such as the Pacific Multidecadal Oscillation (PMO) or the Atlantic Multidecadal Oscillation (AMO), which can exert a substantial control on global temperature:[75,105] up to 0.2°C in control climate simulations;[106] and finally stochastic short-term variability in the climate system.

Having reviewed four methods for investigating ΔT_g increments in *Review of Methods*, we here reflect on how each represents the uncertainty in the global temperature response, and on implications for policy. The cascade of uncertainty in future projections, from emissions, to concentrations and radiative forcing, to global temperature, regional climate, and impacts, is illustrated conceptually in Figure 4.[107] In an emissions or concentrations scenario approach, emissions (for SRES, Figure 4(b)) or concentrations (for RCPs, Figure 4(c)) are prescribed, and uncertainty in the other components can be explored.[108] This means that any estimate of regional climate responses associated with different ΔT_g increments is also subject to uncertainty in the global temperature response (pink areas in Figure 4 (b) and (c)). In contrast, pattern scaling or time sampling approaches seek to constrain the global temperature response to one warming level (e.g., 2°C or 1.5°C), and only explore climate and impact uncertainties for that level (Figure 4(d)).

These distinct approaches to handling uncertainty relate to the wider challenge of research into 1.5°C and 2°C. In asking for information about 1.5°C,[1] the UNFCCC is challenging scientists to 'pin' the analysis at a different point in the uncertainty cascade from the usual IPCC approach; generating distinct research questions about GHG pathways toward 1.5°C (referred to as the 'emissions question' in Figure 4(d)), and about the impacts associated with 1.5°C (the 'impacts question' in Figure 4(d)). The focus of this article is only on regional climate signals (shown with an orange arrow in Figure 4(d)), but the uncertainty in regional climate is influenced by the other elements of the uncertainty cascade; and where the analysis is 'pinned.'

The more useful point at which to 'pin' the uncertainty (Figure 4(c) or (d)) thus depends upon whether there is more interest in a 2°C *world* or

