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CAMA Working Paper 37/2024
June 2024

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Abstract

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Keywords

climate change, extreme events, physical climate risks, macroeconomics, CGE, DSGE, machine learning

JEL Classification

C51, C53, C54, C55, C68, F41, Q51, Q54

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ISSN 2206-0332

GLOBAL ECONOMIC IMPACTS OF PHYSICAL CLIMATE RISKS ON AGRICULTURE AND ENERGY

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ABSTRACT

Climate change continues to be an existential threat to humanity. With intrinsic linkages to the natural environment, food and energy supply chains are two fundamental channels via which climate risks could spill over into the economy. This paper explores the global economic consequences of the physical climate impacts on agriculture and energy. Firstly, we construct a range of chronic and extreme climate risk indicators. Secondly, we incorporate those climate risk indicators, alongside the historical data on global agriculture and energy, in machine learning algorithms to estimate the historical responsiveness of agriculture and energy to climate risks. Thirdly, we project agriculture and energy production changes under three Shared Socioeconomic Pathways (SSPs). Finally, the derived shocks are introduced as economic shocks to the G-Cubed model, which is a global multisectoral intertemporal general equilibrium model. We evaluate the G-Cubed model simulation results for various economic variables, including real GDP, consumption, investment, exports and imports, real interest rates, and sectoral production. We observe substantial losses to all economies and adjustments to consumption and investment under the SSPs. The losses worsen with warming. Developing countries are disproportionately affected. However, we observe the potential for double dividends from transitioning to sustainable livestock production and renewable energy sources, preventing further warming and physical damages, and enhancing the resilience of food and energy supply chains to climate risks.

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[1] I am grateful to Professor Warwick McKibbin and Dr. Weifeng Liu for their guidance and to the two reviewers and the participants of the 26th Annual Conference on Global Economic Analysis and the 12th South Asia Economic Policy Network Conference for their comments on an initial draft of the paper. I am also thankful to the Australian National University and the Australian Research Council Centre of Excellence in Population Ageing Research (ARC CEPAR) (CE170100005) for their funding to support my Ph.D. research.

1 INTRODUCTION

Until the latter half of the 20th century, climate change remained a theoretical or scientific phenomenon. In 1896, Svante Arrhenius illustrated the role of CO_2 in long-term variations in climate for the first time. However, climate change did not enter the global policy arena until 1972, when the first international environmental summit was held in Stockholm and the United Nations Environment Program (UNEP) was established. The first international climate conference in 1979 in Geneva, the Toronto Conference on the Changing Climate in 1988, and the establishment of the Intergovernmental Panel on Climate Change (IPCC) in the same year were significant milestones. These developments led to the United Nations Framework Convention on Climate Change (UNFCCC) adoption in 1992, with a global membership of 197 countries. Since then, the IPCC has published six assessment reports. Meanwhile, the parties, or the member countries, have continued to meet annually at the Conferences of Parties (COPs). Adopting The Kyoto Protocol in 1997 and The Paris Agreement in 2015 are landmarks in a global commitment toward mitigating climate change. COP 26, held in Glasgow in 2021, finalized The Paris Rulebook, which focuses on delivering The Paris Agreement. It includes several important agreements covering emission reporting, timeframes for emission reduction targets, and mechanisms and standards for global carbon markets. COP 27, held in Egypt in November 2022, marked the 30th anniversary of establishing the UNFCCC and further focused on implementing The Paris Agreement (Carver 2022; Harvey 2022; Hirst 2020).

Despite global efforts to mitigate climate change since the 1970s, climate change remains an existential threat to humanity. How greenhouse gas emissions and their accumulation in the atmosphere affect the earth's climate and the human footprint in accelerating global warming and climate change since industrialization are now understood with much scientific rigor (Hertzberg & Schreuder 2016). Yet, after a mild slowdown owing to the COVID-19 pandemic in 2020, global emissions have rebounded to their historical highest in 2021. The earth is already 1.1^{0}C warmer compared to the 1800s, and 2011-2020 was the warmest decade on record. The climate change mitigation commitments agreed upon at COP 26 are inadequate to prevent global warming from exceeding the 1.5^{0}C target, a scientifically critical threshold to avoid catastrophic outcomes and natural tipping points. The increasing frequency, intensity, and duration of adverse consequences of climate change, ranging from melting polar ice, sea-level rise, heat and cold waves, intense droughts and floods, water scarcity, severe wildfires, and more frequent and stronger storms, are early signs of the catastrophic outcomes to expect (International Energy Agency 2022; United Nations [UN] 2018). Accordingly, the World Economic Forum (WEF) recognizes the climate crisis as the most significant long-term threat to humanity. Failing to act on climate change and extreme weather poses the worst short-term threats (UNFCCC 2022; WEF 2022). The changes in the natural environment disrupt lives and livelihoods and spill over into the economies. Implications for food and energy security are two primary channels of these spillovers, with their intrinsic linkages to the natural environment.

Climate change has a two-way relationship with food and energy production.[2] On the one hand, the current global non-renewable energy and agriculture practices are the two highest emitters of greenhouse gases and, thus, the leading contributors to anthropogenic climate change. In addition to emissions produced by energy consumption mainly by households, industries, and transportation sectors, energy production (which includes electricity generation, heat generation, and refining of fossil fuels) directly produces emissions from exploration, processing, production, transmission, and storage of fossil fuels (European Environment Agency 2008). Land use changes from deforestation for cultivation, burning of residues, and fuel consumption for farming practices are significant sources of CO_2 emissions from agriculture. Enteric fermentation, adding fertilizers to soils, and manure management are the primary sources of non-CO_2 emissions in agriculture (Food and Agriculture Organization [FAO] 2018).

On the other hand, energy and agriculture are affected by climate change. In 2020, 87 percent of global electricity production directly depended on water. Accordingly, thermal power generation (using fossil fuels, nuclear sources, and biomass) and hydropower generation are particularly affected by the worsening water scarcity under climate change. Increasing temperature also reduces the turbine efficiencies in the power generation plants. Furthermore, climate change threatens the energy production, transmission, and distribution infrastructure. Rising sea levels also affect nuclear power plants often located closer to the coast (World Meteorological Organization [WMO] 2022).[3]

Livestock is one of the agriculture subsectors expected to suffer the most from climate change. The impacts on livestock include changes in, the production and quality of feed crops and forage, water availability, animal growth, exposure to diseases, reproduction, and milk production (Rojas-Downing et al. 2017). Compared to livestock, crops could experience a mix of positive and negative effects depending on the crop types and geographical locations. For example, while the growing seasons could become longer with the increased CO_2 concentration, the increased incidence of attacks from pests, droughts, and floods adversely affect crops.[4] Forestry could experience reduced productivity from the loss of trees from droughts, temperature stress, landslides, increased wind and storm damage, increased saltwater intrusion and inundation from floods, increased frequency of forest fires, and increased incidence of pest and disease outbreaks. Fishery and aquaculture would be affected by the changes in physical (such as surface temperature, waves, and ocean circulation) and chemical (salinity, oxygen concentration, and acidification) properties of the aquatic environment. These changes could promote migration and inhibit the biological processes of aquatic species (FAO 2015).

By 2050, the global population is expected to exceed 9.7 billion, the demand for food is expected to increase by 50 percent (compared to 2010) (van Dijk et al. 2021), and the global energy demand is expected to grow

[2] Liu (2016) details the interlinkages of climate change with the water-energy-food nexus.

[3] Yalew et al. (2020) review the implications of climate change on energy systems. They evaluate implications on demand for energy services and supply-side effects on renewable energy resources and thermal power generation.

[4] National Geographic (2022) provides a clear illustration of both the positive and negative impacts of climate change on crops across the world.

by 50 percent (compared to 2020) (Energy Information Administration [EIA] 2021). Meeting the food and energy demands of the growing population will thus require enhancing the resilience of the global food and energy supply chains and expanding them. The disruptions to the global energy and food supply chains created by the Russian invasion of Ukraine and their spillovers into the global economy are a stark reminder of the centrality of food and energy security to the global economies.[5] Therefore, increasing the resilience of the global food and energy supply chains to climate change is vital for climate change adaptation. Given the implications of current agriculture and energy practices on climate change, mitigating climate change by adopting sustainable crop and livestock management patterns, reducing emissions from non-renewable energy sources, and transitioning to low-carbon energy sources will also be vital to reducing the vulnerability of the food and energy supply chains to climate change.

This paper explores the global economic consequences of the physical climate impacts on agriculture and energy. Specifically, we focus on crops and livestock as agriculture subsectors, energy production from non-renewable resources, and power generation from renewable resources.[6] Firstly, the paper develops a range of chronic and extreme climate risk indicators and explores their historical variation. The chronic risks represent the gradual variation in temperature, precipitation, and relative humidity. The extreme risks represent extreme temperature events (heat and cold waves), droughts, floods, and storms. The paper uses machine learning algorithms to estimate the historical responsiveness of agriculture and energy production to physical climate risks. The empirical estimates are discussed with reference to the existing knowledge of the pathways via which climate change affects agriculture and energy production.

Secondly, the paper projects the physical climate impacts on agriculture and energy production under three Shared Socioeconomic Pathways (SSPs). The projected sectoral productivity changes are introduced as economic shocks to the G-Cubed model, a global multisectoral intertemporal general equilibrium model. The simulation results for real GDP, consumption, investment, exports and imports, real interest rates, current account balance, real exchange rate, trade balance, inflation, and sectoral production are then discussed. The real GDP changes are also compared with the existing studies.

The rest of the paper is organized as follows. Section 2 sets the context of this paper. It provides an overview of the various climate risks and climate scenarios currently used, the existing methodologies for assessing the economic consequences of chronic and extreme climate risks, and the current estimates of the economic consequences of the physical climate risks. Section 3 constructs chronic and extreme climate risk indicators and uses machine learning algorithms to empirically estimate the sensitivity of agriculture and energy production to changes in chronic and extreme climate risks. Section 4 extends those climate

[5] See Benton et al. (2022) for a review of the implications of the Russian invasion of Ukraine on food and energy security. IMF (2022a and 2022b) analyse the global economic implications of the Russian invasion of Ukraine.

[6] Energy production from non-renewable resources includes both primary and secondary forms of energy production. Primary forms refer to the unaltered original form of a resource (such as crude oil or natural gas), and secondary forms refer to converted forms of primary energy (such as electricity or heat). Renewable resources are mostly used after conversion to a secondary form, and data is widely available only for using renewable resources in the form of electricity.

indicators for three SSPs: SSP 1-2.6, SSP 2-4.5, and SSP 5-8.5, and projects the physical climate impacts on agriculture and energy. It also discusses in depth the behavior of the projected climate indicators and the worldwide changes in agriculture and energy production. Section 5 models the economic consequences of the projected physical climate impacts on economic sectors within the G-Cubed model and discusses the results. It also illustrates the worldwide variation of the economic consequences. Section 6 distills the policy implications of this paper. Section 7 summarizes and concludes the paper. The historical and projected climate indicators, historical variation in agriculture and energy production, estimated sectoral productivity variations under the three SSPs, and the G-Cubed model simulation results for various economic variables are publicly available via the online interactive dashboard accompanying this paper.

2 ECONOMIC CONSEQUENCES OF CLIMATE CHANGE

2.1 Climate Risks

The IPCC (2020) defines climate risks as the potential adverse consequences for human or ecological systems, given the diversity of values and objectives of those systems, emanating from climate change and/or human responses to climate change. Within the economics and finance literature, climate risks are broadly identified in two broad categories: physical and transition risks, which are indicative of the two sources of risks outlined in the IPCC definition above.

2.1.1 Physical Risks

The physical risks refer to the adverse consequences of changes in the acute short-term events or chronic long-term changes in the weather and climate. An alternative classification of the physical risks considers the adverse consequences of chronic, long-term, gradual changes in the weather and climate as chronic risks and short- (acute) and long-term (chronic) extreme events as extreme risks. The chronic risks include adverse consequences of long-term gradual changes in climate variables, such as temperature, precipitation, and humidity. The adverse consequences include changes in sea level and resulting changes in the availability of land for economic activities, changes in water levels, changes in heat stress affecting plants (e.g., changes in crop yields), animals (e.g., changes in biological processes and migration), and human beings (e.g., changes in productivity), changes in disease incidence, and biodiversity losses. The extreme risks include adverse consequences of both short- and long-lived extreme events. Short-lived extreme events occur due to changes in weather and climate. Floods, heat and cold waves, storms, and wildfires are some examples of short-lived extreme events. Long-lived extreme events primarily occur due to changes in climate. Droughts and seasonal extreme precipitation are some examples of long-lived extreme events.

2.1.2 Transition Risks[7]

The transition risks refer to the adverse consequences of human responses to climate change, particularly when transitioning to a low-carbon economy. The sources of transition risks are changes in international or national policies, legislation, norms, market preferences, and technologies. The adverse consequences of

[7] Transition Risks are discussed only for a complete discussion of climate risks. This paper only focuses on the economic impacts of physical risks.

those sources of transition risks include stranded assets, loss of markets, lower returns from investments, additional litigation liabilities and penalties, loss of reputation, lack of liquidity, and ultimately, insolvency and bankruptcy. Another critical source of transition risks is the deployment of negative emission technologies, such as carbon capture and storage (CCS). While the large-scale development and deployment of CCS are supportive of limiting global warming, CCS also poses risks of toxicological effects (e.g., human health effects and water contamination from CO_2 leakages), environmental effects (e.g., detrimental effects on plants), impact on seismic activity due to higher induced pressure, and climate effects from CO_2 leakages (de Figueiredo et al. 2007).

2.2 Climate Scenarios

2.2.1 Global Warming Scenarios

Since 1990, the IPCC has been developing alternative scenarios of climate risks for climate modelers. The main objective of the exercise is to provide a range of alternative futures representing different carbon emission pathways and associated climate risks within the twenty-first century built on various socioeconomic and technological growth assumptions. Another objective is to harmonize the modeling outputs from impact models for better comparison.

After publishing the first set of scenarios (SA90) for the First Assessment Report in 1990, the IPCC published a second set of scenarios (IS92) for the Second Assessment Report in 1992. The Third and Fourth Assessment Reports by the IPCC were based on an improved set of scenarios published through its Special Report on Emission Scenarios in 2000, which were called SRESs. In 2007, for the Fifth Assessment Report (AR5), the IPCC further developed the scenarios to produce the Representative Concentration Pathways (RCPs) (van Vuuren et al. 2011). Four main RCPs, namely RCP 2.6, 4.5, 6.0, and 8.5, represent different radiative forcing levels (in W/m^2) achieved by the end of the twenty-first century from greenhouse gas concentration in the atmosphere compared to the pre-industrial levels. Although there are socioeconomic narratives underlying the emission outcomes described in the RCPs, RCPs primarily focus on the climate risks of the alternative emission pathways. Supplementary Annexure 1 summarizes the RCPs and the temperature outcomes expected by 2100.

Extending the RCPs, the IPCC 6th Assessment Report (AR6) uses the Shared Socioeconomic Pathways (SSPs). SSPs provide particular attention to socioeconomic changes over the twenty-first century, including population, economic growth, education, urbanization, and technological development. SSPs indicate future energy use and greenhouse gas emissions within Integrated Assessment Models (IAMs). SSPs, in combination with RCPs, show how different greenhouse gas concentration pathways defined by RCPs could be matched with the socioeconomic narratives defined by the SSPs. Therefore, SSPs are complementary to RCPs (Riahi et al. 2017). Supplementary Annexure 2 summarizes the five main SSPs and the temperature outcomes expected by 2100. Combining SSPs with RCPs enables researchers and policymakers to examine the economic consequences of structural changes (particularly in the energy, transportation, and land-use sectors) for the same emission outcome and design efficient and effective mitigation policies.

2.2.2 Transition Scenarios

The emphasis on transition risks is not explicit in either the RCPs or SSPs. With the considerable increase in interest from central banks and financial markets, the Network for Greening the Financial System (NGFS), a network of central banks and regulators from over 140 countries, has organized climate scenarios emphasizing both the physical and transition risks. Physical risks tend to be inversely related to transition risks. Depending on the ambition of climate policy, the NGFS divides scenarios into three broad groups: (1) Orderly scenarios: Climate policies are introduced early and become gradually more stringent, with both physical and transition risks relatively subdued; (2) Disorderly scenarios: Policies are delayed or divergent across countries and sectors, resulting in higher transition risk; (3) Hothouse world scenarios: Global efforts are insufficient to halt significant global warming, resulting in severe physical risk, including irreversible impacts. When evaluating NGFS climate scenarios, the IAMs use SSP2 as the baseline. Supplementary Annexure 3 summarizes the NGFS scenarios and the temperature outcomes expected by 2100.

2.3 Methodologies for Assessing Economic Consequences of Physical Climate Risks

Assessing the economic consequences of climate change requires a transdisciplinary approach where the physical mechanisms of natural systems (atmosphere, biosphere, cryosphere, and hydrosphere) must be integrated with the mechanisms of socioeconomic systems. Representing the natural and socioeconomic system interactions is also the critical source of distinction for the current methodologies to assess the economic consequences of climate change.

Ciarli and Savona (2019) illustrate five types of models used to assess economy-wide climate damages: (1) Integrated Assessment Models (IAMs), (2) General Equilibrium Models (both Computable General Equilibrium (CGE) models and Dynamic Stochastic General Equilibrium (DSGE) models), (3) Structural Change Models (SCMs), (4) Ecological Macroeconomic Models (EMKs), and (5) Evolutionary Agent-based Models (EABMs). IAMs also include small-scale impact models that focus on assessing the physical climate impacts on specific environmental bodies, such as biomes (e.g., forests), freshwater ecosystems, and marine ecosystems, as well as economic sectors, such as agriculture, energy, and households (health). Economists have also used econometric approaches to estimate the economic consequences of climate change. These span from cross-sectional and panel regressions (e.g., Kalkuhl & Wenz 2020; Kahn et al. 2019) to Structural Vector Auto-Regressive (SVAR) models (e.g., Gallic & Vermandel 2020).

Out of the above approaches for estimating the economic consequences of climate risks, IAMs and general equilibrium models are the most popular. The two subsections below provide an overview of how IAMs and general equilibrium models assess physical climate risks, i.e., chronic and extreme climate risks, following the definitions in Section 2.1.

2.3.1 Integrated Assessment Models (IAMs)

IAMs illustrate the interactions between the natural and socioeconomic systems within a single model. They often have separate climate and economic modules integrated with or without feedback. IAMs could follow either a vertical or horizontal approach to integrating natural and socioeconomic systems (Parson & Fisher-Vanden 1997).

Vertical integration has been commonly used when evaluating the economic consequences of climate change within IAMs. It links the causes and consequences of climate change via a causal chain. Within the causal chain, emissions and their sources, atmospheric and biogeochemical processes of climate change, and physical, ecological, and socioeconomic impacts of climate change are sequentially arranged. It also allows policy responses to adapt to or mitigate the different links. Accordingly, vertical integration starts with assumptions about demographic change, economic growth, technological change, and existing climate policies. The atmospheric accumulation of the emissions from such assumptions is modeled, and the radiation and global climate are then derived. Then, the regional climate and weather are modeled to observe the impacts of climate change on biological ecosystems. The economic consequences are derived from the climate impacts on biological ecosystems. Deviating from the simple causal chain, contemporary models also enable complex linkages across natural systems, socioeconomic systems, and policy responses.

Horizontal integration expands the different vertical integration links horizontally to include additional sources, processes, or impacts. Accordingly, horizontal integration has often been used to evaluate climate change and other environmental concerns, such as ozone depletion, acidification, and air pollution.

The economic modules of the earliest IAMs were neoclassical growth models with an aggregate production sector (Stern 2007). Therefore, those IAMs mostly fed temperature outcomes under alternative scenarios to the economic module via damage functions to obtain economic outcomes, primarily GDP losses. However, more recent IAMs (such as GTEM [Pant 2002] and DART [Deke et al. 2001]) allow for assessing both aggregate and sectoral economic outcomes. Depending on the model focus, IAMs often have detailed energy, transportation, and land-use sectors. Therefore, IAMs could either be solved to obtain the emission trajectories of a given set of socioeconomic, technological, and climate policy assumptions or to illustrate the structural and policy changes necessary to achieve a desired emission outcome. The economic consequences of different scenarios, defined in terms of their socioeconomic and policy assumptions, are then compared against a model baseline. IAMs have also been developed to incorporate both chronic and extreme risks of climate change and illustrate their impacts on different sectors or the broader economy. The chronic risks covered in IAMs include global mean temperature change and sea-level rise, and extreme risks include extreme temperature, precipitation, and heat and cold waves.

Goodess et al. (2003) identify three classes of IAMs: cost-benefit analysis models, biophysical models, and policy guidance models. The cost-benefit analysis models focus on assessing the costs and benefits of climate change against the cost of adaptation and mitigation policies. The Dynamic Integrated Model of the Climate and the Economy (DICE) by William Nordhaus is a popular example of a cost-benefit analysis model. Other popular examples include the Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) model and the Policy Analysis of the Greenhouse Effect (PAGE) model. The cost-benefit analysis models follow the vertical integration approach with the simple causal chain and are widely used to optimize policies. Biophysical impact models emphasize the impacts of climate change on ecosystems and illustrate feedback across systems within the vertical integration approach. However, due to the absence of explicit focus on policies, the economic modules of biophysical impact models are less developed. Therefore, they are better suited for policy evaluation rather than optimization. Policy guidance IAMs combine the policy optimization and evaluation approaches within tolerable windows defined by the policymakers.

2.3.2 General Equilibrium Models

General Equilibrium models are richer in detail about the economic interactions among the economic agents—households, firms, governments, central banks, and the external sector (via trade and investments)—and often disaggregate firms into multiple sectors. However, they are less detailed about climate and energy systems and do not usually directly incorporate biophysical damages. Deriving the economic impacts of climate change using general equilibrium models, which do not explicitly define natural and socioeconomic system interactions, requires the formulation of economic shocks that translate exogenous climate impacts on natural systems to impacts on economic variables.

All general equilibrium models, irrespective of their complexity and details, constitute a production function illustrating the aggregate supply side of the economy. Hence, it is often the starting point when thinking about climate impact transmission channels to the economy. Batten (2018) conceptualizes both the chronic and extreme climate impacts on various forms of capital within the production function (such as natural capital, physical capital (infrastructure), human capital, and social and organizational capital) and productivity (efficiency, technology, and learning) to be the main transmission channels in a real economy. The policy responses to adaptation and mitigation could also be featured as shocks to the above forms of capital and other economic policy variables (e.g., tax rates) depending on the details of the economic models. Changes in private and public consumption (via changes in wealth and consumption preferences), investment (via changes in investment preferences and country/sector risk premia), and international trade (via changes in prices) are some variables from the demand side of the economy that could be used to replicate physical climate risks as economic shocks. The shocks could be formulated either at the aggregate or sector level, depending on the sectoral disaggregation of the models. Like IAMs, general equilibrium models also have a model baseline, and the consequences of the economic shocks from different scenarios could be evaluated against the baseline.

As physical risks of climate change are not endogenous to economic models, assessing the economic consequences of climate change under alternative scenarios within economic models demands at least two prerequisites to formulate the economic shocks under those scenarios: (1) functions translating physical risks to economic shocks (which are commonly referred to as damage functions) either at the sectoral or aggregate macroeconomic level and (2) projections of future physical risks under alternative scenarios.

The formulation of economic shocks from chronic physical risks is widely covered in the existing literature. Firstly, a vast array of literature derives empirical damage functions for certain sectors from chronic climate change (such as agriculture[8] and manufacturing[9] productivity changes, land availability changes due to sea-level rise, and labor productivity changes[10] due to heat stress or disease incidence). Most of the studies are specific to regions, if not countries, depending on the availability of historical data pertaining to impacts (e.g., labor or sector productivity data). Roson and Sartori (2016) collate several damage functions for chronic climate risks in a form amenable to global general equilibrium models. These damage functions primarily account for (1) the loss of land from sea-level rise, (2) agriculture productivity changes, (3) changes in the incidence of vector-borne diseases, and (4) changes in heat stress for agriculture, manufacturing, and services and its implications on sectoral labor productivity. Roson and van der Mensbrugghe (2010) in the ENVISAGE CGE model, Kompas et al. (2018) using the GTAP-INT CGE model, and Fernando et al. (2021) using the G-Cubed model (a hybrid DSGE-CGE model), apply these damage functions to estimate the economic consequences of chronic climate risks under RCPs.

Secondly, historical climate data are globally available, which could be used to derive indicators[11] of historical chronic risks. The same indicators could be constructed under alternative climate change scenarios as projected climate variables (comparable to historical climate variables) are also widely available. Accordingly, the empirical damage functions could be derived using historical climate variables and indicators, and the damages under alternative scenarios could be projected using projected climate variables and indicators.

However, the formulation of economic shocks from extreme physical risks in a comparable format to chronic physical risks is primarily constrained by the lack of historical data on extreme physical risks and the projections of extreme physical risks (comparable to historical extreme physical risks) under alternative climate change scenarios.

Accordingly, most studies evaluating the economic consequences of physical climate risks have overlooked extreme climate risks (Narita et al. 2009). However, as Handmer et al. (2012) illustrate, extreme physical risks are central to economic assessments of climate change. Firstly, global economic losses from extreme physical risks have increased over time and space. Secondly, people and assets are increasingly exposed to extreme physical risks, which could prolong the economic consequences over a longer period. Thirdly, a much wider disparity of economic consequences of extreme physical risks exists across developing and developed countries. Fourthly, extreme physical risks threaten global water, food, and health security. Implications for global health will also lead to significant welfare and distributional implications across generations (Schmitt et al. 2016).

Therefore, incorporating extreme physical risks into economic assessments of climate change is essential. This requires alleviating the constraints to developing indicators of extreme physical risks using historical

[8] See Seo and Mendelsohn (2008) for a global study of climate impacts on agriculture productivity, Mendelsohn (2014) for a study in Asia, and Dinesh et al. (2015) for a study in Africa.

[9] Zhang et al. (2018) study the physical climate impacts on Chinese manufacturing productivity.

[10] Dasgupta et al. (2021) comprehensively illustrate the non-linear labor productivity changes amidst global warming. Levi et al. (2018) provide a comprehensive framework for understanding climate impacts on labor productivity.

[11] Climate indicators are a derivation from the climate variables. For example, the change in mean temperature (climate variable) compared to a baseline is a climate indicator.

climate variables, deriving empirical damage functions for extreme physical risks, and applying the damage functions to comparable projected indicators of extreme physical risks under alternative climate change scenarios. To the best of our knowledge, Fernando et al. (2021) is the first attempt to include extreme physical risks alongside chronic physical risks to evaluate the global economic consequences of RCPs.[12]

The EM-DAT database (2022) currently provides the most comprehensive and open-source collation of historical extreme events and their details, including the location, duration, magnitude, lives affected, lives lost, insured losses, and total damages. However, the details reported, especially pertaining to the location, magnitude, and duration of the events, are not complete and consistent. Furthermore, the database only reports events that meet certain criteria specific to the event category, leading to underreporting. Relying minimally on the database, due to the limitations regarding the quality of the data, Fernando et al. (2021) derive climate damage functions for sectoral productivity (agriculture and energy production) due to extreme physical risks covering droughts, floods, heat and cold waves, storms, and wildfires. Construction of the extreme damage functions closely follows the approach of Roson and Sartori (2016) when deriving the chronic damage functions. Fernando et al. (2021) also derive the impacts of extreme physical risks on labor productivity via morbidity and mortality. They then construct representative indicators of extreme physical risks for the same extreme events using projected climate variables and estimate the economic shocks under RCPs. The shocks are then assessed within the G-Cubed model, which is a hybrid DSGE-CGE model.

To the best of our knowledge, Fernando and Lepore (2023) is the first study to assess the economic consequences of physical climate risks starting at a more granular firm level, going beyond the sector level. They construct a series of chronic and extreme climate indicators to derive sectoral damage functions using machine learning for a global multisectoral sample of 59,554 firms from 147 countries. The extreme climate indicators represent conditions leading to heat and cold waves, droughts, and extreme precipitation events. The climate indicators account for the physical climate risks both at the location of the firm and the country in which the firm is located. The damage functions are estimated separately for agriculture, mining, manufacturing, and services to capture heterogeneous responses to climate risks. The sectoral productivity changes under two SSPs (SSP 1-2.6 and 2-4.5) are projected. They also project persistent productivity changes arising from flood damage to firms' physical capital using estimates from Huizinga et al. (2017). The projected sectoral productivity changes are evaluated using the G-Cubed model to derive the economic consequences of the two SSPs.

2.3.3 Current Estimates of Economic Consequences of Physical Climate Risks

An extensive body of literature assesses the economic consequences of chronic physical risks using either IAMs or general equilibrium models. However, the existing studies on the economic consequences of extreme physical risks using either IAMs or general equilibrium models are limited. The studies evaluating the economic consequences of extreme physical risks also tend to be mostly regional, if not national. The

[12] Fernando et al. (2021) also evaluate economic consequences emanating from two transition risks: (1) a carbon tax as a representative climate policy instrument in transitioning to a low-carbon economy, and (2) changes in asset valuations in financial markets from country and sector risk premia changes due to exposure to extreme climate risks.

following subsections discuss the current estimates of chronic physical risks from IAMs and general equilibrium models before discussing some regional/national studies evaluating extreme physical risks.

2.3.4 Estimates of Chronic Physical Risks from Integrated Assessment Models (IAMs)

Earlier estimates of the global economic consequences of physical climate risks are mostly relatively smaller in IAMs. Tol (2012) reviews thirteen studies and summarizes the global economic losses under warming ranging from 1 to 3^{0}C. The annual GDP changes in those studies vary from 0.1 to -4.8 percent. Weitzman (2012) attributes the lower economic losses to the conventional quadratic damage functions used in IAMs and thin-tailed temperature distributions. Stern (2016) illustrates that the underestimation of economic losses in IAMs could also be due to the limited spatial coverage of the IAMs, where impacts are averaged across countries and regions, and the relative lack of forward-looking behavior in IAMs.

Damage estimates from comparable models for the same temperature outcomes are also vastly different. Diaz and Moore (2017) review the DICE, FUND, and PAGE IAMs from the cost-benefit analysis classification and illustrate that the GDP losses at 2 and 4^{0}C are vastly different due to the changes in damage functions and key characteristics, especially regarding sector details, in those IAMs. Batten (2018) demonstrates subjectivity in choosing parameters and functional forms for damage functions. As Ackerman and Stanton (2012) argue, the damage function estimates have not been consistent with observations partly due to the absence of any economic (or other) theory or empirical foundation underlying the damage functions. They highlight the importance of updating and calibrating damage functions constantly. The oversimplification of climate and economic models and compromising mostly economic details to achieve comprehensive climate modules could mask the dynamic pathways via which physical climate risks affect economic growth and welfare.

2.3.5 Estimates of Chronic Physical Risks from General Equilibrium Models

Most existing studies applying general equilibrium models to assess the economic consequences of chronic physical risks use the CGE model available from the Global Trade Analysis Project (GTAP) or a variant.

Applying a recursive version of the GTAP model (GTAP-E), Bosello et al. (2006) estimate that most regions worldwide would experience labor productivity gains amidst the lack of vector-borne diseases due to higher temperatures. They observe that the decrease in mortality and morbidity from cold stress-related diseases dominates the increase in those from heat stress-related diseases. However, energy-exporting countries and Africa experience lower labor productivity due to the higher incidence of respiratory and gastro-intestinal diseases in the energy-exporting countries and the higher incidence of malaria in Africa. The labor productivity changes result in positive GDP changes ranging from 0.04 to 0.08 percent for countries with productivity gains and negative GDP changes of -0.07 percent and -0.1 percent for energy-exporting countries and Africa, respectively, by 2050. Within the same model, Bosello et al. (2007) evaluate the global and national economic consequences of sea-level rise with two options for adaptation: (1) coasts are unprotected from land loss, and (2) coastal areas are fully protected. They show significant differences in both national and global welfare effects between the two options and argue that the optimal adaptation lies between the two extremes.

