

FUTURE PREDICTIONS OF GLOBAL HOTSPOTS FOR TEMPERATURE AND
PRECIPITATION EXTREMES WITH CMIP6 MODEL

by

Elif Bayındır

B.S., Physics, Boğaziçi University, 2020

Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Master of Science

Graduate Program in Computational Science and Engineering
Boğaziçi University
2023

ACKNOWLEDGEMENTS

I want to express my gratitude to all who supported me and were there for me as I wrote this thesis.

I want to start by saying how grateful I am to Prof. Mehmet Levent Kurnaz, who helped me develop my thesis topic, mapped out a strategy, and was there for me throughout the process. Thanks to Nazan and Tufan Turp, I was able to get through this challenging time with their support and counsel.

I want to thank my friends, Zekican Demiralay and Başak Bilgin, who guided and helped me throughout the whole process. I am also grateful to Assist. Prof. Tuğba Öztürk and Prof. Cem Avcı for their valuable insights and feedback.

I'm thankful to my partner, Bora, for his unwavering support and understanding. To my family, your love has been my rock; I'm thankful for all you've done. I owe so much to my loved ones who supported and helped me through it all.

ABSTRACT

FUTURE PREDICTIONS OF GLOBAL HOTSPOTS FOR TEMPERATURE AND PRECIPITATION EXTREMES WITH CMIP6 MODEL

This study used a climate change hotspot technique using population-weighted Standard Euclidean Distance (SED) measurements to assess climate change risks across regions. The analysis shows changes in the world's climatology for the years 2026-2050 and 2076-2099 under the SSP2-4.5 and SSP3-7.0 scenarios. In the SSP2-4.5 scenario (2026-2050), equatorial regions like China, Japan, and Indonesia are hotspots that would experience increasing sea levels, extreme weather events, and heat waves because of a changing climate and population density. The Americas, Southern Africa, the Mediterranean, Western Europe, and Asia are considered to be risk zones. Concerns include droughts and unpredictable precipitation, which affect economies and food security. Ecosystems and communities must use customized adaptation strategies to meet these difficulties. Moderate adaption issues are anticipated under SSP2-4.5, necessitating focused measures. Distant future trends (2076-1999) align with near-future tendencies, which calls for further efforts. Similar indicator changes may cause a lack of differences between scenarios in the near future. This study enhances our understanding of hotspots and emphasizes the importance of thorough approaches. Innovations and a variety of situations improve climate resilience and adaptation. Future work should focus on improving assessment techniques, improving used data and models, and including socioeconomic issues for effective climate plans.

ÖZET

CMIP6 MODELİ İLE GELECEKTEKİ SICAKLIK VE YAĞIŞ EKSTREMLERİ İÇİN GLOBAL SICAK NOKTALARIN TAHMİNİ

Bu çalışmada, iklim değişikliği risklerini değerlendirmek için nüfus ağırlıklı Standart Öklidyen Mesafesi (SED) ölçümlerinden yararlanarak iklim değişikliği hotspotları belirleme tekniği kullanıldı. Analiz, SSP2-4.5 ve SSP3-7.0 senaryoları altında 2026-2050 ve 2076-2099 yılları için dünyanın klimatolojisindeki değişiklikleri göstermektedir. SSP2-4.5 senaryosunda (2026-2050), Çin, Japonya ve Endonezya gibi ekvator bölgeleri, değişen iklim ve nüfus yoğunluğu nedeniyle deniz seviyelerinin yükselmesi, ekstrem hava olayları ve sıcak hava dalgalarından kaynaklı hotspotlar olarak belirlenmiştir. Amerika, Güney Afrika, Akdeniz, Batı Avrupa ve Asya risk bölgeleri olarak tespit edilmiştir. Bu bölgelerdeki başlıca endişeler, ekonomi ve gıda güvenliğini etkileyen kuraklıklar ve öngörülemez yağışları içerir. Ekosistemler ve toplumlar bu zorluklarla mücadele etmek için çeşitli adaptasyon stratejileri yapmalıdır. SSP2-4.5 senaryosunda orta düzeyde uyum sorunları öngörülmekte olup, sorun kaynaklarına odaklı önlemleri gerektirir. Uzak gelecekteki eğilimler (2076-2099), yakın gelecek eğilimleriyle uyumlu olup, daha fazla çaba gerektireceği öngörülmektedir. Bu çalışma, hotspot anlayışını geliştirirken, kapsamlı yaklaşımların önemini vurgulamıştır. Populasyon ağırlıklı SED değerlerinin kullanılmasıyla ve çeşitli senaryoların incelenmesiyle çok yönlü bir analiz sunulmuştur. Gelecekteki çalışmalarda, etkili iklim planları için değerlendirme yöntemlerini iyileştirebilir, kullanılan metodlar geliştirilebilir ve sosyoekonomik konular daha fazla paratmerye analiz edilebilir.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	iii
ABSTRACT	iv
ÖZET	v
LIST OF FIGURES	vii
LIST OF ACRONYMS/ABBREVIATIONS	ix
1. INTRODUCTION	1
1.1. Climate Change	1
1.2. CMIP6 and SPSS Scenarios	2
1.2.1. GCMs	2
1.2.2. CMIP	4
1.2.3. SSPs	5
1.2.4. Comparison of CMIP6 with Previous CMIPs	9
1.3. Hotspots	10
1.3.1. Hotspot Definitions	10
1.3.2. Global Hotspots	11
1.4. Extreme Events	13
2. METHODS	14
2.1. Global Circulation Models and Regional Climate Models	14
2.2. Data	15
2.3. Hotspot Calculations	28
2.3.1. Hotspot Quantification	28
2.3.2. Climate Indicators	28
2.3.3. Normalization of Climate Indicators	29
3. RESULTS	31
4. CONCLUSION	39
REFERENCES	41

LIST OF FIGURES

Figure 1.1.	Global change projections shown conceptually in the Earth system model (ESM). ESMs can simulate the interplay between climate change and biogeochemical cycles (Kawamiya <i>et al.</i> , 2020).	3
Figure 1.2.	Various combinations of difficulties in adaptation and mitigation are represented by five shared socioeconomic paths (SSPs) (O’Neill <i>et al.</i> , 2016a).	6
Figure 1.3.	The progression through time of the considered scenarios’ enhanced radiative forcing by humans (O’Neill <i>et al.</i> , 2016a).	7
Figure 1.4.	The selected scenarios’ time progression of extra man-made radiative forcing is shown (O’Neill <i>et al.</i> , 2016a).	8
Figure 1.5.	Alternative CO ₂ concentration paths, as represented by the emission trajectories (O’Neill <i>et al.</i> , 2016a).	8
Figure 2.1.	Copernicus temperature data visualization. Model historical data and temperature change according to different SSP scenarios (Copernicus Climate Change Service, 2021).	16
Figure 2.2.	CRU Mean of monthly mean temperature data between 1901-2021.	19
Figure 2.3.	CRU Mean of monthly total precipitation data between 1901-2021.	19
Figure 2.4.	Model biases for temperature.	22
Figure 2.5.	Model biases for precipitation.	22

Figure 2.6.	Correlation between models and CRU data for temperature. . . .	23
Figure 2.7.	Correlation between models and CRU data for precipitation. . . .	23
Figure 2.8.	Ensemble mean of temperature for each grid point.	24
Figure 2.9.	Ensemble mean of monthly total precipitation for each grid point.	25
Figure 2.10.	Temperature anomaly plot.	27
Figure 2.11.	Precipitation anomaly plot.	27
Figure 3.1.	Population weighted SED values under the SSP2-4.5 scenario for the years 2026-2050 for 4 different season.	32
Figure 3.2.	Population weighted SED values under the SSP2-4.5 scenario for the years 2076-2099 for 4 different season.	36
Figure 3.3.	SED values under the SSP2-4.5 scenario for the years 2026-2050 for 4 different season.	37

LIST OF ACRONYMS/ABBREVIATIONS

ADW	Angular-Distance Weighting
CDO	Climate Data Operators
CMIP	The Coupled Model Intercomparison Project
CRU TS	Climatic Research Unit Gridded Time Series
ECS	Effective Climate Sensitivity
ESM	Earth System Model
GCM	General Circulation Model
GDP	Gross Domestic Product
GHG	Greenhouse Gasses
IAM	Integrated Assessment Modeling
ITCZ	Intertropical Convergence Zone
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
MENA	Middle East and North Africa
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
SED	Standard Euclidean Distance
SSP	Shared Socio-Economic Pathways
UNEP	United Nations Environment Programme

1. INTRODUCTION

1.1. Climate Change

To keep the world temperature rise below 1.5°C and avoid a 2°C rise, net-zero carbon dioxide emissions must be reached by the beginning of the 2050s or the beginning of the 2070s. (IPCC, 2022). Also, the goal is to have zero world emissions of greenhouse gases (GHG) between 2063 and 2068, which would be done before the end of the century (IPCC, 2022). Reaching net zero emissions will lead to the stabilization of Earth's temperature. Several countries have committed to achieving net-zero emissions by 2050 (IEA 2021; Hale *et al.*, 2022). While there has been certain headway, the actions taken up to this point are significantly inadequate in achieving the ambitious goal set forth by the Paris Agreement. This goal revolves around curbing the escalation of the Earth's mean temperature to a degree notably beneath the 2 degrees Celsius mark, with a specific focus on striving for a reduction to 1.5 degrees Celsius or below (Höhne *et al.*, 2021; UNEP 2022; Geiges *et al.*, 2019).

The effects of climate change span a variety of fields. Climate change causes ecological shifts, ecosystem disruptions, and risks to biodiversity (Staudt *et al.*, 2013; Weiskopf *et al.*, 2020). Heatwaves, droughts, storms, and floods are only a few examples of the extreme weather occurrences that are getting worse and having an influence on human life, infrastructure, agriculture, and water resources (Le and Bae, 2020). Additionally, millions of people's livelihoods and coastal communities are under serious risk due to increasing sea levels (Griggs and Reguero, 2021). Energy systems, transportation, industry, and land use all need to undergo radical change in order to move toward a low-carbon future (Zhixin and Qiao, 2011). Effective mitigation depends on accelerating the use of renewable energy, increasing energy efficiency, and implementing sustainable practices across all industries (Huang and Tian, 2020). Investment in research and development encourages innovation in sustainable technology and clean energy, lowering reliance on fossil fuels.

In order to confront the inescapable consequences of climate change, it is imperative to integrate mitigation endeavors with effective adaptation strategies (Wilbanks *et al.*, 2003). Successful adaptation depends on building resilience in at-risk populations, implementing climate-smart agriculture, and safeguarding vital ecosystems (Amare and Simane, 2017). Recognizing the varied implications of climate change on regions, communities, and socioeconomic classes, equity and justice considerations are crucial (Moser *et al.*, 2008).

1.2. CMIP6 and SPSS Scenarios

1.2.1. GCMs

To project future climate change, numerical models are used. General circulation models (GCMs) incorporate physical processes from various climate subsystems (atmosphere, hydrosphere, biosphere, cryosphere, and land surface) along with their interactions to project the future climate state (Cos *et al.*, 2021). These models simulate historical and future periods, factoring in both human-caused emissions and natural influences like solar radiation and volcanic aerosols. These variations affect greenhouse gas (GHG) concentrations and radiative forcing (Hawkins and Sutton, 2011). A variety of institutions work on developing GCMs, always using the same physical principles but occasionally with a few different assumptions. This makes it possible to perform the same experiments with various GCM outputs, producing more reliable estimates (Cos *et al.*, 2021).

Multiple institutes are involved in the development of GCMs, using consistent physical principles and occasionally distinct assumptions. By enabling the construction of various model outputs, this diversity in GCM development also increases the robustness and dependability of climate projections (Diallo *et al.*, 2012). The latest iteration of climate models, known as the sixth phase of the Coupled Model Inter-comparison Project (CMIP6), represents a significant advancement compared to its predecessors, showcasing notable improvements (Wyser *et al.*, 2020).

A larger collection of models, including a more accurate depiction of Earth system processes, better geographic resolution, and improved representations of significant climate variables, are included in CMIP6 (Khadka *et al.*, 2021). Advancements in these areas enable more in-depth analysis of regional climate change and a deeper understanding of the uncertainties inherent in future projections.

The CMIP6 framework incorporates Earth system models (ESMs) alongside general circulation models (GCMs) Figure 1.1. ESMs consider biogeochemical cycles and feedback mechanisms between the climate system and Earth's ecosystems, providing a comprehensive view of interactions with land, oceans, and vegetation. This holistic approach enhances our assessment of impending climate change effects Figure 1.1.

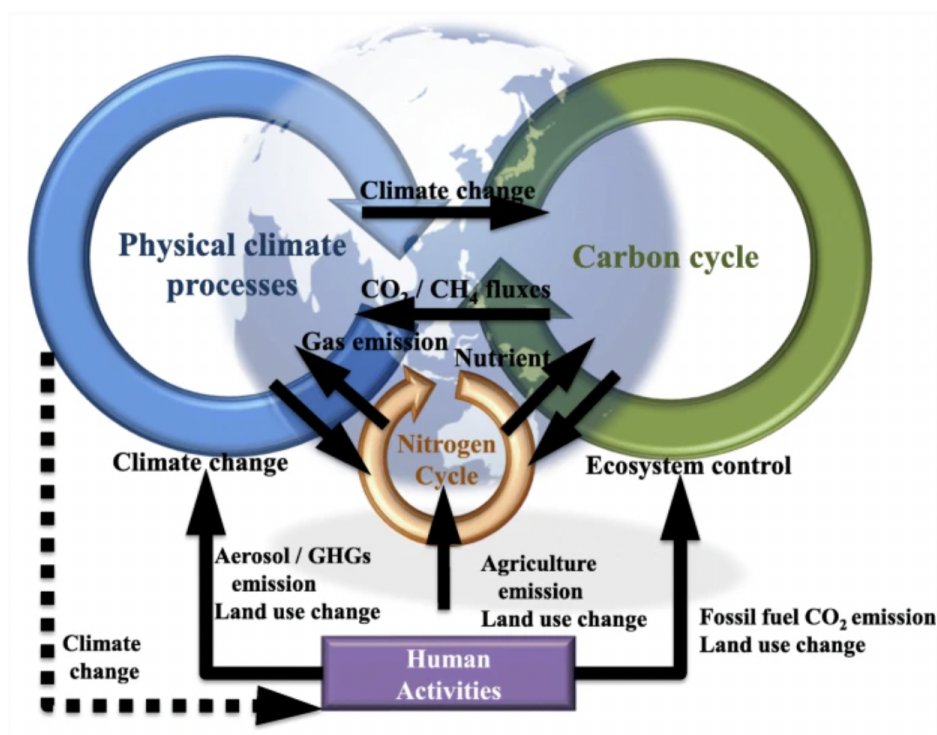


Figure 1.1. Global change projections shown conceptually in the Earth system model (ESM). ESMs can simulate the interplay between climate change and biogeochemical cycles (Kawamiya *et al.*, 2020).

By utilizing the capabilities of GCMs and ESMs inside the CMIP6 framework, scientists may investigate a variety of climate scenarios and look at the possible effects of different emission pathways and policy choices. In order to traverse the difficulties

of climate change mitigation and adaptation, policymakers, stakeholders, and society at large can benefit greatly from understanding the range of potential future climate trajectories through the use of these simulations.

1.2.2. CMIP

The Coupled Model Intercomparison Projects (CMIPs), where both experiment descriptions and scenarios are prescribed, are one of the leading community initiatives in this regard. The Climate Model Intercomparison Project (CMIP) has the objective of simulating Earth's climate and forecasting its forthcoming shifts. Climate models are statistical predictions that encompass multiple facets of the Earth's system, while acknowledging that the resultant simulations are abstractions of reality. Therefore, they cannot depict the observed data entirely accurately. However, they can come close enough to reality to be helpful in assisting us in comprehending climate mechanisms (Notz *et al.*, 2016). Factors like internal variability, the uncertainty of the observational record, and model tuning must be considered when determining the usefulness of climate models (Olonscheck and Notz 2017).

Every new version of the CMIP is based on the idea that newer generations of GCMs will be better than the ones that came before them. This is because models improve over time regarding how well they can be computed, how clear they are, and how well they represent physical processes (Almazroui *et al.*, 2021). In the most recent 6th phase of CMIP, GCMs are presented with new scenario sets (O'Neill, 2016; Petrie *et al.*, 2021). These are a combination of Shared Socioeconomic Pathways (SSPs) (Riahi *et al.*, 2017) and Representative Concentration Pathways (van Vuuren *et al.* 2011).

They aim to comprehend the Earth system response to increased anthropogenic forcing. The various scenarios reflect differences in societal choices that influence GHG emission trajectories and pathways to achieving the goals of the Paris Agreement. Since the fifth phase of CMIP, which only accounted for various emission scenarios through the Representative Concentration Pathways, the incorporation of these societal factors

into the development pathways is an update (Almazroui *et al.*, 2021).

The CMIP framework is essential for facilitating cooperation and knowledge sharing among scientists in addition to taking societal considerations into account. It offers a platform for scientists from different fields and organizations to collaborate on climate modeling projects, communicate model results, and increase our collective knowledge of the Earth system. The collaborative aspect of CMIP allows for the evaluation and comparison of numerous models and scenarios, supporting robust evaluations of uncertainties and improving the accuracy of climate projections. The community continuously works to improve the transparency, reproducibility, and accessibility of climate model simulations through the continued improvement of CMIP procedures, such as better experiment descriptions and standardized data formats.