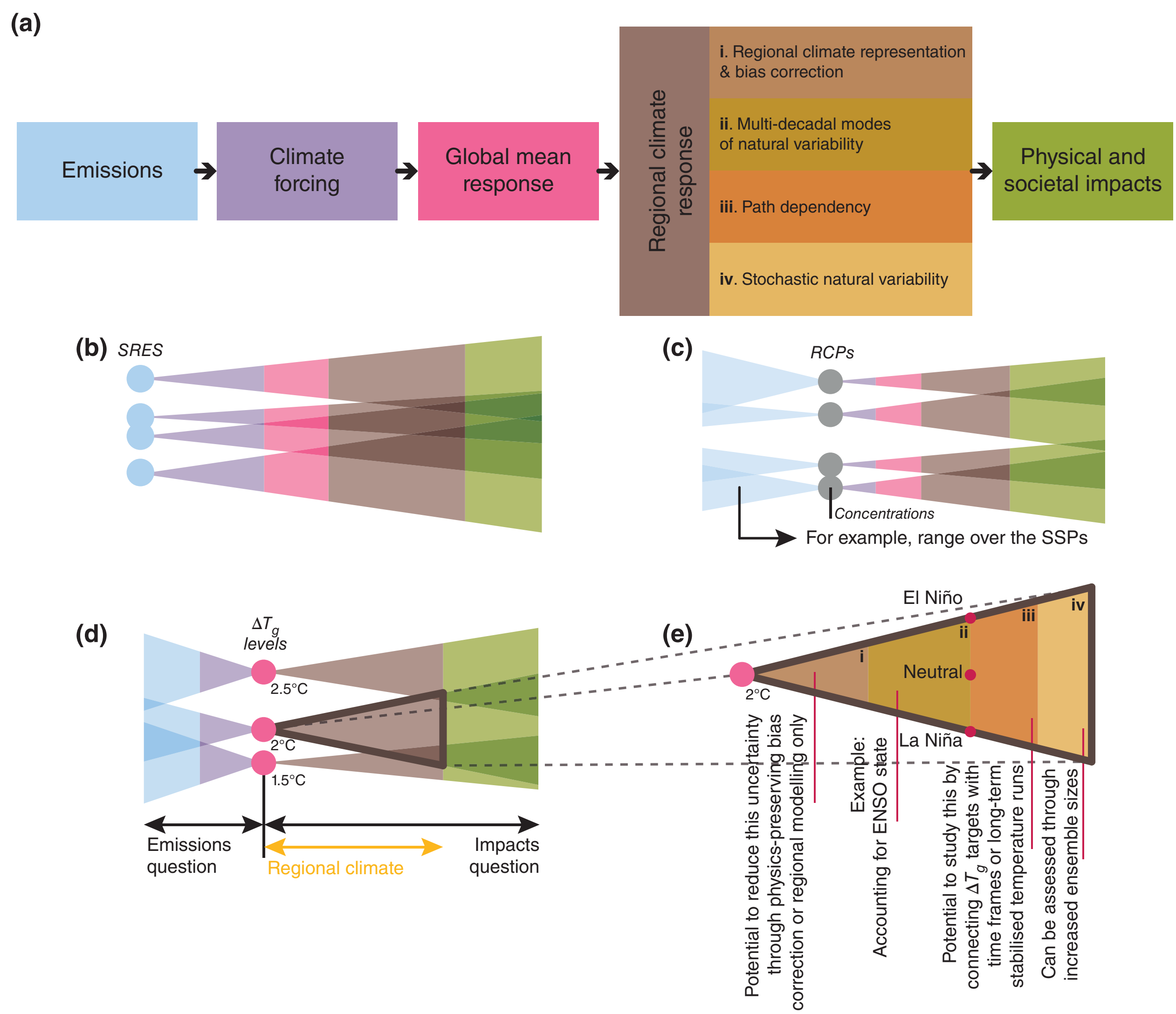

FIGURE 4 | Schematic representation of relationship between emission scenarios, global temperature, regional climate responses, and impacts. (b) and (c) show the uncertainties associated with projections approaches based on Special Report for Emissions Scenario (SRES) and Representative Concentration Pathway (RCP) scenarios. (d) shows the implied uncertainty problem associated with differentiating between 1.5, 2°C, and other ΔT_g increments (2.5°C shown here as an example). Limiting to 1.5 or 2°C raises questions associated with emissions pathways to get to these temperatures (the emissions question), as well as impacts associated with these temperatures (the impacts question). Here we focus on the regional climate aspect, highlighted by the orange arrow. (e) highlights different sources of uncertainty and their contribution to regional uncertainty. (Adapted with permission from Ref 107)

avoiding a 2°C world (this could equally be a discussion for 1.5°C world, but 2°C will again be used as an example). Climate change mitigation policy aims to limit warming well below 2°C relative to preindustrial levels with a specific probability.[61] This probability is often chosen to imply a 'likely' or >66% chance of staying below 2°C (as in RCP2.6[54]). A scenario approach, using RCP2.6, could be seen to explore uncertainty in regional responses to an already defined 2°C mitigation target with a certain probability of *avoiding a 2°C world* (Figure 4(c)); whereas a pattern scaling or time sampling approach focuses on a *2°C world*, eliminating the uncertainty in getting to 2°C from the analysis (Figure 4(d)). To assess the implications of a 2°C mitigation target, which also implies a substantial probability that global mean temperature ends up much >2°C, it would be important to not only consider the impacts in 2°C worlds but also in 2.5, 3°C, or even warmer worlds. This discussion does not lead to a preference for either approach to handling uncertainty, but highlights the implications of different methods for risk assessment and communication to policy-makers.

Uncertainty in Regional Response

Uncertainty in regional climate associated with each ΔT_g increment (depicted by the orange arrow and brown shading in Figure 4(d)) arises from uncertainty in the influence of the forcing pathway, uncertainty in the behavior of the regional climate system (which is partly captured by using an ensemble of different models), and natural variability (both interannual stochastic variability and multi-decadal modes of natural variability). It has already been noted that only the scenario approach has the potential to explore path dependency. However, the representation of inter-model variability and natural variability warrant further discussion.

In order to assess risks associated with 1.5°C, 2°C, and higher degrees of warming, it is important to capture as much of the real uncertainty as possible, while also allowing important distinctions between increments to be identified. So to what extent do the existing studies that analyze 2°C and other ΔT_g increments capture uncertainty in the regional climate response? And might any approach be more advantageous for understanding the different risks at 1.5°C and 2°C?

Inter-Model Variability

The importance of examining multiple modeled futures is increasingly being recognized. Projections from different climate models diverge substantially, and it is difficult to say which is more likely.[109–111] It might therefore be advisable to use as many model experiments as possible; however the large range of responses associated with model ensembles create a challenge for decision makers.[112] So how do existing studies represent inter-model variability?

The four different methodologies in *(see Review of Methods)* have slightly different implications for the uncertainty of the regional response. The method of sub-selecting models based on their global mean temperature generally frustrates the characterization of inter-model uncertainties, because different models are used for each ΔT_g increment, so it is not possible to examine the full ensemble range at any one ΔT_g increment. The pattern scaling and time sampling approaches might be expected to have smaller uncertainty ranges relative to the scenario approach, since the uncertainty in the global temperature response is removed. For some temperature-sensitive variables, notably near surface warming,[87] this does seem to be the case. Inter-model variability in local temperature anomalies for any one region would be expected to be greater for a 2080s sample than a 3°C sample. However, there are some climatic variables for which there does not appear to be a reduction in the range of regional responses when sampling at ΔT_g increments: for example, using a time sampling approach, the modeling uncertainty in African precipitation remains very large,[91] and the range of responses appears to have a similar magnitude to that from the scenario approach; suggesting that much of the variability in projected tropical precipitation cannot be explained by uncertainty in climate sensitivity, in agreement with previous research.[113]

