South Asia Development Matters

South Asia's Hotspots

The Impact of Temperature and Precipitation Changes on Living Standards

Muthukumara Mani
Sushenjit Bandyopadhyay
Shun Chonabayashi
Anil Markandya
Thomas Mosier

WORLD BANK GROUP

South Asia's Hotspots

South Asia's Hotspots

The Impact of Temperature and Precipitation Changes on Living Standards

Muthukumara Mani
Sushenjit Bandyopadhyay
Shun Chonabayashi
Anil Markandya
Thomas Mosier

WORLD BANK GROUP

1818 H Street NW, Washington, DC 20433
Telephone: 202-473-1000; Internet: www.worldbank.org

1 2 3 4 21 20 19 18

ISBN (paper): 978-1-4648-1155-5
ISBN (electronic): 978-1-4648-1156-2
DOI: 10.1596/978-1-4648-1155-5

Library of Congress Cataloging-in-Publication Data has been requested.

Contents

Boxes

Figures

Maps

Tables

The Book at a Glance

About the Book

- The World Bank's regional flagship, *South Asia's Hotspots: The Impact of Temperature and Precipitation Changes on Living Standards,* brings forth new research on the impact of climate change in South Asia by analyzing how changes in average temperature and precipitation—referred to as "average weather"—will affect living standards.
- The book breaks new ground in understanding how weather conditions affect living standards by combining and analyzing granular temperature and precipitation information and household survey data.
- The book identifies climate "hotspots"—areas where changes in average weather are predicted to have a negative impact on living standards—in South Asia.

Main Findings

- The book analyzes two future climate scenarios—one that is "climate-sensitive," in which some collective action is taken to limit greenhouse gas emissions, and one that is "carbon-intensive," in which no action is taken.
- Both scenarios show rising temperatures throughout the region in the coming decades, with the carbon-intensive scenario leading to greater increases. Expected changes in rainfall patterns are more complex in both scenarios.
- Changes in average weather are projected to have overall negative impacts on living standards in Bangladesh, India, Pakistan, and Sri Lanka. While negative impacts are sizable under both climate scenarios, they are more severe under the carbon-intensive scenario.
- Unlike sea-level rise and extreme weather events, changes in average weather will affect inland areas the most.
- For most countries, changes in average weather will also reduce growth of their gross domestic product (GDP) per capita, compared to what it would be under present climate conditions. The GDP losses are greater for severe hotspot regions.
- More than 800 million people—almost half of South Asia's population—currently live in areas that are projected to become moderate to severe hotspots by 2050 under the carbon-intensive scenario. Most projected hotspots are found to be in disadvantaged areas.

Recommendations

- Overall, ensuring good development outcomes is the best strategy to build resilience to changes in average weather and improve hotspots.

- The book identifies interventions tailored to each country that could mitigate hotspots. Interventions must account for differences in local conditions between hotspots.

- *South Asia's Hotspots*, together with existing studies on the impacts of sea-level rise and extreme events, creates a sound foundation for investing in targeted policies and actions to build climate resilience throughout the region.

Foreword

Changes in the Earth's climate will have major effects on the people of South Asia, which is already one of the most affected regions of the world. A number of studies have looked at the consequences of extreme events—droughts, floods, heat waves, and storm surges—as well as those of sea-level rise in general, and have found such events to damage the health and well-being of the population, especially the poor. This book adds to that body of knowledge by investigating the effects on living standards of long-term changes in the climate—of rising average temperatures, but also changes in the patterns of precipitation. It does so by looking at how differences in weather have influenced living standards across the region in recent decades.

The book finds that higher temperatures reduce average living standards in most of South Asia. This finding, combined with the expected changes in climate by 2050, is used to project likely changes in living standards at a detailed, spatial level. Hotspots are identified where people could be most severely affected by changes in average temperature and precipitation. Many of these are in locations that hitherto have not been seen as particularly vulnerable to climate.

Hotspots have distinguishing features that vary from country to country. A detailed assessment of their characteristics, and of their households' characteristics, enriches our understanding of how to address climate change.