1.2.3. SSPs

The CMIP6 models are executed under various scenarios, also referred to as Shared Socio-Economic Pathways (SSPs). The SSPs describe broad social tendencies in the future (O'Neill *et al.*, 2016a). They provide an internally coherent logic of the fundamental causal links, including trends that are hard to model. The narratives help a vast user population understand the quantitative SSP projections by summarizing significant socio-economic, demographic, technological, lifestyle, policy, institutional, and other developments (Riahi *et al.*, 2017).

The narratives span a variety of possible futures in terms of the socio-economic challenges they entail for mitigating and adapting to climate change. Both adaptation and mitigation difficulties are low (SSP1) or high (SSP3) in two SSPs. Two “asymmetric cases” are created: SSP5, which has significant mitigation issues and low adaptation challenges, and SSP4, which is the opposite (Riahi *et al.*, 2017). The final one (SSP2) is a central case that presents a world with intermediate adaptation and mitigation issues (Riahi *et al.*, 2017). SSP1 describes a gradual shift towards sustainable development, with reduced inequality and low resources. SSP2 is a continuation of historical

patterns, with uneven progress toward economic and social development, moderate population growth, and ongoing income inequality. In contrast, SSP3 is characterized by increasing nationalism and regional conflicts, slow economic development, high material intensity consumption, and strong environmental degradation in some regions. SSP4 involves increasing inequality and stratification within and between countries, a mix of high-tech and low-tech economies, and diversified energy sources with local environmental policies. Finally, SSP5 is a future of rapid economic growth, declining population, a firm reliance on fossil fuels, successful management of local environmental problems, and faith in the ability to manage social and ecological systems (O'Neill *et al.*, 2016a).

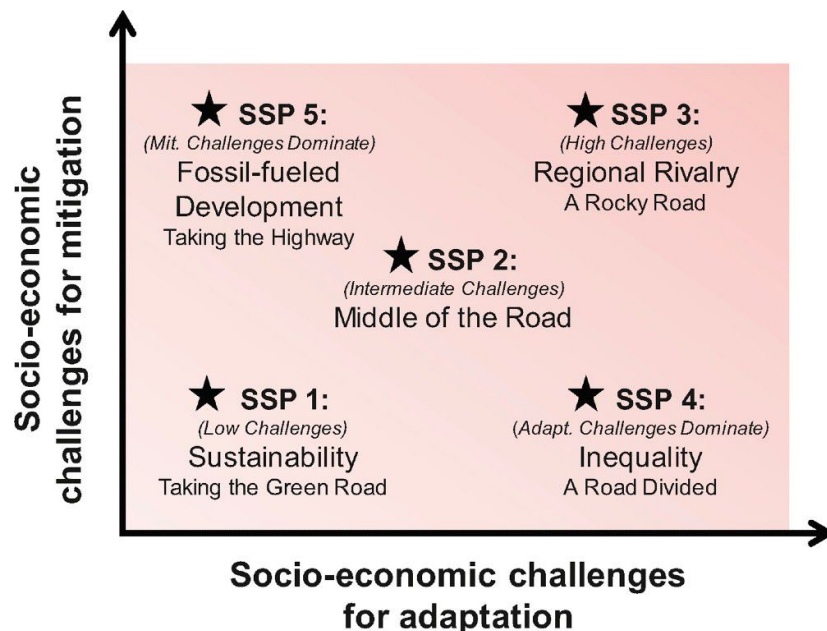


Figure 1.2. Various combinations of difficulties in adaptation and mitigation are represented by five shared socioeconomic paths (SSPs) (O'Neill *et al.*, 2016a).

SSP2 and SSP3 situations will be employed in this thesis. The strongest forcing trajectory, SSP3, was chosen because it sheds light on the potential effects of large greenhouse gas emissions on the climate system. SSP2, on the other hand, presents an opposing scenario that examines difficulties with intermediate adaptation and mitigation (O'Neill *et al.* 2016; Riahi *et al.* 2017; Zelinka *et al.* 2020). This study evaluates climate change implications and adaptation options in these two scenarios Figure 1.2.

It's also important to study the time evolution of rising human-induced radiative forcing and global CO₂ concentrations to comprehend these scenarios. Figure 1.3 shows that radiative forcing has increased by 2.5 Watts since pre-industrialization. This represents the significant energy imbalance caused by human activity in the climate system of the Earth. Figure 1.4 displays the corresponding trajectories of global CO₂ concentrations, highlighting the alarming increase over time.

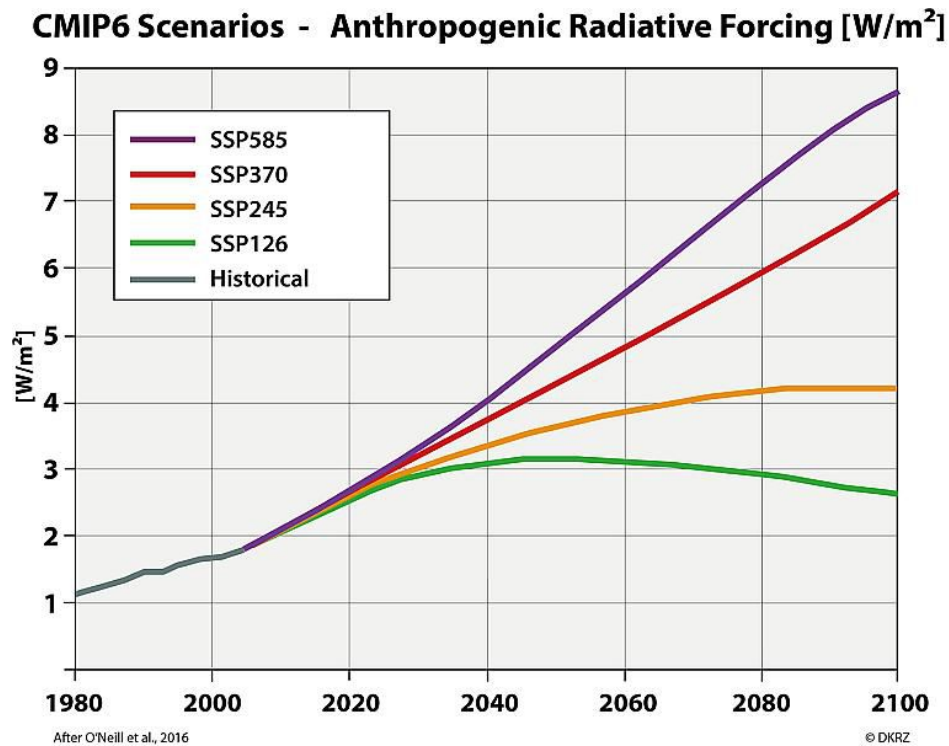


Figure 1.3. The progression through time of the considered scenarios' enhanced radiative forcing by humans (O'Neill *et al.*, 2016a).

Figure 1.5 portrays the essential emission trajectories required to attain the objective of capping global temperature increase at a maximum of 2°C by 2100. It's evident that swift emissions reductions are imperative, leading to eventual attainment of zero emissions by 2075, as demonstrated by the trajectory of the SSP126 scenario (Kriegler *et al.*, 2014; Vuuren *et al.*, 2014). These results emphasize the urgency of enacting efficient mitigation strategies and transitioning towards a low-carbon economy.

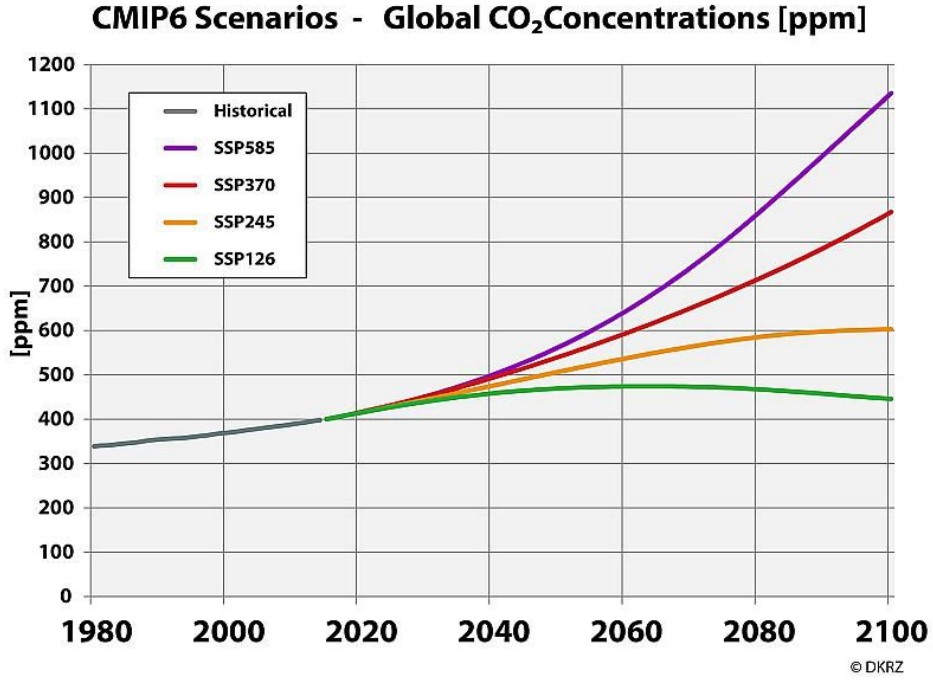


Figure 1.4. The selected scenarios' time progression of extra man-made radiative forcing is shown (O'Neill *et al.*, 2016a).

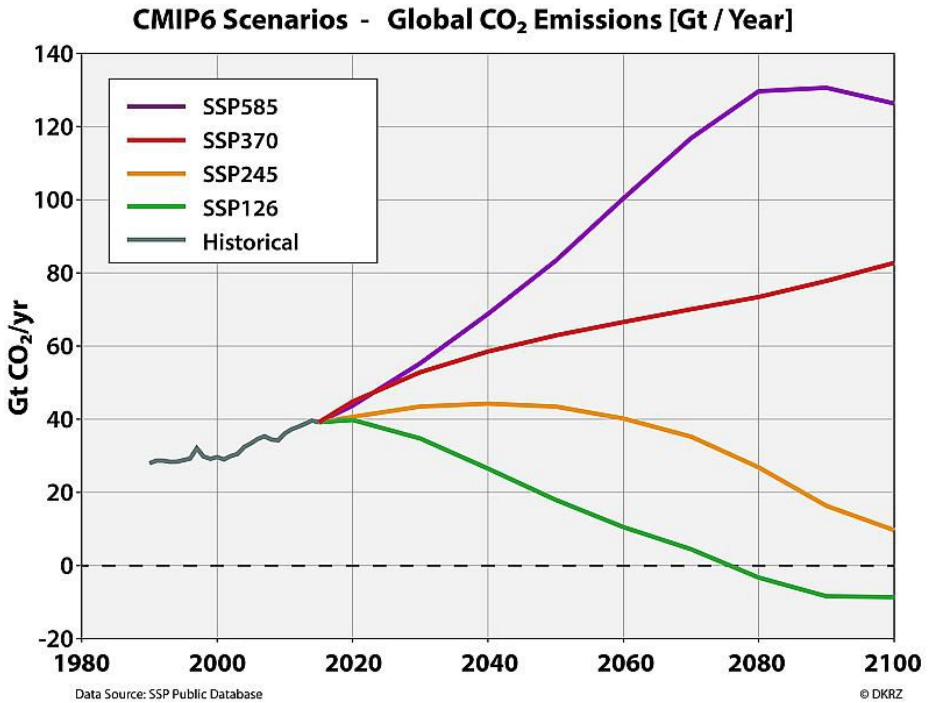


Figure 1.5. Alternative CO2 concentration paths, as represented by the emission trajectories (O'Neill *et al.*, 2016a).

By analyzing the SSP2 and SSP3 scenarios and investigating the associated radiative forcing, CO₂ concentrations, and emission trajectories, this study aims to provide valuable insights into the potential climate change outcomes under different socio-economic pathways. The results of this study will enhance comprehension regarding the obstacles and prospects associated with climate change mitigation and adaptation in the future decades.

1.2.4. Comparison of CMIP6 with Previous CMIPs

The CMIP project began in 1995 and has had multiple phases, including Phase 6 in 2019 (CMIP). CMIP5 and earlier CMIP phases had substantial flaws in quantifying radiative forcings from several stated external forcing components (e.g., GHGs, sulfate aerosols) in each model (Ronald *et al.*, 2016). As more sophisticated mechanisms are incorporated into the numerical and statistical bounds of the models before they are run, their predictive ability improves with each phase (Shen *et al.*, 2021; Eyring *et al.*, 2015). Due primarily to improvements in modeling extratropical cloud feedback and aerosol interactions, CMIP6 models show a wider range of effective climate sensitivity (ECS) (Meehl *et al.*, 2020; Zelinka *et al.*, 2020).

In addition to addressing the shortcomings of previous CMIP phases, CMIP6 has introduced advancements in several key areas. One notable improvement is the inclusion of more comprehensive Earth system components in the models, such as biogeochemical cycles, land surface processes, and dynamic vegetation. This expanded representation of the Earth system allows for a more realistic simulation of the complex interactions between the atmosphere, oceans, land, and biosphere (Döscher *et al.*, 2022). Furthermore, CMIP6 has emphasized the representation of regional climate characteristics and their feedback, enabling a more detailed assessment of regional climate change impacts and vulnerabilities (Grose *et al.*, 2020).

Another notable enhancement in CMIP6 is the increased spatial resolution of the models. Higher-resolution simulations provide more detailed information about

regional climate patterns, extreme events, and localized impacts (Khadka *et al.*, 2021). This improvement is precious for understanding climate processes and impacts at smaller scales, such as changes in precipitation patterns, coastal dynamics, and ecosystem responses (Zhai *et al.*, 2020). The increased resolution captures fine-scale factors like topography and land-use changes, which can affect regional climate variability (Kerkhoven and Gan, 2006; Hackenbruch *et al.*, 2016). CMIP6 advances our understanding of the Earth’s climate system and its response to changing environmental conditions by building on earlier phases.

1.3. Hotspots

1.3.1. Hotspot Definitions

In order to better understand how things may alter at various levels of global warming, there is growing interest in assessing regional responses to climate change (Fan *et al.*, 2021). A region whose climate is particularly responsive to climate change is defined as a climate change hotspot. (Giorgi, 2006; de Sherbinin, 2014). These hotspots are crucial in identifying regions most at risk or significantly impacted by climate change.

The concept of climate change hotspots extends beyond simple temperature rises. It encompasses multiple variables that impact how a region reacts to climate forcing resulting from human-induced greenhouse gas emissions. It’s crucial to recognize that regional reactions to climate change aren’t consistently linear. Certain areas undergo faster warming than the global average due to localized climate feedback mechanisms (Zittis *et al.*, 2022). These feedback mechanisms can amplify the effects of global climate change, resulting in significant regional variations. In addition to changes in the mean climate conditions, changes in the temporal variability of meteorological features are anticipated, supporting a region’s classification as a hotspot for global climate change.

Traditionally, hotspots were primarily characterized by shifts in average climate conditions. Yet, recent advancements in hotspot definitions have embraced a broader perspective. For instance, a recent study introduced risk hotspots, which denote areas where the risk of extreme events is heightened, often coupled with substantial Gross Domestic Product (GDP) and population figures (Estrada *et al.*, 2023). This expanded interpretation recognizes that climate change's repercussions extend beyond mere alterations in temperature and precipitation. They also encompass socio-economic and demographic elements shaping a region's susceptibility.

Understanding and identifying these hotspots is crucial for climate change adaptation and mitigation. By pinpointing regions highly exposed or vulnerable to climate change impacts, policymakers and stakeholders can strategically allocate resources and enact tailored measures to bolster resilience and mitigate vulnerabilities. In addition, the incorporation of numerous components within hotspot classifications offers a more thorough comprehension of the intricate interplay between climate change and socio-economic variables, hence facilitating more knowledgeable decision-making processes.

Overall, hotspot definitions have evolved to incorporate a broader range of factors, allowing for a more nuanced assessment of regions highly responsive to climate change. These definitions provide valuable insights into the differential impacts of climate change across regions and inform strategies for managing climate-related risks.

1.3.2. Global Hotspots

Numerous studies have pinpointed significant worldwide hotspots that show distinctive patterns of climate change. The Sahel region of Africa stands out as a climate change hotspot, grappling with escalating temperatures, prolonged droughts, and encroaching desertification (Zittis *et al.*, 2021). Scholars like Rose (2015) and Vale *et al.* (2015) highlight how these transformations significantly disrupt food security, compromise water availability, and jeopardize local livelihoods. Similarly, shifts in seasonal temperature and precipitation patterns foreseen for the Middle East and North Africa

(MENA) region portray a marked rise in average temperatures paired with a notable decline in precipitation (Öztürk *et al.*, 2018). Additionally, studies have shown how susceptible the Asian monsoon region is to climate change. Monsoon patterns can change, causing floods and droughts that can harm agriculture, water supplies, and many people (Endo and Kitoh, 2016). Climate change increases the risk of rising sea levels, tropical cyclones, and shoreline erosion in the Pacific Islands. Due to their scarce resources and limited capacity for adaptation, these island nations face particular difficulties (Hay and Mimura, 2013). The boreal woods have also been recognized as a significant worldwide hotspot by studies. Rising temperatures and changing precipitation patterns in these regions can have profound impacts on forest ecosystems, carbon storage, and the livelihoods of indigenous communities (Walker *et al.*, 2015). Meanwhile, Bangladesh and analogous low-lying coastal regions stand exposed to the peril of escalating sea levels and the ferocity of storm surges. This vulnerability leads to population displacement, agricultural land erosion, and climate-induced emergencies (Pethick and Orford, 2013; Abdullah *et al.*, 2020).