Eboli et al. (2010) apply another dynamic variant of the GTAP model (ICES) to analyze the effects of temperature change on global economic growth and wealth distribution. They find considerable macroeconomic and distributional effects at the regional and sectoral levels. Roson and van der Mensbrugghe (2012) estimate the economic effects of climate change in the ENVISAGE model via a range of impact transmission channels: sea level rise, agricultural productivity, water availability, human health, tourism, and energy demand. They illustrate that climate impacts highly vary across regions and impact channels. The severest effect is from global labor productivity changes, which accounts for 84 percent of the worldwide damage in 2050 (-1.8 percent of global GDP). The Middle East and North Africa (MENA) is the most seriously impacted region, followed by East Asia. MENA suffers more from direct labor productivity losses, while East Asia suffers more from sea-level rise. They do not, however, observe significant impacts on agriculture by 2050.

Kompas et al. (2018) use another variant of the GTAP model (GTAP-INT) to assess the global economic consequences of physical climate risks under various temperature increments for 140 countries until 2100. They apply the chronic physical climate damage functions developed by Roson and Sartori (2016) for agricultural productivity changes, land availability changes due to sea-level rise, and labor productivity changes due to heat stress and disease incidence. They illustrate that the effects on individual countries could be enormous across various warming scenarios, and averaging across countries into regions could severely mask the heterogeneity across the countries. The GDP impacts in Sub-Saharan Africa, India, and Southeast Asia are around 10 percent by 2100, while most European countries marginally gain by the mid-century and suffer by 2100 with less than 0.5 percent in GDP losses.

2.3.6 Estimates of Extreme Climate Risks

Narita et al. (2010; 2009) evaluate the global economic consequences of increased incidence of tropical cyclones and extratropical storms due to climate change in the FUND model. They illustrate that although the global economic costs of the storms could be relatively lower (~ 0.01 percent of global GDP by 2100), the costs could increase up to 38 percent compared to the baseline. Hsiang et al. (2017) focus on storms in the US and demonstrate that for every 1 cm increase in mean sea level, the damages from storms could amount to 0.0014 percent of GDP.

2.3.7 Estimates of Chronic and Extreme Physical Risks from General Equilibrium Models

Jorgenson et al. (2004) examine the implications of chronic and extreme physical risks in the US. They use the IGEM model to project the macroeconomic consequences for the US arising from physical climate impacts on agriculture, livestock, fisheries, and forestry, energy services related to heating and cooling, commercial water supply, and protection of property and assets. They also evaluate the economic costs associated with the increased storms and floods and changes in labor supply and consumer demand due to heat-induced mortality and morbidity. They consider six scenarios where three levels of climate change (low, central, and high) are combined with two sets of market outcomes (optimistic and pessimistic) and observe that the GDP losses vary from -3 to 1 percent by 2100 across scenarios. The economy partly benefits from climate change from the decline in commodity prices due to higher temperatures and increased precipitation in optimistic scenarios. Accordingly, the effects on agriculture dominate the other market impacts. They also observe that the changes in human mortality and morbidity are small yet essential determinants of the consequences of physical climate risks.

Fernando et al. (2021) evaluate the economic consequences of both chronic and extreme physical risks under RCPs using the G-Cubed model.[13] They observe that the global economic consequences increase across RCPs. However, the temporal distribution of the effects for a given country could change across scenarios. The average GDP losses under RCP 2.6 could vary from -0.48 to -3.78 percent, while under RCP 4.5, the range expands from -0.49 to – 4.96 percent. Under RCP 6.0, the lower bound of the losses increases to -0.43 percent, although the upper bound further decreases to -6.73 percent. Under RCP 8.5, the lower bound increases to -0.31 percent, and the upper bound substantially decreases to -12.6 percent. They also present the results for a wide array of economic sectors. Under RCP 2.6 and 4.5, the agriculture output could reduce by 3.5 to 9 percent compared to the baseline. Manufacturing, which is the second-most affected sector, could experience losses between 1.5 to 5.5 percent compared to the baseline. The mining and energy could contract between 1 to 4 percent under the same scenarios, while the service sector is the least affected and experiences losses between 1 to 3.5 percent.

Fernando and Lepore (2023) also evaluate the economic consequences of both chronic and extreme physical risks under two SSPs (SSP 1-2.6 and SSP 2-4.5) using the G-Cubed model. They also observe that the global economic consequences worsen under continued warming. Under SSP 1-2.6, the global average losses amount to $US 2.38 trillion per annum, equivalent to a global GDP loss of 1.2 percent per annum. Under SSP 2-4.5, the global average losses increase to $US 7.10 trillion per annum, equivalent to a global GDP loss of 3.2 percent per annum. Among the sectors, agriculture suffers the most, followed by mining. The agricultural losses vary between -1.6 to -45 percent without additional adaptation relative to physical climate risks experienced in 2020. Similarly, mining contracts between -1.6 and -34 compared to the baseline. Manufacturing and services are the least affected, and their losses vary between -1.2 to -30 percent and -0.2 to -21 percent.

2.4 Summary

Section 2 illustrates the key differences between the IAMs and general equilibrium models, the two widely used tools, to assess the economic consequences of physical climate risks. The strengths and limitations of the approaches illustrate the complementarity of the approaches rather than the substitutability of one with another. The range of estimates obtained from various modeling exercises also illustrates the uncertainty involved in assessing the economic consequences of climate change. Most importantly, Section 2

[13] Fernando et al. (2021) also evaluate two sources of transition risks (financial risks and carbon prices) besides physical risks. The estimates compared and presented in this paper only relate to the physical climate risks.

emphasizes the importance of continuous improvements to modeling strategies to produce finer economic estimates of physical climate risks to assist policymakers.

3 PHYSICAL CLIMATE IMPACTS ON AGRICULTURE & ENERGY

3.1 Chronic & Extreme Climate Risks

3.1.1 Climate Data

When constructing the chronic and extreme climate risk indicators, we use historical data on six climate variables: Mean Temperature, Maximum Temperature, Minimum Temperature, Precipitation, Relative Humidity, and Wind Speed. We obtain the historical gridded monthly data from 1961 to 2020 for the first four variables from the Climate Research Unit of the University of East Anglia (2022) at 0.5^0 x 0.5^0 resolution.[14] The historical gridded daily data on the remaining variables (i.e., Relative Humidity and Wind Speed) for the same period (1961 – 2020) are obtained from the Earth System Model of the Geophysical Fluid Dynamics Library as reported by the Intersectoral Impact Model Intercomparison Project (ISIMIP) (2022). We then aggregate the gridded data for 256 countries[15] recognized in the Database of Global Administrative Areas (GADM) (2022) and obtain the climate variables at monthly and annual frequencies.

3.1.2 Chronic and Extreme Climate Indicators

When constructing the climate indicators, we use 1961 - 1990 as the climatological baseline following the guidelines of the World Meteorological Organization (WMO) (2017). Table 1 summarizes the climate indicators constructed and used in this paper. Our approaches to constructing the indicators of extreme temperature conditions are similar to those of Lai and Dzombak (2019). We use the Standardized Precipitation Index (SPI) developed by McKee et al. (1993) to identify precipitation-related extreme conditions. Following the insights in the literature[16] using indicators of extreme conditions, our indicators are relatable to heat and cold waves, droughts, extreme precipitation events, and storms.[17, 18]

The indicators of extreme temperature conditions evaluate how the monthly maximum (or minimum) temperature of a given month has deviated from the 90^{th} and 10^{th} percentiles of the historical baseline distribution (1961-1990) of monthly maximum (or minimum) temperatures. Assuming the maximum temperature of a day would be experienced during the day, a maximum temperature exceeding the 90^{th} percentile of the baseline maximum temperature distribution indicates a month with warmer days on average, and a

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[14] The Climate Research Unit of the University of East Anglia provides the historical gridded data from 1901 to 2020 for Cloud cover, Diurnal Temperature Range, Frost Day Frequency, Mean Temperature, Maximum Temperature, Minimum Temperature, Potential Evapotranspiration, Precipitation, Vapor Pressure, and Wet Day Frequency.

[15] See Supplementary Annexure 4 for the list of the 256 countries and their mapping to 15 UN regions, 141 GTAP regions, and 11 regions in the G-Cubed model.

[16] Ruso et al. (2014) use short-term indicators of extreme temperature conditions to project heat and cold waves. A few recent studies using SPI to predict droughts and/or extreme precipitation events include Ekwezuo et al. (2020) for West Africa, Ali et al. (2020) for Pakistan, Bhunia et al. (2020) for India, Golian et al. (2015) for Iran, Wang and Cao (2011) for China, and Manasta et al. (2010) for Zimbabwe.

[17] The indicators of extreme conditions should not be interpreted as indicators of extreme events as the occurrence of extreme events would depend on a complex set of other factors, including local weather conditions and land-use management practices, which we do not account for when constructing the indicators of extreme conditions.

[18] The historical variation of the climate indicators could be closely observed via the online dashboard. Supplementary Annexure 5 presents an overview of the average behavior of the historical climate indicators.

maximum temperature experienced below the 10th percentile of the baseline maximum temperature distribution indicates a month with colder days on average. Similarly, assuming the minimum temperature of a day would be experienced during the night, a minimum temperature exceeding the 90th percentile of the baseline minimum temperature distribution indicates a month with warmer nights on average, and a minimum temperature experienced below the 10th percentile of the baseline minimum temperature distribution indicates a month with colder nights on average.

Table 1: Chronic and Extreme Climate Indicators

	Indicator	Description	Unit
Chronic Climate Indicators			
1	Mean Temperature	Change in the mean annual temperature compared to the mean annual temperature of the baseline period (1961–1990).	^{0}C
2	Precipitation	Percentage change in annual total precipitation compared to the mean annual total precipitation of the baseline period (1961–1990).	%
3	Relative Humidity	Change in the mean annual relative humidity compared to the mean annual relative humidity of the baseline period (1961–1990).	%
Extreme Climate Indicators			
4	Max Temp90P	In a given year, the average percentage change of the monthly maximum temperature from the 90th percentile of the baseline (1961–1990) monthly maximum temperature distribution.	%
5	Max Temp10P	In a given year, the average percentage change of the monthly maximum temperature from the 10th percentile of the baseline (1961–1990) monthly maximum temperature distribution.	%
6	Min Temp90P	In a given year, the average percentage change of the monthly minimum temperature from the 90th percentile of the baseline (1961–1990) monthly minimum temperature distribution.	%
7	Min Temp10P	In a given year, the average percentage change of the monthly minimum temperature from the 10th percentile of the baseline (1961-1990) monthly minimum temperature distribution.	%
8	Extremely Dry Conditions	In a given year, the average percentage deviation of the SPI index from -2 (SPI Index < -2 indicates Extreme Dry conditions).	%
9	Extremely Wet Conditions	In a given year, the average percentage deviation of the SPI index from 2 (SPI Index > 2 indicates Extreme Wet conditions).	%
10	Extreme Wind Speeds	In a given year, the average percentage change of the monthly maximum wind speed from the 90th percentile of the baseline (1961-1990) monthly maximum wind speed distribution.	%

Source: Constructed by the Author.

We construct these short-term extreme temperature indicators for each month for each country and obtain the annual average percentage deviation of the maximum (or minimum) temperatures from the 90th and 10th percentiles of the historical baseline distribution (1961-1990).

The indicators of extreme precipitation conditions evaluate how monthly precipitation patterns for a given country have changed compared to the historical baseline distribution (1961-1990). SPI is one such statistical indicator widely used in meteorology to identify dry and wet conditions. SPI compares the total precipitation observed at a particular location during a period of n months with the long-term rainfall distribution for the same period at the same location. SPI is calculated monthly for a moving window of n months, where n indicates the rainfall accumulation period, typically 1, 3, 6, 9, 12, 24, or 48 months (European Commission 2013).

Following the procedure in McKee et al. (1993), we calculate the monthly SPI for all countries. We then obtain the percentage deviation of those values from extremely dry and wet conditions, defined as SPI values lower than -2 and higher than 2, respectively.[19] We use the annual average of the monthly values to obtain the indicators.

3.2 Historical Agriculture and Energy Production

The Food and Agriculture Organization (FAO 2022) hosts a comprehensive database with annual data on 300 agriculture products in 224 countries. The 300 products are categorized into five categories: Crops, Processed Crops, Live Animals, Primary Livestock, and Processed Livestock. We map and aggregate the 300 products into 13 primary agriculture subsectors and seven manufacturing subsectors in the GTAP 10 database (2022) following the Central Product Classification (CPC Version 2.1) and International Standard Industrial Classification (ISIC Revision 4).[20] For crops and primary livestock, we compute the annual productivity growth as the data on inputs is available. However, for the other three groups (i.e., Processed Crops, Live Animals, and Processed Livestock), the data on inputs is not available. Therefore, we compute the annual growth in production for those three groups.[21]

The Statistical Review of World Energy, conducted by the British Petroleum Company PLC (BP 2022), is a widely used data source for global energy production and electricity generation. We use the annual data for energy production using coal, oil, gas, and electricity generation from nuclear, hydro, solar, wind, and other (which include biomass, tidal, and geothermal energy) sources.[22]

3.3 Empirical Estimation of Physical Climate Impacts on Agriculture and Energy

In this paper, using the data on agriculture and energy production, we first calculated the growth in production or productivity for the five agriculture subsectors and the eight BP energy subsectors for each country for which the data was available. Then, we aimed to understand how the chronic and extreme climate indicators historically affected agriculture and energy production growth in those countries. There, we encountered two challenges.

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[19] Following McKee et al. (1993), World Meteorological Organization (2012) defines SPI ranges as below: Extremely wet: SPI > 2; Very wet: 1.5 < SPI < 1.99; Moderately wet: 1.0 < SPI < 1.49; Near Normal: -0.99 < SPI 0.99; Moderately Dry: -1.0 < SPI < -1.49; Severely Dry: -1.5 < SPI < -1.99; Extremely Dry: SPI < -2.

[20] Supplementary Annexure 6 presents the detailed mapping of the FAO products into categories and FAO sectors into GTAP sectors. Supplementary Annexure 7 maps the 224 FAO countries to 141 GTAP regions, 15 UN regions, and 11 G-Cubed model regions using the International Organization for Standardization (ISO) classification of countries.

[21] The historical variation of agriculture production could be closely observed via the online dashboard. Supplementary Annexure 8 presents an overview of the average behavior of the historical agriculture production/productivity patterns across the UN regions.

[22] Supplementary Annexure 9 summarizes the energy sectors and the number of countries for which the data is available. Supplementary Annexure 10 maps the BP countries to the GTAP Database, the G-Cubed model, and the UN regions. The historical variation of energy production could be closely observed via the online dashboard. Supplementary Annexure 11 presents an overview of the average behavior of the historical energy production patterns across the UN regions.

Firstly, some chronic and extreme climate indicators were linked to the same distributions, although their methods of construction are independent.[23] Secondly, we had a considerably higher number of climate indicators as predictors (especially compared to existing studies that mostly use temperature and rarely precipitation) of changes in agriculture and energy production. Accordingly, both accounting for collinearity and retaining the features were central to our estimations. Therefore, we estimated the penalized regression model illustrated in Equation 1 in the form of a panel regression. Supplementary Annexure 12 discusses the penalized regression algorithms and how they overcome the limitations of conventional least square regressions. We included additional country- and year-specific fixed effects to control for unobserved time-invariant heterogeneities, such as those in climate indicators, and any additional unobserved time-variant effects. These fixed effects also account for time-variant and/or time-invariant historical climate adaptation measures.[24]

Equation 1: Estimated Model Form for a Given Sector in Country i and Year j25

$$Y_{ij} = \beta_0 + \sum_{k=1}^{10} \beta_k * X_{ijk} + \gamma_i + \delta_j + \varepsilon_{ij}$$

3.4 Impact of Physical Climate Risks on Agriculture and Energy Production

3.4.1 Impact of Physical Risks on Agriculture

Agriculture encompasses crops, livestock, fishery, and forestry. As outlined in Hulme (1999), climate risks affect crops at least in three main ways: (1) Changes in the soil moisture content due to evaporation, crop respiration rate, and the length and timing of the growing seasons due to temperature and precipitation variations affecting the crop growth; (2) Changes in the water-use efficiency and photosynthesis due to CO_2 concentration variations, and (3) Changes in quality of water and soil, shifts in weed growth and vulnerability to diseases due to extreme events, such as droughts and floods.

The livestock and fishery are also vulnerable to diseases as climate variability and extreme temperatures affect the physiology, behavior and movements, growth and development, and fertility of animals, birds, and fish. Although higher CO_2 concentrations increase the quantity of feed available for livestock, the quality of the feed could deteriorate, affecting livestock productivity. In fishery, the lifecycle of aquatic species and their migration patterns are also affected by the changes in climate, thus changing sectoral

[23] For example, while a chronic climate indicator could measure the deviation in mean temperature in a given year from baseline, an extreme climate indicator could measure the average deviations of the monthly maximum temperature from a percentile of the distribution. Accordingly, both indicators could be related to the same distribution, but the method of construction enables identifying mean vs extreme values.

[24] The objective of the empirical estimates in this paper is not to comprehensively explain the productivity or production patterns of agriculture and energy but to estimate the sensitivity of those sectors to physical climate impacts. Therefore, the omitted variables (that could contribute to explaining productivity/production patterns) could affect the estimates only to the extent they are correlated with the climate indicators. As climate risks are largely exogenous, we assume the omitted variables do not significantly affect the current estimates. This approach is also consistent with the existing approaches of Roson and Sartori (2016) for estimating the responsiveness of sectoral productivity to chronic climate risks.

[25] Y_{ij}: Annual Growth in Production or Productivity in a given sector in Country *i* and Year *j*; X_{ijk}: Change in the Climate Indicator *k* in Country *i* and Year *j*; γ_i: Country-specific Fixed Effects; δ_j: Year-specific Fixed Effects.

productivity. In forestry, changes in climate could alter the growth cycle of trees and change their resilience to diseases, although increased CO_2 concentration could promote the growth of trees (Rojas-Downing et al. 2017; US Climate Change Science Program 2008a).

The existing studies use both empirical estimates and impact models to evaluate the impacts of climate risks on agriculture. Given their strong reliance on agriculture, most studies have focused on developing countries. Using a Ricardian model of agriculture, Mendelsohn (2014) estimates 13.3 and 28.1 percent reductions in annual revenue from Asian agriculture under 1.5^{0}C and 3^{0}C warming scenarios, respectively. For Africa, Dinesh et al. (2015) estimate that livestock and maize productivity could shrink up to 50 and 25 percent under the RCP 8.5 scenario by 2050. Seo and Mendelsohn (2008) estimate that agriculture could lose 14, 20, and 53 percent of its revenue under a severe climate scenario by 2020, 2060, and 2100, respectively.

Developed countries could also experience substantial climate impacts on agriculture. Sheng and Xu (2019) evaluate the impact of the Millennium drought on Australian agriculture and measure an 18 percent productivity reduction from 2002 to 2010. In Europe, climate change is expected to mainly affect agriculture via droughts, heatwaves, pest diseases, weeds, and soil erosion (Olsen et al. 2011).

Figure 1 presents the empirical estimates of the physical climate impacts on agriculture from this paper. Within the three decades covered in this paper, higher mean temperatures, compared to the baseline, tend to increase crop productivity by almost one percent, potentially due to an increase in the efficiencies of photosynthesis, transpiration, and respiration. However, extremely warm conditions tend to adversely affect crops, with extremely warm temperatures during the day reducing crop productivity by almost two percent.

Precipitation has a positive yet smaller impact on crops. Although the chronic precipitation changes favor crop productivity with higher water availability, both extremely wet and dry conditions could disrupt crops. An increase in relative humidity, potentially leading to inconvenience for growers and increased existence of pests, and extremely windy conditions, potentially due to unfavorable mechanical implications on crops (such as uprooting, shedding, and injuries), reduce crop productivity.[26]

Crop production, which uses crops as inputs and involves manufacturing, is adversely affected by higher temperatures. Precipitation tends to promote the production of crops, potentially via favorable impacts on crop growth. However, extreme temperatures and higher relative humidity decrease production, potentially both via the impacts on crops and discomfort for workers.

Like crops, live animals are also quite adversely affected by extremely warm conditions during the day, potentially via the adverse impacts of warming on their biological processes. They are, however, mainly indifferent to chronic temperature rise, unlike crops. Precipitation could incentivize the production of live animals due to favorable conditions for water and food sources, and habitats. Relative humidity, however, reduces live animal production due to the impacts on animal transpiration.

[26] See TNAU Agritech Portal (2022) for a further description of climate impacts on crops.

Livestock production is affected adversely by both chronic and extreme climate risks. Chronic changes in temperature notably reduce primary and processed livestock production growth. Unlike live animals, which benefit from extremely cold conditions, livestock production suffers, potentially due to the impacts of cold weather on production processes. Extremely windy conditions also affect livestock production adversely, although they are somewhat favorable for live animals. Extremely warm conditions during the day tend to adversely affect livestock processing, potentially due to the impacts on the production equipment and discomfort for workers.

3.4.2 Impact of Physical Risks on Energy

Existing studies explicitly exploring the physical climate impacts on energy are limited. However, the exposure of energy to physical climate risks could be somewhat understood from the studies examining the physical climate impact pathways for mining, which are also limited in number, though more comprehensive. As non-renewable energy subsectors heavily rely on mining, energy could be expected to experience similar production challenges to mining from physical climate risks. Thus, we summarize some relevant insights from the studies exploring mining exposure to climate risks.

In mining, both chronic and extreme climate risks could disrupt and primarily increase the cost of exploration, extraction, production, transportation, and decommissioning. However, newer opportunities could also arise for exploration and to access natural resources that were previously inaccessible.[27] Rising water scarcity is the primary driver of increasing mining costs (Pearce et al. 2011). Rising temperatures could further deteriorate the already environmentally challenging conditions in mining regions and operational sites, reducing the mining labor efficiency (Sun et al. 2020).

In addition to experiencing physical climate risks like the mining sector, the productivity of generation, transmission, and distribution of energy and electricity could deteriorate with the demand for more inputs to produce the same output. The requirement for more cooling water in thermal power plants, disruptions to hydroelectric power plants due to changes in water availability, and more frequent maintenance of transmission and distribution lines due to disruptions from extreme climate risks are exemplary of the climate impacts on energy (US Climate Change Science Program 2008b).

Figure 2 presents the empirical estimates of the physical climate impacts on energy from this paper. Production of fossil fuels is adversely affected by the rising temperature, worsening the already challenging conditions at operational sites, particularly for labor and water scarcity. Fossil fuel production is indifferent to precipitation. However, higher relative humidity could adversely affect it by exposing laborers to unfavorable working conditions and deteriorating the quality of natural gas.

Extreme temperature changes also adversely affect fossil fuel production, with extremely warm days affecting gas production and extremely warm nights affecting oil production. Extremely dry conditions favor

[27] See Odell et al. (2018) for country-level evidence on physical climate impacts on mining.

coal production potentially due to the substitution of renewables with coal during drier periods and disrupt oil and gas production.

Nuclear power generation is not necessarily affected by gradual chronic temperature changes. However, extreme temperature conditions could disrupt its performance stability, primarily via the cooling water supply and the temperature impact on the viscosity of the oil used in process equipment.[28] We observe that the gradual increase in temperature promotes nuclear power generation, potentially due to the more favorable conditions for labor as the plants are heavily concentrated in countries that are generally exposed to prolonged cold weather. This could also be due to the emergence of nuclear power plants as a cleaner alternative to fossil fuels. However, the extremely warm conditions during the night tend to adversely affect nuclear power generation while it is indifferent to extremely warm conditions during the day.

Power generation from renewable resources also illustrates various effects depending on their characteristics. Hydropower generation is adversely affected by chronic temperature rise and extreme temperatures, potentially due to higher evaporation losses in hydropower plants. Higher precipitation, however, is quite favorable for hydropower generation due to the positive impacts on the hydrological cycle.

Chronic temperature rise and prolonged extremely dry conditions positively affect solar power generation. However, it is adversely affected by all other chronic and extreme climate risks. For example, higher precipitation and higher relative humidity could bring in more clouds and reduce solar irradiation exposure.

Wind power generation is potentially incentivized with higher temperatures due to better air particle circulation from temperature-induced excitement. However, extremely high temperatures could reduce air density and, hence, the efficiency of wind turbines.[29] Higher relative humidity reduces the air density and leads to lower power generation from wind turbines.[30] Extremely high wind speeds could also affect the stability of turbines, adversely affecting wind power generation.

Power generation from other sources, mainly biomass, is negatively affected by rising temperatures and higher relative humidity due to higher water vapor concentrations, reducing biomass incineration efficiency. However, prolonged extremely dry and wet conditions seem to affect power generation from other sources positively.

3.5 Summary

Extending the approaches in Fernando et al. (2021) and Fernando and Lepore (2023), Section 3 estimates the impacts of a broader range of physical climate risks on agriculture and energy production. It emphasizes the importance of considering a wide range of physical risks, moving beyond the frequent practice in the existing literature to incorporate only chronic climate risk indicators (primarily temperature and precipitation). Also, using the methodological innovation of regularized regressions and machine learning, it

[28] See Hylko (2014) for a discussion of cold weather impacts on nuclear reactors.
[29] See Aeolos Wind Energy (Ltd.) (2022) for a discussion on factors affecting wind turbines.
[30] See Danook et al. (2019) for a detailed discussion on the impact of humidity on wind turbines.

accounts for potential collinearity among the climate risk indicators and extracts the most important insights to illustrate how physical climate risks affect agriculture and energy production.

4 MODELING ECONOMIC CONSEQUENCES OF PHYSICAL CLIMATE IMPACTS ON AGRICULTURE AND ENERGY

4.1 The G-Cubed Model

The G-Cubed model is a global, multisectoral, intertemporal general equilibrium model developed by McKibbin and Wilcoxen (2013; 1999). The model is designed to bridge the gaps between econometric general-equilibrium modeling, international trade theory, and modern macroeconomics. The model is particularly well suited to capture climate risks due to its regional and sectoral representation. The model has already been used to study the macroeconomic implications of physical and transition climate risks (Fernando & Lepore 2023; Bertram et al. 2022; Fernando et al. 2021; Jaumotte et al. 2021; Liu et al. 2020).

This paper uses the G-Cubed model version (GGG20C_v169), which has eleven regions and twenty sectors. The model regions are presented in Table 2.[31] The model sectors are presented in Table 3. The first twelve sectors are aggregated from the 65 sectors in the GTAP 10 database (Aguiar et al. 2019), as indicated in Supplementary Annexure 13. The electricity sector is then disaggregated into an electricity delivery sector (Sector 1 in Table 3) and eight electricity generation technologies (Sectors 13-20 in Table 3). Supplementary Annexure 14 schematically presents the production structure of the G-Cubed model. The model is comprehensively detailed in McKibbin and Wilcoxen (2013). Several key features of the G-Cubed model relevant to this paper are briefly described below.

Firstly, the model features heterogeneous households and firms, a government, and a central bank in each region. The representative households and firms in each sector could either possess forward-looking expectations or follow more straightforward rules of thumb, which are optimal in the long run but not necessarily in the short run. In the presence of continuing economic shocks, the forward-looking agents would, thus, smoothen their consumption and investment patterns over the horizon.

Secondly, the model illustrates the domestic and international linkages between sectors via trade. As a result, the economic shocks experienced in one sector could spill over into both domestic and foreign sectors relying on that sector. Furthermore, the ultimate impact on a given sector in a given region, even when faced with adverse economic shocks, would depend on the relative dominance of the region in global trade and, hence, its influence on world prices.

Thirdly, the model illustrates global linkages via capital flows and distinguishes physical capital from financial capital. Therefore, financial capital could immediately move across industries and regions in response to an economic shock. Subject to sector-specific quadratic adjustment costs, the physical capital would sluggishly adjust, giving rise to stranded assets.

[31] Supplementary Annexure 1 maps the 256 GADM countries to 141 GTAP countries and the 11 G-Cubed model regions.

Table 2: Regions in the G-Cubed Model

Region Code	Region Description
AUS	Australia
CAN	Canada
CHI	China
EUR	Euro Zone
IND	India
JPN	Japan
OPC	Oil-Producing Countries
OEC	Rest of the OECD
ROW	Rest of the World
RUS	Russian Federation
USA	United States

Source: The G-Cubed Model (GGG20C_v169).

Table 3: Sectors in the G-Cubed Model

Number	Sector Name	Notes
1	Electricity delivery	Energy Sectors excluding Electricity Generation
2	Gas extraction and utilities	
3	Petroleum refining	
4	Coal mining	
5	Crude oil extraction	
6	Construction	Goods and Services
7	Other mining	
8	Agriculture and forestry	
9	Durable goods	
10	Non-Durable goods	
11	Transportation	
12	Services	
13	Coal generation	Non-Renewable Electricity Generation Technologies
14	Natural gas generation	
15	Petroleum generation	
16	Nuclear generation	
17	Wind generation	Renewable Electricity Generation Technologies
18	Solar generation	
19	Hydroelectric generation	
20	Other generation	

Source: The G-Cubed Model (GGG20C_v169).

4.2 Climate Scenarios & Projected Climate Indicators

4.2.1 Baseline

The G-Cubed model baseline replicates how the economies would grow given the historical experiences but without additional future climate risks. The climate scenarios are assessed against this baseline. The baseline starts in 2018 and is projected up to 2100. 2018 corresponds to the latest year for which a comprehensive data collection is available to calibrate the model. The region-specific sectoral productivity growth rates, a function of labor force growth and labor productivity growth in the respective countries, drive the baseline economic growth.

The labor force growth rates are derived from the working-age population projections from the United Nations Population Prospects study (UN 2019). The sectoral labor productivity growth rates (labor-augmenting technological progress) are determined using a Barro-style catch-up model, which assumes that the average annual catch-up rate of an individual sector to the worldwide frontier would be two percent. The initial sectoral productivity data are obtained from the Groningen Growth and Development database (2022), and the corresponding sectors in the US are assumed to form the frontier. The sectors in individual economies would try to close the gap with the corresponding sector in the US at two percent per annum. The G-Cubed model also varies the catch-up rates of different economies, given the most recent growth experiences.

Given the above approach to baseline construction, the baseline would inherently include the various climate policies and adaptation measures the different economies had implemented by 2018. When the climate shocks imposed under the climate scenarios are normalized relative to 2020, the model simulations effectively assess the economic outcomes relative to a baseline simulation that includes climate shocks up to the 2020 levels. In summary, there are effectively two layers to the baseline. Firstly, there is a model baseline that assumes historical climate policies and adaptation measures and no climate shocks. Secondly, there is an effective baseline simulation from 2021 to 2100, which has climate shocks equivalent to 2020 levels and assumes adaptation for those shocks. Thus, when the normalized shocks under the SSPs from 2020 to 2100 are introduced as unanticipated disturbances to the G-Cubed model baseline described above, the simulation results indicate how the economies adjust, given the shocks imposed.

4.2.2 Climate Scenarios

SSPs are the latest set of scenarios the IPCC uses for assessing the impacts of climate change and recommending policy measures for climate change mitigation and adaptation. This paper assesses the economic consequences of physical climate impacts on agriculture and energy under three SSPs: SSP 1-2.6, SSP 2-4.5, and SSP 5-8.5.