Another distinction between methods is in the ability to represent differences in uncertainty estimates between ΔT_g increments. Higher anthropogenic forcing, and higher levels of global warming, might be expected to be associated with greater uncertainty, as the climate system (and climate model) is pushed further away from current conditions. For example, inter-model variability might be expected to be greater for 4 than 2°C. The pattern scaling approach cannot directly investigate these differences, since modeled ranges would simply be scaled by global temperature.

These inferences suggest that there may be difficulties in representing inter-model uncertainty using a sub-selection approach, and to a lesser extent with a pattern scaling approach. For all methods, inter-model variability can be large, and may make distinction between ΔT_g increments challenging. In the existing literature, some climate projection and climate change impact studies have compared ΔT_g increments based on only one model,[90] but most use multiple models.[84–87] Some are based on the ensemble mean response,[92,114] but others incorporate a range of futures.[71] Those studies with a large number of model runs demonstrate overlapping uncertainty bands between ΔT_g increments, as shown in Figure 5, from James et al.,[91] based on four ensembles of climate models. This highlights the importance of risk assessment to establish whether there are detectable distinctions between half degree increments in spite of model uncertainty. Another approach is to base statements on the significance of differences on pairwise comparisons of projections, based on the same model rather than looking at full ensemble results, which demonstrates significant differences between 1.5°C and 2°C.[37]

Natural Variability

Even with a perfect model there would be considerable uncertainty in the regional signal associated with 1.5°C or 2°C ΔT_g, due to natural variability in the climate system. Stochastic variability plays an important role, in particular for impacts relevant climate