The Mediterranean is a climate change hotspot with rising temperatures, diminishing precipitation, and extreme weather (Dubrovsky *et al.*, 2014). Tuel and Eltahir, 2020; Zittis *et al.*, 2016 have found this region vulnerable to climate change. Lovelli *et al.* (2014) also observed that Mediterranean precipitation is declining and droughts are lengthening and intensifying. Other findings show a significant increase in future surface mean air temperatures during summer and a decrease in precipitation across all seasons in most parts of the basin, suggesting potential shifts in extreme temperature and precipitation events (Öztürk *et al.*, 2015). These changes affect regional water, agriculture, and ecosystems. Studies also highlight the Mediterranean region's increased risk of heatwaves, wildfires, and coastal flooding caused by sea-level rise (Vacchi *et al.*, 2018; Ruffault *et al.*, 2020). These climate change impacts threaten the Mediterranean's biodiversity, cultural legacy, and socio-economic systems, requiring focused adaptation and sustainable management techniques to boost resilience.

It is significant to emphasize that the process of identifying global hotspots is continuing, and fresh research keeps advancing our knowledge of the implications of regional climate change. Updating and improving our understanding of global hotspots is essential for enabling informed decision-making and successful climate action on a global scale. This requires continuous monitoring, interdisciplinary study, and collaboration.

1.4. Extreme Events

The phenomena of climate change is commonly linked to a variety of extreme weather occurrences, such as droughts, heatwaves, storms, and floods. These events are widely acknowledged as substantial and consequential outcomes of climate change (Lange *et al.*, 2020). These events can potentially inflict severe damage on ecosystems, human lives, and infrastructure (Le and Bae, 2020). It is necessary to have a solid understanding of extreme events' frequency, characteristics, and intensity to properly assess the risks posed by climate change and design viable adaptation solutions (Perera *et al.*, 2020; Winne and Peersman, 2021).

Climate models like CMIP6 can anticipate and simulate extreme event changes. These models consider temperature, precipitation, wind patterns, and atmospheric circulation to simulate the complex dynamics that cause extreme weather phenomena (Xu *et al.*, 2021). Extreme events can influence just causing physical damage. Agriculture, water resources, energy systems, and public health may all be negatively impacted, among other significant socioeconomic effects. Vulnerable populations, including coastal communities, low-income groups, and marginalized locations, often have a disproportionate impact from extreme events due to their poor capacity for adaptation and recovery (Hay and Mimura, 2010; Bell *et al.*, 2018).

2. METHODS

2.1. Global Circulation Models and Regional Climate Models

Global Circulation Models (GCMs) and Regional Climate Models (RCMs) play pivotal roles in climate modeling, facilitating the simulation and projection of climate changes on both global and regional scales. GCMs are sophisticated numerical models specifically crafted to depict the overarching circulation patterns of Earth's atmosphere and oceans, effectively capturing extensive climate trends worldwide (Grassl, 2000). These models stand as indispensable tools within the realm of climate research, providing invaluable insights into the intricate workings of the Earth's climate system. Such insights encompass the system's intricate responses to external forces, including shifts in greenhouse gas emissions and fluctuations in solar radiation (Khalili and Nguyen, 2017).

GCMs operate on a coarse grid that covers the entire Earth, making them suitable for capturing global-scale climate features. However, due to their coarse resolution, they may not adequately represent regional climate processes, especially in complex terrain or coastal regions (Schiemann *et al.*, 2018; Demory and Berthou, 2020). This limitation led to the development of RCMs, which are nested within GCMs and provide more detailed projections for specific regions.

RCMs downscale the information from GCMs to higher spatial resolutions, offering more accurate and region-specific climate projections (Gutowski *et al.*, 2020). By simulating regional climate processes in finer detail, RCMs can capture localized phenomena, such as temperature gradients, precipitation patterns, and coastal influences. This downscaling process is essential for assessing the impacts of climate change on a local scale and for informing adaptation strategies in vulnerable regions.

2.2. Data

Copernicus data used in the analyses (Copernicus Climate Change Service, 2021). Copernicus data are primarily utilized to address scientific questions that arose during the IPCC reporting process. It helps enhance our understanding of the climate system and provides valuable insights into future climate change and associated uncertainties. These data also play a crucial role in supporting adaptation efforts to climate change. Additionally, they contribute to the examination of climate predictability and evaluate the accuracy of models in predicting climate patterns over extended periods. They are instrumental in assessing how well different models simulate recent historical climate data.

The term “experiments” in CMIP6 refers to three main categories of simulations. Firstly, the historical experiments focus on the period for which modern climate observations are available. These experiments assess the performance of General Circulation Models (GCMs) in representing past climates and serve as a reference for comparing future scenario runs. The typical period covered is from 1850 to 2014. Secondly, the climate projection experiments follow the combined pathways of the Shared Socioeconomic Pathway (SSP) and the Representative Concentration Pathway (RCP). The SSP scenarios offer different future climate forcing pathways, and the period covered typically ranges from 2015 to 2100 (O’Neill *et al.*, 2016).

The Copernicus data type is gridded, the projections are a regular latitude-longitude grid and an ocean grid, it has global horizontal coverage, horizontal resolution varies between models, temporal coverage is from 1850 to 2014 for historical experiments and from 2015 to 2100 for SSP experiments. Our data has a monthly temporal resolution. The file format is NetCDF4. Convention is Climate and Forecast (CF) Metadata Convention CF-1.7 CMIP-6.2 (Copernicus Climate Change Service, 2021). Two variables were chosen, precipitation ($\text{m}^{-2} \text{s}^{-1}$) and near-surface air temperature (K). Near-Surface air temperature is, the temperature of air measured two meters above the surface of land, sea, or inland waters. It is derived by interpolating

between the lowest level of the model and the Earth’s surface while considering atmospheric conditions Figure 2.1. Precipitation is the total amount of liquid and frozen water that descends to Earth’s surface, including rain and snow. It is the combination of large-scale and convective precipitation. This parameter excludes fog, dew, and precipitation that evaporates in the atmosphere before reaching the Earth’s surface. This variable represents the quantity of water per unit of time and area (Copernicus Climate Change Service, 2021).

The models that downloaded are, ‘access_cm2 (Australia)’, ‘awi_cm1_1_mr (Germany)’, ‘bcc_csm2_mr (China)’, ‘cams_csm1_0 (China)’, ‘canesm5_canoe (Canada)’, ‘cnrm_cm6_1_hr (France)’, ‘fgoals_f3_l (China)’, ‘inm_cm5_0 (Russia)’, ‘ipsl_cm6a_lr (France)’, ‘miroc6 (Japan)’, ‘miroc_es2l (Japan)’, ‘mri_esm2_0 (Japan)’, ‘noresm2_mm (Norway)’, ‘taiesm1’, ‘cesm2 (USA)’, ‘cmcc_cm2_sr5 (Italy)’, ‘cnrm_cm6_1 (France)’, ‘cnrm_esm2_1 (France)’, ‘fgoals_g3 (China)’, ‘gfdl_esm4 (USA)’, ‘inm_cm4_8 (Russia)’, ‘kace1_0_g (South Korea)’, ‘mcm_ua_1_0 (USA)’, ‘mpi_esm1_2_lr (Germany)’, ‘ukesm1_0_ll’ Our historical period, 1900-2014, and for SSP2-4.5 and SSP3-7.0 periods, 2015-2099.

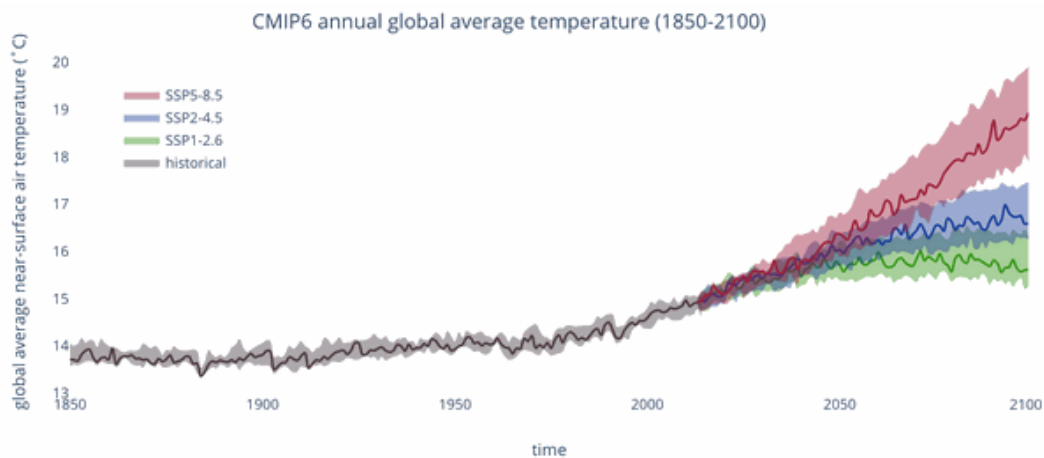


Figure 2.1. Copernicus temperature data visualization. Model historical data and temperature change according to different SSP scenarios (Copernicus Climate Change Service, 2021).

The CRU TS (Climatic Research Unit gridded Time Series) dataset, which is extensively utilized, offers comprehensive climatic data on a grid of 0.5°C latitude by

0.5°C longitude. This dataset encompasses all geographic areas with the exception of Antarctica. This dataset is created by interpolating monthly climate anomalies using observations from weather stations. CRU TS v4 has been developed, covering the period from 1901 to 2021 with additional station observations and future annual updates. The interpolation process uses angular-distance weighting (ADW), which improves the traceability between gridded values and input observations (Harris *et al.*, 2020).

CRU historical data downloaded. It turned out that not all of the 25 models downloaded were found. Because of this situation, models that did not exist were discarded. In addition, some model files did not work and they were also eliminated. In the last case, we have 15 models left. (“ACCESS-CM2 (Australia)”, “BCC-CSM2-MR (China)”, “CAMS-CSM1-0 (China)”, “CanESM5-CanOE (Canada)”, “CMCC-CM2-SR5 (Italy)”, “CNRM-CM6-1 (France)”, “CNRM-CM6-1-HR (France)”, “CNRM-ESM2-1 (France)”, “FGOALS-f3-L (China)”, “IPSL-CM6A-LR (France)”, “KACE-1-0-G (South Korea)”, “MCM-UA-1-0 (USA)”, “MIROC-ES2L (Japan)”, “MRI-ESM2-0 (Japan)”, “TaiESM1”)

The accurate interpretation of future climate scenarios and their potential implications hinges significantly on the climate sensitivity inherent in the selected general circulation models (GCMs). The model’s reactivity to adjustments in greenhouse gas levels indicates its ability to assess the possible scope of climate change (Stainforth *et al.*, 2005).

The GCM ensemble utilized in this investigation demonstrates a range of climate sensitivities, reflecting the variety of assumptions, parameterizations, and representations of Earth’s climate processes. Models characterized by higher climate sensitivity predict more significant temperature increases due to elevated carbon dioxide (CO₂) levels, amplifying the consequences of climate change, such as heightened occurrences of severe heatwaves, escalating sea levels, and modifications in precipitation patterns. On the other hand, models with reduced sensitivity suggest less pronounced temperature

variations and milder climate consequences (Kirk-Davidoff, 2008). The recognition of the intrinsic uncertainty in projecting future climate conditions is acknowledged by including General Circulation Models (GCMs) that encompass a range of climate sensitivities (Chen *et al.*, 2011; Song *et al.*, 2020). This approach aims to achieve a comprehensive assessment of possible scenarios.

Several climate models, including Australia’s ACCESS-CM2, offer a comprehensive perspective, projecting a calibrated response to fluctuations in CO₂ levels (Bi *et al.*, 2020). Chinese climate models such as BCC-CSM2-MR and CAMS-CSM1-0 offer a valuable contribution to the field of climate scenario exploration by providing a range of sensitivities, hence enhancing the depth of analysis (Sang *et al.*, 2020). The CanESM5-CanOE model from Canada provides a mild forecast (Sospedra-Alfonso *et al.*, 2021), whereas the CMCC-CM2-SR5 model from Italy encompasses a broad range of sensitivities (Scoccimarro *et al.*, 2022). The models developed by the French CNRM offer comprehensive and nuanced insights over a range of sensitivities, spanning from moderate to higher levels (Jones, 2020). The FGOALS-f3-L climate model developed in China (Zhou *et al.*, 2018) and the IPSL-CM6A-LR model developed in France exhibit high sensitivity in their simulations (Yin *et al.*, 2016).

On the other hand, the KACE-1-0-G model from South Korea provides a more balanced perspective. The MCM-UA-1-0 model from the United States presents a moderate position, whereas the Japanese models MIROC-ES2L and MRI-ESM2-0 exhibit differing degrees of sensitivity. Finally, the TaiESM1 model has considerable sensitivity, providing valuable insights into situations when climate impacts may be significantly magnified (Wang *et al.*, 2020). Including a wide range of models enhances the analytical process by enabling a thorough assessment of possible climatic trajectories and deepening the comprehension of future climate consequences.

CRU data are a gridded time-series dataset. The version I used was released 26 May 2022, and covers the period 1901-2021. It’s coverage contains all land areas (excluding Antarctica) at 0.5° resolution. It has several variables inside: pre, tmp,

tmx, tmn, dtr, vap, cld, wet, frs, pet. Pre and tmp are used. Precipitation unit is mm/month and temperature unit is degrees Celsius. Below you see the visualization of the CRU data for temperature and precipitation Figure 2.2 and Figure 2.3.

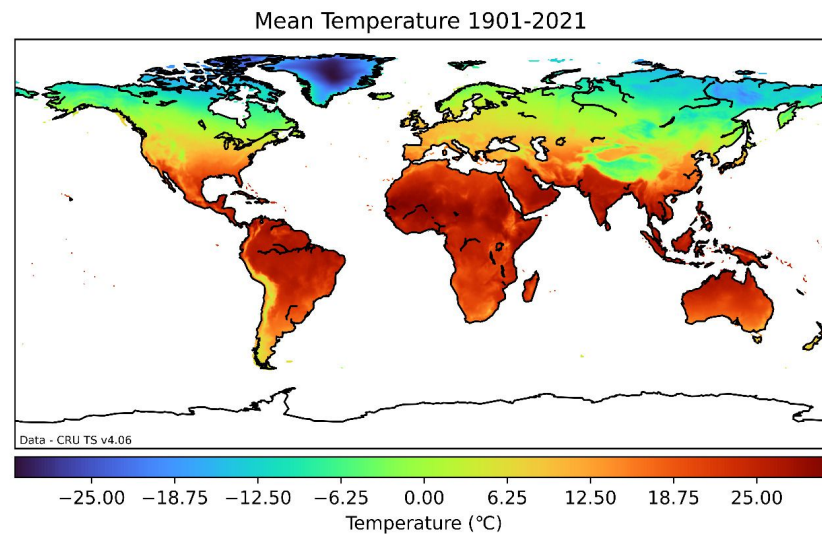


Figure 2.2. CRU Mean of monthly mean temperature data between 1901-2021.

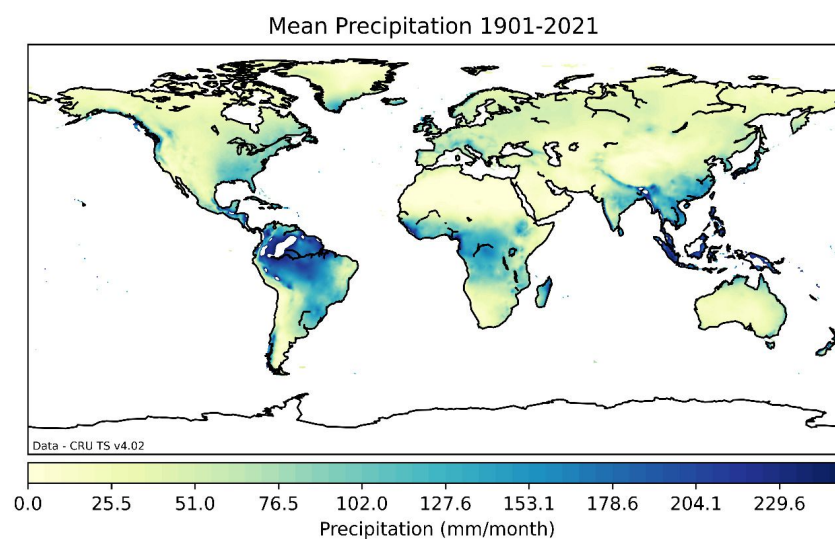


Figure 2.3. CRU Mean of monthly total precipitation data between 1901-2021.