Actions needed to adapt to climate include many with which we are already familiar. Reducing emissions of greenhouse gases will mitigate the size of the climate impacts, and inclusive economic growth across the subcontinent will help its population to adapt more easily. In addition, the potential effects of specific actions on the hotspots are discussed. These actions vary across countries, and the analyses provide further guidance on what kinds of policy responses are most likely to be beneficial.

This book is a major contribution to our understanding of how increasing temperatures and changing precipitation patterns interact with social and economic structures at a very granular level across South Asia. The book should be of great value to all those concerned with the development of the region over the coming decades.

Annette Dixon
Vice President
South Asia Region
World Bank Group

Acknowledgments

This book was prepared by a team led by Muthukumara Mani (Lead Economist) under the guidance of Martin Rama (Chief Economist) and Annette Dixon (Vice President) of the South Asia Region of the World Bank. The book is a collaborative effort of the Office of the Chief Economist and the Disaster and Climate Change Unit of the South Asia Region. The core team members include Sushenjit Bandyopadhyay, Shun Chonabayashi, Anil Markandya, and Thomas Mosier. The team was supported in the climate-modeling work by a team of climate scientists from the Columbia University's International Research Institute for Climate and Society, led by Lisa Goddard.

The team greatly benefited from insightful comments and guidance from internal peer reviewers—Stephane Hallegatte, Emmanuel Skoufias, Harshadeep Nagaraja Rao, and Erick Fernandes—and from external peer reviewers—Robert Mendelsohn, Rajat Kathuria, Saleemul Huq, and Shantanu Mitra.

The team is also grateful to other colleagues from the World Bank for their thoughtful comments and suggestions at various stages of the book, including, most notably, Marianne Fay, Christophe Pusch, Stephen Hammer, Bernice Van Bronkhorst, Chandra Shekar Sinha, Gladys Lopez-Acevedo, Dhushyanth Raju, Fan Zhang, Yue Li, Alex Ferguson, Tatiana Nenova, Sanjay Srivastava, Kanta Kumari Rigaud, and Rafik Hirji.

The book could not have been produced without the support of Elena Karaban, Yann Doignon, Joe Qian, Jewel McFadden, Rumit Pancholi, Michael Harrup, Jeffrey Lawrence, Bruno Bonansea and Neelam Chowdhry. Thomas Cohen provided editorial support.

The team gratefully acknowledges timely financial support from the Australian Department of Foreign Affairs and Trade. In producing this report, the World Bank emphasizes that climate change initiatives and projects shall respect the sovereignty of the countries involved, and notes that the findings and conclusions in the report may not reflect the views of individual countries or their acceptance.

About the Authors

Muthukumara Mani is a Lead Economist in the Office of the Chief Economist of the World Bank's South Asia Region. He primarily works on climate change mitigation and adaptation and water and environmental issues in the region. Prior to joining the region, he led the Bank's work on assessing environmental implications of development policy reforms in the Bank's Environmental and Natural Resources Global Practice. His work also has focused on country environmental assessments, natural resources management, environmental institutions and governance, and trade and climate change issues. Prior to joining the Bank in this position, he was an economist in the Fiscal Affairs Department of the International Monetary Fund, where he was responsible for analyzing environmental implications of macroeconomic policies and programs and in integrating environmental considerations broadly in the IMF's country programs. Mani has an MA and a PhD in economics from the University of Maryland, College Park.

Sushenjit Bandyopadhyay is an empirical environmental economist with a special interest in linkages between climate change and household welfare. He studied economics in India and the United States. His first research on droughts in India was published in 1992. Since then he has published on a variety of topics, such as the environmental Kuznets curves, overcompliance with water pollution controls, linkages between poverty and natural resource management, and autonomous adaptation to climate change and its effects on household welfare. Sushenjit has worked in the World Bank in various research capacities. He has an MA in economics from Jawaharlal Nehru University in India and a PhD in economics from the University of Maryland, College Park.

Shun Chonabayashi is an environmental economist at the World Bank. He has extensive experience in economic analysis of impacts of climate change and extreme weather events and has carried out many research projects in both developing and developed countries. His special interests include economic modeling, sustainability, climate change, and the poverty-environment nexus. Prior to joining the World Bank, he was a postgraduate fellow at the Yale School of Forestry and Environmental Studies. He received a BA from Soka University and an MA from Yale University and is a PhD candidate at Cornell University.