These scenarios (particularly SSP 5-8.5) are only used to obtain a range of estimates about the economic consequences of physical climate risks. We do not attribute any likelihood to any of the scenarios and do not assume any scenario to be "business as usual". Hausfather and Peters (2020) provide a detailed discussion on how best to interpret RCPs in line with the most recent developments. We follow the literature to interpret RCP 8.5 (linked to SSP 5-8.5) as an upper bound of the estimates.

4.2.3 Projected Climate Indicators

Given the G-Cubed model baseline projection, economic shocks representative of the SSPs are necessary to model the economic consequences of the SSPs. We use projected climate variables and the empirical estimates derived and discussed in Sections 3.3 and 3.4 to formulate the economic shocks. We obtain the projected climate variables from the daily data gridded at 0.5^0 x 0.5^0 resolution from 2021 to 2100 for all the climate variables introduced in Section 3.1: Mean Temperature, Maximum Temperature, Minimum Temperature, Precipitation, Relative Humidity, and Wind Speed from the Earth System Model of the Geophysical Fluid Dynamics Laboratory as reported by ISIMIP (2022). We then derive the chronic and extreme physical climate indicators introduced in Table 1 using the projected climate variables. The online dashboard presents the projected climate indicators, and Supplementary Annexure 15 discusses their behavior under SSPs.

4.3 Formulation of Economic Shocks

Section 4.3 discusses the projected productivity changes in agriculture and energy production due to physical climate risks under the three SSPs. The productivity changes have been derived from the empirical estimates obtained and discussed in Sections 3.3 and 3.4 and the physical climate risk indicators discussed in Section 4.2. They have then been normalized to eliminate any shocks in 2020 to account for some adaptation to climate risks (equivalent to 2020 levels) to observe the dynamic effects specific to the given sector in a given region. Thus, we discuss the shocks relative to the year in which the shock occurs adjusted by any changes in 2020 levels.

When discussing physical climate risks, aggregating the countries by the UN regions is more meaningful, as the climate conditions are more comparable across geographical regions. However, as presented in Section 4.1, the regions of the G-Cubed model version used in this paper differ from the UN regions. The choice of the G-Cubed model regions has been primarily determined by the importance of countries and regions in climate negotiations, and the overall number of countries/regions is constrained by the computational demands and the data requirements for model calibration. Therefore, shocks in the subsequent sections and results in Section 5 will be discussed for the 11 G-Cubed model regions.

The shocks and their decomposition by climate indicators for the G-Cubed model regions could be viewed via the online dashboard. The discussion below focuses on the aggregated shocks, i.e., those resulting from aggregating the climate-indicator-specific shocks (decomposed shocks).

4.3.1 Shocks on Agriculture

The online dashboard presents the productivity variation in agriculture subsectors across the G-Cubed model regions under the three SSPs. When considering crop productivity changes, Canada and China are affected the most under SSP 1-2.6, with Canada experiencing a productivity decline exceeding three percent by 2100. Canada and Russia are most affected across SSP 2-4.5 and SSP 5-8.5, with productivity reductions exceeding eight and 20 percent by 2100. Decomposing the shocks for climate indicators illustrates that the declines in Canada and Russia are driven by the extremely warm conditions experienced both during the day and night.

The impacts on processed crops are smaller than those on crops. Yet, analogous to crops, the reductions increase with warming. Under SSP 1-2.6, the processed crops are affected the most in Canada and Oil-Producing Countries. Under SSP 2-4.5 and SSP 5-8.5, Russia also experiences substantial reductions. Decomposing the shocks for climate indicators illustrates that the declines are primarily driven by the extremely warm conditions during the day and gradual temperature rise.

The impacts on live animals and livestock are generally more significant than on crops. However, some similarities exist across the impacts on the regions. Under SSP 1-2.6, live animals in India, the Rest of the

OECD Countries, and Europe are affected the least by physical climate risks. Similar to crops, Canada and China experience the strongest effects. India remains the least affected across SSP 2-4.5 and 5-8.5, while Canada and Russia experience the severest effects where losses are closer to four and exceed eight percent, respectively, under SSP 2-4.5 and 5-8.5. The effects are driven by the extremely warm conditions during the day, as the decomposed shocks indicate.

The livestock sector experiences the most adverse effects among all the agriculture subsectors. The productivity reductions under SSP 1-2.6 reach almost 1.5 and two percent for primary livestock and four and five percent for processed livestock in the US and Canada, respectively. The adverse effects increase amidst warming. Canada and Russia experience losses exceeding four and 10 percent under SSP 2-4.5 and SSP 5-8.5, respectively, for primary livestock and nine and 20 percent for processed livestock. The productivity reductions in primary and processed livestock sectors are both predominantly driven by the gradual temperature rise and extremely warm conditions during the day. Primary livestock are also affected by extremely warm conditions during the night.

Our projections for some regions, such as Canada and Russia, differ from existing estimates in the literature (e.g., Moody's Analytics 2019), identifying those regions as climate winners. While this claim in the existing literature is still debated (e.g., Coffman & Ness 2021), there are two main reasons for the differences between this paper and the current studies.

Firstly, different from this paper, the existing studies assume additional adaptation (such as mass migration and wider labor availability) in agriculture amidst global warming (e.g., Lustgarten 2020). As the projections in this paper are based on historical empirical estimates, they only assume historical adaptation. They do not assume any additional adaptation in agriculture.

Secondly, the existing studies primarily only consider the gradual temperature rise as a representative climate risk. This paper, in contrast, considers both chronic and extreme climate risks, decomposes the productivity effects across different climate risks, and illustrates how extreme risks (such as extremely warm conditions during the day and night) predominantly affect agriculture subsectors. This quantitative illustration is also consistent with the scientific literature describing how warmer nights increase plant respiration and reduce crop productivity (Paschal 2022; Muthuraj 2021) and how warmer nights affect reproduction patterns among cattle and hence reduce livestock productivity (Tesfaye 2022).

4.3.2 Shocks on Energy Production from Non-renewable Resources

The online dashboard presents the productivity changes in energy subsectors across the G-Cubed model regions under the three SSPs. Among non-renewable energy subsectors, nuclear power generation is the most vulnerable subsector. Although some G-Cubed model regions do not currently generate nuclear power, the projections indicate the impacts if there were nuclear power generation in those regions. Under SSP 1-2.6, Europe, Russia, and the Rest of the OECD Countries face minimal reductions in nuclear power generation productivity. In contrast, Canada faces the highest decline, where productivity is almost six percent by 2100. Canada remains vulnerable across all three SSPs due to the increasing prevalence of extremely warm conditions during the night, which disrupts the nuclear power generation operations. Russia is affected the second most under SSP 2-4.5 and SSP 5-8.5, although it is among the least affected under SSP 1-2.6. The case of Russia also, thereby, illustrates how fast the vulnerability of a production sector could change amidst continued warming.

The coal production changes across SSPs depict a non-linear distribution among the regions. Australia is among the most affected in all scenarios. Under SSP 2-4.5, it experiences almost a two percent reduction by 2100. Under SSP 5-8.5, the losses increase in all regions, with Canada and Russia suffering the strongest.

Under SSP 1-2.6, Russian oil production is affected the least, while Australia, Europe, and Canada are the most affected. Europe and Canada remain significantly affected under SSP 2-4.5, and Russia, too, experiences similar effects, exceeding a 1.5 percent reduction by 2100. The losses further increase for Canada and Russia under SSP 5-8.5, and the effects are mostly attributable to extremely warm conditions during the night.

Gas production experiences increasing losses amidst continued warming. India experiences the most substantial losses (equivalent to 3.5 percent by 2100) under SSP 1-2.6. Under SSP 2-4.5, Japan is the least affected, while the US and Canada experience productivity losses exceeding 3.5 percent by 2100. Under SSP 5-8.5, Canada and Russia experience losses exceeding seven percent.

4.3.3 Shocks on Electricity Generation from Renewable Resources

The online dashboard presents the electricity generation variation from renewable resources across the G-Cubed model regions under the SSPs. Under both SSP 1-2.6 and 2-4.5, with the rise in drier climate conditions from continued warming, hydropower generation in the Oil-Producing Countries heavily reduces, reaching almost 15 and 20 percent by 2100. Under SSP 5-8.5, other regions, such as Australia, Canada, and Russia, also experience severe reductions in hydropower generation attributable to lower precipitation and an increase in extremely warm conditions.

Although warmer and drier climate conditions generally favor solar power generation, extreme heat reduces the thermal efficiency of solar panels and degrades the material used for thermal panels. Under SSP 1-2.6 and SSP 2-4.5, solar power generation is relatively less affected by continued warming compared to hydropower generation. Canada and India are the most vulnerable under SSP 1-2.6, where the productivity reductions exceed seven percent towards 2100. Under SSP 2-4.5 and SSP 5-8.5, Canada and Russia experience substantial reductions with the increase in warmer nights.

The impacts on wind power generation are roughly within the range of those on solar power generation, although the impact distribution across the regions differs. Wind power generation is also relatively less vulnerable to climate risks compared to hydropower generation. While the chronic temperature rise may not substantially impact wind power generation productivity, extremely warm conditions could reduce the air density and, hence, the power output from turbines. This effect is apparent in Canada and Russia.

4.4 Summary

Section 4 illustrates how agriculture and energy in different G-Cubed model regions are affected under the SSPs. The shocks could have two interpretations. Firstly, as the SSPs inherently assume structural economic characteristics (e.g., the sectoral composition of the economies), the shocks could be interpreted as deviations from the underlying production patterns of those sectors due to the feedback effects of climate outcomes of the SSPs. However, as discussed in Section 2.3, many variations to the sectoral composition of the economies could exist while still producing the same emission outcome.

The second interpretation is independent of the assumption of the underlying structural characteristics of the economy. The shocks could be interpreted as additional sectoral impacts arising from temperature outcomes produced by an exogenous emission path equivalent to a given SSP (e.g., RCP 2.6 in the case of SSP 1-2.6) compared to a baseline. As the G-Cubed model is a general equilibrium economic model, it does not have a climate module, and it follows the second interpretation when introducing the shocks to its baseline.

One highlight from Section 4.3 is that the non-renewable energy subsectors, which also contribute to emissions and thereby to global warming, are also adversely affected due to the feedback effects of global warming. This observation applies to the coal and gas production in most leading producers, including Russia. Oil production is adversely affected across all regions, including Australia and Canada. Accordingly, continued warming further compromises global energy security, and the transition to renewables will yield a double dividend, mitigating further worsening of the global climate while reducing energy sector vulnerability to climate risks.

Another similar highlight from Section 4.4 is that the livestock sector is also significantly affected by continued warming. As the demand for livestock is expected to double by 2050 (compared to 2006) (Garnett 2009), climate change poses an imminent threat to global food security. At the same time, analogous to non-renewable energy subsectors, livestock influences climate change via emissions from land use changes, feed and animal production, manure processing, and transportation. Therefore, improving livestock production efficiency and substitution where possible will deliver another double dividend (analogous to substituting non-renewables with renewables) by mitigating further anthropogenic climate change while increasing global food security.

5 ECONOMIC CONSEQUENCES OF PHYSICAL CLIMATE IMPACTS ON AGRICULTURE AND ENERGY

Section 5 discusses the global economic consequences of physical climate impacts on agriculture and energy. While the G-Cubed model produces results for a wide range of both real and nominal economic variables and sector results for several variables, Section 5 focuses on a few selected real variables, which include real GDP, consumption and investment, exports and imports, sectoral output, real interest rates, current account balance, real exchange rate, trade balance, inflation. Figures 3-22 illustrate the short, medium, and long-run changes in those variables, i.e., the changes achieved by 2030, 2050, and 2080, compared to the baseline. In addition to the discussed results, the online dashboard presents the dynamic results for all the above variables from 2021 to 2080, the decomposition of the real GDP for its constituents, and the sectoral decomposition of consumption, investment, exports, and imports.

The results are primarily driven by the supply-side effects arising from the physical climate impacts on the productivity of agriculture and energy. These ultimate effects are also affected by the reactions of economic agents, particularly forward-looking households and firms, and monetary and fiscal authorities. There are also general equilibrium effects, particularly from the price effects (whereby regions dominant in certain sectors could influence the global prices and subsequent changes in trade and consumption patterns worldwide), due to changes in production patterns worldwide. Accordingly, given the sophistication of the G-Cubed model and close reflection of the realistic responses of the world to global economic shocks, the ultimate effects observed could be very different from what could be linearly predicted from the economic shocks discussed in Section 4.3.

The results are discussed relative to a baseline. As discussed in Section 4.2, the G-Cubed model baseline does not assume any climate shocks. However, as the shocks have been normalized in each G-Cubed model region for their 2020 levels, the current baseline assumes climate shocks equivalent to their respective 2020 levels. Therefore, the results should be interpreted as the economic consequences of additional climate shocks under SSPs relative to a baseline where climate shocks are assumed at 2020 levels.

5.1 Changes in Real GDP

When assessing the global economic consequences of physical climate impacts on agriculture and energy, given the sectoral disaggregation in the G-Cubed model, productivity shocks are introduced at the sectoral level. This approach distinguishes our study from most existing studies, which use either econometric or DSGE models without sector disaggregation, where a cumulative productivity shock is introduced to economies. Given the ability to introduce the shocks at the sectoral level, from the supply side of the economy, the ultimate real GDP changes are the cumulative effect of the sectoral production changes. From the demand side of the economy, the ultimate real GDP changes are the cumulative effect of the changes in consumption, investment, government expenditure, and expenditure on net exports.

This section presents an overview of the real GDP changes under the three SSPs. We also compare our estimates for real GDP losses with the existing studies. In Sections 5.2 and 5.3, we decompose demand-side changes in real GDP. Section 5.5 discusses the changes in sectoral production that drive the real GDP changes from the supply side of the economy.

As observed in Figure 3, all regions experience increasing losses as the warming increases across SSPs. For a given region, the losses increase within a given scenario with time as warming continues. Under SSP 1-2.6, Canada, China, and Oil-Producing Countries suffer the highest percentage reduction in GDP compared to the baseline. In contrast, India and the Rest of the OECD countries suffer the least. The GDP reductions vary between -0.2 and -2.3 percent from the baseline by 2080. Under SSP 2-4.5 and 5-8.5, Russia is substantially affected by continued warming, where GDP reductions could exceed 11 and 26 percent from the baseline, respectively.

As discussed in Section 4.3, agriculture and energy in both Canada and Russia are noticeably vulnerable to climate risks. However, when those shocks are assessed within a general equilibrium setting, Canada is less affected than Russia. These differential effects on Russia illustrate how the existing structural characteristics of the country could magnify the adverse consequences of climate impacts. The historical economic data used for model calibration introduces these country-specific structural characteristics to the G-Cubed model.

Table 4 summarizes the economic consequences of climate change from some existing studies discussed in Section 2.4 and compares the estimates from this paper with them. As observed, Kahn et al. (2019), assessing both chronic risks and some extreme risks, illustrate that the GDP losses per capita could vary between 0.58 to 9.96 percent across RCPs by 2100. Kompass et al. (2018) expect the annual global losses to be between $US5.55 and 23.15 trillion under three warming scenarios. Roson and van der Mensbrugghe (2010) illustrate that the GDP could vary between 3.5 to -12 percent on average under an extreme warming scenario. Fernando et al. (2021), evaluating the global economic consequences of both chronic and extreme physical risks of RCPs, illustrate global annual losses to be between $US4 and 14 trillion.[32] Assessing SSP 1-2.6 and SSP 2-4.5, Fernando and Lepore (2023) estimate global annual losses at $US2.4 and 7.1 trillion.

Fernando and Lepore (2023) adopt a similar approach to this paper when modeling the economic consequences of physical climate risks. They adopt the same climate indicators, excluding relative humidity and extremely windy conditions, and the same approach to estimating productivity responsiveness to physical climate risks. The impacts are also assessed within the same G-Cubed model version used for this paper. Different from this paper, they consider a global multisectoral (agriculture, mining, manufacturing, and services) sample of 59,554 firms from 147 countries. The firms are globally leading, with the largest asset base in their respective countries. The productivity observations have been available for all the sectors, and thus, the shocks on manufacturing and services are also estimated in Fernando and Lepore (2023). Given the limited granularity of agriculture and energy sectors, they cannot break down the estimates for agriculture subsectors (crops vs. livestock) and energy subsectors (non-renewables vs. renewables).

Despite those differences, the cumulative impact on real GDP from Fernando and Lepore (2023) is marginally higher than the cumulative impact of this paper. This suggests that other pathways directly affecting manufacturing and services could exist beyond the input-output linkages and general equilibrium effects in the G-Cubed model. They are not being captured in this paper as the explicit focus is on physical climate impacts on agriculture and energy and the spillover effects into other sectors.

The studies compared in Table 4 also have important differences from each other. The methodologies they have followed, the scenarios they have focused on, and the characteristics of the scenarios are some sources of differences. Therefore, a comprehensive comparison across the studies is not possible. For example, compared to other general equilibrium studies, Roson and van der Mensbrugghe (2010) and Kompass et

[32] Fernando et al. (2021) also evaluate two sources of transition risks besides physical risks. The estimates compared and presented in this paper only relate to the physical risks.

al. (2018), this paper includes the climate impacts on energy production and uses estimates derived from a combined framework that incorporates both chronic and extreme climate risks and accounts for their potential multicollinearities.

Table 4: Summary of Estimates of the Global Economic Impacts of Physical Climate Risks

Study	Risks	Scenario	Focus	Horizon	Unit	Estimates
Fernando & Lepore (2023)	Chronic and extreme risks	SSP 1-2.6 SSP 2-4.5	World	2021 - 2100	$US Trillion in GDP per annum	-2.38 -7.10
Fernando (2023)	Chronic and extreme risks	SSP 1-2.6 SSP 2-4.5 SSP 5-8.5	World	2021 - 2100	$US Trillion in GDP per annum	-2.00 -6.50 -15.00
Fernando et al. (2021)	Chronic and extreme risks	RCP 2.6 RCP 4.5 RCP 6.0 RCP 8.5	World	2021 - 2100	$US Trillion in GDP per annum	-3.82 -6.91 -7.85 -13.83
Kahn et al. (2019)	Chronic and (some) extreme risks	RCP 2.6 RCP 8.5	World World	2100 2100	% GDP per capita Loss	0.58% to 1.57% 4.44% to 9.96%
Kompas et al. (2018)	Chronic risks	2 ^{0}C 3 ^{0}C 4 ^{0}C	World	2020 - 2100	$US Trillion in GDP per annum	-5.55 -9.59 -23.15
Roson & van der Mensbrugghe (2010)	Chronic risks	5.2 ^{0}C	World	2100	% GDP Change	+3.5% to -12%
Hsiang et al. (2017)	Extreme risks	2 ^{0}C 4 ^{0}C	USA	2080 - 2099	% GDP Change	0.5% 2.0%
Narita et al. (2010)	Storms		World	2100	% GDP Change	0.006%

Source: Constructed by the Author.

Yet, as Fernando et al. (2022) argue, following an illustration of the methodological difference between IAMs and general equilibrium models and their estimates of economic consequences of three NGFS scenarios (Bertram et al. 2022), these methodological and philosophical differences of a wide range of different studies and the estimates they produce are precisely what is necessary for policymaking under the enormous uncertainty climate change involves. The diversity across the studies enriches the discussion of the economic consequences of climate change by bringing in different insights.

5.2 Changes in Consumption and Investment

As observed in Figure 4, the consumption change patterns closely follow the real GDP changes, indicating the income effects on consumption. However, the changes, especially in the early periods, are more substantial than real GDP. This observation is mainly due to the behavior of the forward-looking agents, who make up 30 percent of the agents. They observe the future trends in physical risks and smooth their consumption patterns across the century. Consequently, they consume less than the income effects demand in the early periods and then experience consumption reductions less than those of real GDP. Despite the smoothing, the consumption patterns remain closer to real GDP, with the rule-of-thumb agents leading the overall consumption in the economy.

Under SSP 1-2.6, China experiences the most substantial consumption reduction, three percent below the baseline by 2080. India and Australia minimally adjust their consumption across the SSPs. Under SSP 2-4.5 and SSP 5-8.5, the consumption reductions could exceed five to ten percent from the baseline for most regions. Sectoral analysis of the consumption changes reveals that in developed countries (such as Australia and Europe), the consumption changes are driven by services. However, in developing countries (such as India, China, and the Rest of the World), consumption from agriculture also reduces. This observation illustrates a higher vulnerability of subsistence consumption to climate risks in developing countries, leading to more adverse welfare consequences for them under the SSPs.

Analogous to consumption changes, the behavior of the heterogeneous agents influences investment changes. However, the investment changes could be much larger than consumption and real GDP changes. Notably, the investment reductions in the G-Cubed model could be larger than those of similar CGE/DSGE models and especially IAMs. This is mainly due to the explicit distinction of capital as physical and financial capital. In response to an economic shock or a series of economic shocks expected in the future for a given sector, the financial markets in the G-Cubed model swiftly respond. As a result, the financial capital in a relatively more vulnerable sector could immediately get relocated to markets with sectors experiencing lower risks. Furthermore, the physical adjustment costs of readjusting investment discourage investors from reinvesting in the sectors and countries more vulnerable to physical climate risks. The investment adjustment costs give rise to stranded assets or an idling capital stock without productive use in the exposed sectors, which also have feedback effects on the real GDP.[33] Investment readjustments are also affected by the structural features of economies, such as capital controls. Therefore, countries/regions with capital controls could experience much larger investment reductions when investors respond to physical climate risks.

As observed in Figure 5, under SSP 1-2.6, Canada, Japan, Oil-Producing Countries, and Russia experience substantial investment reductions that exceed three percent below the baseline. Amidst continued warming, under SSP 2-4.5 and SSP 5-8.5, the reductions non-linearly increase and reach close to ten percent for most

[33] See Bertram et al. (2022) for a discussion of the implications of investment adjustment costs on determining carbon prices as an instrument to incentivize transitions to low-carbon economies in the G-Cubed model vs. IAMs.

regions. A sectoral decomposition of investment illustrates that the bulk of the investment reduction comes from services. However, Russia, Canada, and Oil-Producing Countries also experience substantial investment reductions in crude oil extraction. Australia observes notable investment reductions in coal mining. This illustrates how markets would observe future climate risks and factor them into their investment decisions. Accordingly, promoting such sunset industries as non-renewables may prove futile in a globally connected financial market.

5.3 Changes in Exports and Imports

In the G-Cubed model, the changes in exports and imports are affected not only by the physical climate impacts on sectoral productivity. They are also affected by the income and price effects via feedback.

As observed in Figure 6, under all three SSPs, Japan experiences substantial reductions in exports, primarily driven by reductions in durable manufacturing. Canada also experiences significant decreases in exports under SSP 1-2.6, driven by a mix of sectors, including durable manufacturing, crude oil extraction, and services. Due to their exposure to physical climate risks, exports from agriculture and non-durable manufacturing also decrease. Oil-Producing Countries and Russia are also exposed to significant export contractions, primarily driven by crude oil and gas extraction.

Changes in imports in Figure 7 are a particular reflection of the changes in consumption patterns due to both income and price effects. However, across the SSPs, the reductions in imports are generally lower than those in consumption. Under all three SSPs, Canada and Russia experience the highest declines in imports in the long run by 2080. These changes are mainly driven by demand reduction for durable manufacturing goods amidst reduced investment attributable to physical climate risks. Given the vulnerability of global agriculture and energy to climate risks, developing countries (such as India and China) reduce their imports of fossil fuels.

5.4 Changes in Sectoral Output

The sectoral output changes are driven mainly by the sectoral economic shocks discussed in Section 4.3. As the G-Cubed model is a general equilibrium model, moderating effects could also exist, which we highlight in this discussion. Figures 8-16 provide the results for sectoral output.

Agriculture: As predicted by economic shocks in Section 4.3 and illustrated in Figure 8, the agriculture output globally reduces across all three SSPs. The global reduction illustrates that without additional adaptation and/or mitigation, compensating for the productivity losses from physical climate risks would be impossible, and physical climate risks threaten global food supply and security.

Energy: Analogous to agriculture, global electricity generation reduces (Figure 9). The cumulative reduction in electricity generation is driven by the climate impacts on both renewable and non-renewable energy subsectors, discussed in depth in Section 4.3. Similar to electricity, the global use of gas and petroleum refining reduces (Figures 10 and 11). These effects illustrate how, in the absence of additional adaptation and/or mitigation, the world would be forced to consume less energy due to the climate impacts on energy.

Manufacturing: The G-Cubed model distinguishes manufacturing as durable and non-durable. Durable manufacturing includes the production of capital goods, while non-durable manufacturing mainly includes consumables. The physical climate impacts on agriculture and energy and their spillover effects into other sectors reduce the global investment demand and, thus, shrink the global durable manufacturing sector (Figure 12). Given the additional impacts on consumption demand globally, the non-durable manufacturing sector shrinks even more than the durable manufacturing sector (Figure 13).

Services: The G-Cubed model version used in this paper includes three service sectors.[34] construction, transportation, and other services. Potentially driven by the lack of global investment, construction globally contracts from the baseline levels (Figure 14). Transportation, although not affected as much as construction, also shrinks following the energy production reduction due to its exposure to physical climate risks (Figure 15). Though marginal, services (other than construction and transportation) increase in regions such as the US, Canada, and Australia (Figure 16).

5.5 Changes in Real Interest Rates

Amidst the productivity changes induced by climate risks, the marginal productivity of capital falls. This reduces the long-term interest rate, which, combined with the loosening monetary policy by central banks to raise growth to target rates, leads to a decline in the short-term nominal interest rate. Figures 17 and 18 illustrate the long- and short-term real interest rate changes. Given the continued exposure of economies to climate risks, the long-term real interest rates reduce. Under all scenarios, China experiences the highest reduction. Under SSP 2-4.5 and 5-8.5, the Rest of the World also experiences quite close reductions from the baseline, which exceed 0.4 and 1 percent below the baseline by 2080. The variations in short-term real interest rates remain similar to those of long-term real interest rates.

5.6 Changes in Current Account Balance

The changes in real interest rates trigger investment flows. The countries experiencing relatively lower productivity reductions experience capital inflows, and those experiencing somewhat higher productivity reductions experience capital outflows. As observed in Figure 19, under SSP 1-2.6, China, Canada, and the Oil-Producing Countries experience capital inflows in the long run. In contrast, the others experience capital outflows, with Russia experiencing the highest capital outflow. Under SSP 2-4.5, Europe and the Rest of the World also experience capital inflows, while Russia, Canada, and Japan experience capital outflows.

5.7 Changes in Real Exchange Rate

The changes in capital flows trigger exchange rate changes. As observed in Figure 20, China, Canada, and the Rest of the World experience a real exchange rate appreciation under SSP 1-2.6, while most other regions experience a depreciation. Under SSP 2-4.5, Canada, Russia, and the Rest of the World experience a real exchange rate appreciation. Similar to SSP 1-2.6, under SSP 2-4.5, the US experiences a real exchange rate appreciation in the short run, followed by a depreciation in the medium to long run.

[34] Energy utilities have been discussed as part of the Energy sector.

5.8 Changes in Trade Balance

Trade flow changes have to be consistent with the movement of the current account and capital account. This is achieved through real exchange rate changes, which affect the prices of exports and imports. Those countries experiencing capital inflows observe appreciating real exchange rates and, hence, higher imports due to income effects and lower exports due to reduced competitiveness, and vice versa.

As observed in Figure 21, Oil-Producing Countries experience trade balance improvements amidst the deterioration of the current balance due to capital outflows. Although China and Canada are experiencing an improvement in the short run, they experience a reduced trade balance in the medium to long run. In contrast, some other regions, such as Russia, observe an improved trade balance in the long run. Under SSP 2-4.5, the trade balance changes become less dynamic for most regions, although the range of changes increases. However, Japan experiences a sharp trade balance improvement in the long run.

5.9 Changes in Inflation

Two main factors drive changes in inflation in the G-Cubed model. Firstly, the changes in production patterns, income, and prices triggered by the productivity impacts of physical climate risks affect inflation in the regions. Secondly, the effects will be moderated by the central banks in the respective regions depending on their objectives. As observed in Figure 22, inflation will permanently be higher under both climate scenarios as we assume that central banks have not adjusted their baseline projections of real economic growth. Thus, an inflation bias emerges from the central bank reaction functions. The long-term inflation increases across the scenarios. China and Europe mainly observe significant inflation variations amidst the climate risks at the beginning. Under SSP 1-2.6, the inflation is highest in China, while under SSP 2-4.5 and SSP 5-8.5, Russia and the Rest of the World also experience higher inflation compared to the other regions.

6 IMPLICATIONS FOR RESEARCH AND POLICY

6.1 Implications for Research

Importance of Chronic and Extreme Climate Risks

This paper illustrates the importance of incorporating a wide range of both chronic and extreme climate indicators when estimating the sensitivity of agriculture and energy to historical physical climate impacts. As illustrated in Section 3.4, considering only chronic risks overlooks the critical extreme physical impacts on agriculture and energy. We also emphasize that such estimations should be conducted using methodologies that could handle a large group of potentially correlated variables and produce estimates robust to multicollinearity and the number of climate indicators. We illustrate how machine learning algorithms are helpful in those exercises to overcome the limitations of conventional approaches.

Importance of Heterogeneity and Granularity

Section 3.4 discusses the responsiveness of five agriculture and eight energy subsectors to physical climate risks. Those estimates illustrate that the exposure of subsectors to different climate risks is different.

Estimations for agriculture and energy as broad sectors could have masked the wide heterogeneity and granularity. Furthermore, comparing this paper to Fernando and Lepore (2023), we demonstrated how further increasing the granularity beyond the sector level (potentially firm level) could capture additional impact pathways. Therefore, deep bottom-up estimates should always be preferred when exploring sectoral impacts of physical climate risks.

Utility of Machine Learning

As illustrated in this paper, machine learning is another beneficial computational advancement that could be harnessed in economic analyses of climate change to overcome the limitations of conventional econometric approaches. Specifically, we utilized machine learning to obtain unbiased coefficients when a large number of correlated predictors are present. Furthermore, the cross-validation and subset learning regressions help extract the most critical insights from the estimates. Moreover, they could be used to overcome challenges pertaining to big data handling and large-scale (both temporal and spatial) analyses frequently encountered in climate studies.

Importance of General Equilibrium Effects and Realistic Model Calibration

This paper illustrates how the magnitude of climate risks is moderated (either amplified or diluted) within a globally interconnected economy depending on the responses of economic agents. Using the G-Cubed model, which is a global multisectoral intertemporal general equilibrium model, Section 5 discusses the changes in an array of economic variables under three SSPs. There, through changes in consumption and investment, we demonstrate how the characteristics of the agents, such as the forward-looking behavior, could moderate the economic effects from what could be linearly and explicitly predicted from a series of economic shocks. Through changes in investments, we also illustrate the importance of distinguishing physical capital from financial capital and the implications of investment adjustment costs when assessing climate risks. We also demonstrate how existing economic vulnerabilities due to structural features of the economies (such as capital controls) could further aggravate the economic impacts of physical climate risks. Thus, general equilibrium models embedding the actual behavior of the countries/regions in the model via calibrations could portray the realistic economic consequences of climate change.