CDO (Climate Data Operators) was used to process the data. CDO is a set of command line tools designed for the manipulation and analysis of climate model data. It supports various data formats including GRIB, netCDF, SERVICE, EXTRA, and IEG. With over 400 operators, CDO provides a wide range of capabilities for working with climate data, allowing users to perform various operations and analyses on the datasets.

All models use the CRU dataset, but they have different projections. I remap them and interpolate them to a 1-degree projection. Each model has a different resolution. Higher resolutions are downgraded to 180x360 through extrapolation without data loss. Alternatively, lower resolutions are interpolated to higher resolutions.

Model uncertainty, which is sometimes referred to as error, can be influenced by data resolution. This includes not only the uncertainty inherent in the original data but also the process of combining multiple rasters and interpolating data to higher resolutions (Stampfl *et al.*, 2007). One degree is not a very high resolution, so going from lower to higher (1 degree) does not introduce significant errors. By remapping, we bring all of them to the exact locations when interpolating them to the grid points of 1 degree (360x180) resolution.

Bilinear interpolation is used for remapping. In practical applications, both naive interpolation and bilinear interpolation methods are straightforward and cost-effective (Shao *et al.*, 2007). These methods have found extensive application across various disciplines, including digital image processing (Pratt, 1991), geostatistics (Legates and Deliberty, 2007), and ecological modeling (Matsushita *et al.*, 2004). A comparative analysis of the precision of interpolated data suggests that bilinear interpolation offers superior estimates compared to nearest-neighbor interpolation (Kvasov *et al.*, 2013). While naive interpolation is commonly employed in diverse situations, the research suggests a preference for adopting bilinear interpolation based on the results (Shao *et al.*, 2007).

In terms of precipitation, the CRU dataset provides monthly total data, while the Copernicus model provides total precipitation per second ($\text{kg/m}^{**2}\cdot\text{s}$). Therefore, the Copernicus data was also transformed into monthly total data. The number of 259200 was multiplied to get the total precipitation in 1 month. The temperature data remained unchanged in terms of temporal alignment; no additional modifications were made. However, it should be noted that the Copernicus temperatures were originally provided in Kelvin units, and they were subsequently converted to Celsius units for consistency with other datasets.

Although climate models are essential for comprehending climate change, their outputs could be biased and have lower resolutions than impact models demand as we saw. Many people turn to bias correction and downscaling strategies to close this gap. Bias correction is predicated on the premise that the climate model provide knowledgeable input for the correction procedure and accurately depicts climate change. The effectiveness of downscaling and correcting trends related to climate change is, however, constrained by the limitations of current bias correction approaches. For some areas, cross-validation is insufficient to evaluate bias correction; further research is required (Maraun, 2016).

An ensemble means was created in which all models were included. The ensemble was created by averaging all model values. Then the difference between the temporal averages for temperature was looked at. All values were added together and divided by the number of years. For precipitation, the difference between the annual total was taken into account. In this way, the temporal average in temperature and the temporal total in precipitation were calculated for each grid point. Since the precipitation change is wanted to be expressed as the annual total precipitation as a unit, the total is taken instead of the average, unlike the temperature. Then, the temporal averages and sums differences were summed by taking the single value of all points in the areal and dividing by the number of grid points. In this way, the areal average was taken. In this way, the bias value of each model was calculated. The following graphs show the bias values of temperature and precipitation variables Figure 2.4-Figure 2.5.

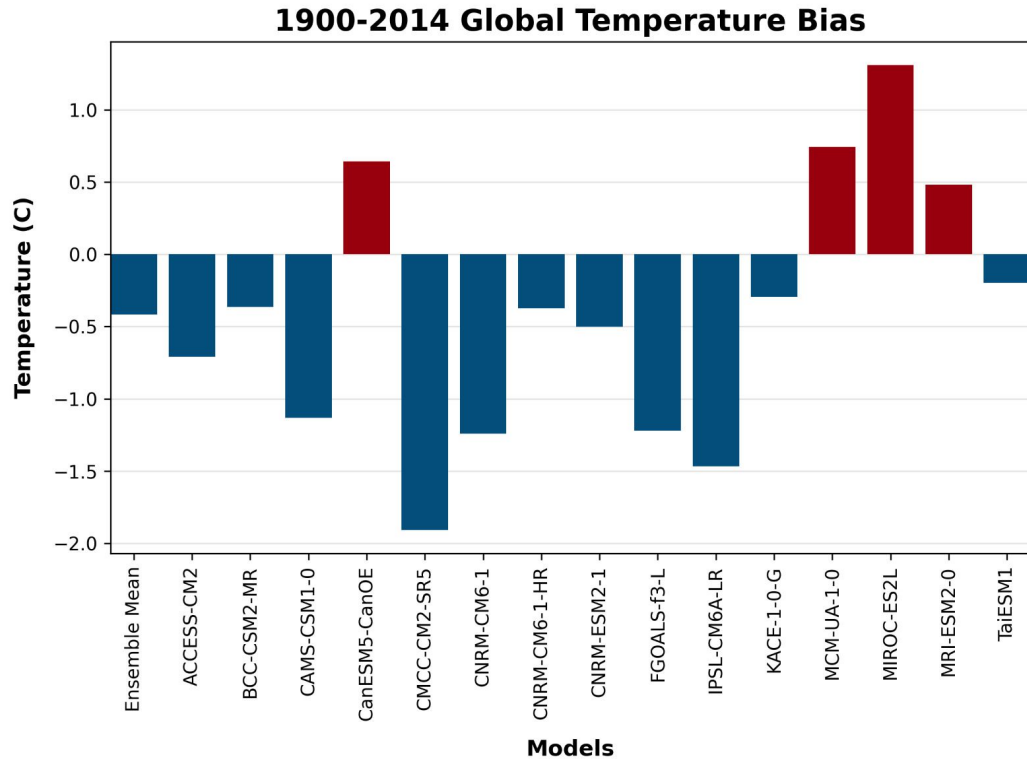


Figure 2.4. Model biases for temperature.

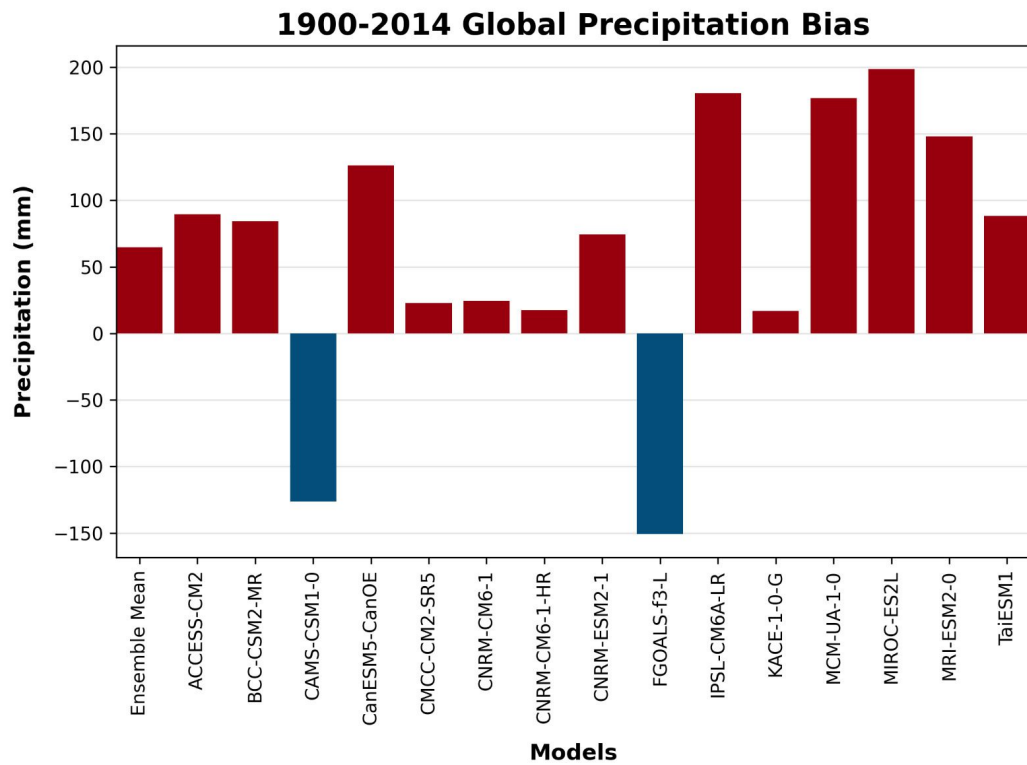


Figure 2.5. Model biases for precipitation.

In line with these results, the models with the lowest bias are chosen. Since ensemble bias is also low bias, the ensemble mean where all models are included was chosen to use. However, deciding according to the bias will be insufficient on its own because some models with low bias, since they are calculated by taking the difference, may not explain it very well. Another method that can be evaluated in the model selection process is to look for correlation. The spatial correlation of the CRU data with the model data was looked at to see how well the models described the region spatially Figure 2.6, Figure 2.7. Below are the correlation graphs.

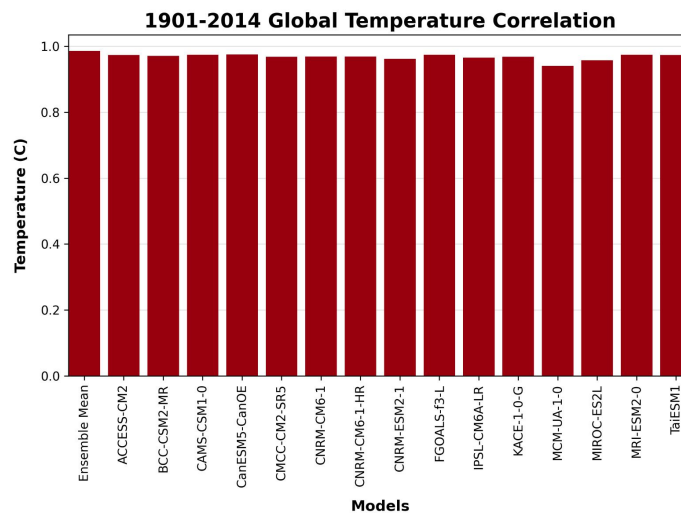


Figure 2.6. Correlation between models and CRU data for temperature.

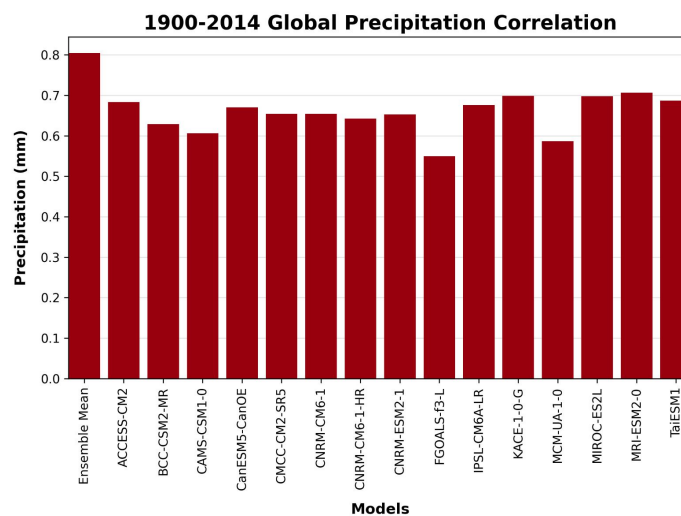


Figure 2.7. Correlation between models and CRU data for precipitation.

Models with low correlation and high bias were selected and discarded, a new ensemble was created over the remaining models, and its correlation and bias values were examined, but not much improvement was observed. As a result, it was decided to work with the ensemble mean, which includes 15 models.

The temperature averages of the historical Ensemble mean data are given below Figure 2.8. For each grid point on a global scale, the map displays the ensemble mean temperature throughout the historical period between 1901 and 2014. The graphic displays a significant temperature difference between the equatorial zone, which encompasses tropical regions near the equator, and other geographic locations. This pattern corresponds to the well-established climatic phenomenon in which tropical regions experience higher temperatures due to their consistent exposure to solar radiation and increased solar energy absorption. Due to the Intertropical Convergence Zone (ITCZ), which converges warm air masses, and its proximity to the sun, the equatorial belt has greater temperatures.

The transition from the equatorial to polar areas has cooler colors, signifying lower temperatures. This cooling trend in polar regions is due to the Earth's axial tilt, reducing solar radiation and direct sunlight. Additionally, the polar regions have a higher albedo because of ice and snow, reflecting more solar radiation into the atmosphere and contributing to their lower temperatures.

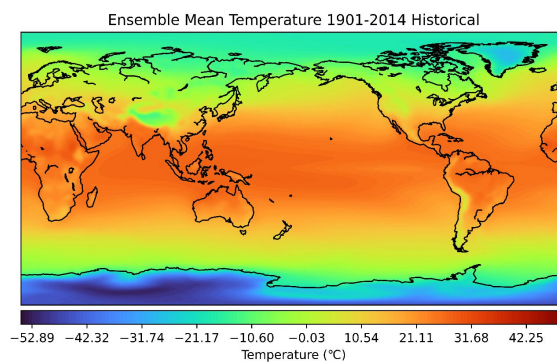


Figure 2.8. Ensemble mean of temperature for each grid point.

The graphic below showing the distribution of global mean precipitation of Ensemble over the period from 1901 to 2014 offers important insights into the spatial variability of global mean precipitation Figure 2.9. Each grid point in this graphic has a color corresponding to the amount of mean precipitation recorded in that specific area. Higher average precipitation indicates abundant rainfall in darker blue areas. The Intertropical Convergence Zone (ITCZ) and associated atmospheric circulation patterns raise moist air, condense it, and create rainfall in equatorial and tropical regions. Yellow parts representations have lower average precipitation amounts, indicating drier conditions. These locations, where subsidence and reduced rainfall are caused by atmospheric circulation cells' descending limbs, are frequently seen in subtropical and polar latitudes.

Darker blue hues in the plot also indicate mountainous areas like the Andes, Rockies, and Himalayas. Mountains exert a significant influence on local precipitation patterns by facilitating the ascent, cooling, and subsequent release of moisture as precipitation on their windward side.

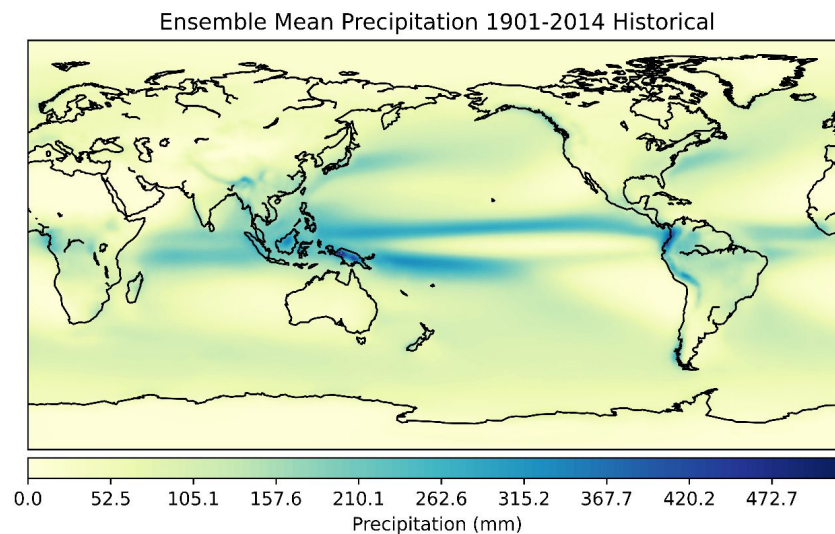


Figure 2.9. Ensemble mean of monthly total precipitation for each grid point.

Understanding the expected changes in global temperatures and precipitation over time is made possible by having the ensemble mean of temperature or precipitation as a time series for historical and model data for many scenarios Figure 2.10, Figure 2.11. The historical data, which spans the years 1901 to 2014, provides a starting point for comprehending the behavior and variability of earlier climates. The ensemble mean of temperature or precipitation for the future scenarios, covering the period from 2014 to 2099, enables a prospective investigation of the effects of climate change under various emission scenarios. The two specific scenarios, SSP2-4.5 and SSP3-7.0, reflect various paths for socioeconomic advancement and greenhouse gas emissions. SSP2-4.5 shows a course with modest greenhouse gas reductions and an emphasis on sustainable development, whereas SSP3-7.0 shows a course with high emissions and little effort put into mitigating climate change.

Anomaly plots Figure 2.10, Figure 2.11 are valuable for understanding how global temperatures and precipitation have deviated from their historical averages. Anomalies represent the difference between the current temperature or precipitation and the long-term average for a specific reference period. The difference between the current temperature and the reference period average is the temperature anomaly for that year. Positive anomalies indicate that the temperature is higher than the reference period average, while negative anomalies indicate cooler temperatures. Analyzing these anomaly plots helps identify long-term climate trends and potential shifts in temperature and precipitation patterns.

In order to generate a plot of a time series, the data must first be averaged over all of the grid points to produce a single global value vs. time. It is necessary to derive an annual average from the monthly data to mitigate the impact of seasonal variation depicted in this time series graph. For this plot, it is helpful to consider the temperature values with a particular temperature period as an anomaly. In order to determine the yearly temperature anomaly, the average temperature from 1961-1990 is compared to the current temperature. Similarly, for the precipitation anomaly plot, you follow a similar process.