Anil Markandya has worked in the field of resource and environmental economics for more than 35 years. He was a lead author for the 3rd and 4th *IPCC Assessment Reports on*

Climate Change (which were awarded a share of the Nobel Peace Prize in 2007) as well as for the 5th *IPCC Report* published in 2014. He has worked extensively as an advisor on climate change adaptation policies in Europe, the United States, and several developing countries. He was President of the European Association of Environmental and Resource Economics from 2014 to 2015. Anil is a Distinguished Ikerbasque Professor at the Basque Centre for Climate Change in the Basque Country, Spain, and a Honorary Professor of Economics at the University of Bath, UK. He has a PhD from the London School of Economics.

Thomas Mosier is a research scientist specializing in climate, energy, and water, with extensive experience in development contexts. At the World Bank, Thomas has blended his background with economics to examine the impacts of climate change on people and water resources in South Asia. Thomas earned a dual-major PhD in water resources engineering and mechanical engineering at Oregon State University. His graduate research investigated the linkages between climate, cryosphere (snow and ice), surface water resources, and hydropower in mountain environments. Before graduate school, Thomas served as a Peace Corps volunteer in Kenya, where he taught high school physics and mathematics. He earned his undergraduate degree from Reed College, where he majored in physics.

Abbreviations

AGDP	agricultural gross domestic product
GDP	gross domestic product
GHG	greenhouse gas
IIASA	International Institute for Applied Systems Analysis
IMD	Indian Meteorological Department
RCP	representative concentration pathway
RMSE	root mean squared error
SSP	shared socioeconomic pathway

Overview

South Asia's Hotspots: The Impact of Temperature and Precipitation Changes on Living Standards is the first book of its kind to conduct granular spatial analyses of the long-term effects of changes in average temperature and precipitation—referred to throughout the book as "average weather"—in one of the world's poorest regions. This book builds upon accumulated research on climate change by analyzing how trends in average temperatures and precipitation patterns over the coming years will affect living standards. It uses weather data from global climate models to predict changes in average weather at the local level. The book analyzes these climate data in combination with household surveys to explain how changes in average weather will affect living standards.

Research on the effects of climate change has focused mostly on the immediate shocks of extreme events, such as major storms, droughts, and floods. Valuable insights have also been gained on the effects of sea-level rise. This book complements the existing body of knowledge by providing granular analyses of projected changes in average weather. It shows how these changes in average weather conditions will differ across regions.

Furthermore, the book analyzes how living standards, measured by per capita consumption expenditures, will be affected by these changes in average weather. Analyses of the relationship between weather conditions and living standards are conducted separately for individual countries. The combination of localized climate projections and household survey analyses yields a granular picture of the expected effects.

The book shows that average temperatures have risen over the past six decades and will continue to rise. Over the 2050 horizon, it predicts more warming inland and less warming in coastal areas. Changes in precipitation patterns have been more mixed, and this diversity will persist in the future. These weather changes are expected to result in a decrease in living standards in most countries in the region, compared with a situation in which current weather conditions are preserved.

In the coming decades, changes in average weather will have a clearly negative effect on living standards in Bangladesh, India, Pakistan, and Sri Lanka. Overall, inland areas will be more severely affected than those near the coast. In India and Pakistan, water-stressed areas will be more adversely affected compared with the national average.

Many parts of Afghanistan and Nepal are relatively cold at present, so warming will not have a negative effect on living standards in these countries. In addition, climate change may increase precipitation in Afghanistan, which is predicted to have a positive effect.

These predicted positive effects do not account for the projected negative effects of natural disasters and extreme events, to which these countries are highly vulnerable, according to other studies.

Scenarios representing atmospheric emissions of greenhouse gases (GHGs) and their associated atmospheric concentrations are referred to as representative concentration pathways (RCPs). The trends and impacts just described will occur under both a climate-sensitive scenario (RCP 4.5) and a carbon-intensive scenario (RCP 8.5). In the former, some collective global action is undertaken to reduce the GHG emissions that are a major cause of climate change. In the latter scenario, the assumption is that there is no global action. Adverse effects on living standards in South Asia are greater under the carbon-intensive scenario.