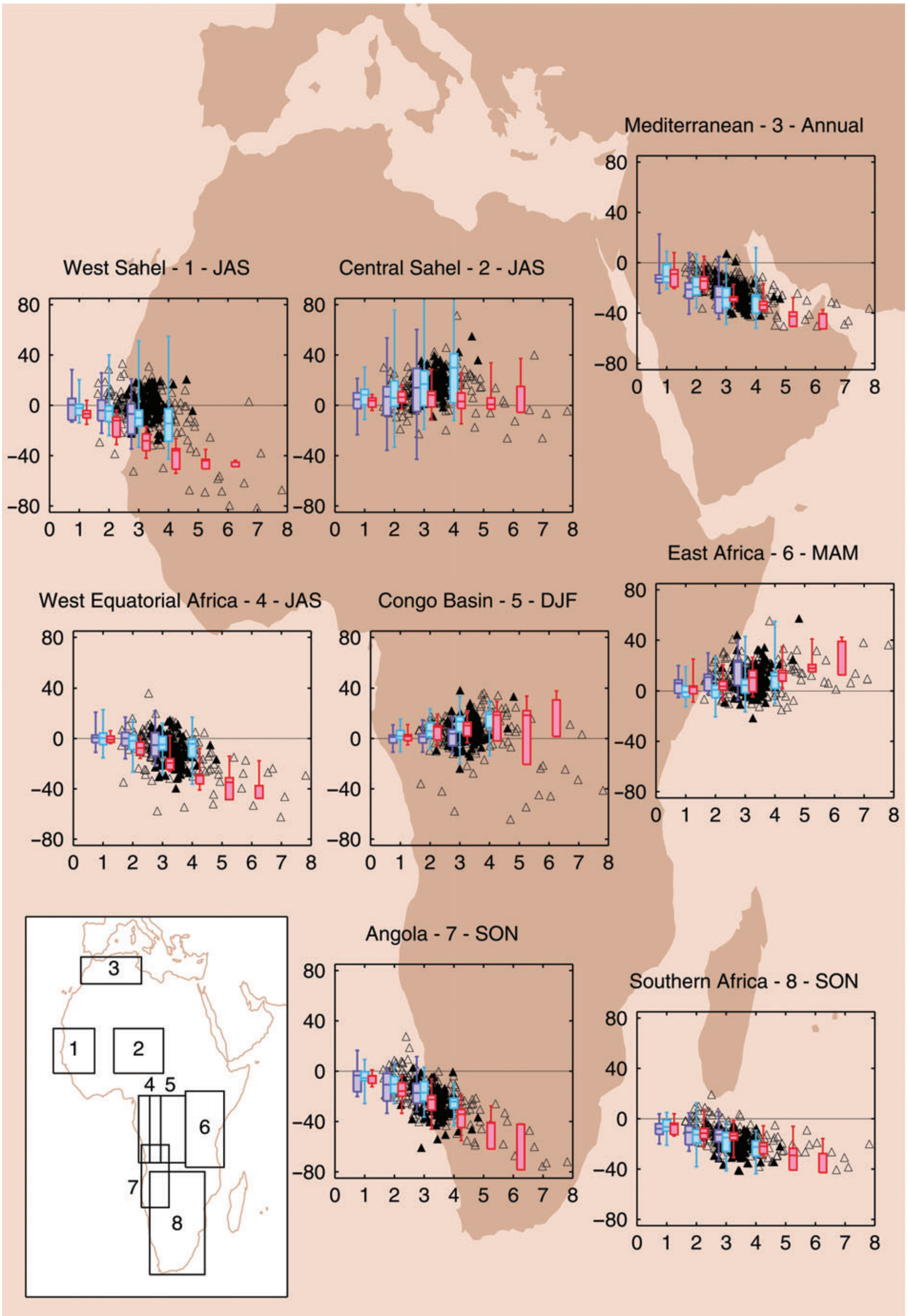

FIGURE 5 | Regional precipitation change (%) associated with global warming from four different ensembles of climate models: responses to $2 \times CO_2$ in a large perturbed physics ensemble (PPE) (triangles), changes at 1, 2, 3, 4°C, etc. extracted using a time sampling approach from transient experiments from Coupled Model Intercomparison Project (CMIP) 3 [Special Report for Emissions Scenario (SRES) A2], CMIP5 (Representative Concentration Pathway 8.5), and a PPE (SRES A1FI) (purple, blue, and red box plots, respectively). The reference period is preindustrial for the PPEs and 1985–1999 for CMIP. (Reprinted with permission from Ref 91. Copyright 2014 American Meteorological Society)

signals such as extreme weather events which are defined relative to a stochastic background.

In addition to a stochastic natural variability component, decadal to multi-decadal modes of variability, including El Niño Southern Oscillation (ENSO), the PMO, and the AMO, strongly affect regional climate,[105] and also influence extreme weather event occurrences. For example, the ENSO cycle strongly affects atmospheric circulation patterns in the tropics, with global teleconnections, thereby introducing regionally dependent extreme precipitation or drying;[75] whereas the AMO strongly influences the

Atlantic tropical cyclone activity as well as high northern latitude temperatures and sea-ice extent.[106,115,116]

There are some distinctions between the four methods for extracting signals at ΔT_g increments in terms of their ability to represent natural variability. Using a time sampling approach, multi-decadal modes of variability could be conflated with an anthropogenic warming signal. A pattern scaling approach may have advantages in this regard, in that the influence of temperature increase might be detected in spite of short-term variations in climate: but only if the relationship between global temperature and local climate can be assumed to be linear.

The size of the ensemble used in existing studies also determines their ability to capture natural variability. Some of the spread in multi-model ensemble responses can be expected to be due to natural variability,[117] although it is difficult to quantify exactly how much. Initial condition ensembles provide a more comprehensive way to quantify natural variability, however there has so far been very little analysis of ΔT_g increments using varying initial conditions (excepting Ref 51). Most of the existing studies are limited by the number of years simulated in 1.5°C or 2°C worlds. To conduct a risk assessment at 1.5°C or 2°C incorporating natural variability, it would be useful to have many years of data to understand changes in the probability of rare events. More years of data might also facilitate research into the role of modes of variability: to investigate whether any differences between ΔT_g increments can be attributed to modes of variability, by either phase specific selection or integration over different phases, and to examine the influence of anthropogenic warming on these modes.[118,119] While models may struggle to represent some extreme events, and have different representations of modes of variability,[120] it is nevertheless important to understand the natural variability within each model to interpret their results.

EMERGING ISSUES

Several issues emerge which require further research attention in order to robustly assess differential climate signals at 1.5°C and 2°C. First, more research is required which focuses on 0.5°C ΔT_g increments, and which specifically addresses 1.5°C. Second, novel approaches are needed to model and understand uncertainties at each ΔT_g increment, to identify whether and where there are distinctions between 1.5°C and 2°C despite uncertainty. Third, more attention should be given to the implications of mitigation for regional climate. Finally, the mechanisms of change deserve further investigation, to assess the extent to which modeled signals are plausible, and to understand the potential for nonlinear change.