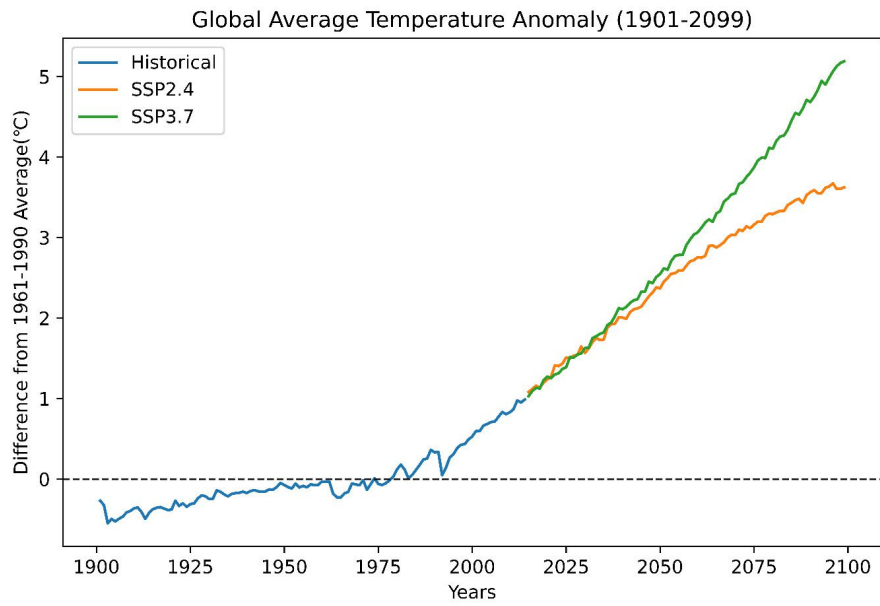


Figure 2.10. Temperature anomaly plot.

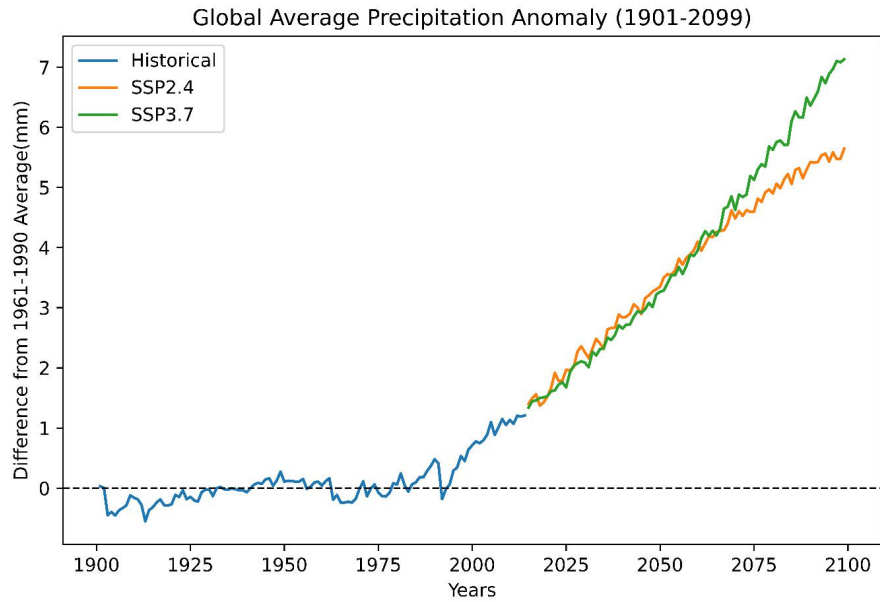


Figure 2.11. Precipitation anomaly plot.

2.3. Hotspot Calculations

2.3.1. Hotspot Quantification

The study quantifies global climate change hotspots using Williams *et al.* (2007) and Diffenbaugh (2008) statistical methods. Williams *et al.*'s (2007) Standard Euclidean Distance (SED) is used to assess the change in physical distance between two places in multidimensional space between current and future periods and it is written as

$$SED_{total} = (\sum_v SED_v)^{1/2}, \quad (2.1)$$

$$SED_v = (abs(\Delta_v)/max[abs(\Delta_v)]_{ij})^2, \quad (2.2)$$

where the symbol $abs(\Delta_v)$ represents the absolute value of the change in climate indicator v at each grid point between the present and future periods, and the symbol $max[abs(\Delta_v)]_{ij}$ represents the maximum land-gridpoint absolute value change in climate indicator v across all land grid points ij during our periods (2026-2050 and 2076-2099) for SSP2-4.5 and SSP3-7.0 scenarios.

2.3.2. Climate Indicators

The indicators taken into account include mean surface air temperature (T), mean precipitation (P), interannual coefficient of variation of mean precipitation (Pvar), interannual standard deviation of surface air temperature (Tvar), occurrences of years exceeding baseline maximum temperature (Hot), years with precipitation falling below baseline minimum (Dry), and years with precipitation exceeding baseline maximum (Wet), as well as a number of other climatic factors. For the purpose of calculating the SED, these indicators are handled as distinct variables for each of the four seasons (DJF, MAM, JJA, and SON). This results in a total of 28 climatic dimensions.

The changes (Δ_v) in 28 variables from the baseline (1901-2014) to the future eras (2026-2050 and 2076-2099) are calculated at each grid point. The interannual

standard deviation of seasonal temperature (T_{SD-e}) and seasonal precipitation (P_{SD-e}), ensemble mean extreme hot years (T_{hot-e}), extreme wet years (P_{wet-e}), and extreme dry years (P_{dry-e}) for the DJF, MAM, JJA, and SON seasons are used to determine these changes at each 1-degree grid. This method covers the baseline period 1901-2014 and future periods such as 2026-2050 and 2076-2099. Mean temperature, mean precipitation, temperature variability, and precipitation variability are written as

$$\Delta_T = (T_{mean-e})_{future} - (T_{mean-e})_{baseline}, \quad (2.3)$$

$$\Delta_P = \frac{(P_{mean-e})_{future} - (P_{mean-e})_{baseline}}{(P_{mean-e})_{baseline}}, \quad (2.4)$$

$$\Delta_{Tvar} = \frac{(T_{SD-e})_{future} - (T_{SD-e})_{baseline}}{(T_{SD-e})_{baseline}}, \quad (2.5)$$

$$\Delta_{Pvar} = \frac{\frac{(P_{SD-e})_{future}}{(P_{mean-e})_{future}} - \frac{(P_{SD-e})_{baseline}}{(P_{mean-e})_{baseline}}}{(P_{SD-e})_{baseline}/(P_{mean-e})_{baseline}}. \quad (2.6)$$

Extreme hot, wet, and dry occurrences are written as

$$\Delta_{Hot} = (T_{hot-e})_{future}, \quad (2.7)$$

$$\Delta_{Wet} = (P_{wet-e})_{future}, \quad (2.8)$$

$$\Delta_{Dry} = (P_{dry-e})_{future}, \quad (2.9)$$

and they represent extreme weather events.

2.3.3. Normalization of Climate Indicators

First, masking was done. Seas and lakes were extracted from the whole world by using the shape files of the World's seas and lakes according to the 1 degree grid. The aim of constructing a land mask was to find hotspots of climate change over inhabited land areas. Additionally, we normalize the change in each climate indicator v to the greatest land-grid-point change in that climate indicator that is found in the 2026-2050 and 2076-2099 periods of both SSP2-4.5 and SSP3-7.0 in order to treat the change in each of the 28 climate indicators equally in the SED calculation.

For each climatic indicator in each of the two future periods, Δ_v is first determined in order to carry out this normalization. The absolute value of the Δ_v for each climatic indicator v in each of the two future periods is then determined as

$$(\Delta_v)_{abs} = abs(\Delta_v), \quad (2.10)$$

and then the maximum land-grid-point change $max[abs(\Delta_v)]_{ij}$ for each climatic indicator v over all land grid points ij determined during the 2026-2050 and 2076-2099 timeframe of SSP2-4.5 and SSP3-7.0 with

$$(\Delta_v)_{max} = (max[abs(\Delta_v)]_{ij})_{time\ period}. \quad (2.11)$$

After that, SED value for each climate indicator at each grid point computed by taking the square of the ratio that exists between the absolute value of change in each climate indicator v and the maximum land-grid-point absolute value change in that climate indicator throughout the periods 2026-2050 and 2076-2099 for SSP2-4.5 and SSP3-7.0. It can be observed as

$$SED_v = ((\Delta_v)_{abs}/(\Delta_v)_{max})^2, \quad (2.12)$$

and the total SED is computed by taking the square root of the sum of the 28 which can be seen as

$$SED_{total} = (sum(SED_v))^{1/2}. \quad (2.13)$$

The analyses involved an expansion of the hotspot approach by integrating demographic data to evaluate the susceptibility of regions to climate change. The population value at each grid point was normalized by dividing it by the maximum population value. This normalization process transformed the population values at all grid points into a standardized range between 0 and 1. Population-weighted SED values were determined through the multiplication of normalized population figures by the corresponding SED values within a specific grid. The aim was to calculate population-weighted standard Euclidean distance values across the entire globe. This methodology not only incorporates alterations in environmental factors like temperature and precipitation but also incorporates population density. This consideration holds significance as regions with denser populations may encounter heightened difficulties and consequences.

3. RESULTS

The study aims to analyze changes in the climatology of the globe under the SSP2-4.5 and SSP3-7.0 scenarios for the years 2026-2050 and 2076-2099. This analysis is achieved by calculating the Standard Euclidean Distance (SED) values for four seasons using seven climate indicators. The regions with the highest SED values will be identified as the most affected by climate change and designated as climate change hotspots. To further assessing the risks, the study incorporates population-weighted SED values, allowing for the consideration of population density alongside environmental changes. This study offers a comprehensive understanding of the likely effects of climate change across various geographical locations through the examination of both SED and population-weighted SED metrics.

In the near future (2026-2050), the analysis of weighted SED values reveals a concentration of maximum values, particularly in equatorial regions Figure 3.1. Notably, regions like China, Japan, and Indonesia emerged as prominent hotspots due to the combined effects of environmental changes and population dens

ity. Considering the number of people exposed to changing climate conditions, it becomes evident why these areas are identified as significant hotspots. The incorporation of population-weighted SED values enriches the hotspot assessment, offering valuable insights into the potential impacts of climate change on both the environment and human populations.

In the near future (2026-2050), the weighted SED value analysis highlights several regions particularly at risk from climate change. In the Americas, the eastern parts of the United States, Central America, and the coasts of Peru, Ecuador, Colombia, and Venezuela exhibit higher weighted SED values, indicating increased climate impacts. The southern coasts of Brazil also emerge as susceptible areas.

Moving to the African continent, a significant portion are under the risk of climate change, with notably higher weighted SED values observed in the southern region. In the northern reaches, regions such as Western Sahara and Morocco and segments of the Middle East encompassing Saudi Arabia, Turkey, Iran, Syria, and Iraq also emerge prominently as hotspots.

The Mediterranean region and Western Europe demonstrate higher SED values, indicating their susceptibility to climate change impacts. Furthermore, in Asia, countries such as Pakistan, Afghanistan, Bangladesh, Myanmar, Cambodia, Vietnam, Indonesia, Malaysia, and the eastern part of China stand out as regions with elevated weighted SED values, rendering them at risk from climate change.

By evaluating the population-weighted SED values, this analysis identifies environmental hotspots and underscores the significance of considering the potential impacts on human populations in these regions.

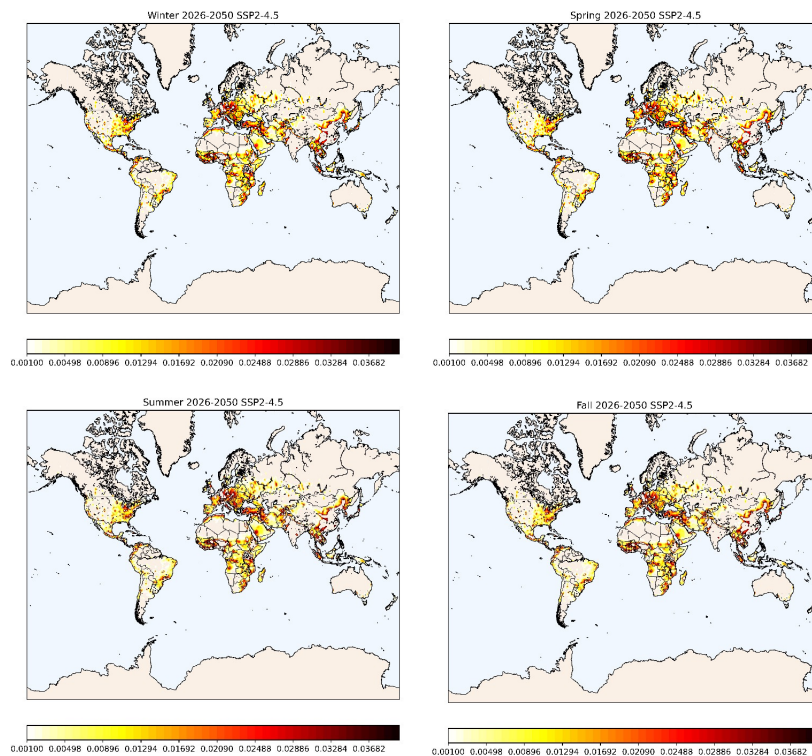


Figure 3.1. Population weighted SED values under the SSP2-4.5 scenario for the years 2026-2050 for 4 different season.

Typhoons, cyclones, and extended heat waves are examples of the extreme weather that poses a hazard to China, Japan, and Indonesia (Róyski *et al.*, 2009; Kan, 2011; Constantine *et al.*, 2019). These densely inhabited regions are potentially exposed to the repercussions of climate change, encompassing potential disruptions to agricultural systems, water availability, and public health concerns (Tao *et al.*, 2011). Navigating these risks demands a concentrated approach toward strengthening infrastructure resilience and the execution of robust disaster preparedness plans.

In the Eastern United States, Central America, and the coastal zones of South America, specifically Peru, Ecuador, Colombia, and Venezuela, distinctive climate-induced emergencies are expected to arise. Increased variability in precipitation leads to more frequent and intensified floods, landslides, and soil erosion in these locales (Harris and Mix, 2002; Mo and Berbery, 2011; Mollier-Vogel *et al.*, 2013). Furthermore, the amplified threat of tropical cyclones and hurricanes accentuates the challenge (Mendelsohn *et al.*, 2012; Jesus *et al.*, 2020). Effectively addressing the climate change risk in these areas necessitates strategically deploying integrated water management methodologies, establishing early warning mechanisms, and strategically allocating resources toward community-oriented adaptation initiatives that safeguard livelihoods and ecological systems.

The higher weighted SED values for Southern Africa highlight the growing difficulties brought on by climate change, including extended droughts and decreasing water supply (LópezCarr *et al.*, 2014). With potential negative implications on agricultural production and economic stability, these changes in climatic patterns raise questions about food security (Crespo *et al.*, 2011; Conway *et al.*, 2014; Serdeczny *et al.*, 2017). Addressing these challenges necessitates the adoption of sustainable land and water management practices, promoting crop diversity, and making strategic financial investments in adaptable agricultural systems capable of coping with evolving environmental conditions.

Increase in frequency and severity of heatwaves and water scarcity create significant issues in arid and semi-arid countries including Western Sahara, Morocco, Saudi Arabia, Turkey, Iran, and Syria (Ghamdi *et al.*, 2019; Öztürk *et al.*, 2021). These regions are already dry, which makes climate change effects worse and could cause desertification and habitat loss. Effective drought management methods must be put into place, funding for renewable energy projects must be raised, and sustainable water use must be encouraged. The development of climate resilience in these areas depends on these actions.

There has been some research that indicates a shift towards warmer and drier climate conditions in the Mediterranean region (Turp *et al.*, 2015; Dubrovsk *et al.*, 2014; Ribes *et al.*, 2018) during the study periods. Alterations in precipitation patterns alongside the potential for heatwaves and wildfires are becoming increasingly probable in the Mediterranean and Western European regions. Furthermore, the rise in sea levels and the potential for storm surges are emerging as potential threats to coastal areas. Improving these areas' ability to adapt would need intensive efforts at urban design, environmental restoration, and the safeguarding of coastal communities.

The coastal regions of Southern Asia, encompassing nations like Bangladesh, Myanmar, Indonesia, and sections of Pakistan, Afghanistan, Cambodia, Vietnam, and Malaysia, confront a myriad of climate-associated concerns (Öztürk *et al.*, 2017; Schrier *et al.*, 2018; Sarker *et al.*, 2019). As the ongoing increase in sea levels persists, the loss of fertile land, intrusion of saline water, and erosional processes collectively pose significant hardships to susceptible coastal communities. Devastating floods and landslides are possible results of excessive precipitation. To solve these concerns, it is essential to promote climate-resilient infrastructure, fortified early warning systems, and meticulously devised disaster preparedness protocols.

The countries and regions mentioned earlier encounter a range of climate-associated issues, encompassing alterations in precipitation patterns, scarcity of water, intensified extreme weather occurrences, and the elevation of sea levels. To safeguard communi-

ties, ecosystems, and economies in these susceptible areas, targeted climate adaptation strategies must be swiftly enacted.