6.2 Implications for Policy

Importance of Climate Change Action

This paper illustrates how costly the economic consequences of physical climate impacts on agriculture and energy could be without substantial mitigation and adaptation. The continued warming aggravates the economic consequences. Decomposing the results for real GDP, we illustrated how changes in consumption, investment, exports, and imports contribute to the real GDP changes. Sectoral decomposition of consumption demonstrated that in developing countries, such as China, India, and the Rest of the World, subsistence consumption also reduces, indicating pathways via which the physical climate impacts would reduce global welfare.

Double Dividends from Transitioning to Sustainable Agriculture and Renewables

By analyzing the behavior of agriculture and energy under three SSPs, this paper illustrates the potential for double dividends from climate mitigation. Non-renewables and livestock sectors significantly contribute to greenhouse gas emissions and anthropogenic climate change. Those sectors are also experiencing significant adverse physical climate impacts as the feedback effects from the emissions they contribute. The vulnerability of those sectors to climate risks will also threaten global energy and food security. Thus, transitioning to low-carbon economies with higher use of renewables and improved efficiency and substitution in the livestock sector could reduce emissions and the vulnerability of global food and energy supply chains to physical climate risks.

Considerations for Locating Renewable Infrastructure

Generally, when determining the locations for renewables, the generation potential or the generation density is prioritized. However, as Section 3.4 illustrates, renewables are not immune to physical climate risks either. Their operations could also be affected by extreme climate risks. To ensure operational stability, the exposure to extreme risks should be minimized when establishing renewable power generation plants.

Investment Reallocation to Renewables Independent of Transition Policies

In this paper, we did not consider any explicit transition risks, such as carbon prices, which would increase the operational costs of non-renewables and would favor low-carbon energy sources. Yet, given the disproportionate vulnerability of non-renewables to physical climate risks, in Section 5.2, we observed that investors responded by reducing investments in crude oil extraction in Oil-Producing Countries and Russia and gas extraction in Australia. Therefore, even without explicit transition policies, investment reallocations are possible if the financial markets factor in the disproportionate exposure of non-renewables to aggravating physical climate risks. Such information is complementary to transition policies, and those could reduce the distortionary effects of transition policies and help improve their efficiency.

Importance of Diversity to Account for Uncertainty

As Sections 2.3, 2.4, and 5.1 illustrate, assessing the economic consequences of climate change involves enormous uncertainty. All modeling efforts reflect, at most, a part of the problem. Therefore, incorporating a wide array of studies focusing on different climate scenarios, employing different methodologies, and producing different estimates is vital to enriching the climate policy discourse. The global understanding of the complex system dynamics of climate change is inadequate to recognize a single framework as superior to other frameworks when assessing the economic consequences of physical climate risks. Accordingly, the consensus across estimates from various frameworks is not necessary. As argued in detail by Fernando et al. (2022), diverse philosophical viewpoints on how physical climate risks affect socioeconomic systems and different estimates should precisely be the input to policymaking on climate change amidst uncertainty.

7 CONCLUSION

Climate change poses an existential threat to humanity. With their intrinsic linkages to the natural environment, agriculture and energy sectors are fundamental channels via which the impacts of physical climate risks spill over into the economy. This paper evaluates the global economic impacts of the physical climate risks on agriculture and energy.

The paper first introduces the climate risks and scenarios widely used in policymaking and reviews the existing methodologies for assessing the global economic consequences of physical climate risks and their estimates, focusing on IAMs and general equilibrium models. The paper then evaluates the historical sensitivity of agriculture and energy to physical climate risks. Agriculture includes crops, live animals, and livestock, while energy consists of both non-renewables and renewables. Ten climate indicators representative of chronic and extreme physical climate risks are constructed, which are then used in machine learning algorithms to estimate the historical responsiveness of agriculture and energy production to physical climate risks.

The empirical estimates project agriculture and energy production changes under three SSPs: SSP 1-2.6, SSP 2-4.5, and SSP 5-8.5. Then, we discuss the variation of global impacts of physical climate risks on agriculture and energy under the SSPs in-depth. Subsequently, the shocks are assessed within the G-Cubed model: a global multisectoral intertemporal general economic model. The results from G-Cubed model simulations for real GDP, consumption, investment, exports and imports, sectoral output, real interest rates, current account balance, real exchange rates, trade balance, and inflation are discussed with reference to the existing studies. We then extract the implications of this paper for research and policy.

A general question concerning studies incorporating historical estimates to project impacts under future scenarios is to what extent the historical patterns reflect the future. Especially in climate change-related studies, extensive focus on historical estimates could cloud the impacts of unprecedented events, such as those arising from natural and socioeconomic tipping points. Nevertheless, we illustrate that the projections based on historical estimates are a helpful starting point, and sensitivity analyses could account for the sources of uncertainty related to the studies (construction of climate indicators, empirical estimations, model calibration, etc.). Future studies could also attempt to incorporate non-linear estimations for historical responsiveness. Furthermore, granular estimations at individual firm level (within the sectors) may provide additional insights into the heterogeneity of the climate impact transmission pathways.

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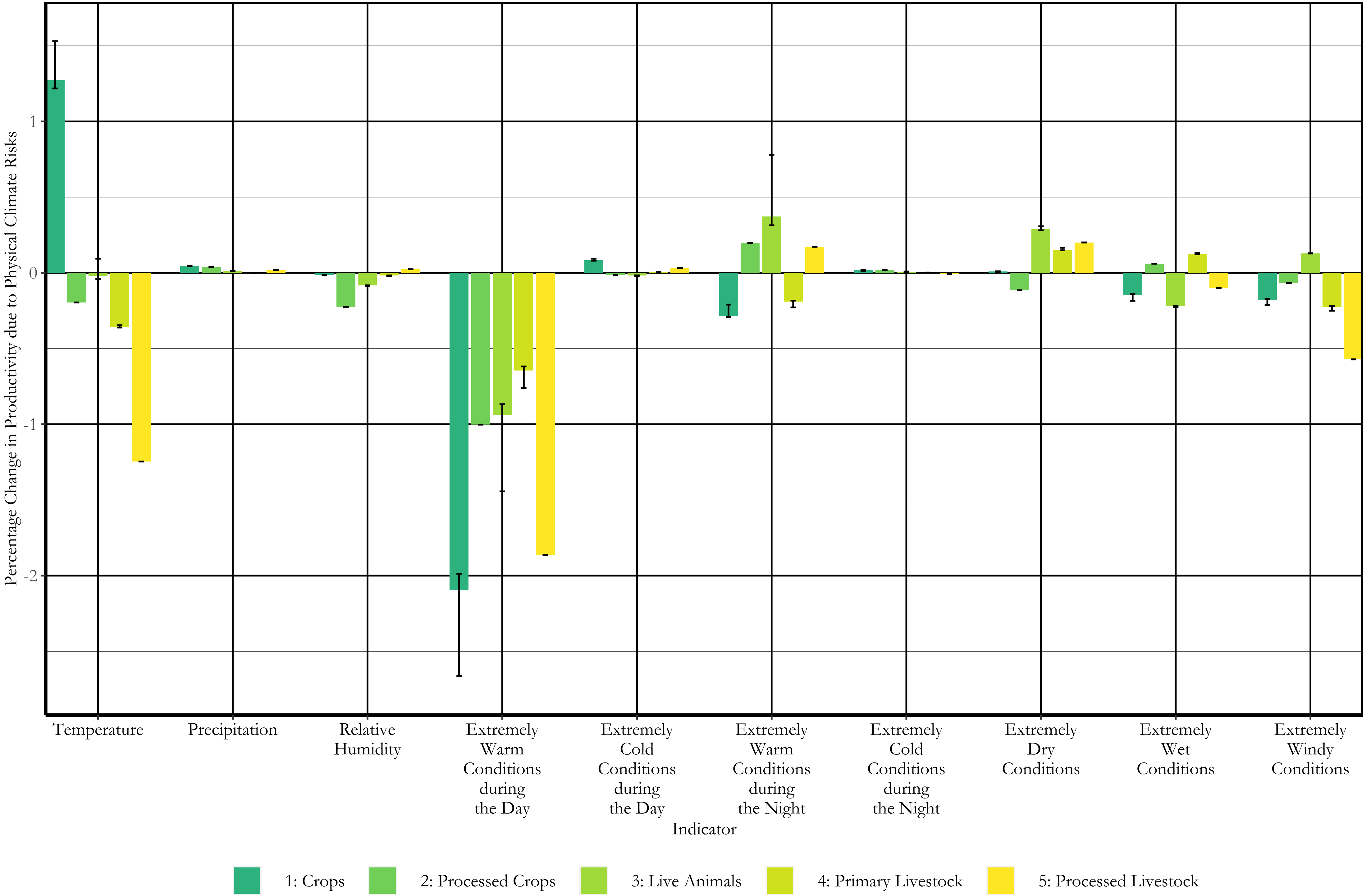
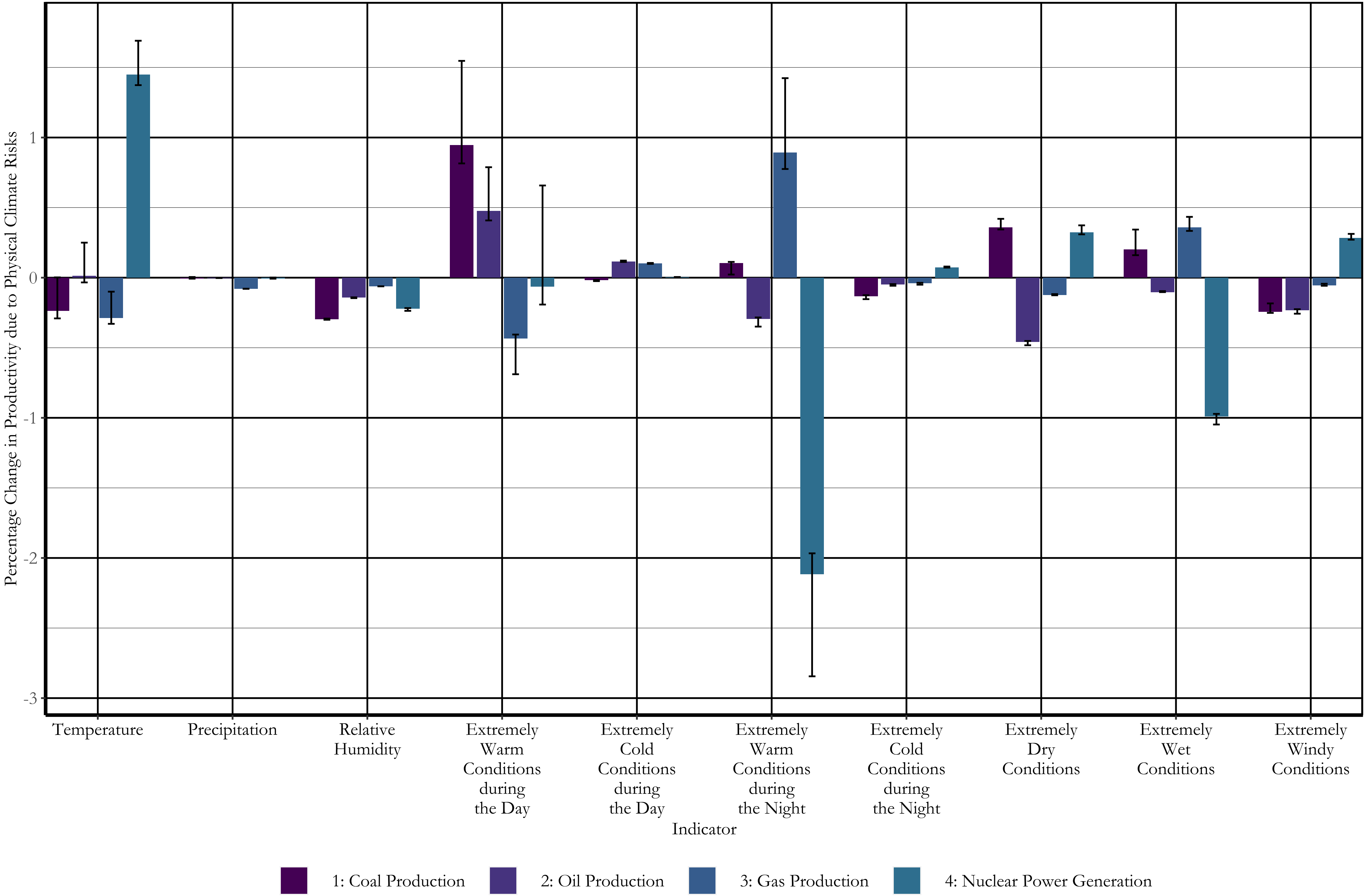
Figure 1: Average Historical Responsiveness of Agriculture Productivity to Physical Climate Risks from 1991 to 2020



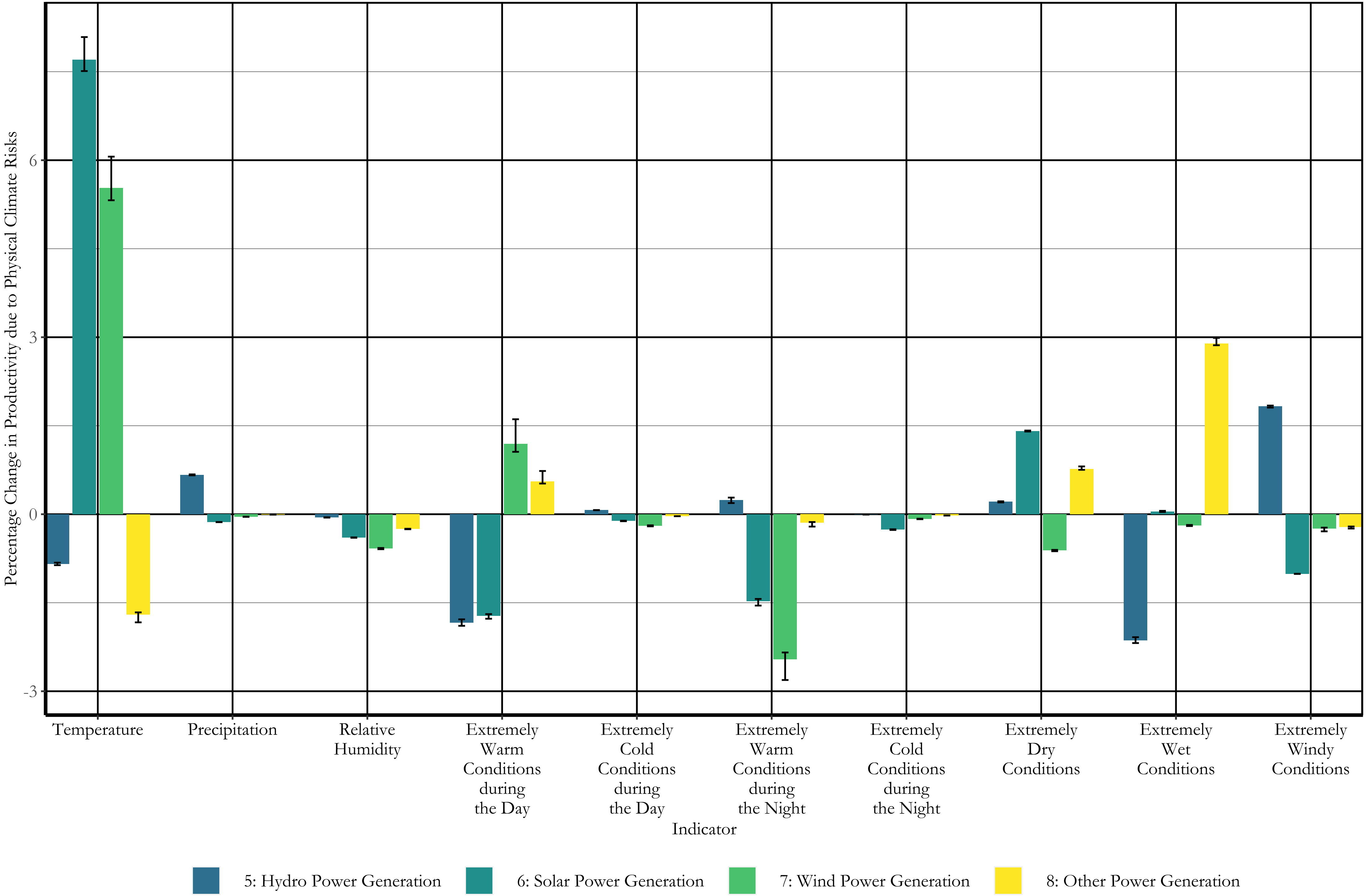
Source: Author's Calculations.

Figure 2: Average Historical Responsiveness of Non-renewable Energy Productivity to Physical Climate Risks from 1991 to 2020



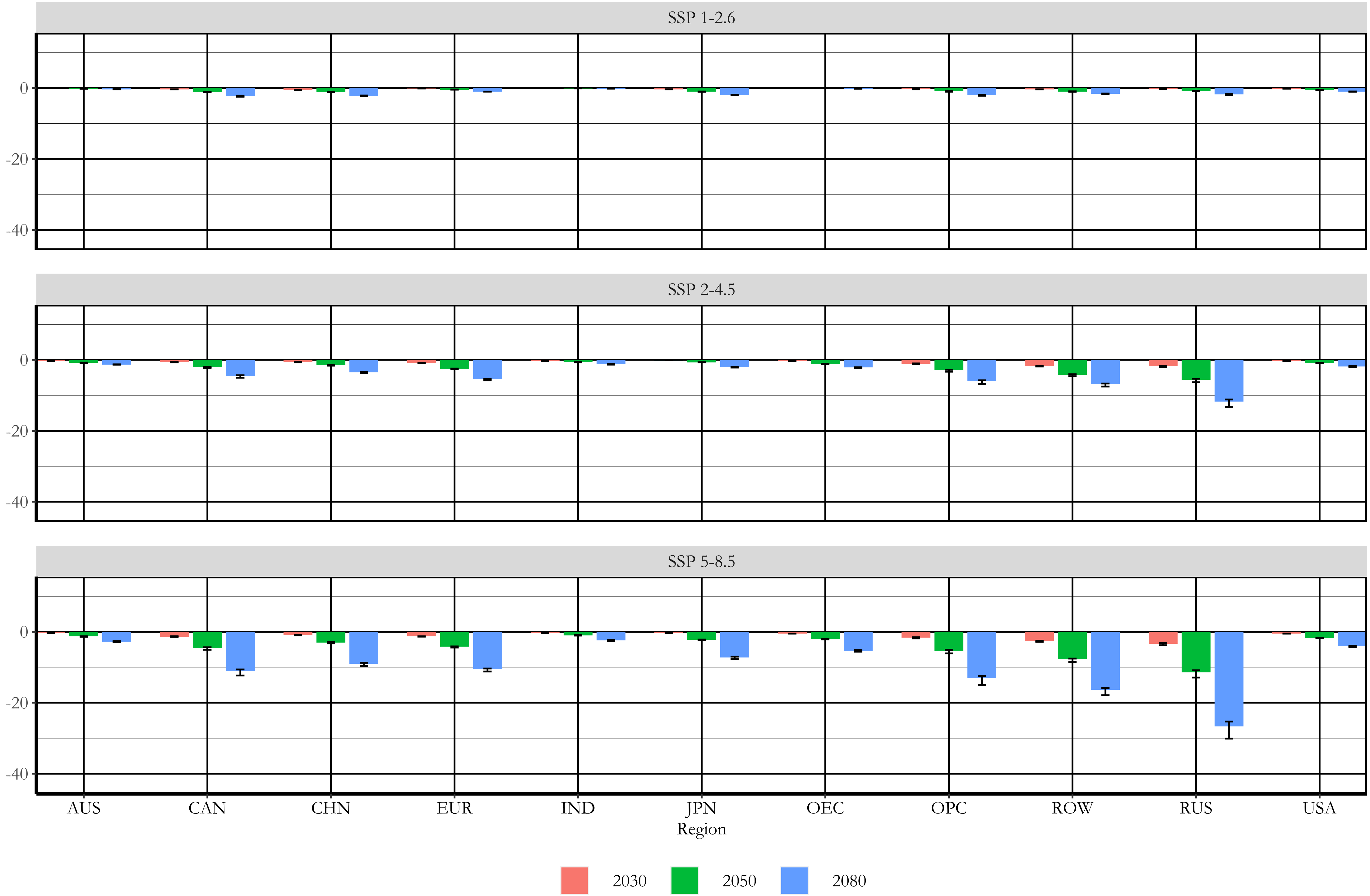
Source: Author's Calculations.

Figure 2 (Contd.): Average Historical Responsiveness of Renewable Energy Productivity to Physical Climate Risks from 1991 to 2020



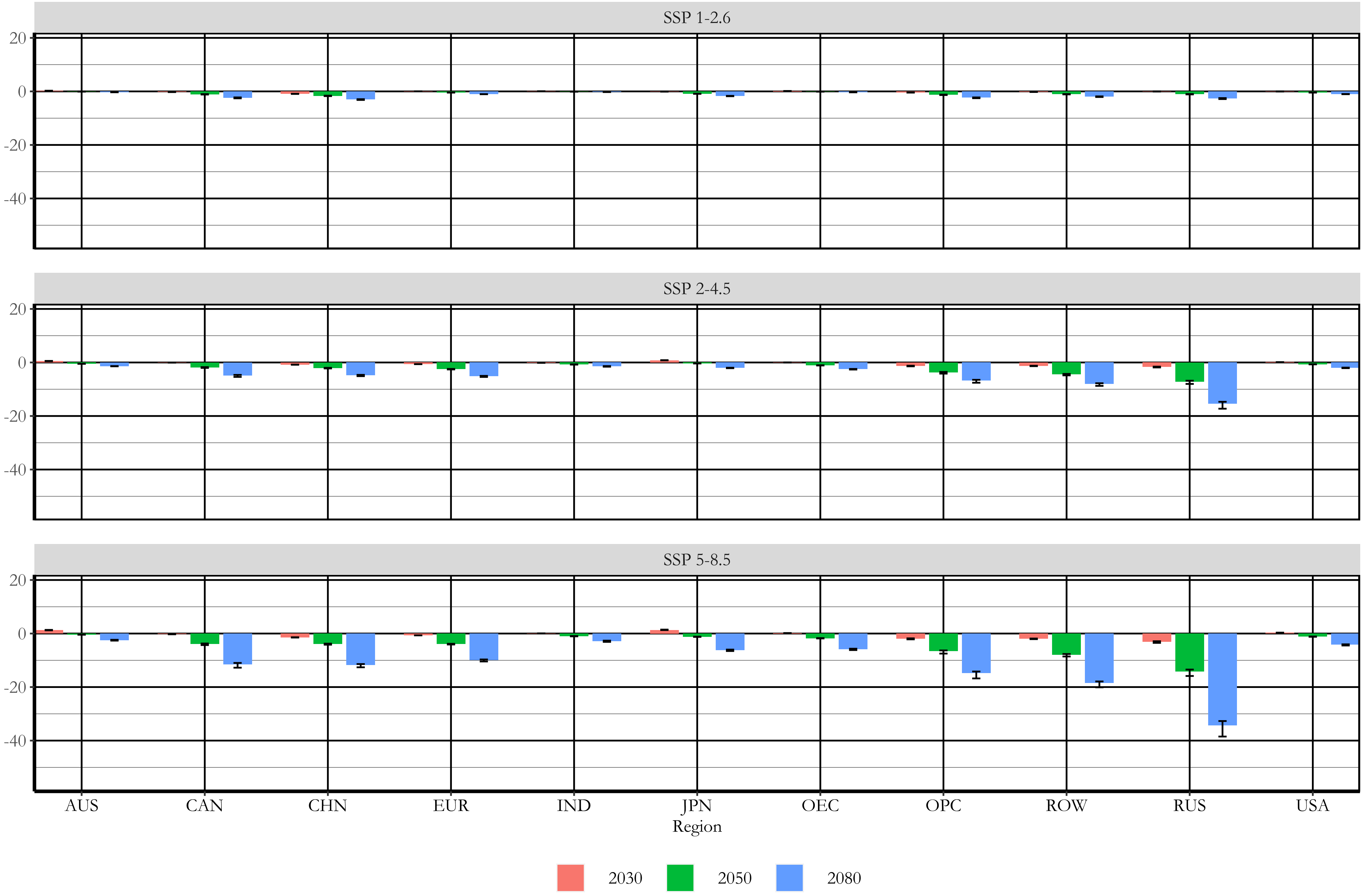
Source: Author's Calculations.

Figure 3: Real GDP: Percentage Deviation from Baseline



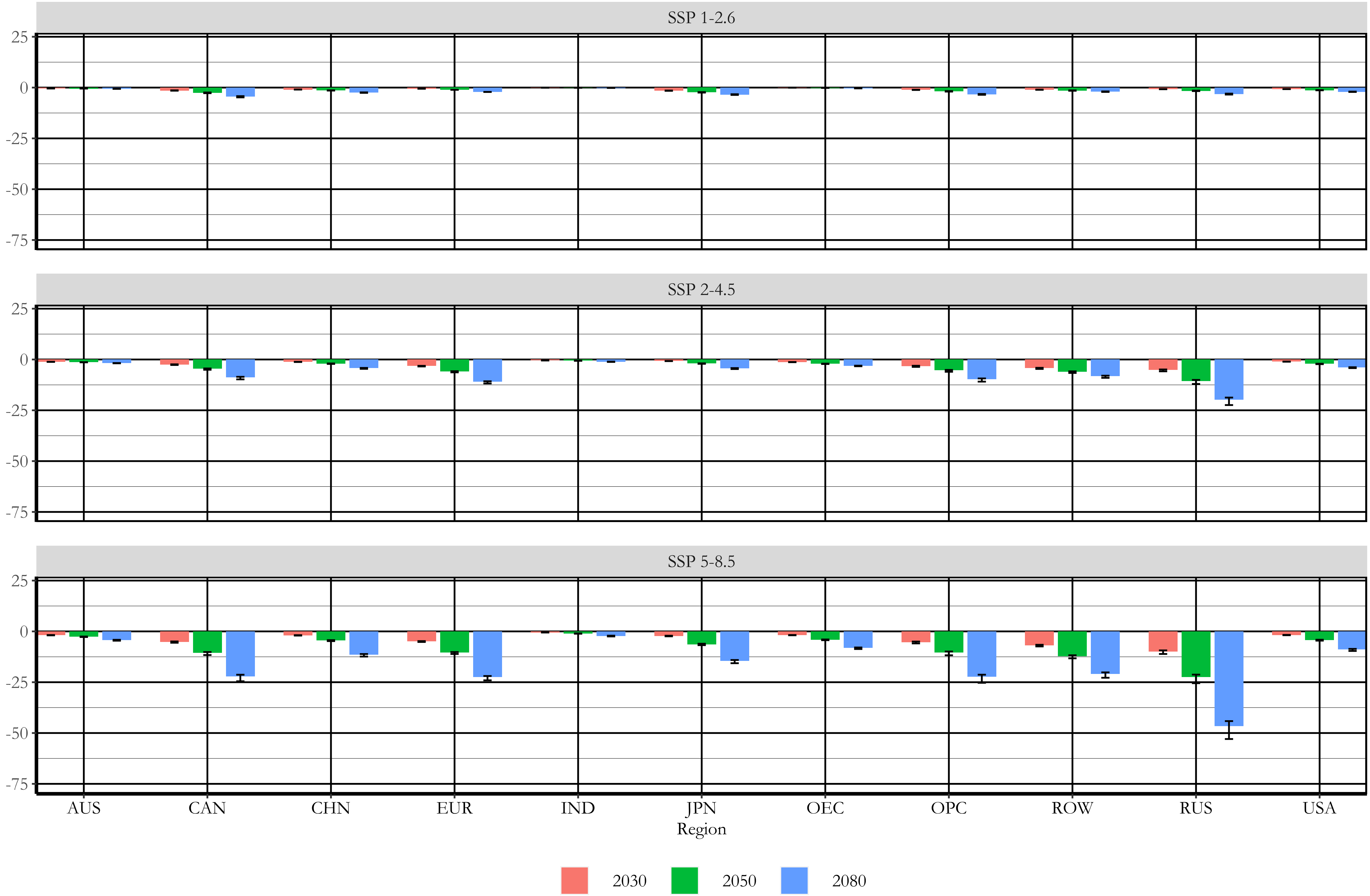
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 4: Consumption: Percentage Deviation from Baseline



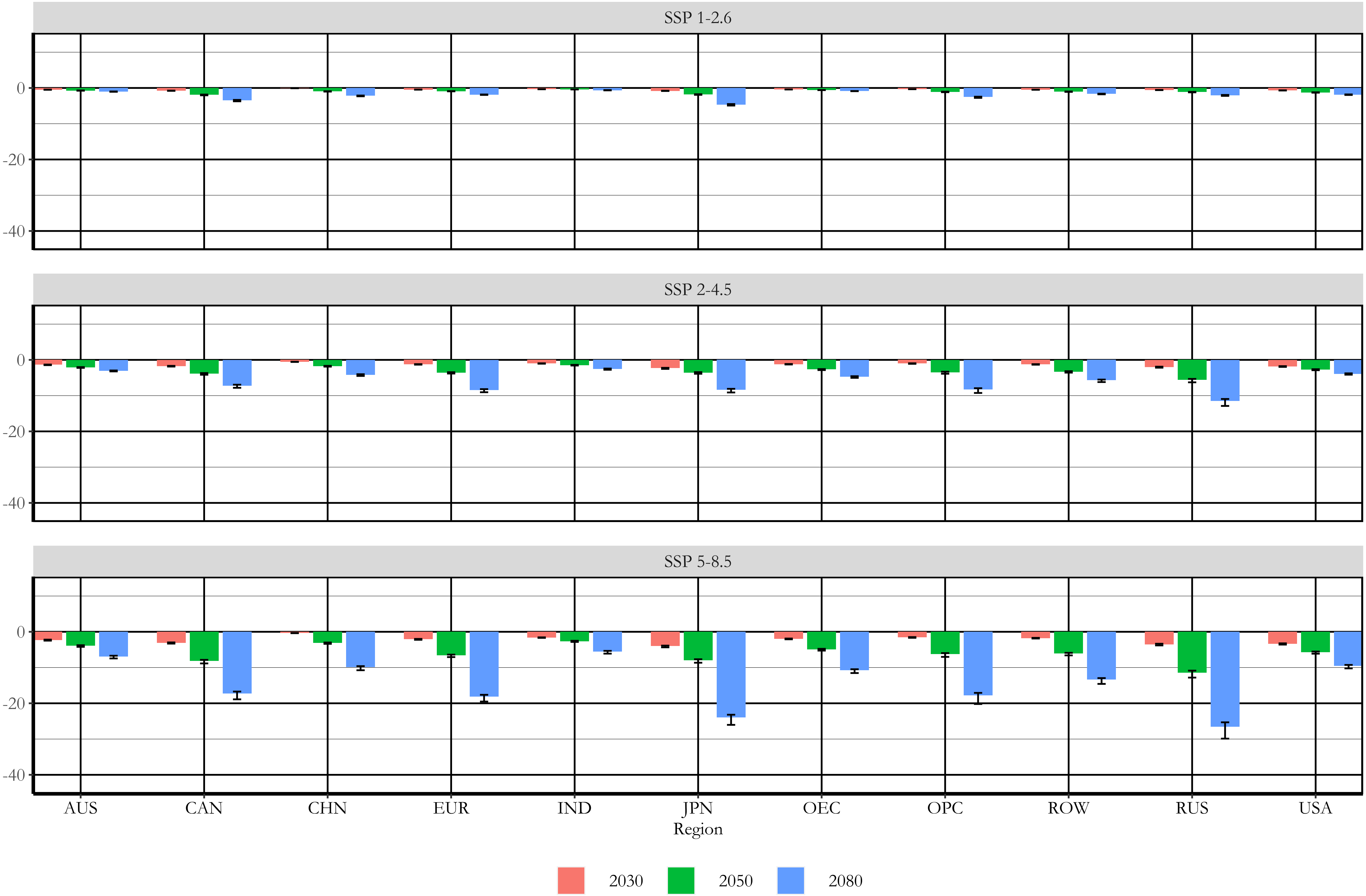
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 5: Investment: Percentage Deviation from Baseline