Focusing Attention on Half Degree Increments

A key issue in setting policy targets, and driving ambition to meet them, is how much influence a specific difference in global temperature has on regional climate. Comparison between ΔT_g increments is all important in order to identify the relative merits between, for example, 2°C, 1.5°C, and other temperature limits. Generally, scientific research has not focused on this question (with some important exceptions[37,38]). RCP2.6 represents a below 2°C pathway, but there are currently no other mitigation pathways to compare it to. Pattern scaling and time sampling studies also rarely compare 1.5°C and 2°C. Several projects which have sought to analyze 2°C in order to support policy decisions, and have not directly compared it to 1.5°C.[10,69] The IPCC AR5 presents impacts at 2 and 4°C but not 1.5°C.[32]

This lack of attention on 1.5°C may be in part due to it being a relatively new topic for debate. The 2°C target has been discussed since the 1990s or earlier,[29] but campaigns for 1.5°C have arisen in the last decade.[33,121] Now that the UNFCCC has invited scientists to address 1.5°C, there may be a shift in attention.[39] However, there is also debate among scientists about whether research to compare 1.5°C and 2°C is a good use of scientific resources.[39,122,123] Some scientists have critiqued the focus on global temperature in climate policy, suggesting that other metrics may be more important indicators of dangerous climate change, or that analysis related to temperature levels is difficult due to the complex links between emissions, concentrations, radiative forcing, temperature, and impacts.[79,124,125] Enthusiasm might also be limited by doubts about the technical or political feasibility of achieving 1.5°C.[60] These debates raise philosophical questions about the role of scientists in responding to policy-makers,[123] which are beyond the scope of this review. Yet even focusing on purely scientific matters, there are disagreements among scientists about whether 1.5°C is worthy of attention, in that some suggest low signal to noise ratios will preclude distinction between 1.5°C and 2°C:[123] either because they assume natural variability is sufficiently large that there would be no significant difference between 1.5°C and 2°C, or they conclude that our scientific methods and understanding are not advanced enough to identify distinctions, even if there in reality. So, having reviewed existing approaches, to what extent can we distinguish half degree increments?

Distinguishing Between Half Degree Increments Given Uncertainty

Many different sources of uncertainty were discussed in *Common Methodological Concerns*, and Figure 5 demonstrates the potential for large ranges of modeled responses associated with each ΔT_g increment for some regions and variables. This raises interesting and important scientific questions about the extent to which differences between ΔT_g increments are detectable; and the challenge is perhaps escalated for 1.5°C and 2°C, for which the anthropogenic forcing component of global temperature is small relative to natural variability. Presenting the range of modeled responses (as in Figure 5) is not sufficient to address this question: more innovative methods are needed.

Some recent studies have addressed related questions by calculating at what global temperature increment local change becomes significant relative to interannual variability.[126–128] For example, Mahlstein et al.[126] (Figure 6) show that for many low latitude countries, where interannual variability in temperature is small, a 0.4°C global warming is enough to make a significant difference in summer temperature (these countries are shaded red on the map in Figure 6). These results do not provide regional climate change signals for specific ΔT_g increments such as 1.5°C or 2°C, but they do give an indication of regions where a 0.5°C global temperature difference might correspond to a significant difference locally (and using a conservative test, since it only shows changes which are detectable on the individual grid cell level).

Analysis of extreme events is also important, given their impacts for society, and that changes in extreme weather are likely to be manifest before changes in the mean,[129] although it can be challenging to understand how rare events may change in each location. Spatial aggregation can help to overcome the issue of limited sample sizes on an individual grid cell level. It has been shown to have great merit for identifying regions and indices for which there is a distinction between 1.5°C and 2°C which is large relative to the inter-model variability and significant relative to natural variability.[37,38] Figure 7 shows an example of this approach, displaying cumulative density functions (CDFs) of heat extremes and dry spell lengths aggregated over three different spatial domains.[37] The gray shading represents the uncertainty associated with natural variability, and the blue and red shading show the likely range (66% range over the model ensemble) of model CDFs for 1.5°C and 2°C respectively. For some regions and indices there are clear distinctions between ΔT_g increments: for heat extremes there is limited overlap between the modeled ranges, particularly when aggregated over global land, and in the Mediterranean region. For dry spell lengths the difference between 1.5°C and 2°C is less clear-cut on a global level, but there is a more robust message for some regions, particularly the Mediterranean. Other regions like Central North America exhibit large natural variations in drought over the reference period and no change in the signal is detectable at 1.5°Cor 2°C.

Larger model ensembles, with varied initial conditions, would enable analysis of extreme weather events with an enhanced representation of uncertainty. Very few studies have examined ΔT_g increments using initial condition ensembles (one exception being May[51]), but several initial condition ensembles are available[117,130,131] and could be investigated using a pattern scaling or time sampling approach. There are also plans to build large ensembles of model runs designed specifically to investigate 1.5°C and 2°C, using SSTs associated with these ΔT_g increments in CMIP5 data to force multi-hundred-member ensembles of atmosphere-only models.[132,133] This approach represents a new, fifth, method for identifying regional climate signals associated with ΔT_g, and could allow for comparisons of 1.5°C and 2°C in a shorter timeframe than running new mitigation scenarios, which are more computationally expensive.