The results of this study, identifying areas of risk as hotspots under the SSP2-4.5 scenario, are consistent with this middle-of-the-road scenario's features. The varying consequences seen in the selected hotspots are reflected in the moderate hurdles to adaptation efforts that are expected in SSP2-4.5. Regions with higher weighted SED values are likely to see a variety of environmental changes as a result of the 2.7°C increase in temperature projected for the end of the century, including altered precipitation patterns, more frequent extreme weather events, and water scarcity. In light of gradual but considerable climate change, these difficulties emphasize the necessity for comprehensive and focused climate adaptation methods.

The analysis reveals similarities to the near-term estimates for the extended horizon (2076-1999) within the SSP2-4.5 framework (see Figure 3.2). Equatorial zones like China, Japan, and Indonesia persist in confronting amplified climate adversities, while the Eastern United States, Central America, and coastal sectors of South America endure susceptibilities to climate-related influences. Southern Africa is nevertheless plagued by prolonged droughts and declining water supplies. The Mediterranean and Western Europe are particularly exposed to the effects of changing precipitation trends and catastrophic weather occurrences. South and Southeast Asian coastal areas, in particular, continue to be at risk from high precipitation events and sea level rise. The persistence of these patterns highlights the ongoing importance of specialized climate adaptation methods to foster resilience and negotiate the changing aspects of climate change issues in various fields. Incorporating population-weighted SED values improves our understanding of the possible effects of climate change on ecosystems and societal groups.

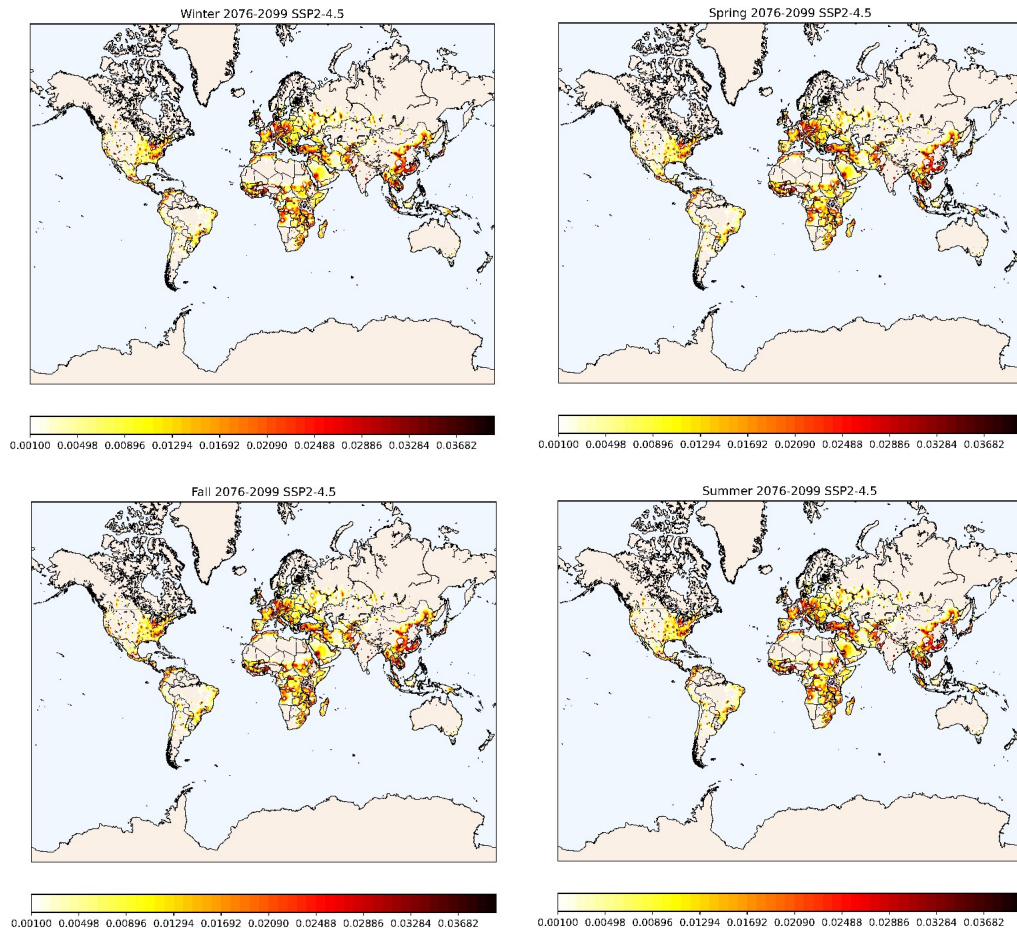


Figure 3.2. Population weighted SED values under the SSP2-4.5 scenario for the years 2076-2099 for 4 different season.

In the context of the SSP3-7.0 scenario, often referred to as the “Regional rivalry scenario,” long-term projections (2076-2099) paint a picture of sustained elevated emissions of greenhouse gases and a consistent upward trajectory in temperatures. Forecasts suggest a scenario where CO₂ emissions experience an almost twofold increase from their current levels by the close of the century, ultimately resulting in an anticipated surge of 3.6°C above the pre-industrial temperature baseline. This scenario is characterized by increased international competition as countries prioritize national and food security. In this context, it is envisaged that adaptation will present significant challenges while mitigation efforts remain relatively neglected.

During the analysis of the near future period (2026-2050) under the SSP2-4.5 and SSP3-7.0 scenarios, it was determined that the visual differences between them were less pronounced than they were. Several variables could contribute to this difficulty. Initially, the magnitude of change in climate indicators for both scenarios during this period may be similar, resulting in subtle variations in the plotted data. In addition, the overlap of uncertainty ranges between the projections of various climate models and scenarios may further obscure distinctions. In addition, the seasonal variability of climate indicators may exhibit similar patterns across seasons for both scenarios, making visual differentiation difficult. Additional quantitative analysis using statistical tests to ascertain the significance of variations between situations as well as additional visualizations like difference plots or comparative distributions can be used to address this problem and enhance the interpretability of the results.

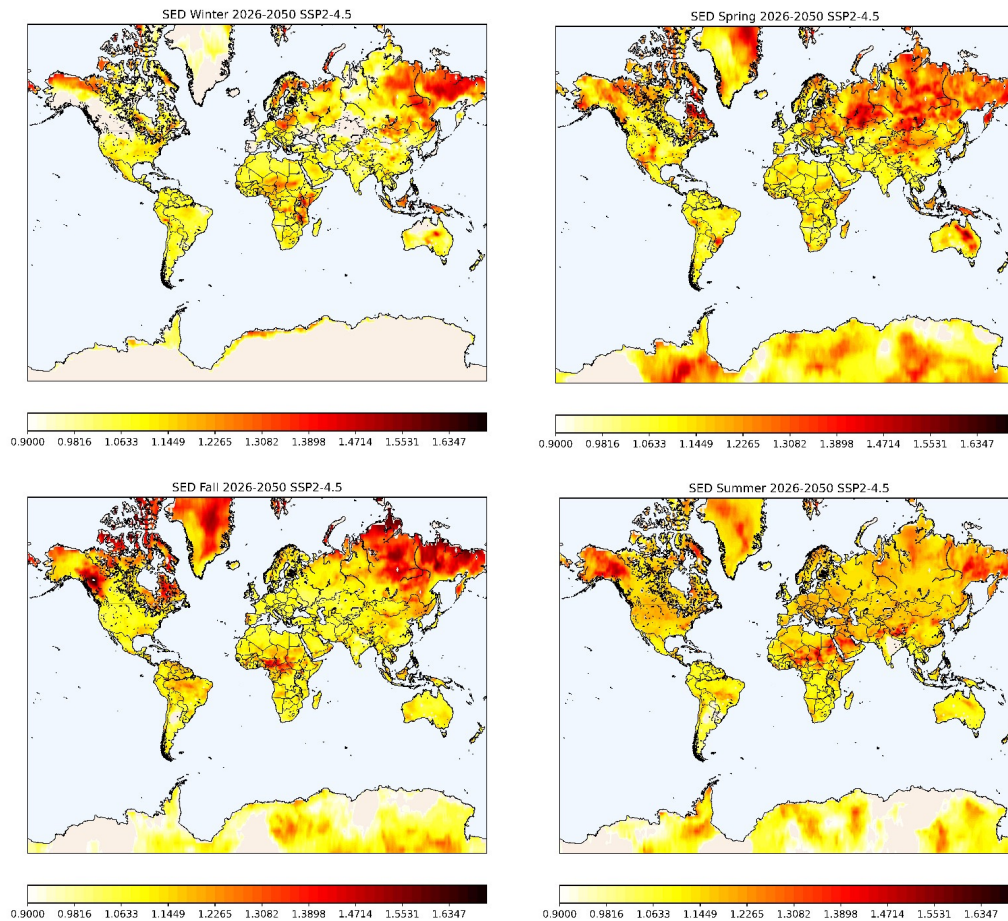


Figure 3.3. SED values under the SSP2-4.5 scenario for the years 2026-2050 for 4 different season.

When examining the near-future SED values for the SSP2-4.5 scenario Figure 3.3, the north of Russia, Canada, Greenland, South America, and Central Africa have been identified as hotspots. Unlike the population-weighted SED analysis, the risk of places with a dense population could not be emphasized because the effect of 7 climate indicators came to the fore. When the SED analysis results are compared with similar studies in the past (Fan *et al.*, 2021), similar patterns are seen. In these studies (Fan *et al.*, 2021), there was no significant difference between the near-term SED distributions of the SSP2-4.5 and SSP3-7.0 scenarios, as in our study.

In the realm of future research and improvements, several promising directions emerge. Refining the normalization process is essential, necessitating reducing the dominant influence of population density and exploring alternative normalization methods. Additionally, incorporating secondary variables like GDP per capita could offer a more comprehensive risk assessment. Regional and seasonal hotspot analysis can be pursued to enhance precision, allowing for tailored climate adaptation strategies. Exploring a more comprehensive array of climate scenarios beyond SSP2-4.5 and SSP3-7.0 holds the potential to provide deeper insights into diverse vulnerability trajectories. Tackling data limitations is pivotal, involving the integration of additional climate indicators and a nuanced understanding of uncertainties in climate models. Lastly, acknowledging socio-economic dynamics as influencers of vulnerability underscores the importance of comprehending policy decisions and socio-economic inequalities. These future paths promise a more comprehensive and refined understanding of climate change impacts, guiding more effective and targeted adaptation strategies.

4. CONCLUSION

This study employs a hotspot methodology coupled with population-weighted Standard Euclidean Distance (SED) measurements, yielding valuable insights into climate change risks across diverse geographical regions. Notably, equatorial areas like China, Japan, and Indonesia emerge as hotspots within the SSP2-4.5 scenario (2026-2050), are at risk from the interplay of changing climate patterns and population density. These regions face heightened risks, including rising sea levels, intensified extreme weather events, and prolonged heatwaves, accentuating their susceptibility to cumulative climate impacts.

The investigation further pinpoints risk zones encompassing the Americas, Southern Africa, the Mediterranean, Western Europe, and Asia. The spectrum of climate-related concerns, from erratic precipitation patterns to droughts and limited water availability, cast a shadow over critical aspects such as food security, agricultural yield, and economic equilibrium. Crafting adaptive measures fine-tuned to the distinct needs of ecosystems, economies, and communities is essential to balance these impending challenges effectively.

Furthermore, the findings under the SSP2-4.5 scenario align with the characteristics of this middle-of-the-road pathway, which projects moderate challenges to adaptation efforts. As temperatures rise, regions with higher weighted SED values will likely face a combination of environmental changes, emphasizing the need for comprehensive and targeted climate adaptation strategies. Looking towards the distant future (2076-2099) under the SSP2-4.5 scenario, the analysis reveals similar patterns to the near future results, indicating the persistence of heightened climate challenges in specific regions. The identified hotspots continue to face climate impacts, necessitating ongoing efforts to build resilience and address the evolving challenges of climate change.

On the other hand, under the SSP3-7.0 scenario, characterized by increased greenhouse gas emissions and steady temperature rise, adaptation challenges are expected to be high. At the same time, mitigation efforts are neglected. This scenario highlights the importance of addressing climate change globally to tackle its challenges effectively. In interpreting the near future results, it was observed that the differences between the SSP2-4.5 and SSP3-7.0 scenarios were less pronounced than expected. This could be attributed to the similarity in the magnitude of change in climate indicators for both scenarios during this period, the overlap of uncertainty ranges between projections and the seasonal variability of climate indicators exhibiting similar patterns. Additional quantitative analysis and visualizations can be employed to discern better and understand these differences' significance.

In summary, this work advances our knowledge of climate change hotspots. It emphasizes the necessity of thorough and focused methods to deal with how climate change affects both the environment and human populations. By combining innovative methodologies and considering a range of scenarios, we are better prepared to navigate the challenges of climate change and work toward a resilient and sustainable future. Future research endeavors should focus on refining assessment methodologies, exploring diverse scenarios, addressing data limitations, and integrating socioeconomic factors for a more comprehensive understanding of climate change impacts and the effective formulation of adaptation strategies.

REFERENCES

- Abdullah, A., M. Bhuian, G. Kiselev, A. Dewan, Q. Hasan and M. Rafiuddin, 2020, “Extreme Temperature and Rainfall Events in Bangladesh: A Comparison Between Coastal and Inland Areas”, *International Journal of Climatology*, Vol. 42, pp. 3253-3273.
- Al-Ghamdi, A. and J. Harrington, 2019, “Synoptic Climatology and Sea Surface Temperatures Teleconnections for Warm Season Heat Waves”, *Atmospheric Research*, Saudi Arabia.
- Almazroui, M., M. Ashfaq, M. N. Islam, I. U. Rashid, S. Kamil, M. A. Abid, E. O’Brien, M. Ismail, M. S. Reboita, A. A. Sörensson, P. A. Arias, L. M. Alves, M. K. Tippett, S. Saeed, R. Haarsma, F. J. Doblas-Reyes, F. Saeed, F. Kucharski, I. Nadeem, Y. Silva-Vidal, J. A. Rivera, M. A. Ehsan, D. Martínez-Castro, Á. G. Muñoz, M. A. Ali, E. Coppola and M. B. Sylla, 2021, “Assessment of CMIP6 Performance and Projected Temperature and Precipitation Changes Over South America”, *Earth Systems and Environment*, Vol. 5, pp. 155-183.
- Amare, A. and B. Simane, 2017, “Climate Change Induced Vulnerability of Smallholder Farmers: Agroecology-Based Analysis in the Muger Sub-Basin of the Upper Blue-Nile Basin of Ethiopia”, *American Journal of Climate Change*, Vol. 6, pp. 668-693.
- Bell, J., C. Brown, K. Conlon, S. Herring, K. Kunkel, J. Lawrimore, G. Luber, C. Schreck, A. Smith and C. Uejio, 2018, “Changes in Extreme Events and the Potential Impacts on Human Health”, *Journal of the Air and Waste Management Association*, Vol. 68, pp. 265 - 287.
- Bi, D., M. Dix, S. Marsland, S. O’Farrell, A. Sullivan, R. Bodman, R. Law, I. Harman, J. Srbinovsky, H. Rashid, P. Dobrohotoff, C. Mackallah, H. Yan, A. Hirst, A. Savita,

F. Dias, M. Woodhouse, R. Fiedler and A. Heerdegen, 2020, “Configuration and Spin-up of ACCESS-CM2, the New Generation Australian Community Climate and Earth System Simulator Coupled Model”, *Journal of Southern Hemisphere Earth Systems Science*, Vol, 70, No. 1, pp. 225-251.

Chen, J., F. Brissette, A. Poulin and R. Leconte, 2011, “Overall Uncertainty Study of the Hydrological Impacts of Climate Change for A Canadian Watershed”, *Water Resources Research*, Vol. 47, No. 12, pp. 123-140.

The Coupled Model Intercomparison Project (CMIP), 2023, <https://www.wcrp-climate.org/wgcm-cmip>, accessed on May 07, 2023.

Constantine, M., M. Kim and J. Park, 2019, “Mid- To Late Holocene Cooling Events in the Korean Peninsula and Their Possible Impact on Ancient Societies”, *Quaternary Research*, Vol. 92, pp. 98-108.

Conway, D., E. Garderen, D. Deryng, S. Dorling, T. Krueger, W. Landman, B. Lankford, K. Lebek, T. Osborn, C. Ringler, J. Thurlow, T. Zhu and C. Dalin, 2014, “Climate and Southern Africa’s Water-Energy-Food Nexus”, *Nature Climate Change*, Vol. 5, pp. 837-846.

Copernicus Climate Change Service, Climate Data Store, CMIP6 Climate Projections. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), 2021 <https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip6?tab=overview>, accessed on June 08, 2023.

Cos, J., F. Doblas-Reyes, M. Jury, R. Marcos, P. A. Bretonniere and M. Samsó, 2022, “The Mediterranean Climate Change Hotspot in the CMIP5 and CMIP6 Projections”, *Earth System Dynamics*, Vol. 13, No. 1, pp. 321-340.