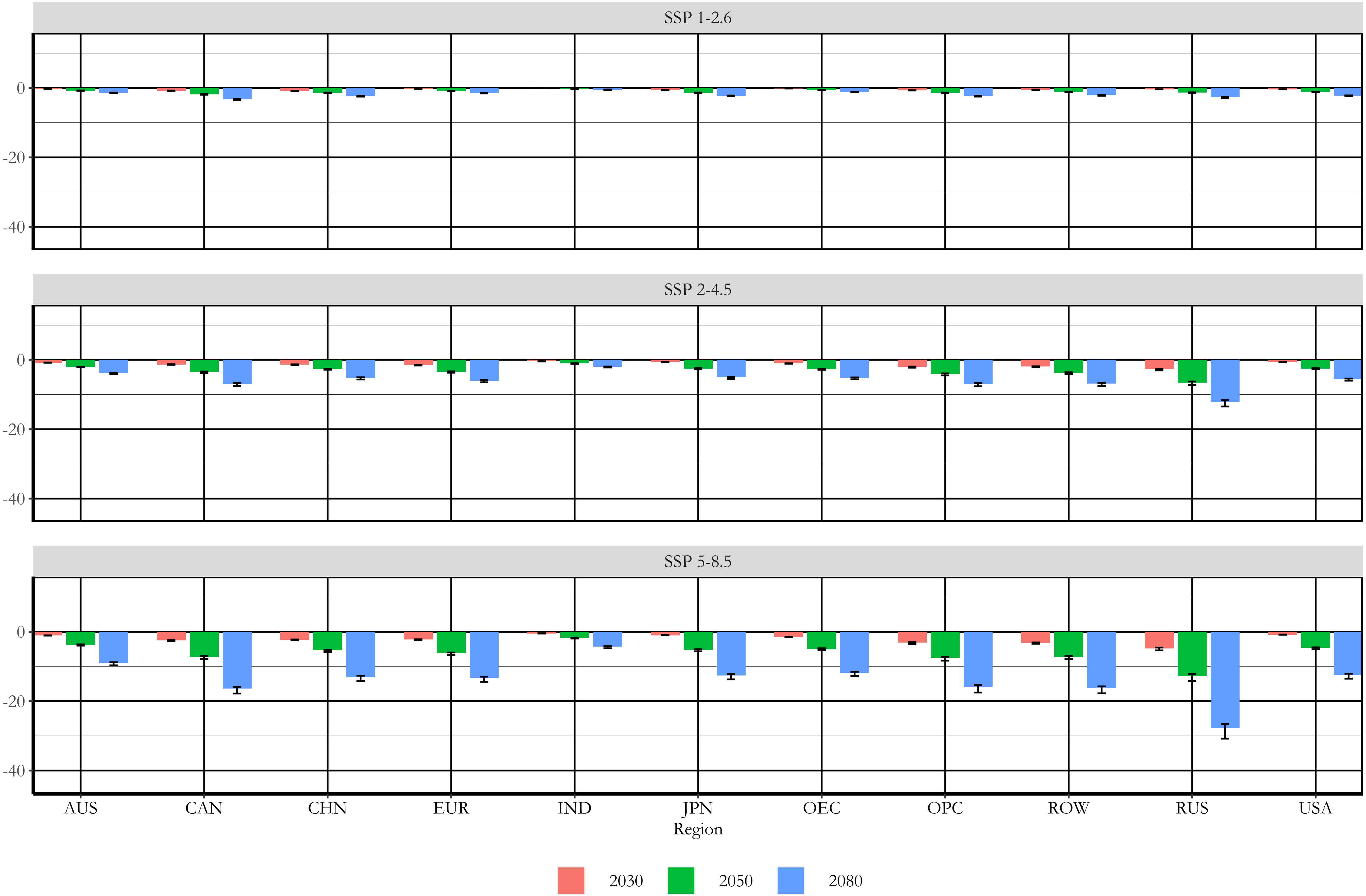
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 6: Exports: Percentage Deviation from Baseline



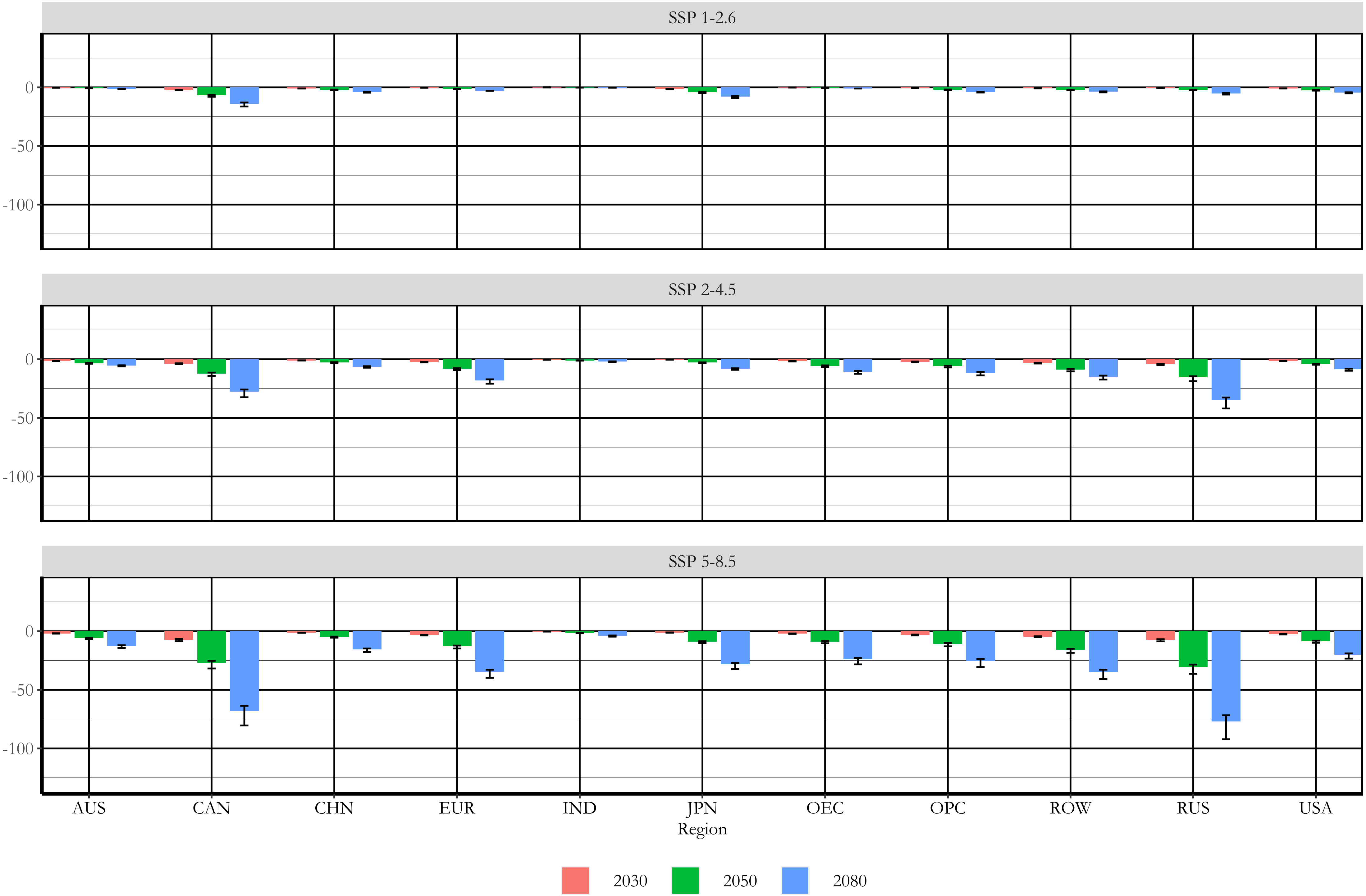
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 7: Imports: Percentage Deviation from Baseline



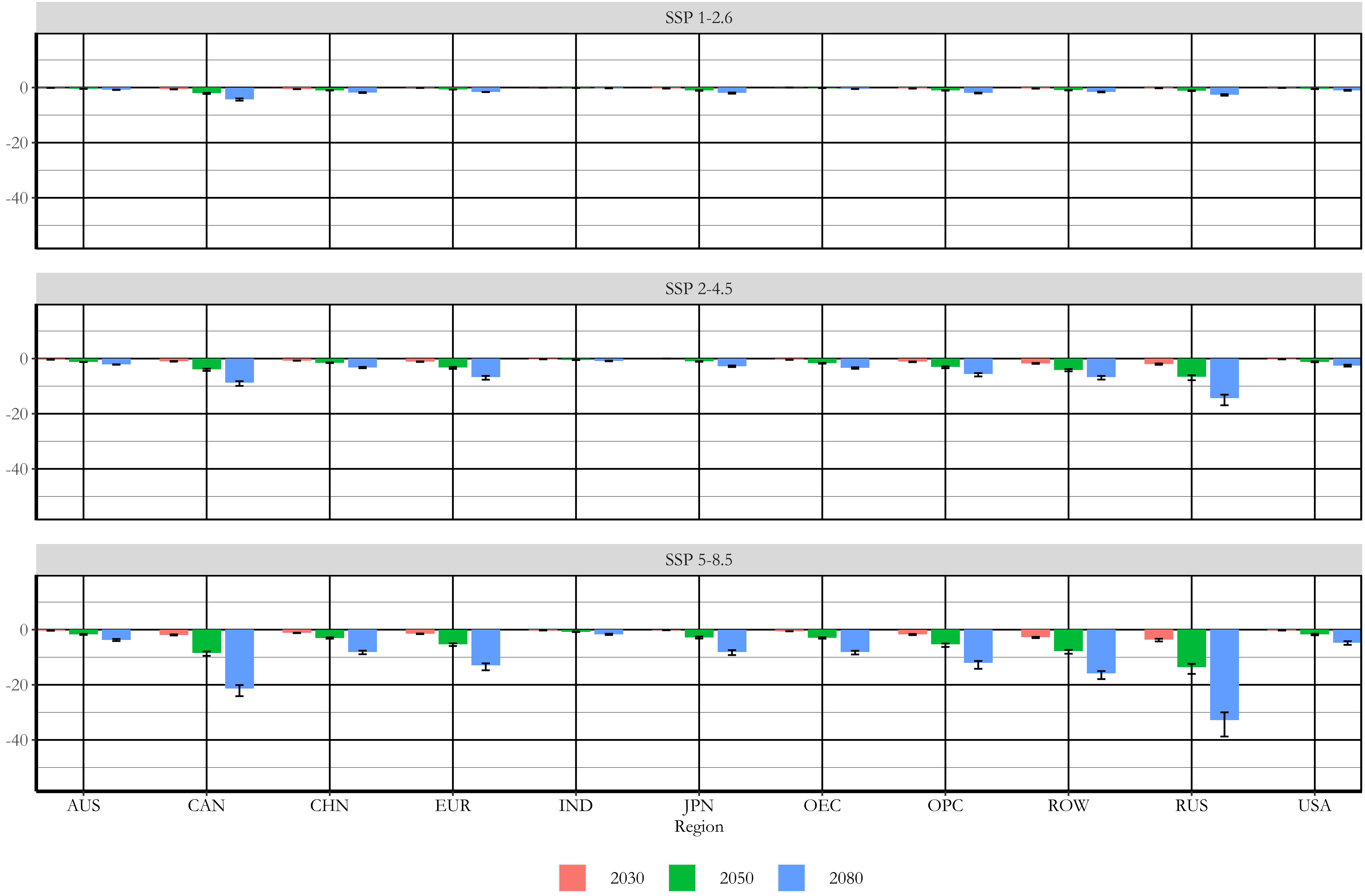
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 8: Percentage Change in Sectoral Output from the Baseline: Agriculture



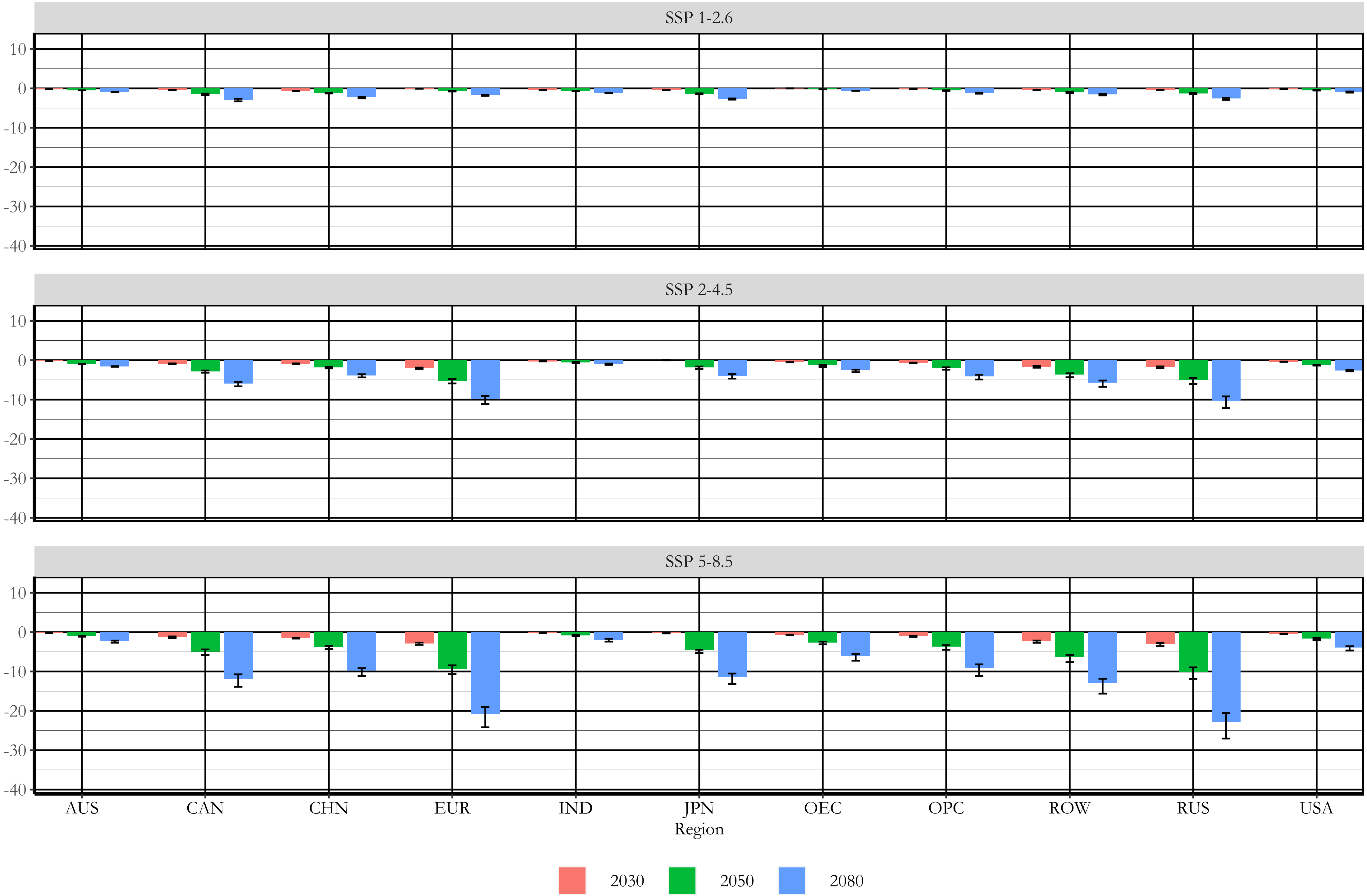
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 9: Percentage Change in Sectoral Output from the Baseline: Electric Utilities



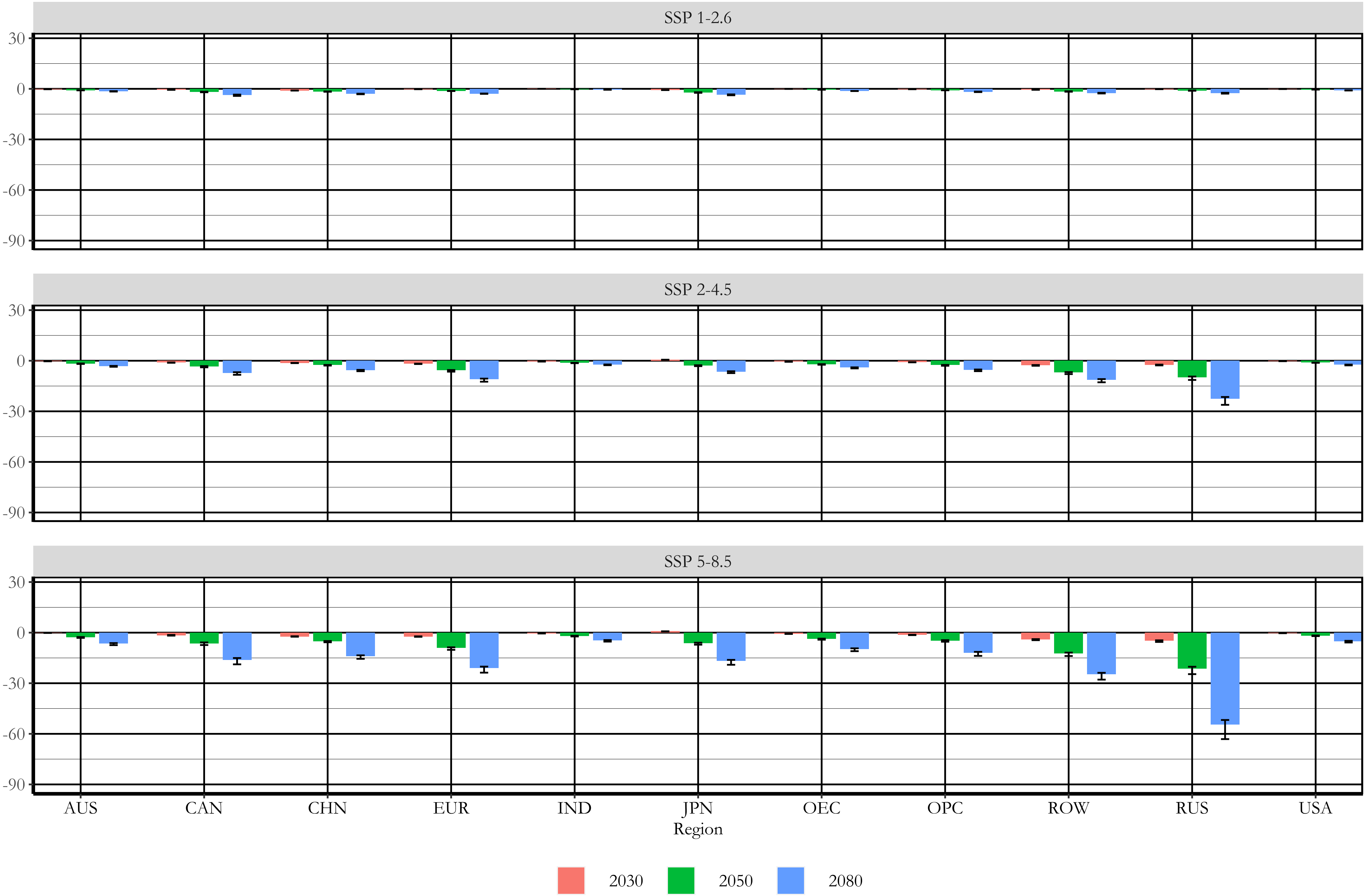
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 10: Percentage Change in Sectoral Output from the Baseline: Gas Utilities



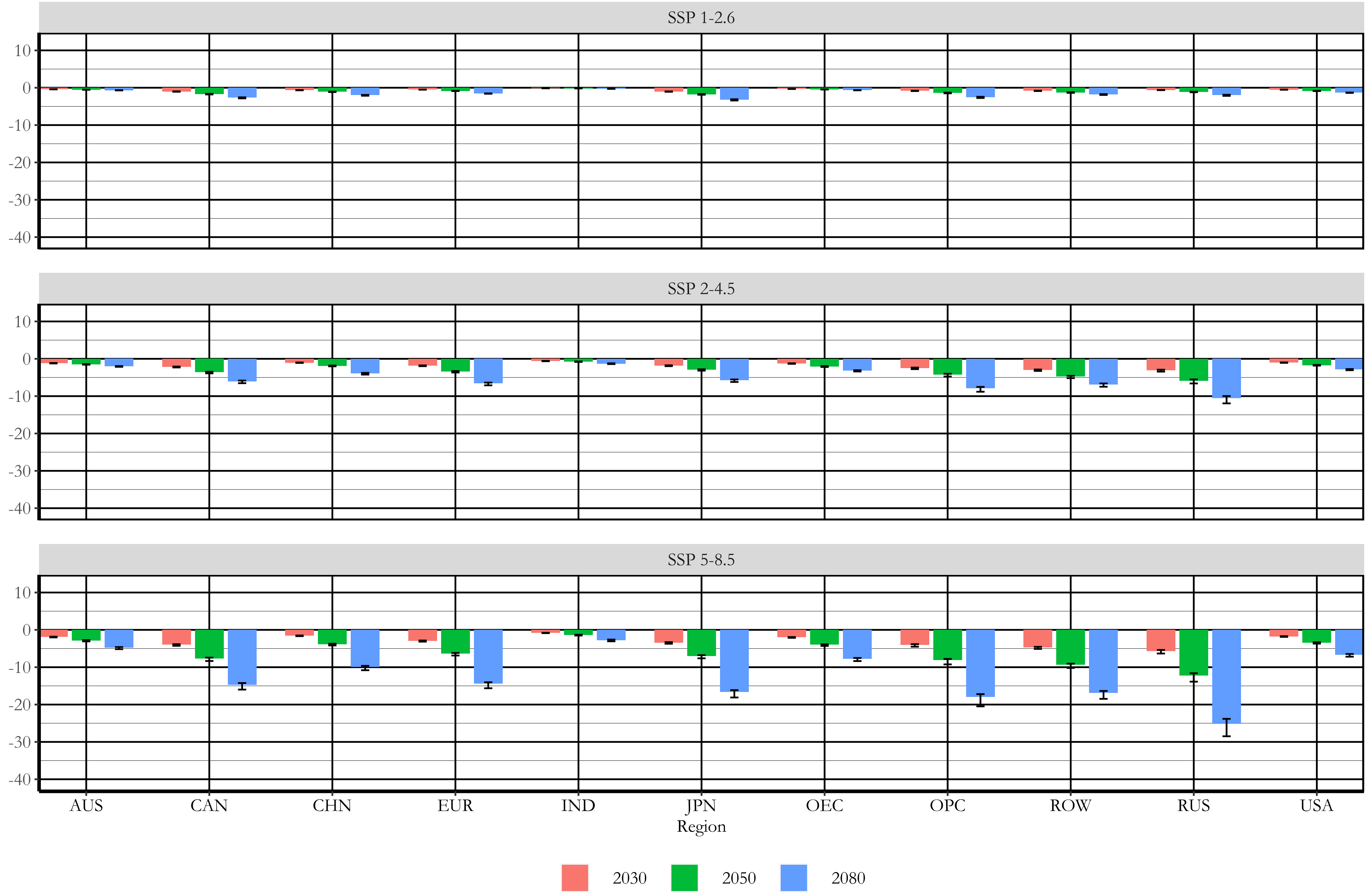
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 11: Percentage Change in Sectoral Output from the Baseline: Petroleum Refining



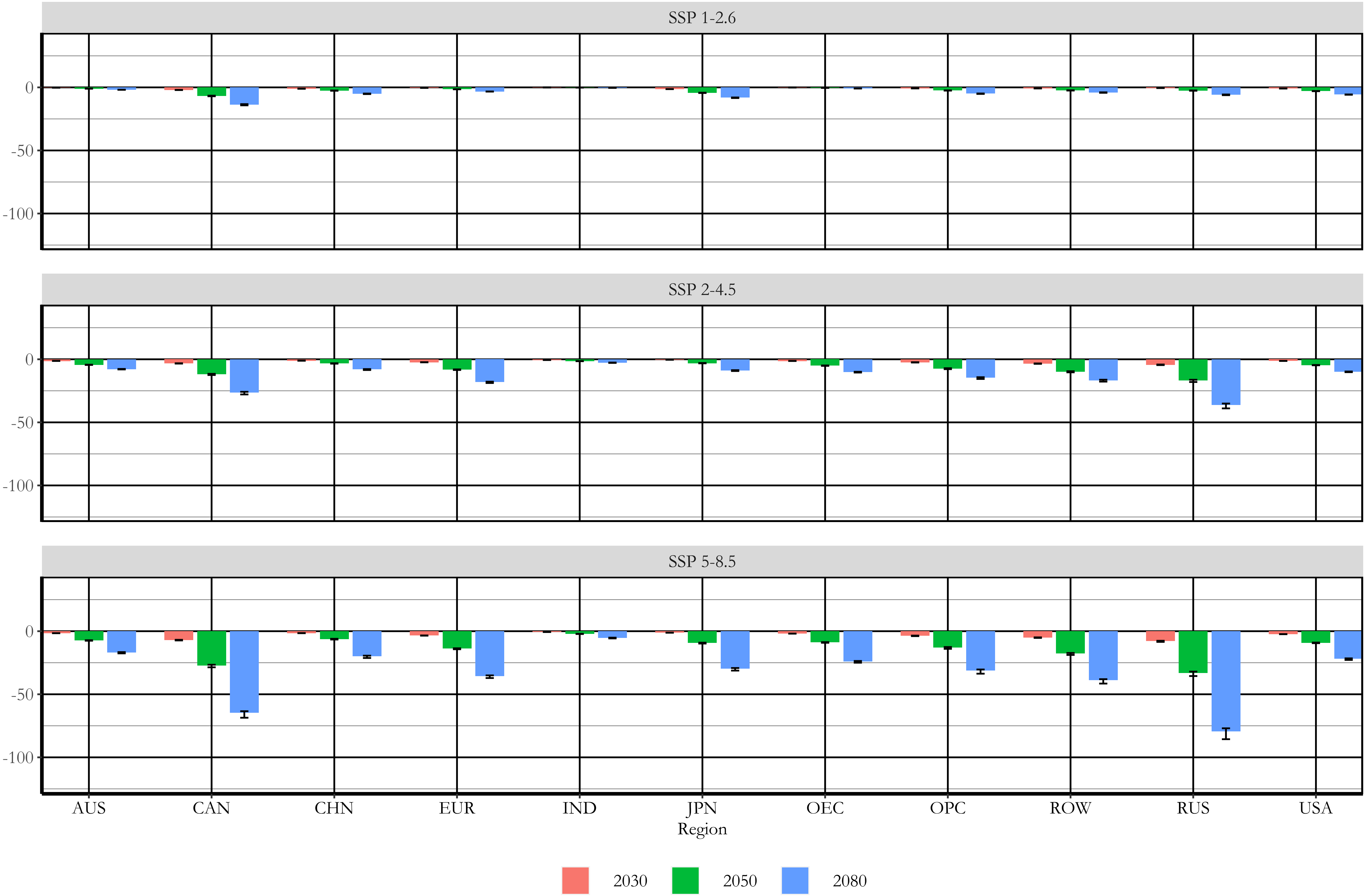
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 12: Percentage Change in Sectoral Output from the Baseline: Durable Manufacturing



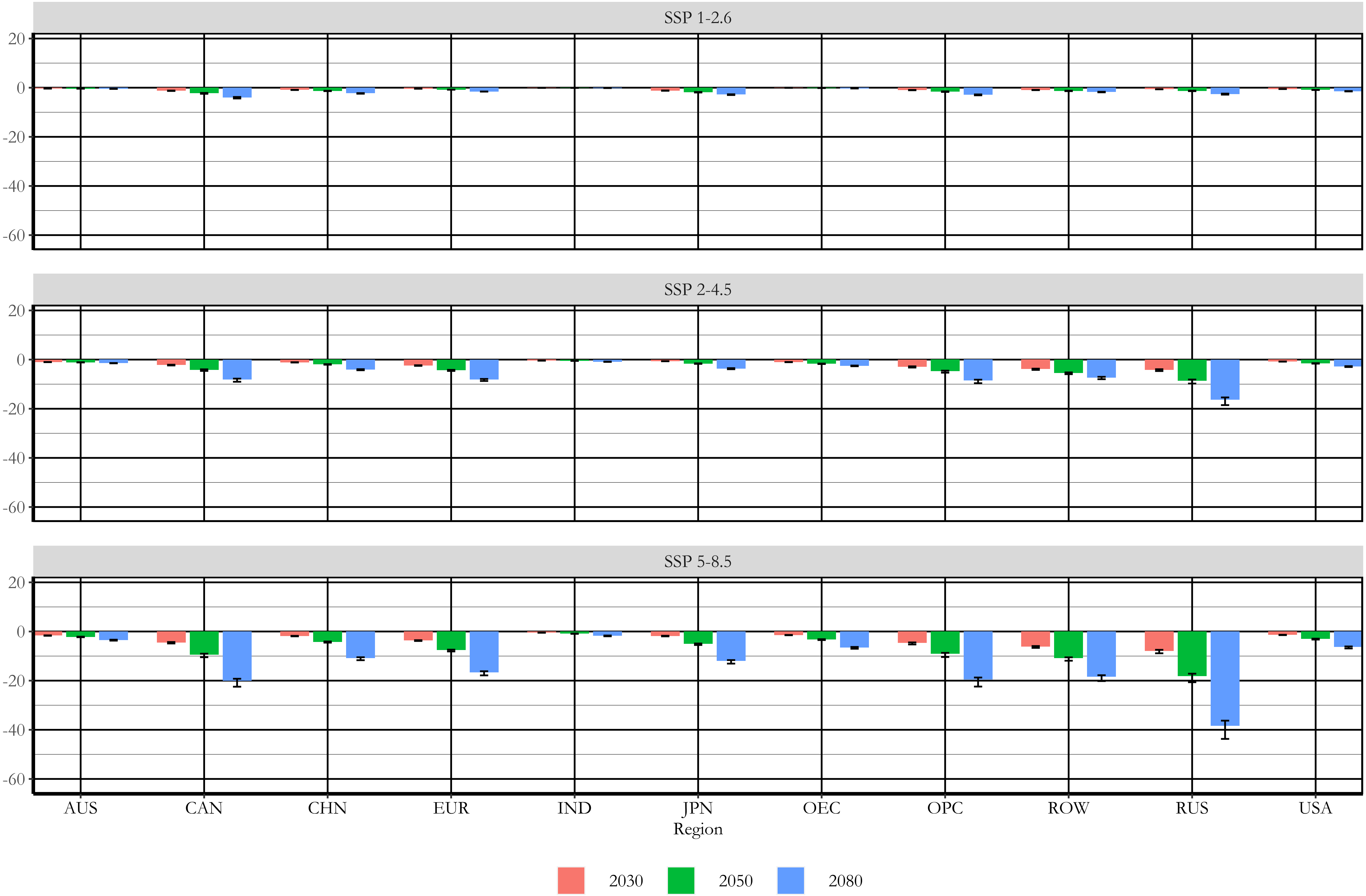
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 13: Percentage Change in Sectoral Output from the Baseline: Non-durable Manufacturing