There is thus evidence that, for some regions and variables, distinctions can be found between 1.5°C and 2°C in spite of uncertainty. It is difficult to quantify uncertainties at 1.5°C and 2°C using existing model experiments, but there are scientific methodologies available and new experiments planned which offer the potential to produce better model-based estimates.

Exploring the Implications of Mitigation

The Paris Agreement explicitly aims to reach net zero GHG emissions in the second half of this century.[1] To achieve this, steep GHG emissions reductions will be necessary over the coming decades, and negative CO_2 emissions will be required.[61] A review of the literature suggests that decreasing CO_2 and lags in the climate system could complicate regional responses to global temperature increase, but also that these effects are difficult to study using existing methods.

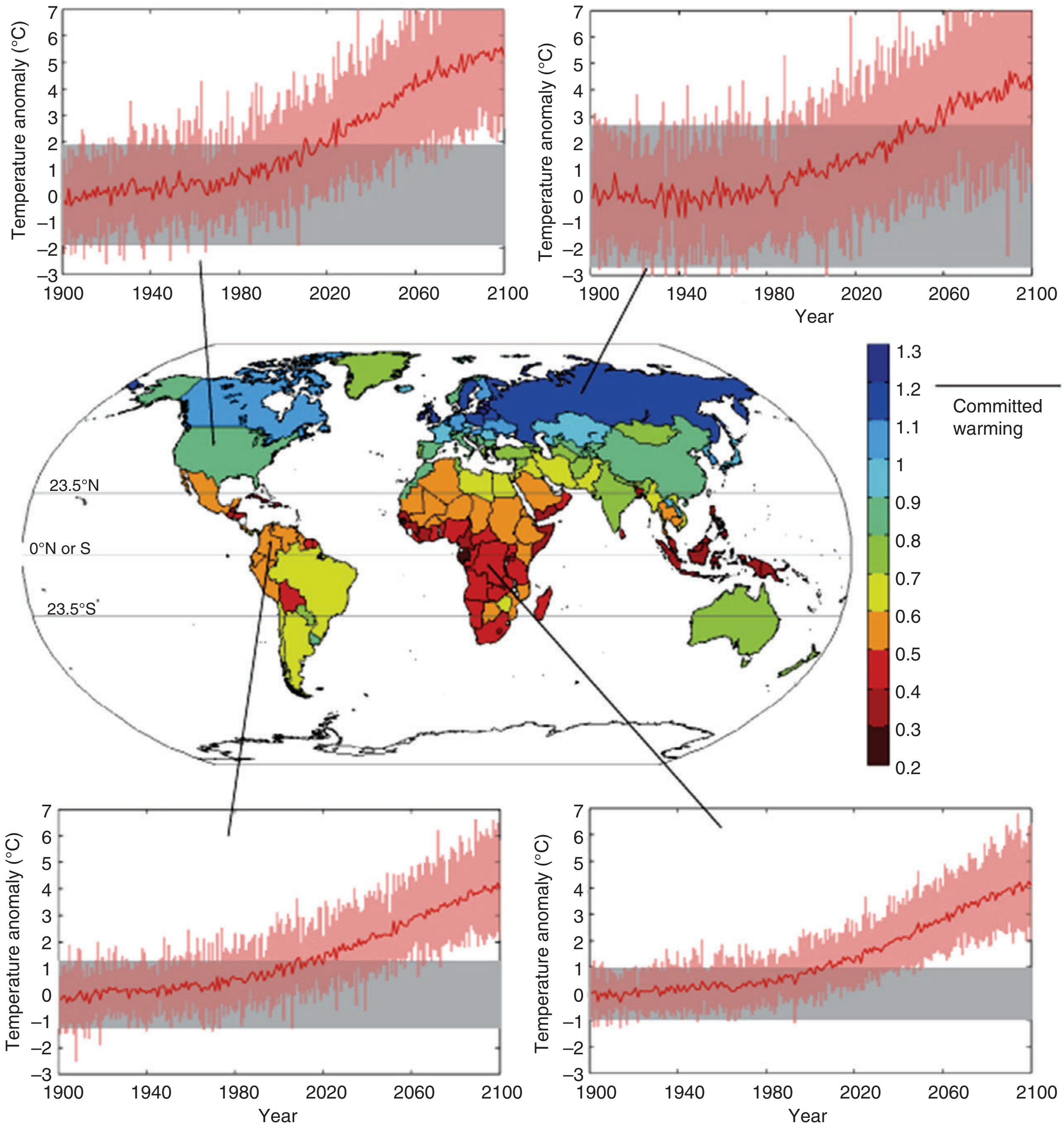

FIGURE 6 | The map shows the global temperature increase (°C) needed for single locations to undergo a statistically significant change in average summer seasonal surface temperature over a 30-year time slice, aggregated on a country level. The black line near the color bar denotes the committed global average warming if all atmospheric constituents were fixed at year 2000 levels. The small panels show the interannual summer-season variability during the base period (1900–1929) (±2 standard deviations shaded in gray) and the multi-model mean summer surface temperature (red line) of one arbitrarily chosen grid cell within the specific country. The shading in red indicates the 5 and 95% quantiles across all model realizations. (Reprinted with permission from Ref 126. Copyright 2011 IOP Publishing)