The current research adds to the understanding of the effects of climate change through a more granular approach that yields predictions at the district level. The book identifies "hotspots"— districts where rising average temperatures and changing precipitation patterns will have a notable negative effect on living standards. Almost half of South Asia's population now lives in areas that are projected to become moderate to severe hotspots under the carbon-intensive scenario.

The book uses granular information from the South Asia Spatial Database to examine the characteristics of the hotspots and of the households that are located in them. The analyses reveal that hotspots tend to be more disadvantaged districts, even before the effects of changes in average weather are felt. Hotspots are characterized by low household consumption, poor road connectivity, limited access to markets, and other development challenges.

This level of granularity provides new awareness of how effects will differ from country to country and from district to district throughout the region. Such granularity increases the ability of decision makers to focus resilience-building efforts on the most vulnerable locations and population groups. The hotspots analysis contained herein can serve as a development blueprint by providing region-specific insights on the effects of these changes and ways to adapt.

The analyses in the full book complement a body of well-documented work on emergency response and disaster preparedness, with a view to informing long-term development planning to build climate change resilience. The findings can help governments, aid agencies, and others involved in development efforts expand beyond policies to tackle natural disasters and vulnerability of coastal areas.

At the regional level, the book shows the certainty of adverse long-term effects in South Asia under all climate change scenarios. Smaller effects under the climate-sensitive scenario emphasize the need for nations to work together to reduce GHG emissions, as called for by the Paris Agreement of 2015. The link between climate effects and living standards, especially among the poorest populations, provides an economic argument for stronger mitigation efforts.

At the local level, the hotspot analyses provide guidance for decision makers in South Asia on where to focus investments that increase resilience to the effects of changes in average weather. Investing now in building resilience will equip populations in South Asia that are particularly vulnerable to climate change with the needed tools and resources to break the downward spiral of poverty and inequality, helping them become drivers of growth and sustainable development. For example, prioritizing investments in climate resilience based on needs identified by the book's hotspots modeling can get resources to where they will be most needed in coming decades. The research discusses how specific actions—such as moving people out of agriculture, increasing educational attainment, and providing access to electricity—could ease the decline in living standards caused by changes in average weather. The research also points out that the actions with the greatest potential to make a difference vary across countries and locations.

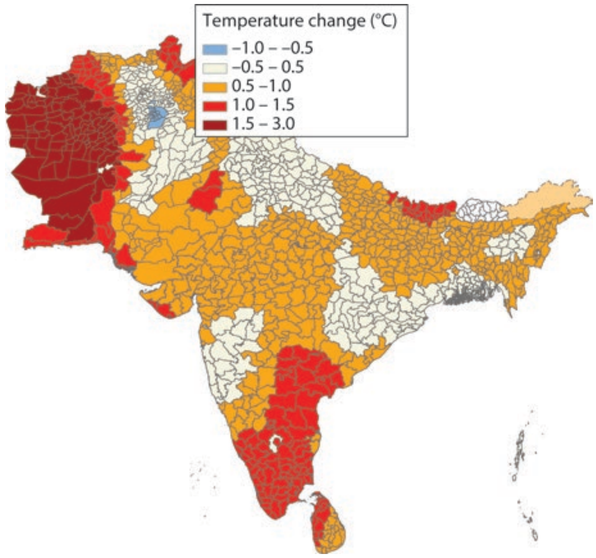
A Vulnerable Region

South Asia is recognized as being very vulnerable to climate change. The region's varied geography combines with regional circulation patterns to create a diverse climate. The glaciated northern parts—which include the Himalayas, Karakoram, and Hindu Kush mountains—have annual average temperatures at or below freezing, whereas much of the Indian subcontinent averages 25°C to 30°C (77°F to 86°F). Both the hot and cold extremes are challenging for human well-being, and climate change heightens these challenges.