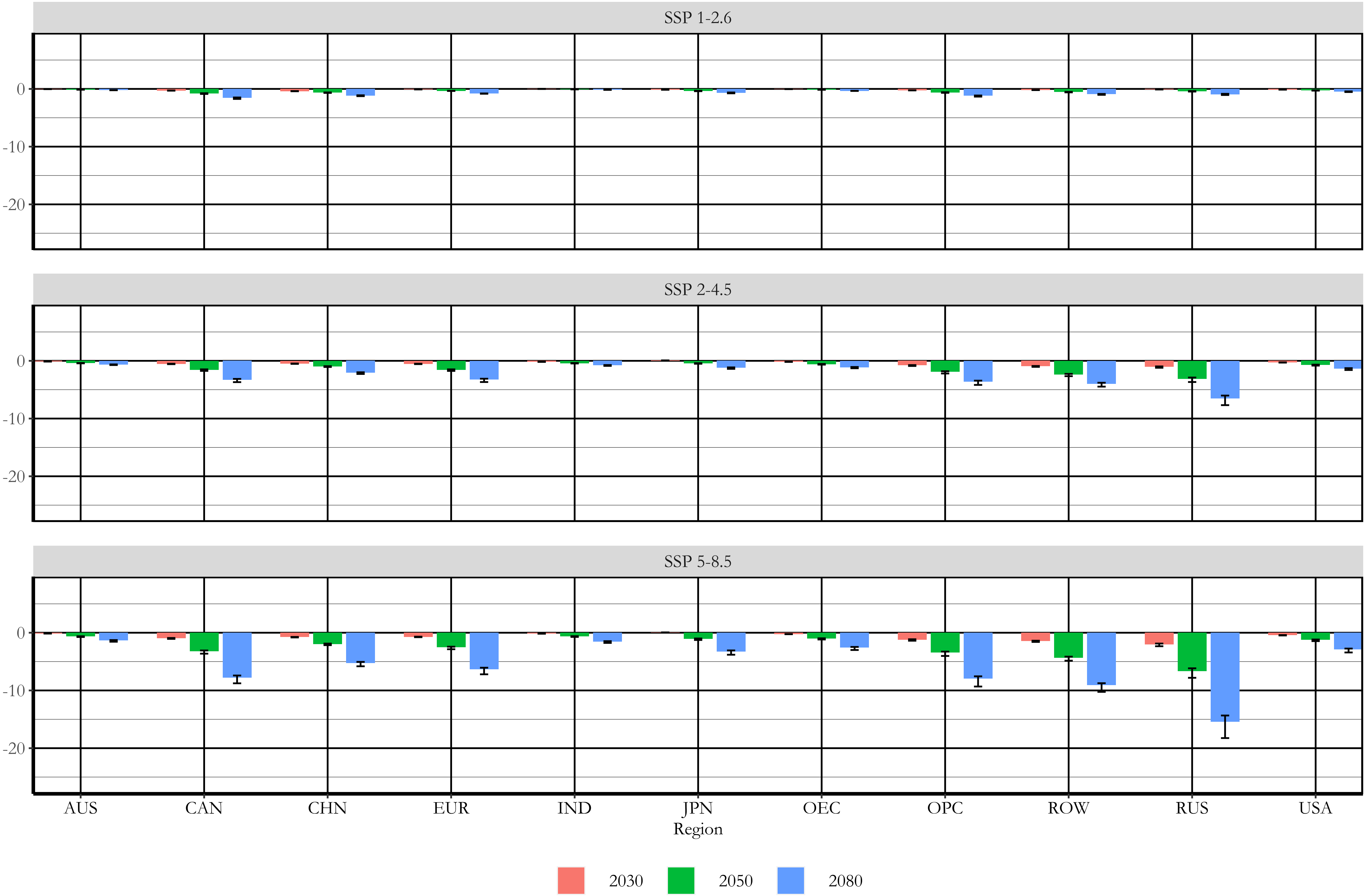
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 14: Percentage Change in Sectoral Output from the Baseline: Construction



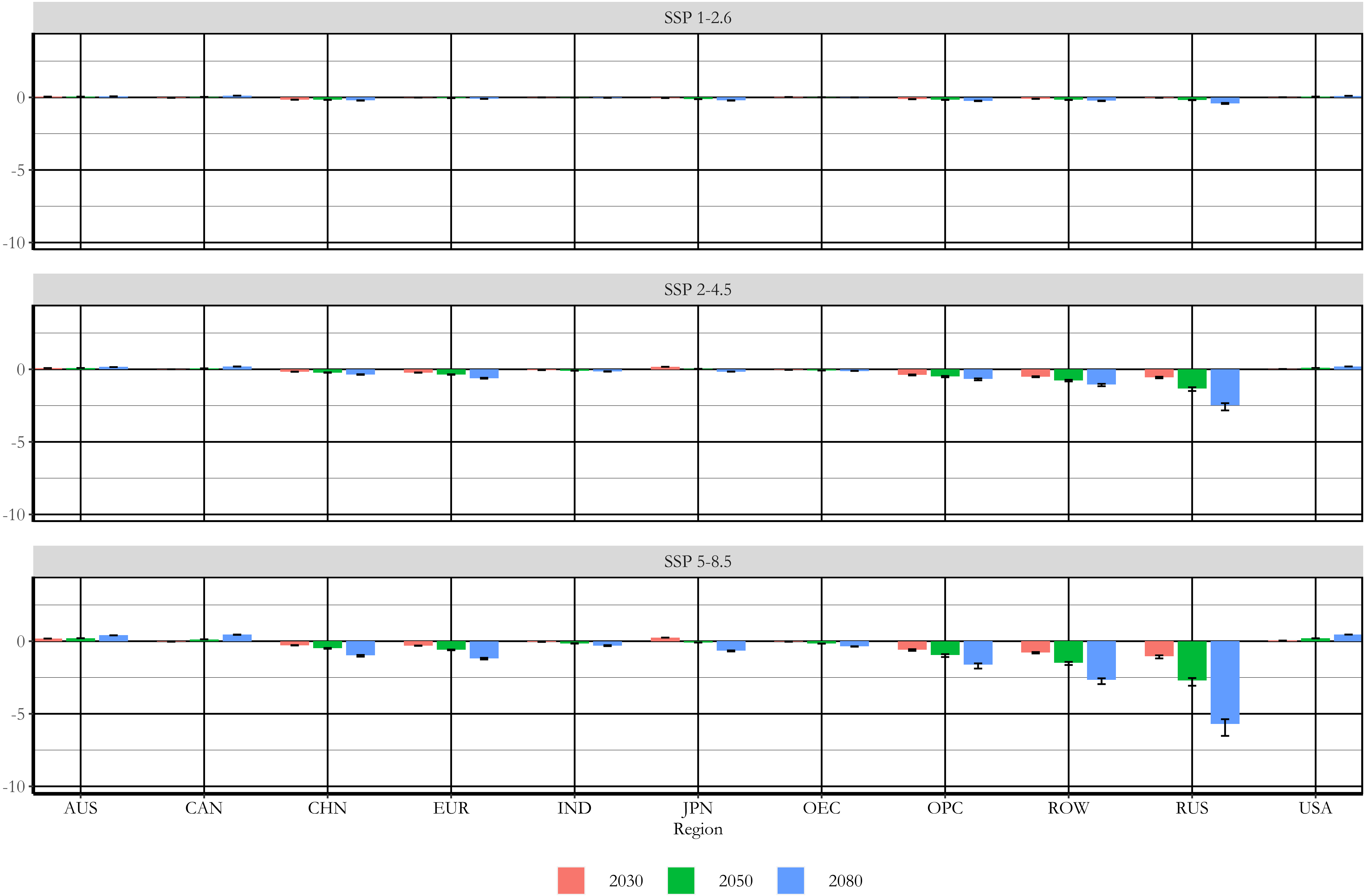
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 15: Percentage Change in Sectoral Output from the Baseline: Transportation



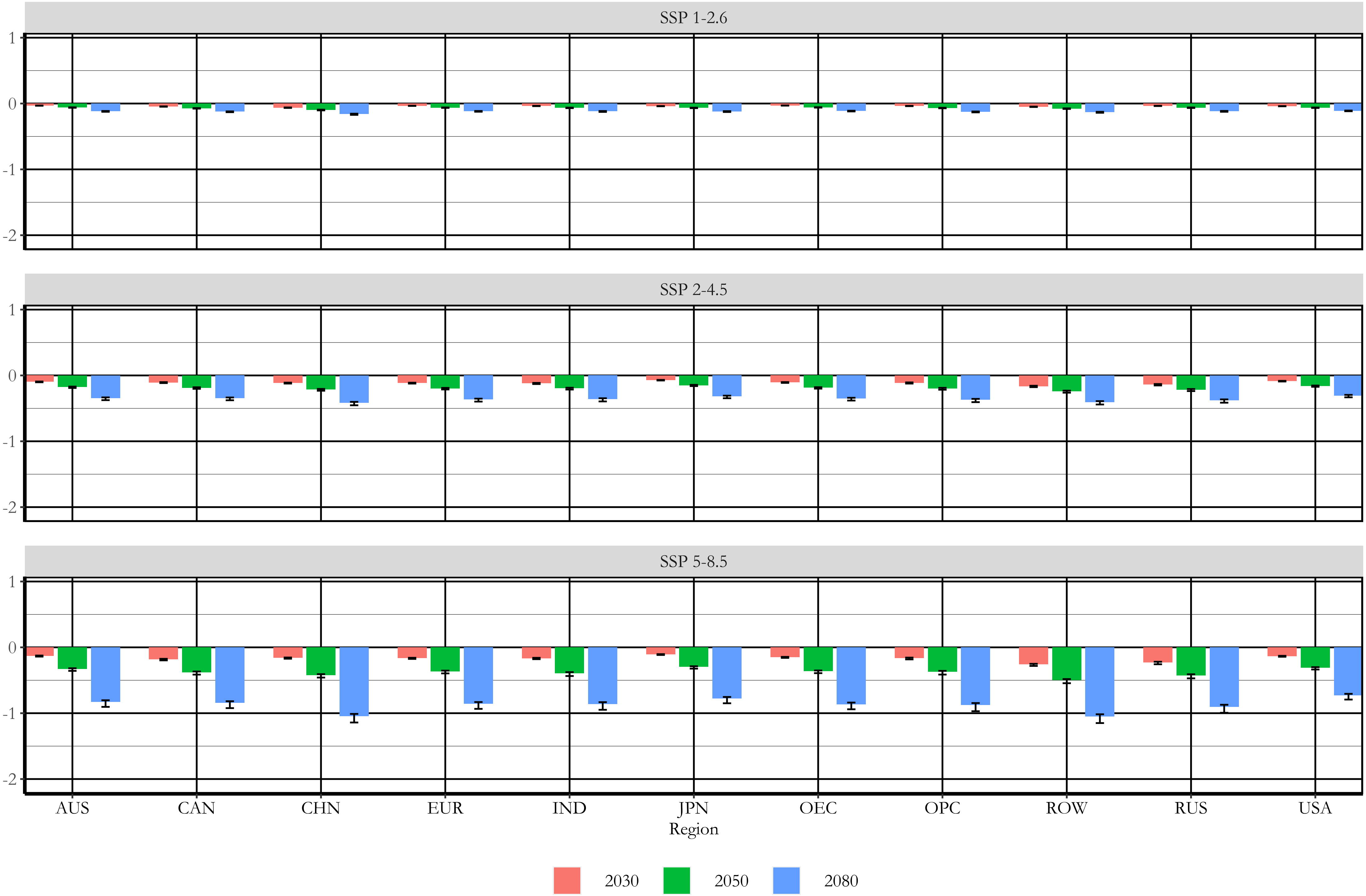
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 16: Percentage Change in Sectoral Output from the Baseline: Services



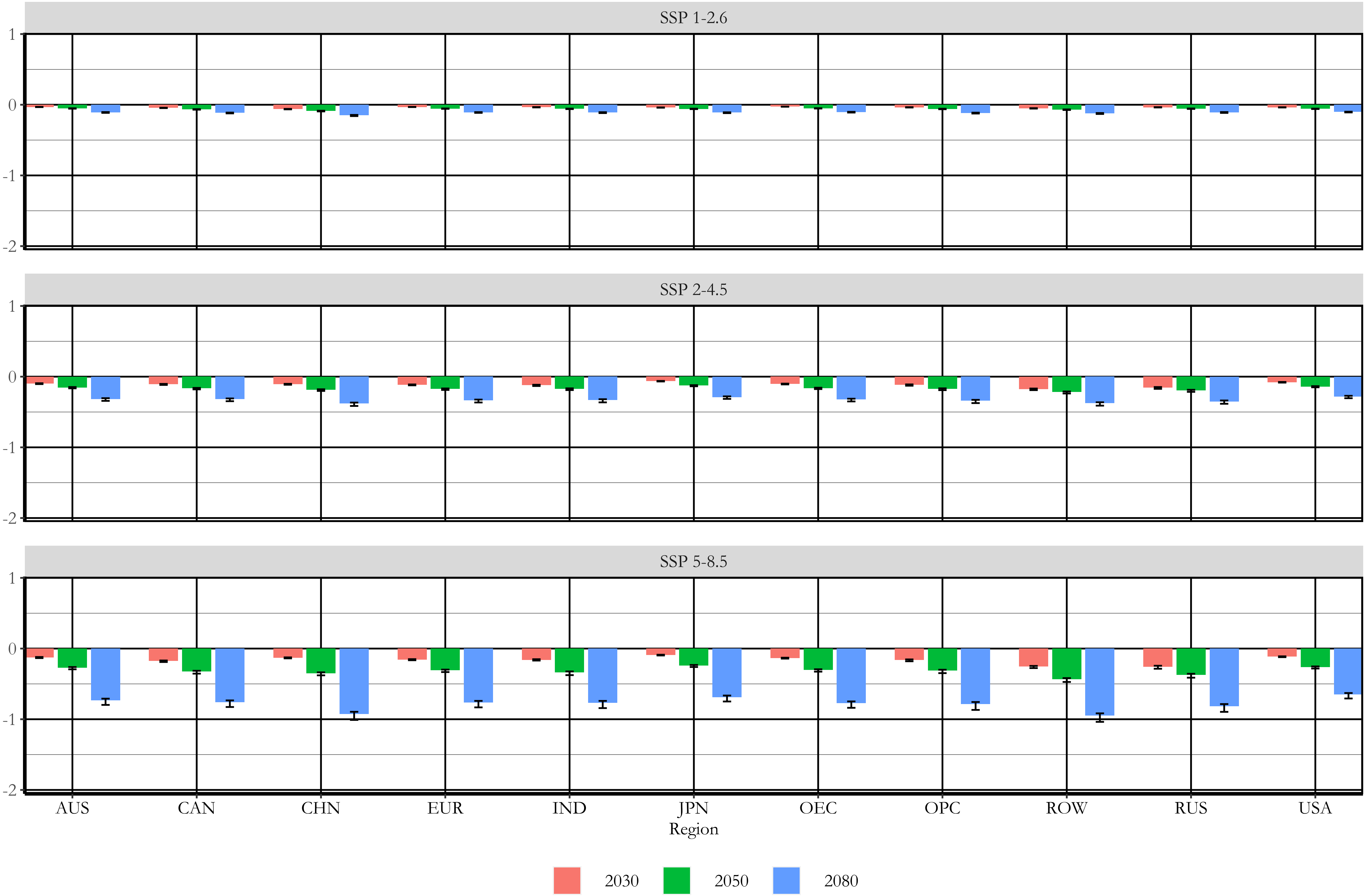
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 17: Long-term Real Interest Rate: Percentage Points from Baseline



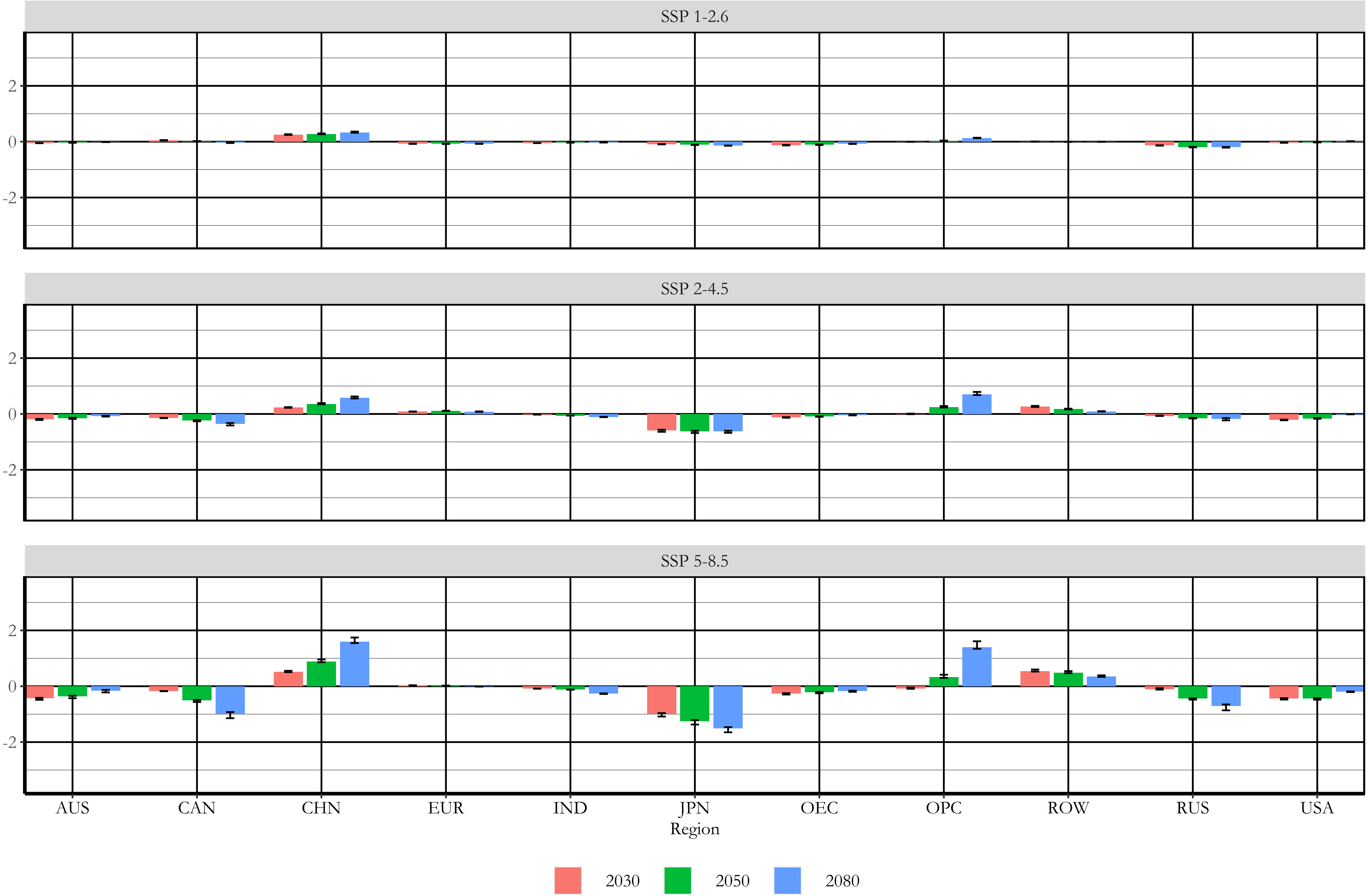
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 18: Short-term Real Interest Rate: Percentage Points from Baseline



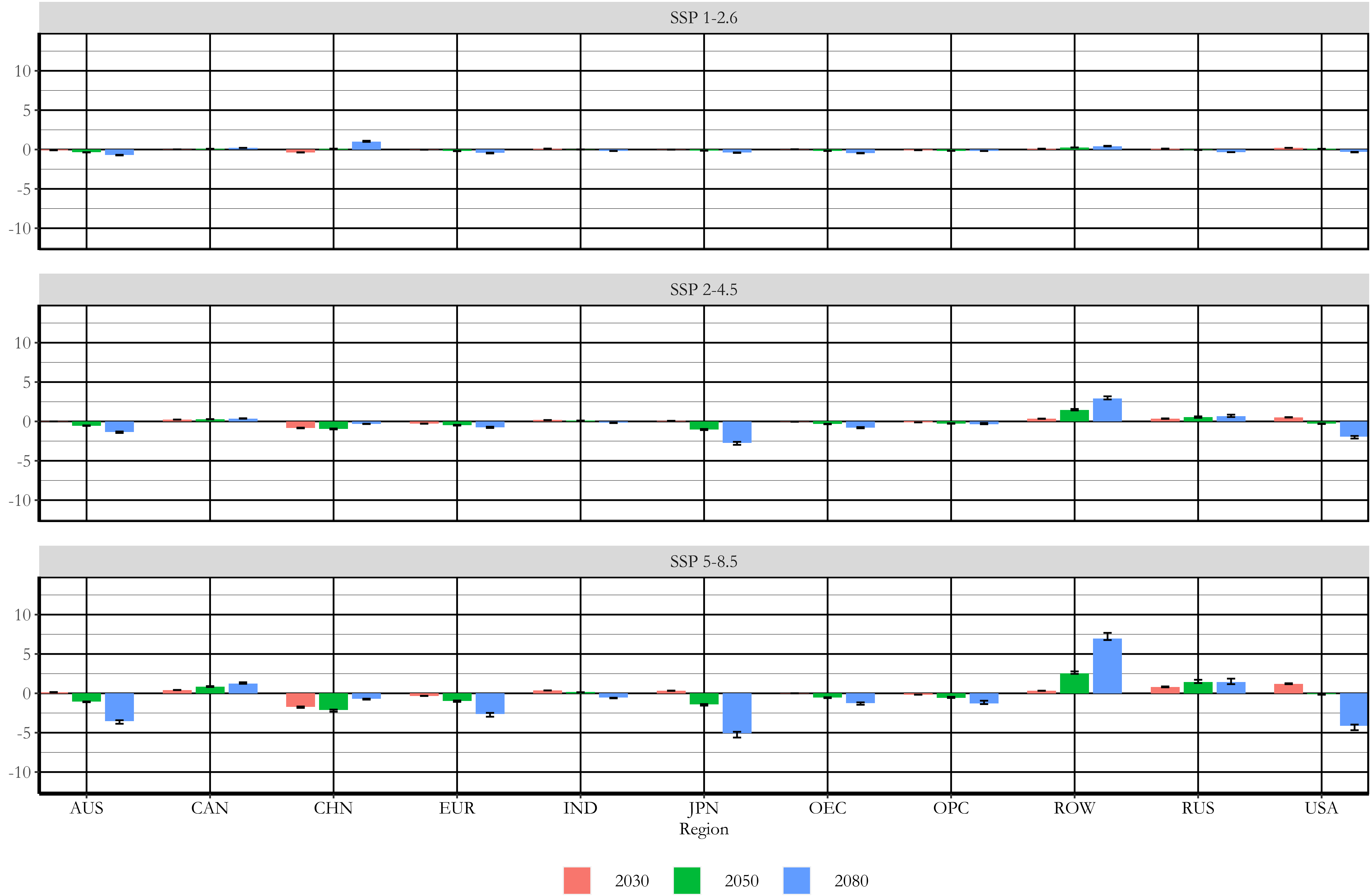
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 19: Current Account Balance: Percentage GDP Deviation from Baseline



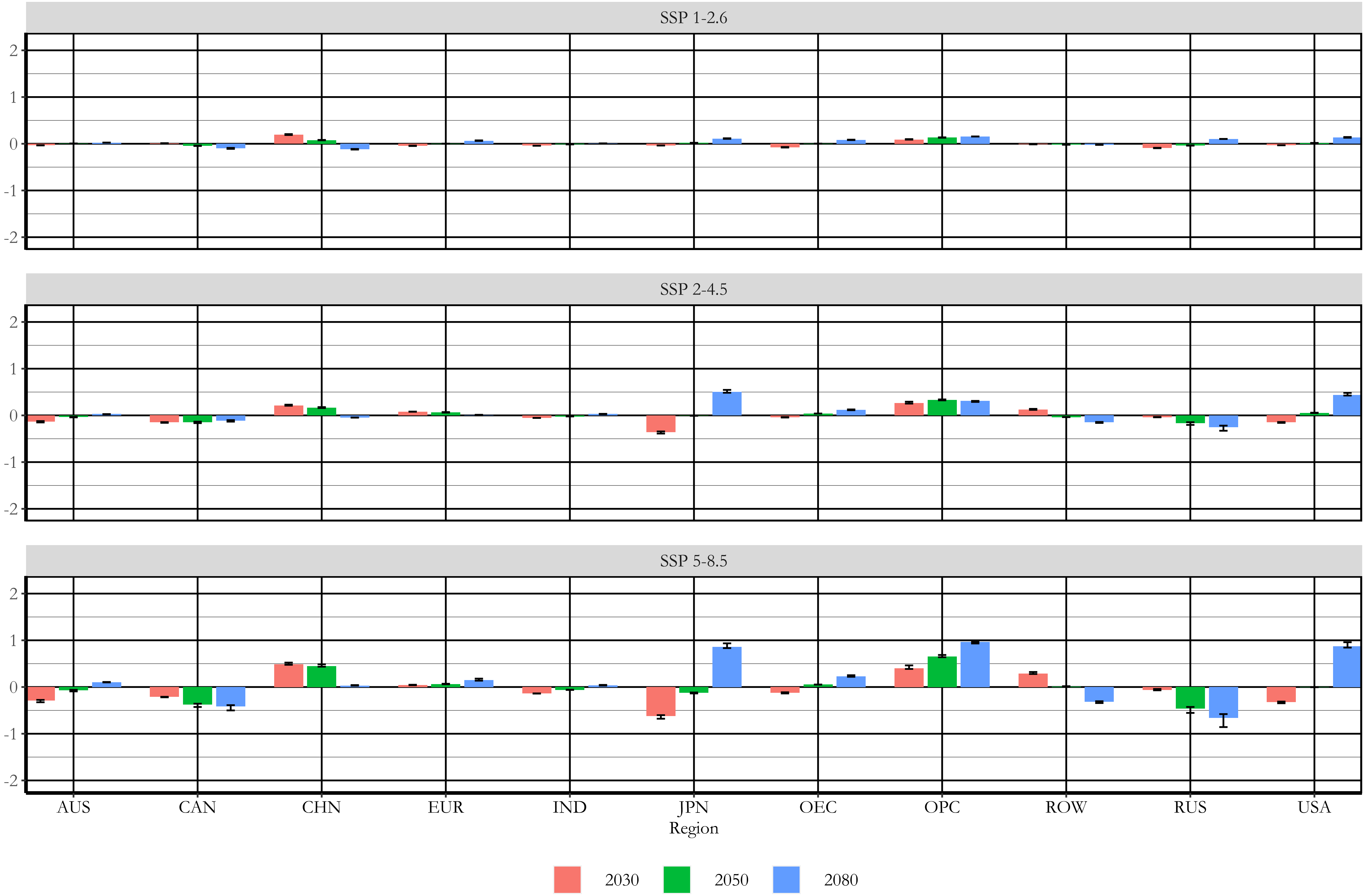
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 20: Real Exchange Rate: Percentage Points from Baseline



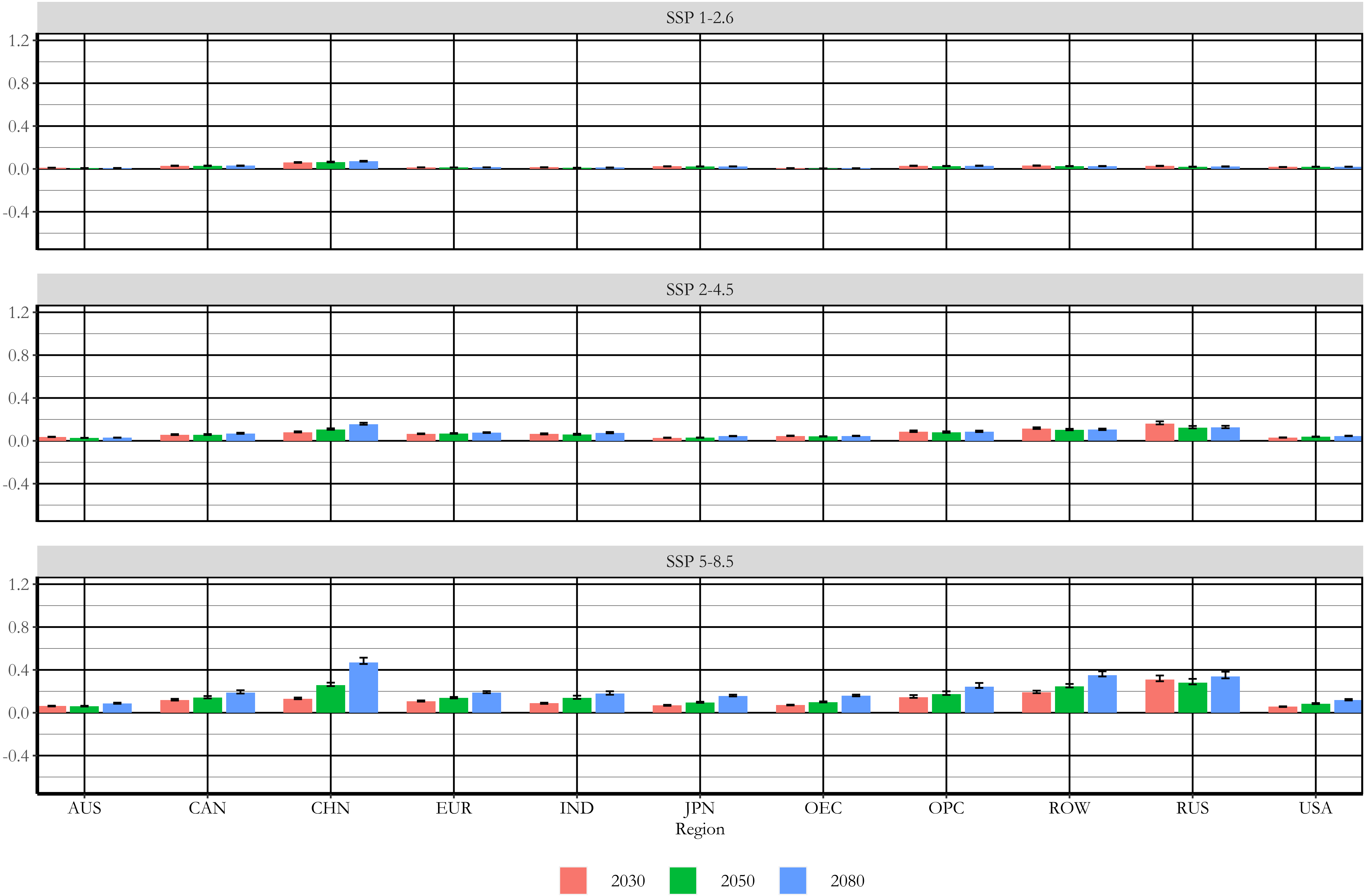
Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 21: Trade Balance: Percentage GDP Deviation from Baseline



Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

Figure 22: Inflation: Percentage Points from Baseline



Source: Constructed by the Author using the G-Cubed Model (GGG20C_v169) Simulations.