The exception is the scenario approach, but this is also currently limited by a lack of existing experiments. Testing the sensitivity of regional climates to mitigation pathways using state-of-the-art climate models may be prohibited by the computational costs, but perhaps warrants further research using more simple models. There is also potential to learn more through analysis of existing experiments including RCP2.6,[101] and idealized CO_2 rampdown experiments.[81]

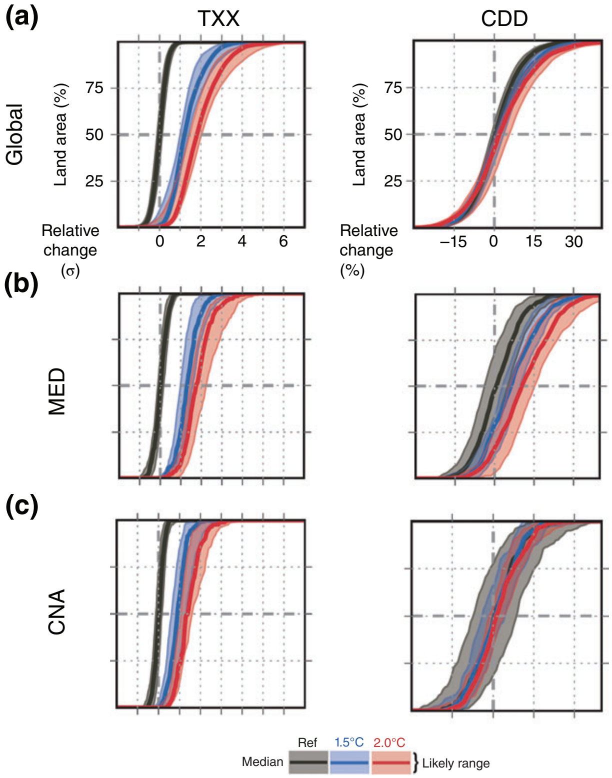

FIGURE 7 | Cumulative density functions (CDFs) of projected regional aggregate changes at 1.5 and 2°C for the global land area between 66°N and 66°S (a) as well as two regions based on Intergovernmental Panel on Climate Change domains: the Mediterranean (b) and Central North America (c), for TXX (annual maximum value of daily maximum temperature) measured relative to standard deviation (σ) over 1986–2005, and CDD (annual maximum number of consecutive dry days for which precipitation is below 1 mm day^{-1}) as change (%) relative to 1986–2005. Based on 11 Coupled Model Intercomparison Project 5 models for TXX and 14 for CDD. The solid lines indicate the median CDFs over the model ensemble and the shading, the respective likely range (that includes 66% of all ensemble members). (Adapted with permission from Ref 37)

A further complication is the potential influence of negative emission technologies,[134] which could have distinct feedback effects on regional climate, for example, large-scale afforestation could have implications for the albedo and the local hydrological cycle.[135,136] Risk assessment at 1.5°C and 2°C should include analysis of the trade-offs between reduced global warming versus potential anthropogenic forcing from mitigation interventions. To the authors' knowledge, such integrated analysis has not yet been attempted. Case studies to conceptually analyze these trade-offs, compile existing evidence, and propose research questions and potential methodologies, could be a useful first step.

Investigating Modeled Mechanisms of Change

All of the methods discussed in this article rely on climate model results. Distinguishing between 1.5°C and 2°C represents a huge challenge for these tools. In order to get a complete answer, the model must be able to simulate the influence of global anthropogenic emissions on climate, the role of local forcings, and adequately represent natural variability. As highlighted by Shepherd,[137] projecting climate changes at a regional scale is very challenging due to the importance of atmospheric circulation and the control of dynamics, which are characterized by large uncertainties that are difficult to reduce. This is perhaps particularly relevant for understanding the distinction between ΔT_g increments, which may be strongly determined by shifts in dynamical systems. Where variables are influenced predominantly by local thermodynamics, for example local increases in temperature and humidity, more warming might bring more of the same; but where dynamical changes are responsible for the changes, a higher ΔT_g increment could be associated with a trend reversal, slow down, acceleration, or step change. For example, Hawkins et al.[138] find that, in model experiments run with RCP8.5 extensions, the movement of the Inter-Tropical Convergence Zone toward the equator results in wetting then drying for some tropical regions. Given the importance of circulation changes on precipitation, it is perhaps surprising that previous studies based on increasing GHG emissions find progressive strengthening of regional changes with global warming in climate models,[87,91] and an approximately linear relationship with global temperature for some variables.[66,79] In other words, for some regions and variables, the main difference between ΔT_g increments is in the strength and magnitude of change, and additional warming appears to amplify existing modeled responses, rather than generating trend reversals or changes in the rate of response.