Crespo, O., S. Hachigonta and M. Tadross, 2011, “Sensitivity of Southern African

- Maize Yields to the Definition of Sowing Dekad in A Changing Climate”, *Climatic Change*, Vol. 106, pp. 267-283.
- De Sherbinin, A., 2014, “Climate Change Hotspots Mapping: What Have We Learned?”, *Climate. Change*, Vol. 123, No. 1, pp. 23-37.
- Demory, M. and S. Berthou, 2020, “European Daily Precipitation According to EURO-CORDEX Regional Climate Models (RCMs) and High-Resolution Global Climate Models (GCMs) from the High-Resolution Model Intercomparison Project (High-ResMIP)”, *Geoscientific Model Development*, Vol. 13, No. 1, pp. 5485-5506.
- Diallo, I., M. Sylla, F. Giorgi, A. Gaye and M. Camara, 2012, “Multimodel GCM-RCM Ensemble-Based Projections of Temperature and Precipitation over West Africa for the Early 21st Century”, *International Journal of Geophysics*, Vol. 12, pp. 1-19.
- Diffenbaugh, N. S., F. Giorgi and J. S. Pal, 2008, “Climate Change Hotspots in the United States”, *Geophysical Research Letters*, Vol. 35, No. 16, pp. 135-158.
- Döscher, R., M. Acosta, A. Alessandri, P. Anthoni, T. Arsouze, T. Bergman, R. Bernardello, S. Boussetta, L. Caron, G. Carver, M. Castrillo, F. Catalano, I. Cvijanovic, P. Davini, E. Dekker, F. Doblas-Reyes, D. Docquier, P. Echevarria, U. Fladrich, R. Fuentes-Franco, M. Gröger, J. Hardenberg, J. Hieronymus, M. Karami, J. Keskinen, T. Koenigk, R. Makkonen, F. Massonnet, M. Ménégoz, P. Miller, E. Moreno-Chamarro, L. Nieradzic, T. Noije, P. Nolan, D. O’Donnell, P. Ollinaho, G. Oord, P. Ortega, O. Prims, A. Ramos, T. Reerink, C. Rousset, Y. Ruprich-Robert, P. Sager, T. Schmith, R. Schrödner, F. Serva, V. Sicardi, M. Madsen, B. Smith, T. Tian, E. Tourigny, P. Uotila, M. Vancoppenolle, S. Wang, D. Wårlind, U. Willén, K. Wyser, S. Yang, X. Yepes-Arbós and Q. Zhang, 2022, “The EC-Earth3 Earth System Model for the Coupled Model Intercomparison Project 6”, *Geoscientific Model Development*, Vol. 685, pp. 2973- 3020.

- Dubrovský, M., M. Hayes, P. Duce, M. Trnka, M. Svoboda and P. Zara, 2014, “Multi-GCM Projections of Future Drought and Climate Variability Indicators for the Mediterranean Region”, *Regional Environmental Change*, Vol. 14, pp. 1907-1919.
- Endo, H. and A. Kitoh, 2016, “Projecting Changes of the Asian Summer Monsoon Through the Twenty-First Century”, *The Monsoons And Climate Change: Observations and Modeling*, Vol. 12, pp. 47-66.
- Estrada, F., P. Perron and Y. Yamamoto, 2023, “Anthropogenic Influence on Extremes and Risk Hotspots”, *Scientific Reports*, Vol. 13, pp. 35-40.
- Eyring, V., S. Bony, G. Meehl, C. Senior, B. Stevens, S. Ronald and K. Taylor, 2015, “Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) Experimental Design and Organisation”, *Geoscientific Model Development Discussions*, Vol. 8, pp. 539-583.
- Fan, X., C. Miao, Q. Duan, C. Shen and Y. Wu, 2021, “Future Climate Change Hot-Spots Under Different 21st Century Warming Scenarios”, *Earth's Future*, Vol. 9, No. 6, pp. 2027-2065.
- Geiges, A., P. Yanguas-Parra, M. Andrijevic, B. Hare, A. Nauels, P. Pfleiderer, M. Schaeffer and C. F. Schleussner, 2019, “Incremental Improvements of 2030 Targets Insufficient to Achieve the Paris Agreement Goals”, *Earth System Dynamics Discussions*, Vol. 1, pp. 1-18.
- Giorgi, F., 2006, “Climate Change Hot-Spots”, *Geophysical Research Letters*, Vol. 33, No. 8, pp. 8707-8747.
- Grassl, H., 2000, “Status and Improvements of Coupled General Circulation Models”, *Science*, Vol. 288, No. 5473, pp. 1991-1997.

- Griggs, G. and B. Reguero, 2021, “Coastal Adaptation to Climate Change and Sea-Level Rise”, *Water*, Vol, 13, No. 16, pp. 2151-2171.
- Grose, M., S. Narsey, F. Delage, A. Dowdy, M. Bador, G. Boschat, C. Chung, J. Kajtar, S. Rauniyar, M. Freund, K. Lyu, H. Rashid, X. Zhang, S. Wales, C. Trenham, N. Holbrook, T. Cowan, L. Alexander, J. Arblaster and S. Power, 2020, “Insights From CMIP6 for Australia’s Future Climate”, *Earth’s Future*, Vol. 8, pp. 458- 490.
- Gutowski, W., P. Ullrich, A. Hall, L. Leung, T. O’Brien, C. Patricola, R. Arritt, M. Bukovsky, K. Calvin, Z. Feng, A. Jones, G. Kooperman, E. Monier, M. Pritchard, S. Pryor, Y. Qian, A. Rhoades, A. Roberts, K. Sakaguchi, N. Urban and C. Zarzycki, 2020, “The Ongoing Need for High-Resolution Regional Climate Models: Process Understanding and Stakeholder Information”, *Bulletin of the American Meteorological Society*, Vol. 101, No. 5, pp. E664-E683.
- Hackenbruch, J., G. Schädler and J. Schipper, 2016, “Added Value of High-Resolution Regional Climate Simulations for Regional Impact Studies”, *Meteorologische Zeitschrift*, Vol. 25, pp. 291-304.
- Hale T, S. M. Smith, R. Black, K. Cullen, B. Fay, J. Lang and S. Mahmood, 2022, “Assessing the Rapidly-Emerging Landscape of Net Zero Targets”, *Climate Policy*, Vol. 22, No. 1, pp. 18-29.
- Harris, I., T. Osborn, P. Jones and D. Lister, 2020, “Version 4 of the CRU TS Monthly High-Resolution Gridded Multivariate Climate Dataset”, *Scientific Data*, Vol. 7, No. 1, pp. 109-130.
- Harris, S. and A. Mix, 2002, “Climate and Tectonic Influences on Continental Erosion of Tropical South America”, *Geology*, Vol. 30, No. 5, pp. 447-450.
- Hawkins, E. and R. Sutton, 2011, “The Potential to Narrow Uncertainty in Projections

of Regional Precipitation Change”, *Climate Dynamics*, Vol. 37, pp. 407-418.

Hay, J. and N. Mimura, 2010, “The Changing Nature of Extreme Weather and Climate Events: Risks to Sustainable Development”, *Geomatics, Natural Hazards and Risk*, Vol. 1, pp. 18-30.

Hay, J. and N. Mimura, 2013, “Vulnerability, Risk and Adaptation Assessment Methods in the Pacific Islands Region: past approaches, and considerations for the Future”, *Sustainability Science*, Vol. 8, pp. 391-405.

Höhne, N., M. Gidden, M. den Elzen, F. Hans, C. Fryson, A. Geiges, M. L. Jeffery, S. Gonzales-Zuñiga, S. Mooldijk, W. Hare and J. Rogelj, 2021, “Wave of Net Zero Emission Targets Opens Window to Meeting the Paris Agreement”, *Nature Climate Change*, Vol. 11, pp. 820-822.

Huang, R. and L. Tian, 2020, “CO2 Emissions Inequality Through the Lens of Developing Countries”, *Applied Energy*, Vol. 281, pp. 116043-116043.

International Energy Agency (IEA), 2021, *Net Zero by 2050: A Roadmap for the Global Energy Sector*, Organisation for Economic Co-operation and Development (OECD) Publishing, Paris.

Jesus, E., R. Rocha, N. Crespo, M. Reboita and L. Gozzo, 2020, “Multi-Model Climate Projections of the Main Cyclogenesis Hot-Spots and Associated Winds Over the Eastern Coast of South America”, *Climate Dynamics*, Vol. 56, pp. 537-557.

Jones, C., 2020, “So What Is in an Earth System Model?”, *Journal of Advances in Modeling Earth Systems*, Vol. 12, pp. 19-46.

Kan, H., 2011, “Climate Change and Human Health in China”, *Environmental Health Perspectives*, Vol. 119, pp. A60-A61.

- Kawamiya, M., T. Hajima, K. Tachiiri, S. Watanabe and T. Yokohata, 2020, “Two Decades of Earth System Modeling with an Emphasis on Model for Interdisciplinary Research on Climate (MIROC)”, *Progress in Earth and Planetary Science*, Vol.7, pp. 64-90.
- Kerkhoven, E. and T. Gan, 2006, “A Modified ISBA Surface Scheme for Modeling the Hydrology of Athabasca River Basin with GCM-Scale Data”, *Advances in Water Resources*, Vol. 29, pp. 808-826.
- Khadka, D., M. Babel, A. Abatan and M. Collins, 2021, “An Evaluation of CMIP5 and CMIP6 Climate Models in Simulating Summer Rainfall in the Southeast Asian Monsoon Domain”, *International Journal of Climatology*, Vol. 42, pp. 1181-1202.
- Khalili, M. and V. Nguyen, 2017, “An Efficient Statistical Approach to Multi-Site Downscaling of Daily Precipitation Series in the Context of Climate Change”, *Climate Dynamics*, Vol. 49, pp. 2261-2278.
- Kirk-Davidoff, D., 2008, “On the Diagnosis of Climate Sensitivity Using Observations of Fluctuations”, *Atmospheric Chemistry and Physics*, Vol. 9, pp. 813-822.
- Kriegler, E., J. Edmonds, S. Hallegatte, K. Ebi, T. Kram, K. Riahi, H. Winkler and D. Vuuren, 2014, “A New Scenario Framework for Climate Change Research: The Concept of Shared Climate Policy Assumptions”, *Climatic Change*, Vol. 122, pp. 109-140.
- Kvasov, R., S. Cruz-Pol, J. Colom-Ustariz, L. Leon-Colon and P. Rees, 2013, Weather radar data visualization using first-order interpolation, 2013, *Institute of Electrical and Electronics Engineers (IEEE) International Geoscience and Remote Sensing Symposium - International Geoscience and Remote Sensing Symposium (IGARSS)*, Melbourne, VIC, Australia.

- Lamarque, J. F., C. Senior, M. Schlund, G. Flato, S. Ronald and K. Taylor, 2020, “Context for Interpreting Equilibrium Climate Sensitivity and Transient Climate Response from the CMIP6 Earth System Models”, *Science Advances*, Vol. 6, pp. 26-50.
- Lange, S., J. Volkholz, T. Geiger, F. Zhao, I. Vega, T. Veldkamp, C. Reyer, L. Warszawski, V. Huber, J. Jägermeyr, J. Schewe, D. Bresch, M. Büchner, J. Chang, P. Ciais, M. Dury, K. Emanuel, C. Folberth, D. Gerten, S. Gosling, M. Grillakis, N. Hanasaki, A. Henrot, T. Hickler, Y. Honda, A. Ito, N. Khabarov, A. Koutroulis, W. Liu, C. Müller, K. Nishina, S. Ostberg, H. Müller Schmied, S. Seneviratne, T. Stacke, J. Steinkamp, W. Thiery, Y. Wada, S. Willner, H. Yang, M. Yoshikawa, C. Yue and K. Frieler, 2020, “Projecting Exposure to Extreme Climate Impact Events Across Six Event Categories and Three Spatial Scales”, *Earth’s Future*, Vol. 8, pp. 907-970.
- Le, T. and D. Bae, 2020, “Response of Global Evaporation to Major Climate Modes in Historical and Future Coupled Model Intercomparison Project Phase 5 Simulations”, *Hydrology and Earth System Sciences*, Vol. 24, pp. 1131-1143.
- Legates, D. and T. DeLiberty, 2007, “Precipitation Measurement Biases in the United States”, *Journal of the American Water Resources Association (JAWRA)*, Vol. 29, pp. 855-861.
- López-Carr, D., N. Pricope, J. Aukema, M. Jankowska, C. Funk, G. Husak and J. Michaelsen, 2014, “A Spatial Analysis of Population Dynamics and Climate Change in Africa: Potential Vulnerability Hot Spots Emerge where Precipitation Declines and Demographic Pressures Coincide”, *Population and Environment*, Vol. 35, pp. 323-339.
- Lovelli, S., M. Perniola, E. Scalcione, A. Troccoli, and L. Ziska, 2012, “Future Climate Change in the Mediterranean Area: Implications for Water Use and Weed

- Management”, *Italian Journal of Agronomy*, Vol. 7, pp. 7-27.
- Maraun, D., 2016, “Bias Correcting Climate Change Simulations - A Critical Review”, *Current Climate Change Reports*, Vol. 2, pp. 211-220.
- Matsushita, B., M. Xu, J. Chen, S. Kameyama, and M. Tamura, 2004, “Estimation of Regional Net Primary Productivity (NPP) Using A Process-Based Ecosystem Model: How Important is the Accuracy of Climate Data?”, *Ecological Modelling*, Vol. 178, pp. 371-388.
- Mendelsohn, R., K. Emanuel, S. Chonabayashi, and L. Bakkensen, 2012, “The Impact of Climate Change on Global Tropical Cyclone Damage”, *Nature Climate Change*, Vol. 2, pp. 205-209.
- Mo, K. and E. Berbery, 2011, “Drought and Persistent Wet Spells over South America Based on Observations and the U.S. CLIVAR Drought Experiments”, *Journal of Climate*, Vol. 24, pp. 1801-1820.
- Mollier-Vogel, E., G. Leduc, T. Bösch, P. Martinez and R. Schneider, 2013, “Rainfall Response to Orbital and Millennial Forcing in Northern Peru Over the Last 18 ka”, *Quaternary Science Reviews*, Vol. 76, pp. 29-38.
- Moser, S., R. Kasperson, G. Yohe and J. Agyeman, 2008, “Adaptation to Climate Change in the Northeast United States: Opportunities, Processes Constraints”, *Mitigation and Adaptation Strategies for Global Change*, Vol. 13, pp. 643-659.
- Notz, D., A. Jahn, M. Holland, E. Hunke, F. Massonnet, J. Stroeve, B. Tremblay and M. Vancoppenolle, 2016, “The CMIP6 Sea-Ice Model Intercomparison Project (SIMIP): Understanding Sea Ice Through Climate-Model Simulations”, *Geoscientific Model Development*, Vol. 9, pp. 139-160.

- O'Neill B. C., C. Tebaldi, D. P. van Vuuren, V. Eyring, P. Friedlingstein, G. Hurtt, R. Knutti, E. Kriegler, J. F. Lamarque, J. Lowe, G. A. Meehl, R. Moss, K. Riahi and B. M. Sanderson, 2016, "The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6", *Geoscientific Model Development*, Vol. 9, pp. 3461-3482.
- O'Neill, B. C., E. Kriegler, K. L. Ebi, E. Kemp-Benedict, K. Riahi, D. S. Rothman, B. J. van Ruijven, D. P. van Vuuren, J. Birkmann, K. Kok, M. Levy and W. Solecki, 2016a, "The Roads Ahead: Narratives for Shared Socioeconomic Pathways Describing World Futures in the 21st Century", *Global environmental change*, Vol. 42, pp.153-168.
- Olonscheck, D. and D. Notz, 2017, "Consistently Estimating Internal Climate Variability from Climate Model Simulations", *Journal of Climate*, Vol. 30, pp. 9555-9573.
- Orimoloye, I., S. Mazinyo, A. Kalumba, O. Ekundayo and W. Nel, 2019, "Implications of Climate Variability and Change on Urban and Human Health: A Review", *Cities*, Vol. 91, pp. 213-223.
- Öztürk, T., Z. P. Ceber, M. Türkeş and M. L. Kurnaz, 2015, "Projections of Climate Change in the Mediterranean Basin by Using Downscaled Global Climate Model Outputs", *International Journal of Climatology*, Vol. 35, No. 14, pp. 4276-4292.
- Öztürk, T., M. T. Turp, M. Türkeş and M. L. Kurnaz, 2017, "Projected Changes in Temperature and Precipitation Climatology of Central Asia CORDEX Region 8 by using RegCM1.4", *Atmospheric Research*, Vol. 183, pp. 296-307.
- Öztürk, T., M. T. Turp, M. Türkeş and M. L. Kurnaz, 2018, "Future Projections of Temperature and Precipitation Climatology for CORDEX-MENA Domain Using RegCM4.4", *Atmospheric Research*, Vol. 206, pp. 87-107.
- Öztürk, T., F. S. Saygili-Araci, and M. L. Kurnaz, 2021, "Projected Changes in Ex-

treme Temperature and Precipitation Indices Over CORDEX-MENA Domain”, *Atmosphere*, Vol. 12, No. 5, pp. 622.

Perera, A., V. Nik, D. Chen, J. Scartezini and T. Hong, 2020, “Quantifying the Impacts of Climate Change and Extreme Climate Events on Energy Systems”, *Nature Energy*, Vol. 5, pp. 150-159.