GLOBAL ECONOMIC IMPACTS OF PHYSICAL CLIMATE RISKS ON AGRICULTURE AND ENERGY

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Centre for Applied Macroeconomic Analysis,
Crawford School of Public Policy, The Australian National University

SUPPLEMENTARY ANNEXURES

Supplementary Annexure 1: Representative Concentration Pathways

Scenario	Description
RCP 2.6	A peak radiative forcing of ~3 W/m² (~490 ppm CO2 eq) is achieved before 2100 and then declines. (The selected pathway decreases to 2.6 W/m² by 2100.)
RCP 4.5	Stabilization without overshoot pathway to 4.5 W/m² (~650 ppm CO2 eq) at stabilization after 2100.
RCP 6.0	Stabilization without overshoot pathway to 6 W/m² (~850 ppm CO2 eq) at stabilization after 2100.
RCP 8.5	Rising radiative forcing pathway leading to 8.5 W/m² (~1370 ppm CO2 eq) by 2100.

Source: van Vuuren et al (2011). Approximate radiative forcing levels were defined as ±5% of the stated level in W/m² relative to pre-industrial levels. Radiative forcing values include the net effect of all anthropogenic GHGs and other forcing agents.

Supplementary Annexure 2: Shared Socioeconomic Pathways

SSP	Narrative
SSP1	**Sustainability – Taking the Green Road (Low challenges to mitigation and adaptation)** The world shifts gradually, but pervasively, toward a more sustainable path, emphasizing more inclusive development that respects perceived environmental boundaries. Management of the global commons slowly improves; educational and health investments accelerate the demographic transition, and the emphasis on economic growth shifts toward a broader emphasis on human well-being. Driven by an increasing commitment to achieving development goals, inequality is reduced both across and within countries. Consumption is oriented toward low material growth and lower resource and energy intensity.
SSP2	**Middle of the Road (Medium challenges to mitigation and adaptation)** The world follows a path where social, economic, and technological trends do not shift markedly from historical patterns. Development and income growth proceed unevenly, with some countries making relatively good progress while others fall short of expectations. Global and national institutions work toward but make slow progress in achieving sustainable development goals. Environmental systems experience degradation, although there are some improvements, and overall, the intensity of resource and energy use declines. Global population growth is moderate and levels off in the second half of the century. Income inequality persists or improves only slowly, and challenges to reducing vulnerability to societal and environmental changes remain.
SSP3	**Regional Rivalry – A Rocky Road (High challenges to mitigation and adaptation)** A resurgent nationalism, concerns about competitiveness and security, and regional conflicts push countries to increasingly focus on domestic or, at most, regional issues. Policies shift over time to become increasingly oriented toward national and regional security issues. Countries focus on achieving energy and food security goals within their own regions at the expense of broader-based development. Investments in education and technological development decline. Economic development is slow, consumption is material-intensive, and inequalities persist or worsen over time. Population growth is low in industrialized and high in developing countries. A low international priority for addressing environmental concerns leads to strong environmental degradation in some regions.
SSP4	**Inequality – A Road Divided (Low challenges to mitigation, high challenges to adaptation)** Highly unequal investments in human capital, combined with increasing disparities in economic opportunity and political power, lead to increasing inequalities and stratification both across and within countries. Over time, a gap widens between an internationally connected society contributing to knowledge- and capital-intensive sectors of the global economy and a fragmented collection of lower-income, poorly educated societies working in a labor-intensive, low-tech economy. Social cohesion degrades, and conflict and unrest become increasingly common. Technology development is high in the high-tech economy and sectors. The globally connected energy sector diversifies, with investments in both carbon-intensive fuels like coal and unconventional but also low-carbon energy sources. Environmental policies focus on local issues around middle and high-income areas.
SSP5	**Fossil-fueled Development – Taking the Highway** **(High challenges to mitigation, low challenges to adaptation)** This world places increasing faith in competitive markets, innovation, and participatory societies to produce rapid technological progress and development of human capital as the path to sustainable development. Global markets are increasingly integrated. There are also strong investments in health, education, and institutions to enhance human and social capital. At the same time, the push for economic and social development is coupled with the exploitation of abundant fossil fuel resources and the adoption of resource and energy-intensive lifestyles worldwide. All these factors lead to the rapid growth of the global economy while the global population peaks and declines in the 21st century. Local environmental problems like air pollution are successfully managed. There is faith in the ability to effectively manage social and ecological systems, including by geo-engineering if necessary.

Source: Riahi et al (2017).

Supplementary Annexure 3: NGFS Scenarios

Scenario	Policy Ambition (⁰C)	Policy Reaction	Technology Change	CO2 Removal	Regional Policy Variation
Net Zero 2050	1.4	Immediate & Smooth	Fast	Medium to High Use	Medium
Below 2 ⁰C	1.6	Immediate & Smooth	Moderate	Medium to High Use	Low
Divergent Net Zero	1.4	Immediate but Divergent	Fast	Low to Medium Use	Medium
Delayed Transition	1.6	Delayed	Slow/Fast	Low to Medium	High
Nationally Determined Contributions (NDCs)	2.6	NDCs	Slow	Low to Medium	Medium
Current Policies	3	Nothing additional to current policies	Slow	Low	Low

Source: NGFS (2022).

Supplementary Annexure 4:

Concordance between Countries from Different Classifications

	GADM	GTAP	UN	G-Cubed		GADM	GTAP	UN	G-Cubed
1	ABW	XCB	LAM	ROW	62	DMA	XCB	LAM	ROW
2	AFG	XSA	SAS	ROW	63	DNK	DNK	NEU	EUW
3	AGO	XAC	SAF	OPC	64	DOM	DOM	LAM	ROW
4	AIA	XCB	LAM	ROW	65	DZA	XNF	NAF	OPC
5	ALA	FIN	NEU	EUW	66	ECU	ECU	LAM	OPC
6	ALB	ALB	SEU	ROW	67	EGY	EGY	NAF	ROW
7	AND	XER	SEU	ROW	68	ERI	XEC	SAF	ROW
8	ARE	ARE	WAS	OPC	69	ESH	XNF	NAF	OPC
9	ARG	ARG	LAM	ROW	70	ESP	ESP	SEU	EUW
10	ARM	ARM	WAS	ROW	71	EST	EST	NEU	EUW
11	ASM	XOC	ANZ	ROW	72	ETH	ETH	SAF	ROW
12	ATA	XTW	ANT	ROW	73	FIN	FIN	NEU	EUW
13	ATF	XTW	SAF	ROW	74	FJI	XOC	ANZ	ROW
14	ATG	XCB	LAM	ROW	75	FLK	XSM	LAM	ROW
15	AUS	AUS	ANZ	AUS	76	FRA	FRA	WEU	EUW
16	AUT	AUT	WEU	EUW	77	FRO	XER	NEU	ROW
17	AZE	AZE	WAS	ROW	78	FSM	XOC	ANZ	ROW
18	BDI	XEC	SAF	ROW	79	GAB	XCF	SAF	ROW
19	BEL	BEL	WEU	EUW	80	GBR	GBR	NEU	EUW
20	BEN	BEN	SAF	ROW	81	GEO	GEO	WAS	ROW
21	BES	XCB	LAM	ROW	82	GGY	XER	NEU	ROW
22	BFA	BFA	SAF	ROW	83	GHA	GHA	SAF	ROW
23	BGD	BGD	SAS	ROW	84	GIB	XER	SEU	ROW
24	BGR	BGR	EEU	EUW	85	GIN	GIN	SAF	ROW
25	BHR	BHR	WAS	OPC	86	GLP	FRA	LAM	EUW
26	BHS	XCB	LAM	ROW	87	GMB	XWF	SAF	ROW
27	BIH	XER	SEU	ROW	88	GNB	XWF	SAF	ROW
28	BLM	XCB	LAM	ROW	89	GNQ	XCF	SAF	ROW
29	BLR	BLR	EEU	ROW	90	GRC	GRC	SEU	EUW
30	BLZ	XCA	LAM	ROW	91	GRD	XCB	LAM	ROW
31	BMU	XNA	NAM	ROW	92	GRL	XNA	NAM	ROW
32	BOL	BOL	LAM	ROW	93	GTM	GTM	LAM	ROW
33	BRA	BRA	LAM	ROW	94	GUF	XSM	LAM	ROW
34	BRB	XCB	LAM	ROW	95	GUM	XOC	ANZ	ROW
35	BRN	BRN	SEA	ROW	96	XSM	XSM	LAM	ROW
36	BTN	XSA	SAS	ROW	97	HKG	HKG	EAS	ROW
37	BVT	XW	LAM	ROW	98	HMD	AUS	ANZ	AUS
38	BWA	BWA	SAF	ROW	99	HND	HND	LAM	ROW
39	CAF	XCF	SAF	ROW	100	HRV	HRV	SEU	EUW
40	CAN	CAN	NAM	OEC	101	HTI	XCB	LAM	ROW
41	CCK	AUS	ANZ	AUS	102	HUN	HUN	EEU	EUW
42	CHE	CHE	WEU	EUW	103	IDN	INO	SEA	NA
43	CHL	CHL	LAM	ROW	104	IMN	XER	NEU	ROW
44	CHN	CHI	EAS	NA	105	IND	IND	SAS	IND
45	CIV	CIV	SAF	ROW	106	IOT	XTW	SAF	ROW
46	CMR	CMR	SAF	ROW	107	IRL	IRL	NEU	EUW
47	COD	XAC	SAF	OPC	108	IRN	IRN	SAS	OPC
48	COG	XCF	SAF	ROW	109	IRQ	XWS	WAS	OPC
49	COK	XOC	ANZ	ROW	110	ISL	XEF	NEU	OEC
50	COL	COL	LAM	ROW	111	ISR	ISR	WAS	OPC
51	COM	XEC	SAF	ROW	112	ITA	ITA	SEU	EUW
52	CPV	XWF	SAF	ROW	113	JAM	JAM	LAM	ROW
53	CRI	CRI	LAM	ROW	114	JEY	XER	NEU	ROW
54	CUB	XCB	LAM	ROW	115	JOR	JOR	WAS	OPC
55	CUW	XCB	LAM	ROW	116	JPN	JPN	EAS	JPN
56	CXR	AUS	ANZ	AUS	117	KAZ	KAZ	CAS	ROW
57	CYM	XCB	LAM	ROW	118	KEN	KEN	SAF	ROW
58	CYP	CYP	WAS	EUW	119	KGZ	KGZ	CAS	ROW
59	CZE	CZE	EEU	EUW	120	KHM	KHM	SEA	ROW
60	DEU	DEU	WEU	EUW	121	KIR	XOC	ANZ	ROW
61	DJI	XEC	SAF	ROW	122	KNA	XCB	LAM	ROW

	GADM	GTAP	UN	G-Cubed		GADM	GTAP	UN	G-Cubed
123	KOR	KOR	EAS	ROW	190	RUS	RUS	EEU	RUS
124	KWT	KWT	WAS	OPC	191	RWA	RWA	SAF	ROW
125	LAO	LAO	SEA	ROW	192	SAU	SAU	WAS	OPC
126	LBN	XWS	WAS	OPC	193	SDN	XEC	NAF	ROW
127	LBR	XWF	SAF	ROW	194	SEN	SEN	SAF	ROW
128	LBY	XNF	NAF	OPC	195	SGP	SGP	SEA	ROW
129	LCA	XCB	LAM	ROW	196	SGS	XSM	LAM	ROW
130	LIE	XEF	WEU	OEC	197	SHN	XWF	SAF	ROW
131	LKA	LKA	,SAS	ROW	198	SJM	NOR	NEU	EUW
132	LSO	XSC	SAF	ROW	199	SLB	XOC	ANZ	ROW
133	LTU	LTU	NEU	EUW	200	SLE	XWF	SAF	ROW
134	LUX	LUX	WEU	EUW	201	SLV	SLV	LAM	EUW
135	LVA	LVA	NEU	EUW	202	SMR	XER	SEU	ROW
136	MA	XEA	EAS	ROW	203	SOM	XEC	SAF	ROW
137	MAF	XCB	LAM	ROW	204	SPM	XNA	NAM	ROW
138	MAR	MAR	NAF	ROW	205	SRB	XER	SEU	ROW
139	MCO	XER	WEU	ROW	206	SSD	NA	SAF	NA
140	MDA	XEE	EEU	ROW	207	STP	XCF	SAF	ROW
141	MDG	MDG	SAF	ROW	208	SUR	XSM	LAM	ROW
142	MDV	XSA	SAS	ROW	209	SVK	SVK	EEU	EUW
143	MEX	MEX	LAM	ROW	210	SVN	SVN	SEU	EUW
144	MHL	XOC	ANZ	ROW	211	SWE	SWE	NEU	EUW
145	MKD	XER	SEU	ROW	212	SWZ	XSC	SAF	ROW
146	MLI	XWF	SAF	ROW	213	SXM	XCB	LAM	ROW
147	MLT	MLT	SEU	EUW	214	SYC	XEC	SAF	ROW
148	MMR	XSE	SEA	ROW	215	SYR	XWS	WAS	OPC
149	MNE	XER	SEU	ROW	216	TCA	XCB	LAM	ROW
150	MNG	MNG	EAS	ROW	217	TCD	XCF	SAF	ROW
151	MNP	XOC	ANZ	ROW	218	TGO	TGO	SAF	ROW
152	MOZ	MOZ	SAF	ROW	219	THA	THA	SEA	ROW
153	MT	XWF	SAF	ROW	220	TJK	TJK	CAS	ROW
154	MSR	XCB	LAM	ROW	221	TKL	XOC	ANZ	ROW
155	MTQ	FRA	LAM	EUW	222	TKM	XSU	CAS	ROW
156	MUS	MUS	SAF	ROW	223	TLS	XSE	SEA	ROW
157	MWI	MWI	SAF	ROW	224	TON	XOC	ANZ	ROW
158	MYS	MYS	SEA	ROW	225	TTO	TTO	LAM	ROW
159	MYT	XEC	SAF	ROW	226	TUN	TUN	NAF	ROW
160	NAM	NAM	SAF	ROW	227	TUR	TUR	WAS	ROW
161	NCL	XOC	ANZ	ROW	228	TUV	XOC	ANZ	ROW
162	NER	XWF	SAF	ROW	229	TWN	TWN	EAS	ROW
163	NFK	AUS	ANZ	AUS	230	TZA	TZA	SAF	ROW
164	NGA	NGA	SAF	OPC	231	UGA	UGA	SAF	ROW
165	NIC	NIC	LAM	ROW	232	UKR	UKR	EEU	ROW
166	NIU	XOC	ANZ	ROW	233	UMI	XOC	ANZ	ROW
167	NLD	NLD	WEU	EUW	234	URY	URY	LAM	ROW
168	NOR	NOR	NEU	EUW	235	USA	USA	NAM	USA
169	NPL	NPL	SAS	ROW	236	UZB	XSU	CAS	ROW
170	NRU	XOC	ANZ	ROW	237	VAT	XER	SEU	ROW
171	NZL	NZL	ANZ	OEC	238	VCT	XCB	LAM	ROW
172	OMN	OMN	WAS	OPC	239	VEN	VEN	LAM	OPC
173	PAK	PAK	SAS	ROW	240	VGB	XCB	LAM	ROW
174	PAN	PAN	LAM	ROW	241	VIR	XCB	LAM	ROW
175	PCN	XOC	ANZ	ROW	242	VNM	VNM	SEA	ROW
176	PER	PER	LAM	ROW	243	VUT	XOC	ANZ	ROW
177	PHL	PHL	SEA	ROW	244	WLF	XOC	ANZ	ROW
178	PLW	XOC	ANZ	ROW	245	WSM	XOC	ANZ	ROW
179	PNG	XOC	ANZ	ROW	246	XAD	NA	NA	NA
180	POL	POL	EEU	EUW	247	XCA	NA	NA	NA
181	PRI	PRI	LAM	ROW	248	XCL	NA	NA	NA
182	PRK	XEA	EAS	ROW	249	XKO	NA	NA	NA
183	PRT	PRT	SEU	EUW	250	XNC	NA	NA	NA
184	PRY	PRY	LAM	ROW	251	XPI	NA	NA	NA
185	PSE	XWS	WAS	OPC	252	XSP	NA	NA	NA
186	PYF	XOC	ANZ	ROW	253	YEM	XWS	WAS	OPC
187	QAT	QAT	WAS	OPC	254	ZAF	ZAF	SAF	ROW
188	REU	FRA	SAF	EUW	255	ZMB	ZMB	SAF	ROW
189	ROU	ROU	EEU	EUW	256	ZWE	ZWE	SAF	ROW

Supplementary Annexure 5: Behavior of Historical Climate Indicators

The Behavior of Historical Chronic Climate Indicators

The mean temperature continuously increased across all the regions, with Eastern, Southern, and Western Europe reaching temperature differences above 1.5^{0}C compared to the 1961-1990 baseline by 2020. In contrast to temperature, precipitation patterns vastly differed across the regions, demonstrating a much stronger cyclical variation. Latin America and Southeast Asia experienced an increase in precipitation towards the mid-2000s and observed a reduction in precipitation since then. Relative humidity also demonstrated a higher cyclicality compared to the temperature, although not as strong as precipitation. While some regions experienced lower relative humidity compared to the baseline, many regions were either indifferent or experiencing mild increments compared to the early 1990s.

The Behavior of Historical Extreme Climate Indicators

The deviation of the maximum temperature from the 90th percentile of the baseline distribution (which is representative of months with warmer days on average) increased across all the regions between 1991 and 2000, notably in North America. Eastern and Western Europe were also on a notably increasing path. The deviation of the minimum temperature from the 90th percentile of the baseline distribution (which is representative of months with warmer nights on average) was similar. Central Asia and Europe experienced significant increases compared to the other regions.

The deviation of the maximum temperature from the 10th percentile of the baseline distribution (which is representative of months with colder days on average) did not change much for most regions. Eastern Europe and Western Asia observed a cyclical reduction towards the early 2000s and an increase since then. Southern Europe experienced an opposite cycle, with the deviations reducing since the mid-2000s. North America, too, demonstrated a similar pattern to Eastern Europe. The deviation of the minimum temperature from the 10th percentile of the baseline distribution (which is representative of months with colder nights on average) remained constant for almost all the regions. However, Southern Europe observed a notable decline since the early 1990s.

Historically, extremely wet and dry conditions demonstrated cyclical patterns like precipitation. However, the lengths of the cycles and the timing of the different phases of the cycle were different. Extremely windy conditions remained above the bassline and were volatile for some regions. Southeast Asia and Western Europe notably experienced higher wind speeds from 1991 to 2020.

Supplementary Annexure 6: Concordance between FAO and GTAP Sectors

Distribution of FAO Sectors across FAO Groups

	FAO Group	Number of FAO Sectors
1	Crops	173
2	Processed Crops	23
3	Live Animals	20
4	Primary Livestock	53
5	Processed Livestock	31

Source: FAO (2022).

Distribution of FAO Sectors across GTAP Sectors

GTAP Sector Code	Description	Number of FAO Sectors	Corresponding FAO Group
1	Paddy Rice	2	Crops
2	Wheat	1	Crops
3	Other Cereal Grains	14	Crops
4	Vegetables, Fruits, and Nuts	98	Crops
5	Oil Seeds	23	Crops
6	Sugar Cane & Beet	4	Crops
7	Plant-based Fibres	11	Crops
8	Other Crops	19	Crops
9	Bovine Cattle, Sheep, Goats, and Horses	11	Live Animals
10	Other Animal Products	25	Live Animals
11	Raw Milk	5	Primary Livestock
12	Wool and Silk-worm Cocoons	2	Primary Livestock
13	Forestry	1	Crops
19	Bovine Meat Products	18	Processed Livestock
20	Other Meat Products	12	Processed Livestock
21	Vegetables, Oils, and Fats	17	Processed Crops
22	Dairy Products	30	Processed Livestock
24	Processed Sugar	2	Processed Crops
26	Beverages and Tobacco Products	2	Processed Crops
27	Textiles	3	Processed Crops

Source: FAO (2022) and GTAP (2022).

Mapping of FAO and GTAP Sectors

	FAO	GTAP		FAO	GTAP
FAO Group: Crops					
1	Agave fibres nes	7	61	Fruit, stone nes	4
2	Almonds, with shell	4	62	Fruit, tropical fresh nes	4
3	Anise, badian, fennel, coriander	8	63	Garlic	4
4	Apples	4	64	Ginger	8
5	Apricots	4	65	Gooseberries	4
6	Areca nuts	4	66	Grain, mixed	3
7	Artichokes	4	67	Grapefruit (inc. pomelos)	4
8	Asparagus	4	68	Grapes	4
9	Avocados	4	69	Groundnuts, with shell	5
10	Bambara beans	4	70	Gums, natural	13
11	Bananas	4	71	Hazelnuts, with shell	4
12	Barley	3	72	Hemp tow waste	7
13	Bast fibres, other	7	73	Hempseed	5
14	Beans, dry	4	74	Hops	8
15	Beans, green	4	75	Jojoba seed	5
16	Berries nes	4	76	Jute	7
17	Blueberries	4	77	Kapok fruit	5
18	Brazil nuts, with shell	4	78	Karite nuts (shea nuts)	5
19	Broad beans, horse beans, dry	4	79	Kiwi fruit	4
20	Buckwheat	3	80	Kola nuts	4
21	Cabbages and other brassicas	4	81	Leeks, other alliaceous vegetables	4
22	Canary seed	3	82	Lemons and limes	4
23	Carobs	4	83	Lentils	4
24	Carrots and turnips	4	84	Lettuce and chicory	4
25	Cashew nuts, with shell	4	85	Linseed	5
26	Cashew apple	4	86	Lupins	4
27	Cassava	4	87	Maize	3
28	Cassava leaves	4	88	Maize, green	4
29	Castor oil seed	5	89	Mangoes, mangosteens, guavas	4
30	Cauliflowers and broccoli	4	90	Manila fibre (abaca)	7
31	Cereals nes	3	91	Maté	8
32	Cereals, Total	3	92	Melons, other (Inc. Cantaloupes)	4
33	Cherries	4	93	Melon seed	5
34	Cherries, sour	4	94	Millet	3
35	Chestnut	4	95	Mushrooms and truffles	4
36	Chickpeas	4	96	Mustard seed	5
37	Chicory roots	8	97	Nutmeg, mace, and cardamoms	8
38	Chillies and peppers, dry	8	98	Nuts nes	4
39	Chillies and peppers, green	4	99	Oats	3
40	Cinnamon (cannella)	8	100	Oil palm fruit	5
41	Citrus Fruit, Total	4	101	Oil crops, Cake Equivalent	5
42	Cloves	8	102	Oil crops, Oil Equivalent	5
43	Cocoa, beans	8	103	Oilseeds nes	5
44	Coconuts	5	104	Okra	4
45	Coffee, green	8	105	Olives	5
46	Coir	7	106	Onions, dry	4
47	Cowpeas, dry	4	107	Onions, shallots, green	4
48	Cranberries	4	108	Oranges	4
49	Cucumbers and gherkins	4	109	Papayas	4
50	Currants	4	110	Peaches and nectarines	4
51	Dates	4	111	Pears	4
52	Eggplants (aubergines)	4	112	Peas, dry	4
53	Fibre crops nes	7	113	Peas, green	4
54	Figs	4	114	Pepper (piper spp.)	8
55	Flax fibre and tow	7	115	Peppermint	8
56	Fonio	3	116	Persimmons	4
57	Fruit Primary	4	117	Pigeon peas	4
58	Fruit, citrus nes	4	118	Pineapples	4
59	Fruit, fresh nes	4	119	Pistachios	4
60	Fruit, pome nes	4	120	Plantains and others	4

Source: FAO (2022) and GTAP (2022).

Mapping of FAO and GTAP Sectors

	FAO	GTAP		FAO	GTAP
FAO Group: Crops					
121	Plums and sloes	4	148	String beans	4
122	Poppy seed	5	149	Sugar beet	6
123	Potatoes	4	150	Sugar cane	6
124	Pulses nes	4	151	Sugar crops nes	6
125	Pulses, Total	4	152	Sugar Crops Primary	6
126	Pumpkins, squash and gourds	4	153	Sunflower seed	5
127	Pyrethrum, dried	8	154	Sweet potatoes	4
128	Quinces	4	155	Tallow tree seed	5
129	Quinoa	3	156	Tangerines, mandarins, clementines, satsumas	4
130	Ramie	7	157	Taro (cocoyam)	4
131	Rapeseed	5	158	Tea	8
132	Raspberries	4	159	Tobacco, unmanufactured	8
133	Rice, paddy	1	160	Tomatoes	4
134	Rice, paddy (rice milled equivalent)	1	161	Tree nuts, Total	4
135	Roots and tubers nes	4	162	Triticale	3
136	Roots and Tubers, Total	4	163	Tung nuts	5
137	Rubber, natural	8	164	Vanilla	8
138	Rye	3	165	Vegetables Primary	4
139	Safflower seed	5	166	Vegetables, fresh nes	4
140	Seed cotton	7	167	Vegetables, leguminous nes	4
141	Sesame seed	5	168	Vetches	4
142	Sisal	7	169	Walnuts, with shell	4
143	Sorghum	3	170	Watermelons	4
144	Soybeans	5	171	Wheat	2
145	Spices nes	8	172	Yams	4
146	Spinach	4	173	Yautia (cocoyam)	4
147	Strawberries	4			

Source: FAO (2022) and GTAP (2022).

Mapping of FAO and GTAP Sectors

	FAO	GTAP		FAO	GTAP
FAO Group: Processed Crops					
174	Beer of barley	26	186	Oil, olive, virgin	21
175	Cotton lint	21	187	Oil, palm	21
176	Cottonseed	21	188	Oil, palm kernel	21
177	Kapok fibre	27	189	Oil, rapeseed	21
178	Kapok seed in shell	27	190	Oil, safflower	21
179	Margarine, short	21	191	Oil, sesame	21
180	Molasses	24	192	Oil, soybean	21
181	Oil, coconut (copra)	21	193	Oil, sunflower	21
182	Oil, cottonseed	21	194	Palm kernels	21
183	Oil, groundnut	21	195	Sugar Raw Centrifugal	24
184	Oil, linseed	21	196	Wine	26
185	Oil, maize	21			

Source: FAO (2022) and GTAP (2022).

Mapping of FAO and GTAP Sectors

	FAO	GTAP		FAO	GTAP
FAO Group: Live Animals					
197	Asses	9	207	Goats	9
198	Beehives	10	208	Horses	9
199	Buffaloes	9	209	Mules	9
200	Camelids, other	9	210	Pigs	10
201	Camels	9	211	Poultry Birds	10
202	Cattle	9	212	Rabbits and hares	10
203	Cattle and Buffaloes	9	213	Rodents, other	10
204	Chickens	10	214	Sheep	9
205	Ducks	10	215	Sheep and Goats	9
206	Geese and guinea fowls	10	216	Turkeys	10

Source: FAO (2022) and GTAP (2022).

Mapping of FAO and GTAP Sectors

	FAO	GTAP		FAO	GTAP
FAO Group: Primary Livestock					
217	Beef and Buffalo Meat	19	244	Meat, other camelids	19
218	Beeswax	10	245	Meat, other rodents	20
219	Eggs Primary	10	246	Meat, pig	20
220	Eggs, hen, in shell	10	247	Meat, Poultry	20
221	Eggs, other birds, in shell	10	248	Meat, rabbit	20
222	Fat, buffaloes	10	249	Meat, sheep	19
223	Fat, camels	10	250	Meat, Total	20
224	Fat, cattle	10	251	Meat, turkey	20
225	Fat, goats	10	252	Milk, whole fresh buffalo	11
226	Fat, pigs	10	253	Milk, whole fresh camel	11
227	Fat, sheep	10	254	Milk, whole fresh cow	11
228	Hides, buffalo, fresh	10	255	Milk, whole fresh goat	11
229	Hides, cattle, fresh	10	256	Milk, whole fresh sheep	11
230	Honey, natural	10	257	Offals, edible buffaloes	19
231	Meat nes	20	258	Offals, edible, camels	19
232	Meat, ass	19	259	Offals, edible, cattle	19
233	Meat, bird nes	20	260	Offals, edible goats	19
234	Meat, buffalo	19	261	Offals, horses	19
235	Meat, camel	19	262	Offals, pigs, edible	19
236	Meat, cattle	19	263	Offals, sheep, edible	19
237	Meat, chicken	20	264	Sheep and Goat Meat	19
238	Meat, duck	20	265	Silk-worm cocoons, reelable	12
239	Meat, game	20	266	Skins, goat, fresh	10
240	Meat, goat	19	267	Skins, sheep, fresh	10
241	Meat, goose, and guinea fowl	20	268	Snails, not sea	10
242	Meat, horse	19	269	Wool, greasy	12
243	Meat, mule	19			

Source: FAO (2022) and GTAP (2022).

Mapping of FAO and GTAP Sectors

	FAO	GTAP		FAO	GTAP
FAO Group: Processed Livestock					
270	Butter and Ghee	22	286	Milk, dry buttermilk	22
271	Butter and ghee, sheep milk	22	287	Milk, skimmed condensed	22
272	Butter, buffalo milk	22	288	Milk, skimmed cow	22
273	Butter, cow milk	22	289	Milk, skimmed dried	22
274	Butter, goat milk	22	290	Milk, skimmed evaporated	22
275	Cheese (All Kinds)	22	291	Milk, Total	22
276	Cheese, buffalo milk	22	292	Milk, whole condensed	22
277	Cheese, goat milk	22	293	Milk, whole dried	22
278	Cheese, sheep milk	22	294	Milk, whole evaporated	22
279	Cheese, skimmed cow milk	22	295	Silk, raw	27
280	Cheese, whole cow milk	22	296	Skim Milk & Buttermilk, Dry	22
281	Cream fresh	22	297	Tallow	22
282	Evaporated & Condensed Milk	22	298	Whey, condensed	22
283	Ghee, buffalo milk	22	299	Whey, dry	22
284	Ghee, butteroil of cow milk	22	300	Yoghurt	22
285	Lard	22			

Source: FAO (2022) and GTAP (2022).