Process-based analysis of model behavior in future simulations could play an important role here, to examine the modeled mechanisms of change,[139] and evaluate the extent to which they are plausible. Relevant processes to target for evaluation might include circulation patterns and energy and moisture fluxes associated with modes of variability. Process-based analysis could also distinguish between linear and nonlinear mechanisms,[81] such as feedbacks from surface snow and ice cover, evaporation,[80] and changes in the Atlantic meridional overturning circulation.[106] Investigating the occurrence of abrupt shifts is also very important, particularly as existing work finds evidence for abrupt change in climate model runs below 2°C of warming, but with little consistency between models;[140] and expert elicitation suggests a >56% probability of crossing at least one large-scale tipping point if warming exceeds 4°C, with some systems likely being sensitive to lower levels of ΔT_g.[141]

CONCLUSION

Following the Paris Agreement, countries have agreed to "Holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change."[142] Further analysis of the implications of 1.5°C relative to 2°C is now important to inform discussions about appropriate levels of mitigation efforts. This article has reviewed studies which identify regional climate signals at specific ΔT_g increments, to assess the extent to which their methods provide useful information to distinguish at regional scale between 1.5°C and 2°C. In recent years there has been a growth in the number of papers and projects designed to investigate the regional response to ΔT_g, and these have expanded the evidence base. However, many papers do not compare 2°C with other ΔT_g increments, and relatively few compare 2°C with 1.5°C. If the IPCC is to produce a Special Report by 2018, further work is needed, so which are the most promising research directions?

Existing climate model experiments are not designed to present changes at specific ΔT_g increments, but many studies have sought to overcome this by extracting regional signals from transient scenarios with increasing GHGs and rising global temperature; either by sampling at the time each ΔT_g increment is exceeded, or by calculating spatial patterns which are linearly scaled to each degree of warming. Pattern scaling may have advantages in its ability to isolate the global warming signal from some forms of natural variability, but this approach is only valid if the relationship between global temperature and local climate can be assumed to be linear. Many climate model experiments show progressive change with warming, and therefore pattern scaling may be a reasonable approximation for some seasons and variables; however, sampling at the time of warming has revealed some important nonlinear distinctions between ΔT_g increments, including between 1.5°C and 2°C.

Further work using a time sampling approach has the potential to provide more information about differences between 1.5°C and 2°C, particularly where there is appropriate attention to uncertainty. This is especially important for extreme events, which are, by definition, rare, and therefore difficult to investigate based on the limited number of model years available at 1.5°C and 2°C. One way to address this is to spatially aggregate model data to compute changes in the occurrence of extreme events on a regional basis. Recent studies using this approach have identified important differences in risk between 1.5°C and 2°C.[37,38] Plans to generate large initial condition ensembles corresponding to 1.5°C and 2°C also have the potential to dramatically improve our ability to investigate the difference in climate signal between these warming levels. In particular, such approaches would enable an improved understanding of sources of uncertainty on the regional level by in principle allowing for physically consistent regional bias correction,[143] isolation of effects related to multi-decadal modes, and quantification of stochastic uncertainty due to ensemble size.

Research into 1.5°C and 2°C should also directly consider the influence of mitigation. The transient regional climate response can differ importantly from a response which is closer to equilibrium, and declining emissions can have distinct implications for regional climate. In addition, the potential (ir)reversibility of crossed thresholds of abrupt shifts in the climate system are largely unclear.[140] Mitigation scenarios are therefore important to assess the adjustment to 2 or 1.5°C under peak and decline of anthropogenic emissions. Some initial tests with a single model are available,[122] but there are few model runs available for this purpose. The RCP2.6 scenario in CMIP5, and its extension until 2300, are steps in the right direction, and warrant further analysis, but do not allow for comparison between 1.5°C and 2°C at comparable timescales. Therefore, the development in CMIP6 of a new RCP that lies below RCP2.6 could be an important further step. To understand the implications of mitigating to 1.5°C, researchers should also begin to investigate the trade-offs between GHG-induced climate change and potential feedbacks from negative emission technologies at a regional scale, particularly those associated with changes in land use.

Finally, assessment of 1.5°C and 2°C need not be based on direct model outputs alone, but should also be informed by scientific understanding of the physically plausible implications of anthropogenic warming for regional climate. Existing understanding suggests that rising global temperatures will likely be associated with shifts in circulation systems, nonlinear mechanisms, and possible discontinuities in the climate system, which could lead to non-monotonic changes at a local level. Further research to analyze the mechanisms for climate change is thus important to inform confidence assessments of the possible climate responses associated with ΔT_g increments.

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