Pethick, J. and J. Orford, 2013, “Rapid Rise in Effective Sea-Level in Southwest Bangladesh: Its Causes and Contemporary Rates”, *Global and Planetary Change*, Vol. 111, pp. 237-245.

Petrie, R., S. Denvil, S. Ames, G. Levavasseur, S. Fiore, C. Allen, F. Antonio, K. Berger, P. A. Bretonnière, L. Cinquini, E. Dart, P. Dwarakanath, K. Druken, B. Evans, L. Franchistéguy, S. Gardoll, E. Gerbier, M. Greenslade, D. Hassell, A. Iwi, M. Jukes, S. Kindermann, L. Lacinski, M. Mirto, A. B. Nasser, P. Nassisi, E. Nienhouse, S. Nikonov, A. Nuzzo, C. Richards, S. Ridzwan, M. Rixen, K. Serradell, K. Snow, A. Stephens, M. Stockhause, H. Vahlenkamp and R. Wagner, 2021, “Coordinating an Operational Data Distribution Network for CMIP6 Data”, *Earth Systems and Environment*, Vol. 14, pp. 629-644.

Pratt, W. K., 1991, *Digital Image Processing*, Second Edition, Wiley-Interscience, New York.

Riahi, K., D. P. Van Vuuren, E. Kriegler, J. Edmonds, B. C. O’Neill and S. Fujimori, N. Bauer, K. Calvin, R. Dellink, O. Fricko, W. Lutz, A. Popp, J. C. Cuaresma, M. Leimbach, L. Jiang, T. Kram, S. Rao, J. Emmerling, K. Ebi, T. Hasegawa, P. Havlik, F. Humpenöder, L. A. D. Silva, S. Smith, E. Stehfest, V. Bosetti, J. Eom, D. Gernaat, T. Masui, J. Rogelj, J. Streffer, L. Drouet, V. Krey, G. Luderer, M. Harmsen, K. Takahashi, L. Baumstark, J. C. Doelman, M. Kainuma, Z. Klimont, G. Marangoni, H. Lotze-Campen, M. Obersteiner, A. Tabeau, M. Tavoni, 2017, “The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas

- Emissions Implications: An Overview”, *Global Environmental Change*, Vol. 42, pp. 153-168.
- Ribes, A., S. Thao, R. Vautard, B. Dubuisson, S. Somot, J. Colin, S. Planton and J. Soubeyroux, 2018, “Observed Increase in Extreme Daily Rainfall in the French Mediterranean”, *Climate Dynamics*, Vol. 52, pp. 1095-1114.
- Rogelj, J., D. Shindell, K. Jiang, S. Fifita, P. Forster, V. Ginzburg, C. Handa, H. Kheshgi, S. Kobayashi, E. Kriegler, L. Mundaca, R. Séférian, and M. V. Vilariño, 2018, *Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. In: Global Warming of 1.5°C, An IPCC Special Report on The Impacts of Global Warming of 1.5°C Above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*, Cambridge University Press, Cambridge, UK and New York, NY, USA.
- Ronald, S., V. Eyring, G. Meehl, S. Bony, C. Senior, B. Stevens and K. Taylor, 2016, “Coupled Model Intercomparison Project (CMIP5) Scientific Gaps and Recommendations for Coupled Model Intercomparison Project (CMIP6)”, *Bulletin of the American Meteorological Society*, Vol. 98, No. 1, pp. 95-105.
- Rose, R., 2015, “The Impact of Climate Change on Human Security in the Sahel Region of Africa”, *Journal of African Studies*, Vol. 1, pp. 9-14.
- Różyński, G., N. Hung and R. Ostrowski, 2009, “Climate Change Related Rise of Extreme Typhoon Power and Duration Over South-East Asia Seas”, *Coastal Engineering Journal*, Vol. 51, pp. 205-222.
- Ruffault, J., T. Curt, V. Moron, R. Trigo, F. Mouillot, N. Koutsias, F. Pimont, N. Martin-StPaul, R. Barbero, J. Dupuy, A. Russo and C. Belhadj-Kheder, 2020, “Increased Likelihood of Heat-Induced Large Wildfires in the Mediterranean Basin”,

Scientific Reports, Vol. 10, pp. 13790-13820.

- Sang, Y., H. Ren, X. Shi, X. Xu and H. Chen, 2020, “Improvement of Soil Moisture Simulation in Eurasia by the Beijing Climate Center Climate System Model from Coupled Model Intercomparison Project (CMIP5) to Coupled Model Intercomparison Project (CMIP6)”, *Advances in Atmospheric Sciences*, Vol. 38, pp. 237-252.
- Sarker, M., M. Wu, G. Alam and R. Shouse, 2019, “Livelihood Vulnerability of Riverine-Island Dwellers in the Face of Natural Disasters in Bangladesh”, *Sustainability*, Vol. 11, No. 6 pp. 1623-1667.
- Schiemann, R., P. Vidale, L. Shaffrey, S. Johnson, M. Roberts, M. Demory, M. Mizielinski and J. Strachan, 2018, “Mean and Extreme Precipitation Over European River Basins Better Simulated in A 25Km Autorità Garante della Concorrenza e del Mercato (AGCM)”, *Hydrology and Earth System Sciences*, Vol. 22, No. 7, pp. 3933-3950.
- Schrier, G., L. Rasmijn, J. Barkmeijer, A. Sterl and W. Hazeleger, 2018, “The 2010 Pakistan Floods In A Future Climate”, *Climatic Change*, Vol. 148, pp. 205-218.
- Scoccimarro, E., D. Peano, S. Gualdi, A. Bellucci, T. Lovato, P. Fogli and A. Navarra, 2022, “Extreme Events Representation in Centro Euro-Mediterraneo sui Cambiamenti Climatici - Climate Model Version 2 (CMCC-CM2) Standard And High-Resolution General Circulation Models”, *Geoscientific Model Development*, Vol. 15, No. 4, pp. 1841-1854.
- Serdeczny, O., S. Adams, F. Baarsch, D. Coumou, A. Robinson, W. Hare, M. Schaeffer and M. Perrette and J. Reinhardt, 2017, “Climate Change Impacts In Sub-Saharan Africa: From Physical Changes To Their Social Repercussions”, *Regional Environmental Change*, Vol. 17, pp. 1585-1600.

- Shao, X., M. Stein and J. Ching, 2007, “Statistical Comparisons of Methods for Interpolating the Output of A Numerical Air Quality Model”, *Journal of Statistical Planning and Inference*, Vol. 137, pp. 2277-2293.
- Shao, X., M. Stein and J. Ching, 2007, “Statistical Comparisons of Methods for Interpolating the Output of A Numerical Air Quality Model”, *Journal of Statistical Planning and Inference*, Vol. 137, pp. 2277-2293.
- Shen, Z., A. Duan, D. Li and J. Li, 2021, “Assessment and Ranking of Climate Models in Arctic Sea Ice Cover Simulation: From Coupled Model Intercomparison Project (CMIP5) to Coupled Model Intercomparison Project (CMIP6)”, *Journal of Climate*, Vol. 34, pp. 1-56.
- Song, Y., E. Chung M. Shiru, 2020, “Uncertainty Analysis of Monthly Precipitation in Gas Chromatography-Mass Spectrometry (GCMS), Using Multiple Bias Correction Methods under Different Roanoke City Public Schools (RCPs)”, *Sustainability*, Vol. 12, pp. 256-270.
- Sospedra-Alfonso, R., W. Merryfield, G. Boer, V. Kharin, W. Lee, C. Seiler and J. Christian, 2021, “Decadal Climate Predictions with the Canadian Earth System Model Version 5 (CanESM5)”, *Geoscientific Model Development*, Vol. 14, No. 11, pp. 6863-6891.
- Stainforth, D., T. Aina, C. Christensen, M. Collins, N. Faull, D. Frame, J. Kettleborough, S. Knight, A. Martín, J. Murphy, C. Piani, D. Sexton, L. Smith, R. Spicer, A. Thorpe and M. Allen, 2005, “Uncertainty in Predictions of The Climate Response to Rising Levels of Greenhouse Gases”, *Nature*, Vol. 433, pp. 403-406.
- Stampfl, P., J. Clifton-Brown and M. Jones, 2007, “European-Wide GIS-Based System for Quantifying the Feedstock from Miscanthus and the Potential Contribution to Renewable Energy Targets”, *Global Change Biology*, Vol. 13, pp. 2283-2295.

- Staudt, A., A. K. Leidner, J. Howard, K. A. Brauman, J. S. Dukes, L. J. Hansen, C. Paukert, J. Sabo and L. A. Solórzano, 2013, “The Added Complications of Climate Change: Understanding and Managing Biodiversity and Ecosystems”, *Frontiers in Ecology and the Environment*, Vol. 11, No. 9, pp. 494-501.
- Tao, F., Z. Zhang and M. Yokozawa, 2011, “Dangerous Levels of Climate Change for Agricultural Production in China”, *Regional Environmental Change*, Vol. 11, pp. 41-48.
- Tuel, A. and E. Eltahir, 2020, “Why Is the Mediterranean a Climate Change Hot Spot?”, *Journal of Climate*, Vol. 33, No. 14, pp. 5829-5843.
- Turp, M. T., T. Öztürk, M. Türkeş and M. L. Kurnaz, 2015, “Assessment of Projected Changes in Air Temperature and Precipitation Over the Mediterranean Region Via Multimodel Ensemble Mean of Coupled Model Intercomparison Project (CMIP5) Models”, *Journal of the Black Sea/Mediterranean Environment*, Vol. 21, pp. 93-96.
- United Nations Environment Programme, 2022, “Emissions Gap Report 2022: The Closing Window-Climate Crisis Calls for Rapid Transformation of Societies, Nairobi”, 2022 [https:// www. unep.org/ emissions - gap - report - 2022](https://www.unep.org/emissions-gap-report-2022) accessed on December 17, 2022.
- Vacchi, M., M. Ghilardi, R. Melis, G. Spada, M. Giaime, N. Marriner, T. Lorscheid, C. Morhange, F. Burjachs and A. Rovere, 2018, “New Relative Sea - Level Insights Into the Isostatic History of the Western Mediterranean”, *Quaternary Science Reviews*, Vol. 201, pp. 396-408.
- Vale, C., C. Vale, J. Brito and J. Brito, 2015, “Desert-Adapted Species are Vulnerable to Climate Change: Insights from the Warmest Region on Earth”, *Global Ecology and Conservation*, Vol. 4, pp. 369-379.

- Van Vuuren D. P., J. Edmonds, M. Kainuma K. Riahi, A. Thomson, K. Hibbard, G. C. Hurtt, T. Kram, V. Krey, J. F. Lamarque, T. Masui, M. Meinshausen, N. Nakicenovic, S. J. Smith and S. K. Rose, 2011, “The Representative Concentration Pathways: An Overview”, *Clim Change*, Vol. 109, No. 1, pp. 5-31.
- Vuuren, D., E. Kriegler, B. O’Neill, K. Ebi, K. Riahi, T. Carter, J. Edmonds, S. Hallegatte, T. Kram, R. Mathur and H. Winkler, 2014, “A New Scenario Framework for Climate Change Research: Scenario Matrix Architecture”, *Climatic Change*, Vol. 122, pp. 373-386.
- Walker, X., M. Mack and J. Johnstone, 2015, “Stable Carbon Isotope Analysis Reveals Widespread Drought Stress in Boreal Black Spruce Forests”, *Global Change Biology*, Vol. 21, No. 8, pp. 3102-3113.
- Wang, Y., H. Hsu, C. Chen, W. Tseng, P. Hsu, Y. Chen, C. Lin, L. Jiang, Y. Lee, H. Liang and L. Chang, 2020, “Performance of the Taiwan Earth System Model in Simulating Climate Variability Compared With Observations and Coupled Model Intercomparison Project (CMIP6) Model Simulations”, *Journal of Advances in Modeling Earth Systems*, Vol. 13, No. 7, pp. 2353-2389.
- Weiskopf, S. R., M. A. Rubenstein, L. G. Crozier, S. K. Gaichas, R. B. Griffis, J. E. Halofsky, K. J. Hyde, T. L. Morelli, J. T. Morissette, R. C. Muñoz, A. J. Pershing, D. L. Peterson, R. P. Poudel, M. D. Staudinger, A. E. Sutton-Grier, L. M. Thompson, J. M., Vose, J. F. Weltzin and K. P. Whyte, 2020, “Climate Change Effects on Biodiversity, Ecosystems, Ecosystem Services, and Natural Resource Management in the United States”, *The Science of the Total Environment*, Vol. 733, pp. 137782-137799.
- Wilbanks, T., S. Kane, P. Leiby, R. Perlack, C. Settle, J. Shogren and J. Smith, 2003, “Possible Responses to Global Climate Change: Integrating Mitigation and Adaptation”, *Environment: Science and Policy for Sustainable Development*, Vol.

45, pp. 28-38.

Williams, J. W., S. T. Jackson and J. E. Kutzbach, 2007, “Projected Distributions of Novel and Disappearing Climates by 2100”, *AD, Proceedings of the National Academy of Sciences of the United States of America*, Vol. 104, No. 14, pp. 5738-5742.

Winne, J. and G. Peersman, 2021, “The Adverse Consequences of Global Harvest and Weather Disruptions on Economic Activity”, *Nature Climate Change*, Vol. 11, pp. 665-672.

Wyser, K., T. Noije, S. Yang, J. Hardenberg, D. O’Donnell and R. Döscher, 2020, “On the Increased Climate Sensitivity In The EC-Earth Model from Coupled Model Intercomparison Project (CMIP5) to Coupled Model Intercomparison Project (CMIP6)”, *Geoscientific Model Development*, Vol. 13, pp. 3465-3474.

Xu, H., H. Chen and H. Wang, 2021, “Future Changes in Precipitation Extremes Across China Based on Coupled Model Intercomparison Project (CMIP6) Models”, *International Journal of Climatology*, Vol. 42, pp. 635 - 651.

Xu, Y., X. Zhang, Z. Hao, F. Hao and C. Li, 2021, “Projections of Future Meteorological Droughts in China Under CMIP6 From A Three-Dimensional Perspective”, *Agricultural Water Management*, Vol. 252, pp. 106849-106862.

Yin, J., D. Yan, Z. Yang, Z. Yuan, Y. Yuan and C. Zhang, 2016, “Projection of Extreme Precipitation in the Context of Climate Change in Huang – Huai - Hai Region”, *China, Journal of Earth System Science*, Vol. 125, pp. 417-429.

Zelinka, M., T. Myers, D. Mccoy, S. Po-Chedley, P. Caldwell, P. Ceppi, S. Klein and K. Taylor, 2020, “Causes of Higher Climate Sensitivity in Coupled Model Intercomparison Project (CMIP6) Models”, *Geophysical Research Letters*, Vol. 47, No.1, pp.

85782-85798.

Zhai, J., S. Mondal, T. Fischer, Y. Wang, B. Su, J. Huang, H. Tao, G. Wang, W. Ullah and M. Uddin, 2020, “Future Drought Characteristics Through A Multi-Model Ensemble from Coupled Model Intercomparison Project (CMIP6) Over South Asia”, *Atmospheric Research*, Vol. 246, pp. 105111-105135.

Zhixin, Z. and X. Qiao, 2011, “Low-Carbon Economy, Industrial Structure and Changes In China’s Development Mode Based on the Data of 1996-2009 in Empirical Analysis”, *Energy Procedia*, Vol. 5, pp. 2025-2029.

Zhou, T., B. Wang, Y. Yu, Y. Liu, W. Zheng, L. Li, B. Wu, P. Lin, Z. Guo, W. Man, Q. Bao, A. Duan, H. Liu, X. Chen, B. He, J. Li, L. Zou, X. Wang, L. Zhang, Y. Sun and W. Zhang, 2018, “The Flexible Global Ocean-Atmosphere-Land System (FGOALS) Climate System Model as A Modeling Tool For Supporting Climate Sciences: An Overview”, *Earth and Planetary Physics*, Vol. 2, No. 4, pp. 276-291.

Zittis, G., M. Almazroui, P. Alpert, P. Ciais, W. Cramer, Y. Dahdal, M. Fnais, D. Francis, P. Hadjinicolaou, F. Howari, A. Jrrar, D. Kaskaoutis, M. Kulmala, G. Lazoglou, N. Mihalopoulos, X. Lin, Y. Rudich, J. Sciare, G. Stenchikov and J. Lelieveld, 2022, “Climate Change and Weather Extremes in the Eastern Mediterranean and Middle East”, *Reviews of Geophysics*, Vol. 60, No. 3 pp. 762-782.

Zittis, G., P. Hadjinicolaou, M. Almazroui, E. Bucchignani, F. Driouech, K. Elrhaz, L. Kurnaz, G. Nikulin, A. Ntoumos, T. Öztürk, Y. Proestos, G. Stenchikov, Z. Rashyd and J. Lelieveld, 2021, “Business – as - Usual will Lead to Super and Ultra - Extreme Heatwaves in the Middle East and North Africa”, *Climate and Atmospheric Science*, Vol. 4, No. 1, pp. 20.45.

Zittis, G., P. Hadjinicolaou, M. Fnais and J. Lelieveld, 2016, “Projected Changes in Heat Wave Characteristics in the Eastern Mediterranean”, *Middle East Regional*

Environmental Change, Vol. 16, pp. 1863-1876.