Supplementary Annexure 7:

Concordance between FAO Countries and Different Classifications

	FAO	GTAP	UN	G-Cubed		FAO	GTAP	UN	G-Cubed
1	AFG	XSA	SAS	ROW	61	ESP	ESP	SEU	EUW
2	AGO	XAC	SAF	OPC	62	EST	EST	NEU	EUW
3	ALB	ALB	SEU	ROW	63	ETH	ETH	SAF	ROW
4	ARE	ARE	WAS	OPC	64	ETH	ETH	SAF	ROW
5	ARG	ARG	LAM	ROW	65	FIN	FIN	NEU	EUW
6	ARM	ARM	WAS	ROW	66	FJI	XOC	ANZ	ROW
7	ASM	XOC	ANZ	ROW	67	FRA	FRA	WEU	EUW
8	ATG	XCB	LAM	ROW	68	FSM	XOC	ANZ	ROW
9	AUS	AUS	ANZ	AUS	69	GAB	XCF	SAF	ROW
10	AUT	AUT	WEU	EUW	70	GBR	GBR	NEU	EUW
11	AZE	AZE	WAS	ROW	71	GEO	GEO	WAS	ROW
12	BDI	XEC	SAF	ROW	72	GHA	GHA	SAF	ROW
13	BEL	BEL	WEU	EUW	73	GIN	GIN	SAF	ROW
14	BEL	BEL	WEU	EUW	74	GLP	FRA	LAM	EUW
15	BEN	BEN	SAF	ROW	75	GMB	XWF	SAF	ROW
16	BFA	BFA	SAF	ROW	76	GNB	XWF	SAF	ROW
17	BGD	BGD	SAS	ROW	77	GNQ	XCF	SAF	ROW
18	BGR	BGR	EEU	EUW	78	GRC	GRC	SEU	EUW
19	BHR	BHR	WAS	OPC	79	GRD	XCB	LAM	ROW
20	BHS	XCB	LAM	ROW	80	GTM	GTM	LAM	ROW
21	BIH	XER	SEU	ROW	81	GUF	XSM	LAM	ROW
22	BLR	BLR	EEU	ROW	82	GUM	XOC	ANZ	ROW
23	BLZ	XCA	LAM	ROW	83	GUY	XSM	LAM	ROW
24	BMU	XNA	NAM	ROW	84	HKG	HKG	EAS	ROW
25	BOL	BOL	LAM	ROW	85	HND	HND	LAM	ROW
26	BRA	BRA	LAM	ROW	86	HRV	HRV	SEU	EUW
27	BRB	XCB	LAM	ROW	87	HTI	XCB	LAM	ROW
28	BRN	BRN	SEA	ROW	88	HUN	HUN	EEU	EUW
29	BTN	XSA	SAS	ROW	89	IDN	INO	SEA	ROW
30	BWA	BWA	SAF	ROW	90	IND	IND	SAS	IND
31	CAF	XCF	SAF	ROW	91	IRL	IRL	NEU	EUW
32	CAN	CAN	NAM	OEC	92	IRN	IRN	SAS	OPC
33	CHE	CHE	WEU	EUW	93	IRQ	XWS	WAS	OPC
34	CHL	CHL	LAM	ROW	94	ISL	XEF	NEU	OEC
35	CHN	CHI	EAS	NA	95	ISR	ISR	WAS	OPC
36	CIV	CIV	SAF	ROW	96	ITA	ITA	SEU	EUW
37	CMR	CMR	SAF	ROW	97	JAM	JAM	LAM	ROW
38	COD	XAC	SAF	OPC	98	JOR	JOR	WAS	OPC
39	COG	XCF	SAF	ROW	99	JPN	JPN	EAS	JPN
40	COK	XOC	ANZ	ROW	100	KAZ	KAZ	CAS	ROW
41	COL	COL	LAM	ROW	101	KEN	KEN	SAF	ROW
42	COM	XEC	SAF	ROW	102	KGZ	KGZ	CAS	ROW
43	CPV	XWF	SAF	ROW	103	KHM	KHM	SEA	ROW
44	CRI	CRI	LAM	ROW	104	KIR	XOC	ANZ	ROW
45	CSK	NA	NA	NA	105	KNA	XCB	LAM	ROW
46	CUB	XCB	LAM	ROW	106	KOR	KOR	EAS	ROW
47	CYM	XCB	LAM	ROW	107	KWT	KWT	WAS	OPC
48	CYP	CYP	WAS	EUW	108	LAO	LAO	SEA	ROW
49	CZE	CZE	EEU	EUW	109	LBN	XWS	WAS	OPC
50	DEU	DEU	WEU	EUW	110	LBR	XWF	SAF	ROW
51	DJI	XEC	SAF	ROW	111	LBY	XNF	NAF	OPC
52	DMA	XCB	LAM	ROW	112	LCA	XCB	LAM	ROW
53	DNK	DNK	NEU	EUW	113	LIE	XEF	WEU	OEC
54	DNK	DNK	NEU	EUW	114	LKA	LKA	SAS	ROW
55	DOM	DOM	LAM	ROW	115	LSO	XSC	SAF	ROW
56	DZA	XNF	NAF	OPC	116	LTU	LTU	NEU	EUW
57	ECU	ECU	LAM	OPC	117	LUX	LUX	WEU	EUW
58	EGY	EGY	NAF	ROW	118	LVA	LVA	NEU	EUW
59	ERI	XEC	SAF	ROW	119	MAC	XEA	EAS	ROW
60	ESH	XNF	NAF	OPC	120	MAR	MAR	NAF	ROW

Source: FAO (2022) and GTAP (2022).

	FAO	GTAP	UN	G-Cubed		FAO	GTAP	UN	G-Cubed
121	MDA	XEE	EEU	ROW	181	SPM	XNA	NAM	ROW
122	MDG	MDG	SAF	ROW	182	SRB	XER	SEU	ROW
123	MDV	XSA	SAS	ROW	183	SSD	NA	SAF	NA
124	MEX	MEX	LAM	ROW	184	SSD	NA	SAF	NA
125	MHL	XOC	ANZ	ROW	185	STP	XCF	SAF	ROW
126	MKD	XER	SEU	ROW	186	SUR	XSM	LAM	ROW
127	MLI	XWF	SAF	ROW	187	SVK	SVK	EEU	EUW
128	MLT	MLT	SEU	EUW	188	SVN	SVN	SEU	EUW
129	MMR	XSE	SEA	ROW	189	SWE	SWE	NEU	EUW
130	MNE	XER	SEU	ROW	190	SWZ	XSC	SAF	ROW
131	MNG	MNG	EAS	ROW	191	SYC	XEC	SAF	ROW
132	MOZ	MOZ	SAF	ROW	192	SYR	XWS	WAS	OPC
133	MRT	XWF	SAF	ROW	193	TCD	XCF	SAF	ROW
134	MSR	XCB	LAM	ROW	194	TGO	TGO	SAF	ROW
135	MTQ	FRA	LAM	EUW	195	THA	THA	SEA	ROW
136	MUS	MUS	SAF	ROW	196	TJK	TJK	CAS	ROW
137	MWI	MWI	SAF	ROW	197	TKL	XOC	ANZ	ROW
138	MYS	MYS	SEA	ROW	198	TKM	XSU	CAS	ROW
139	NA	XTW	ANT	ROW	199	TLS	XSE	SEA	ROW
140	NAM	NAM	SAF	ROW	200	TON	XOC	ANZ	ROW
141	NCL	XOC	ANZ	ROW	201	TTO	TTO	LAM	ROW
142	NER	XWF	SAF	ROW	202	TUN	TUN	NAF	ROW
143	NGA	NGA	SAF	OPC	203	TUR	TUR	WAS	ROW
144	NIC	NIC	LAM	ROW	204	TUV	XOC	ANZ	ROW
145	NIU	XOC	ANZ	ROW	205	TWN	TWN	EAS	ROW
146	NLD	NLD	WEU	EUW	206	TZA	TZA	SAF	ROW
147	NOR	NOR	NEU	EUW	207	UGA	UGA	SAF	ROW
148	NPL	NPL	SAS	ROW	208	UKR	UKR	EEU	ROW
149	NRU	XOC	ANZ	ROW	209	URY	URY	LAM	ROW
150	NZL	NZL	ANZ	OEC	210	USA	USA	NAM	USA
151	OMN	OMN	WAS	OPC	211	UZB	XSU	CAS	ROW
152	PAK	PAK	SAS	ROW	212	VCT	XCB	LAM	ROW
153	PAN	PAN	LAM	ROW	213	VEN	VEN	LAM	OPC
154	PER	PER	LAM	ROW	214	VGB	XCB	LAM	ROW
155	PHL	PHL	SEA	ROW	215	VIR	XCB	LAM	ROW
156	PNG	XOC	ANZ	ROW	216	VNM	VNM	SEA	ROW
157	POL	POL	EEU	EUW	217	VUT	XOC	ANZ	ROW
158	PRI	PRI	LAM	ROW	218	WLF	XOC	ANZ	ROW
159	PRK	XEA	EAS	ROW	219	WSM	XOC	ANZ	ROW
160	PRT	PRT	SEU	EUW	220	YEM	XWS	WAS	OPC
161	PRY	PRY	LAM	ROW	221	ZAF	ZAF	SAF	ROW
162	PSE	XWS	WAS	OPC	222	ZMB	ZMB	SAF	ROW
163	PYF	XOC	ANZ	ROW	223	ZWE	ZWE	SAF	ROW
164	QAT	QAT	WAS	OPC					
165	REU	FRA	SAF	EUW					
166	ROU	ROU	EEU	EUW					
167	RUS	RUS	EEU	RUS					
168	RUS	RUS	EEU	RUS					
169	RWA	RWA	SAF	ROW					
170	SAU	SAU	WAS	OPC					
171	SCG	XER	SEU	ROW					
172	SCG	XER	SEU	ROW					
173	SDN	XEC	NAF	ROW					
174	SEN	SEN	SAF	ROW					
175	SGP	SGP	SEA	ROW					
176	SHN	XWF	SAF	ROW					
177	SLB	XOC	ANZ	ROW					
178	SLE	XWF	SAF	ROW					
179	SLV	SLV	LAM	EUW					
180	SOM	XEC	SAF	ROW					

Source: FAO (2022) and GTAP (2022).

Supplementary Annexure 8: Historical Agriculture Production Patterns

The online dashboard presents the historical agriculture production patterns across the UN regions for five subsectors. The historical annual crop productivity growth remained constant across many regions. However, some regions, such as Southern Asia, Latin America, and Oceania, experienced notable declines. In contrast, Central Asia, Western Asia, and Eastern Europe increased crop productivity. Annual growth in processed crop production diminished starting from the early 2010s. A few regions, such as Western and East Asia and most parts of Europe, demonstrated increased growth before the decline.

Annual growth in live animal production remained constant, with some reductions starting from the early 2010s. The annual productivity growth of primary livestock decreased since the early 1990s in most regions, except for Western Asia and Latin America, which showed signs of increase since the mid-2000s. The annual growth in processed livestock production decreased since the early 2010s across all regions after remaining constant since the early 1990s for most regions.

Supplementary Annexure 9:

Country Coverage for Energy Production and Electricity Generation Data

	Sector	Number of Countries Covered
1	Coal Production	34
2	Oil Production	48
3	Gas Production	49
4	Electricity Generation: Nuclear	79
5	Electricity Generation: Hydro	79
6	Electricity Generation: Solar	79
7	Electricity Generation: Wind	79
8	Electricity Generation: Other	79

Source: BP (2022).

Supplementary Annexure 10:

Concordance between BP Countries and Different Classifications

	BP	GTAP	UN	G-Cubed		BP	GTAP	UN	G-Cubed
1	AGO	XAC	SAF	OPC	61	MDG	MDG	SAF	ROW
2	ANT	XCB	LAM	ROW	62	MEX	MEX	LAM	ROW
3	ARE	ARE	WAS	OPC	63	MKD	XER	SEU	ROW
4	ARG	ARG	LAM	ROW	64	MMR	XSE	SEA	ROW
5	AUS	AUS	ANZ	AUS	65	MNG	MNG	EAS	ROW
6	AUT	AUT	WEU	EUW	66	MOZ	MOZ	SAF	ROW
7	AZE	AZE	WAS	ROW	67	MYS	MYS	SEA	ROW
8	BEL	BEL	WEU	EUW	68	NCL	XOC	ANZ	ROW
9	BGD	BGD	SAS	ROW	69	NGA	NGA	SAF	OPC
10	BGR	BGR	EEU	EUW	70	NLD	NLD	WEU	EUW
11	BHR	BHR	WAS	OPC	71	NOR	NOR	NEU	EUW
12	BLR	BLR	EEU	ROW	72	NZL	NZL	ANZ	OEC
13	BOL	BOL	LAM	ROW	73	OMN	OMN	WAS	OPC
14	BRA	BRA	LAM	ROW	74	PAK	PAK	SAS	ROW
15	BRN	BRN	SEA	ROW	75	PER	PER	LAM	ROW
16	CAN	CAN	NAM	OEC	76	PHL	PHL	SEA	ROW
17	CHE	CHE	WEU	EUW	77	PNG	XOC	ANZ	ROW
18	CHL	CHL	LAM	ROW	78	POL	POL	EEU	EUW
19	CHN	CHI	EAS	CHN	79	PRT	PRT	SEU	EUW
20	COD	XAC	SAF	OPC	80	QAT	QAT	WAS	OPC
21	COG	XCF	SAF	ROW	81	ROU	ROU	EEU	EUW
22	COL	COL	LAM	ROW	82	ROW	NA	NA	ROW
23	CUB	XCB	LAM	ROW	83	RUS	RUS	EEU	RUS
24	CUW	XCB	LAM	ROW	84	SAU	SAU	WAS	OPC
25	CYP	CYP	WAS	EUW	85	SDN	XEC	NAF	ROW
26	CZE	CZE	EEU	EUW	86	SGP	SGP	SEA	ROW
27	DEU	DEU	WEU	EUW	87	SRB	XER	SEU	ROW
28	DNK	DNK	NEU	EUW	88	SSD	NA	SAF	NA
29	DZA	XNF	NAF	OPC	89	SUN	NA	NA	NA
30	ECU	ECU	LAM	OPC	90	SVK	SVK	EEU	EUW
31	EGY	EGY	NAF	ROW	91	SVN	SVN	SEU	EUW
32	ESP	ESP	SEU	EUW	92	SWE	SWE	NEU	EUW
33	EST	EST	NEU	EUW	93	SYR	XWS	WAS	OPC
34	FIN	FIN	NEU	EUW	94	TCD	XCF	SAF	ROW
35	FRA	FRA	WEU	EUW	95	THA	THA	SEA	ROW
36	GAB	XCF	SAF	ROW	96	TKM	XSU	CAS	ROW
37	GBR	GBR	NEU	EUW	97	TTO	TTO	LAM	ROW
38	GNQ	XCF	SAF	ROW	98	TUN	TUN	NAF	ROW
39	GRC	GRC	SEU	EUW	99	TUR	TUR	WAS	ROW
40	HKG	HKG	EAS	ROW	100	TWN	TWN	EAS	ROW
41	HRV	HRV	SEU	EUW	101	UKR	UKR	EEU	ROW
42	HUN	HUN	EEU	EUW	102	USA	USA	NAM	USA
43	IDN	INO	SEA	ROW	103	UZB	XSU	CAS	ROW
44	IND	IND	SAS	IND	104	VEN	VEN	LAM	OPC
45	IRL	IRL	NEU	EUW	105	VNM	VNM	SEA	ROW
46	IRN	IRN	SAS	OPC	106	YEM	XWS	WAS	OPC
47	IRQ	XWS	WAS	OPC	107	ZAF	ZAF	SAF	ROW
48	ISL	XEF	NEU	OEC	108	ZMB	ZMB	SAF	ROW
49	ISR	ISR	WAS	OPC	109	ZWE	ZWE	SAF	ROW
50	ITA	ITA	SEU	EUW					
51	JPN	JPN	EAS	JPN					
52	KAZ	KAZ	CAS	ROW					
53	KOR	KOR	EAS	ROW					
54	KWT	KWT	WAS	OPC					
55	LBY	XNF	NAF	OPC					
56	LKA	LKA	SAS	ROW					
57	LTU	LTU	NEU	EUW					
58	LUX	LUX	WEU	EUW					
59	LVA	LVA	NEU	EUW					
60	MAR	MAR	NAF	ROW					

Source: BP (2022).

Supplementary Annexure 11: Historical Energy Production Patterns

The online dashboard presents the historical energy production patterns across the UN regions for eight subsectors. The annual coal production growth declined overall since the 1990s. The decline was notable in Southeast Asia and Northern Europe. The change in annual oil production growth was much more cyclical compared to coal production, although some regions experienced overall declines throughout the period. North America was, however, increasing its growth in oil production. The annual gas production growth was less cyclical than oil production and, similar to coal production, was declining for almost all the regions.

Nuclear and hydropower generation remained constant throughout most regions. Solar electricity generation was volatile, with different regions starting to use solar resources at different times. Some regions showed an increasing uptake, while Western Europe appeared to be on a downward trend. Wind power generation was somewhat volatile, with most regions experiencing constant growth. Power generation from other sources remained constant across most regions, with a few experiencing cyclical changes.

Supplementary Annexure 12: Regularized Regressions

Linear regression and its variants are widely used to estimate the empirical relationships between variables. In general, linear regression attempts to find the magnitudes of the coefficients that minimize the residual error between the actual observations and their predicted counterparts. Equation 1 presents the general representation of a linear regression model, and Equation 2 presents the objective function.[1]

Equation 1: General Form of a Linear Regression Model

$$Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij} + \varepsilon$$

Equation 2: Objective Function of a Linear Regression Problem

$$\operatorname{argmin}\left(\sum_{i=1}^{N} (Y_i - \widehat{Y_i})^2 = \sum_{i=1}^{N} \left[Y_i - \beta_0 - \sum_{j=1}^{n} \beta_j X_{ij} \right]^2 \right)$$

However, when using linear regression models for predictions, two major problems could occur: overfitting and underfitting. Overfitting happens when the regression model performs well on the training data but poorly on the testing data. Underfitting occurs when the regression model does not perform well on either data. Regularization prevents overfitting in regression models without changing the number of features or predictor variables. LASSO (Least Absolute Shrinkage and Selection Operator) and Ridge are widely used regularization algorithms. The objective functions of LASSO and Ridge are presented in Equations 3 and 4.[2]

Equation 3: Objective Function of a LASSO Regression Problem

$$\operatorname{argmin}\left(\sum_{i=1}^{N} \left[Y_i - \beta_0 - \sum_{j=1}^{n} \beta_j X_{ij} \right]^2 + \alpha \sum_{j=1}^{n} |\beta_j| \right)$$

Equation 4: Objective Function of a Ridge Regression Problem

$$\operatorname{argmin}\left(\sum_{i=1}^{N} \left[Y_i - \beta_0 - \sum_{j=1}^{n} \beta_j X_{ij} \right]^2 + \alpha \sum_{j=1}^{n} {\beta_j}^2 \right)$$

As illustrated in Equations 3 and 4, both LASSO and Ridge regressions start with the conventional objective function of linear regression and impose a non-negative penalty on the coefficients of the predictors. The penalty prevents the coefficients from being too large when optimizing the conventional objective function.

[1] The notation in the equations follows the standard interpretation of an OLS regression problem, where Y_i is the dependent variable and X_{ij} is an independent variable with β_j as its coefficient. β_0 is the intercept of the regression equation.

[2] The notation in the equations follows the standard interpretation of an OLS regression problem, where Y_i is the dependent variable and X_{ij} is an independent variable with β_j as its coefficient. β_0 is the intercept of the regression equation and α is the regularization parameter.

The penalty in LASSO regression works with the linear summation of coefficients and thus could shrink some coefficients to zero. However, Ridge regression works with the squared summation of the coefficients and does not necessarily reduce the coefficients to zero. This characteristic qualifies LASSO as a feature selection algorithm that could identify the optimum set of predictors from a large group of predictors.

The two algorithms also behave differently when there are correlated predictors. While LASSO would shrink some coefficients of correlated variables to zero, Ridge regression would treat all the correlated variables the same. Given these differences across LASSO and Ridge, a generalized form of regularized regression combining both approaches could also be used. Equation 5[3] presents the objective function of the generalized form.[4]

Equation 5: Objective Function of a General Regularized Regression Problem

$$\operatorname{argmin}\left(\sum_{i=1}^{N}\left[Y_i - \beta_0 - \sum_{j=1}^{n}\beta_j X_{ij}\right]^2 + \alpha\sum_{j=1}^{n}\left((1-\theta)\,{\beta_j}^2 + \theta\,\left|\beta_j\right|\right)\right)$$

[3] The notation in the equations follows the standard interpretation of an OLS regression problem, where Y_i is the dependent variable and X_{ij} is an independent variable with β_j as its coefficient. β_0 is the intercept of the regression equation, α is the regularization parameter, and θ is the weight.

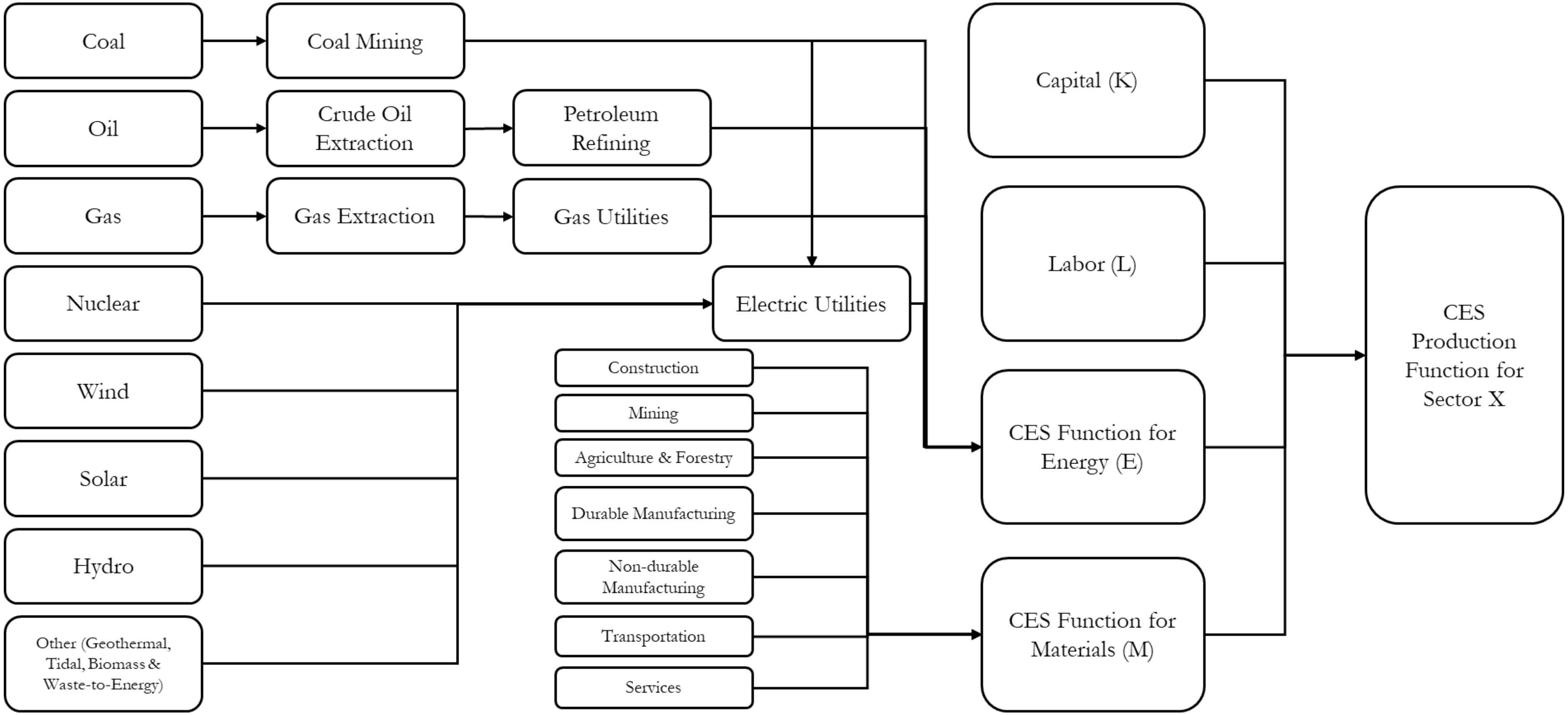
[4] See Hastie et al. (2017) for a detailed discussion on linear, LASSO, and Ridge regression models.

Supplementary Annexure 13: Concordance between GTAP and G-Cubed Sectors

Number	Code	Description	G-Cubed Sector
1	PDR	Paddy Rice	Agriculture
2	WHT	Wheat	Agriculture
3	GRO	Other Cereal grains	Agriculture
4	V_F	Vegetables, Fruits, and Nuts	Agriculture
5	OSD	Oil Seeds	Agriculture
6	C_B	Sugar Cane and Sugar Beet	Agriculture
7	PFB	Plant-based Fibers	Agriculture
8	OCR	Other Crops	Agriculture
9	CTL	Bovine Cattle, Sheep, Goats, and Horses	Agriculture
10	OAP	Other Animal Products	Agriculture
11	RMK	Raw Milk	Agriculture
12	WOL	Wool, and Silk-worm Cocoons	Agriculture
13	FRS	Forestry	Agriculture
14	FSH	Fishing	Agriculture
15	COA	Coal	Coal Mining
16	OIL	Oil	Crude Oil Extraction
17	GAS	Gas	Gas Utilities
18	OXT	Other Extractives	Mining
19	CMT	Bovine Meat Products	Non-durable Manufacturing
20	OMT	Other Meat Products	Non-durable Manufacturing
21	VOL	Vegetable Oils and Fats	Non-durable Manufacturing
22	MIL	Dairy Products	Non-durable Manufacturing
23	PCR	Processed Rice	Non-durable Manufacturing
24	SGR	Sugar	Non-durable Manufacturing
25	OFD	Other Food Products	Non-durable Manufacturing
26	B_T	Beverages and Tobacco Products	Non-durable Manufacturing
27	TEX	Textiles	Non-durable Manufacturing
28	WAP	Wearing Apparel	Non-durable Manufacturing
29	LEA	Leather Products	Non-durable Manufacturing
30	LUM	Wood Products	Agriculture
31	PPP	Paper Products and Publishing	Non-durable Manufacturing
32	P_C	Petroleum and Coal Products	Petroleum Refining
33	CHM	Chemical Products	Non-durable Manufacturing
34	BPH	Basic Pharmaceutical Products	Non-durable Manufacturing
35	RPP	Rubber and Plastic Products	Non-durable Manufacturing
36	NMM	Mineral Products	Durable Manufacturing
37	I_S	Ferrous Metals	Durable Manufacturing
38	NFM	Non-Ferrous Metals	Durable Manufacturing
39	FMP	Metal Products	Durable Manufacturing
40	ELE	Computer, Electronic, and Optical Products	Durable Manufacturing
41	EEQ	Electrical Equipment	Durable Manufacturing
42	OME	Other Machinery and Equipment	Durable Manufacturing
43	MVH	Motor Vehicles and Parts	Durable Manufacturing
44	OTN	Other Transport Equipment	Durable Manufacturing
45	OMF	Other Manufactures	Durable Manufacturing
46	ELY	Electricity	Electric Utilities
47	GDT	Gas Manufacture and Distribution	Gas Utilities
48	WTR	Water	Services
49	CNS	Construction	Construction
50	TRD	Trade	Services
51	AFS	Accommodation, Food, and Service Activities	Services
52	OTP	Other Transport	Transport
53	WTP	Water Transport	Transport
54	ATP	Air Transport	Transport
55	WHS	Warehousing and Support Activities	Transport
56	CMN	Communication	Services
57	OFI	Other Financial Services	Services
58	INS	Insurance	Services
59	RSA	Real Estate Activities	Services
60	OBS	Business Services	Services
61	ROS	Recreational and Other Services	Services
62	OSG	Public Administration and Defense	Services
63	EDU	Education	Services
64	HHT	Human Health and Social Work Activities	Services
65	DWE	Dwellings	Services

Source: The G-Cubed Model (GGG20C_v169).

Supplementary Annexure 14: Schematic G-Cubed Production Structure



Source: The G-Cubed Model (GGG20C_v169).

Supplementary Annexure 15: Projected Climate Indicators under SSPs

The online dashboard presents the projected variation in chronic and extreme climate indicators across the UN regions under the SSPs.

The Behavior of Chronic Climate Indicators under SSPs

Under SSP 1-2.6, the average mean temperature across the period remains almost constant. However, under SSP 2-4.5 and 5-8.5, an apparent temperature rise is observable, with Central Asia and Eastern Europe experiencing the highest increments. Oceania experiences the lowest increase under all three SSPs. By 2100, under SSP 5-8.5, all regions experience higher temperature differences above 2^0C compared to the baseline temperature.

Precipitation changes also remain almost constant under SSP 1-2.6. A few regions (such as Central Asia, Oceania, and Latin America) experience slightly higher precipitation. The range of precipitation further widens under SSP 2-4.5, with more regions experiencing lower precipitation. The pattern continues under SSP 5-8.5 with lower increments compared to the baseline. Few regions (such as North America and Northern Europe) experience higher precipitation.

Changes in relative humidity indicate the trade-offs between temperature and precipitation changes under a given scenario. Under SSP 1-2.6, its behavior is more comparable to precipitation. Some regions (Latin America, Oceania, and Northern Europe) experience higher humidity. In contrast, some regions (such as Eastern Europe, Southern Europe, and Northern Africa) experience lower humidity, indicating drier conditions. The pattern remains essentially the same across the other two SSPs.

The Behavior of Extreme Climate Indicators under SSPs

The deviation of the maximum temperature from the 90^{th} percentile indicates, in a given year, how, on average, the monthly maximum temperature deviates from the 90^{th} percentile of the baseline distribution (1961-1990). Under SSP 1-2.6, all the regions experience some variation in extremely warm conditions during the day, although they remain at similar levels throughout the century. However, under SSP 2-4.5, all regions experience extremely warm conditions, with some regions (such as Western Europe, Southeast Asia, and Southern Europe) experiencing almost a four percent increase compared to the baseline. The pattern becomes stronger under SSP 5-8.5, and some regions (such as North America and Southeast Asia) experience increments above eight percent compared to the baseline. Oceania, Australia, and New Zealand experience minimal increments across all three SSPs.

The deviation of the maximum temperature from the 10^{th} percentile indicates, in a given year, how, on average, the monthly maximum temperature deviates from the 10^{th} percentile of the baseline distribution (1961-1990). Under SSP 1-2.6, most regions experience minimal reductions (between -4 to 0 percent) from the baseline, even though Eastern and Western Europe experience notable declines greater than five percent below the baseline. Under SSP 2-4.5 and SSP 5-8.5, the patterns remain analogous to SSP 1-2.6, and the convergence among regions is faster with the increase in warming.

The deviation of the minimum temperature from the 90th percentile indicates, in a given year, how, on average, the monthly minimum temperature deviates from the 90th percentile of the baseline distribution (1961-1990). Under SSP 1-2.6, most regions experience constant increments, yet within two to eight percent compared to the baseline across the century. Under SSP 2-4.5, all the regions experience upward trends, with the upper bound exceeding 10 percent by 2100. Under SSP 5-8.5, the increases are more pronounced, and all the regions are approximately seven percent above the baseline by 2100.

The deviation of the minimum temperature from the 10th percentile indicates, in a given year, how, on average, the monthly minimum temperature deviates from the 10th percentile of the baseline distribution (1961-1990). Under SSP 1-2.6, most regions experience very minimal changes. The minimal changes reduce to zero amidst continued warming, as observed in SSP 2-4.5. The convergence to zero is more pronounced under SSP 5-8.5.

Extremely dry and wet conditions measure the variation of a given month's SPI index from -2 or +2, respectively, following the definition of the SPI Index. The annual variation is obtained by averaging the monthly variations for a given year. The extremely dry conditions increase compared to the baseline for all regions under all three SSPs, even though the increments remain constant throughout the century for most of them. Southern Europe experiences the most substantial increase, which becomes more pronounced across the scenarios with the temperature rise. North America, Oceania, and Southern Europe experience the lowest increment compared to the baseline.

Extremely wet conditions are more dynamic than extremely dry conditions. However, analogous to extremely dry conditions, the rise in extremely wet conditions remains constant across most regions throughout the century across all three SSPs. Northern Africa, Oceania, and Western Asia experience the highest increment across all three SSPs. While these increments are constant under SSP 1-2.6, they increase under the other two. Oceania experiences a 0.6 and 1.5 percent increase from the baseline under SSP 2-4.5 and SSP 5-8.5, respectively.

The extremely windy conditions measure how a given month's maximum wind speed deviates from the 90th percentile of the underlying distribution of the wind speeds in the baseline period (1961-1990). The annual variation is the average of the monthly deviations. Extremely windy conditions increase with warming. However, for most regions, on average, the increments remain constant. Under SSP 1-2.6, most regions remain below a two percent deviation from the baseline. Eastern Europe and Southeast Asia experience notably higher deviations from the baseline. The variation patterns across the century remain comparable to SSP 1-2.6 under SSP 2-4.5. However, several regions (such as Northern Europe, Western Europe, and Sub-Saharan Africa) exceed a two percent deviation from the baseline earlier in the century under SSP 2-4.5. Though remaining under a two percent increase from the baseline, a few regions, such as Latin America and Western Asia, experience an increasing trend of extremely windy conditions under SSP 5-8.5.