Increasing average temperatures and changes in seasonal rainfall patterns are already having an effect on agriculture across South Asia. Low-lying Bangladesh and the Maldives are increasingly vulnerable to flooding and cyclones in the Indian Ocean. The scientific literature suggests that such events will grow in intensity over the coming decades. Dhaka, Karachi, Kolkata, and Mumbai—urban areas that are home to more than 50 million people—face a substantial risk of flood-related damage over the next century.

Average annual temperatures throughout many parts of South Asia have increased significantly in recent decades, but unevenly (map O.1). Western Afghanistan and southwestern Pakistan have experienced the largest increases, with annual average temperatures rising by 1.0°C to 3.0°C (1.8°F to 5.4°F) from 1950 to 2010. Southeastern India, western Sri Lanka, northern Pakistan, and eastern Nepal have all experienced increases of 1.0°C to 1.5°C (1.8°F to 2.7°F) over the same period. The precise magnitude of the estimated temperature changes varies across locations, but the direction of the changes is unambiguous.

MAP O.1 Temperatures Have Been Increasing in Much of South Asia



Sources: Mani et al. 2018; data from Harris et al. 2014.
Note: Changes are based on trend analysis between 1950 and 2010.

Climate Change and Living Standards

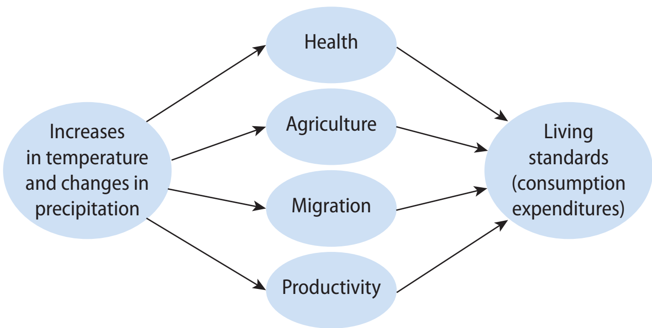
Climate change includes rising temperatures, changing precipitation patterns, and intensifying extreme events, such as storms and droughts. All these have profound repercussions for societies, from sudden economic disruptions to a longer-term decline in living standards. In this analysis, household consumption expenditures are used as a proxy for living standards.

Rising average temperatures can affect living standards through diverse pathways, such as agricultural and labor productivity, health, migration, and other factors that affect economic growth and poverty reduction (figure O.1). They can dampen agricultural productivity, leading to a decline in living standards for agriculture-dependent households. A warmer climate can also increase the propagation of vector-borne and other infectious diseases, resulting in lost productivity and income. At the same time, a warmer climate can increase productivity in historically colder regions, such as mountainous areas.

Days of extreme heat are generally correlated with lower worker productivity, especially in areas that are already warm. A changing climate can force people out of their traditional professional domains, resulting in individuals not earning as much income.

Previous research on climate change in South Asia and associated policy prescriptions has focused on disaster-resilient infrastructure and emergency responses, such as building

FIGURE O.1 Increases in Temperatures and Changes in Precipitation Patterns Are Linked to Living Standards through a Diverse Set of Pathways



Source: Mani et al. 2018.

cyclone shelters and coastal embankments. There has also been a focus on strengthening early warning systems in areas that are highly vulnerable to flooding, storm surges, and sea-level rise. The benefit from these investments is to reduce the economic shocks associated with extreme weather events.

However, little effort has been made to understand the diverse effects of changes in average weather. These effects could be substantial, given the implications of weather conditions for agricultural productivity, health, migration, and other factors. Addressing this knowledge gap is important. Increasing evidence shows that changing temperatures and seasonal precipitation patterns have already altered the growing seasons of regions in Bangladesh, India, and Pakistan, and have resulted in serious health and productivity damage (Burke, Hsiang, and Miguel 2015). Less understood are the economic implications of these long-term changes for households and communities.

The book adds to the accumulated knowledge on climate change in South Asia through a combination of spatially granular weather data and statistical household analyses. The weather data are derived from predictions from global climate models that are especially relevant for South Asia. The household surveys are designed to be representative of conditions at different levels of administrative aggregation, varying by country. For example, survey data for Pakistan are designed to represent provincial conditions, whereas survey data for India can show district conditions.

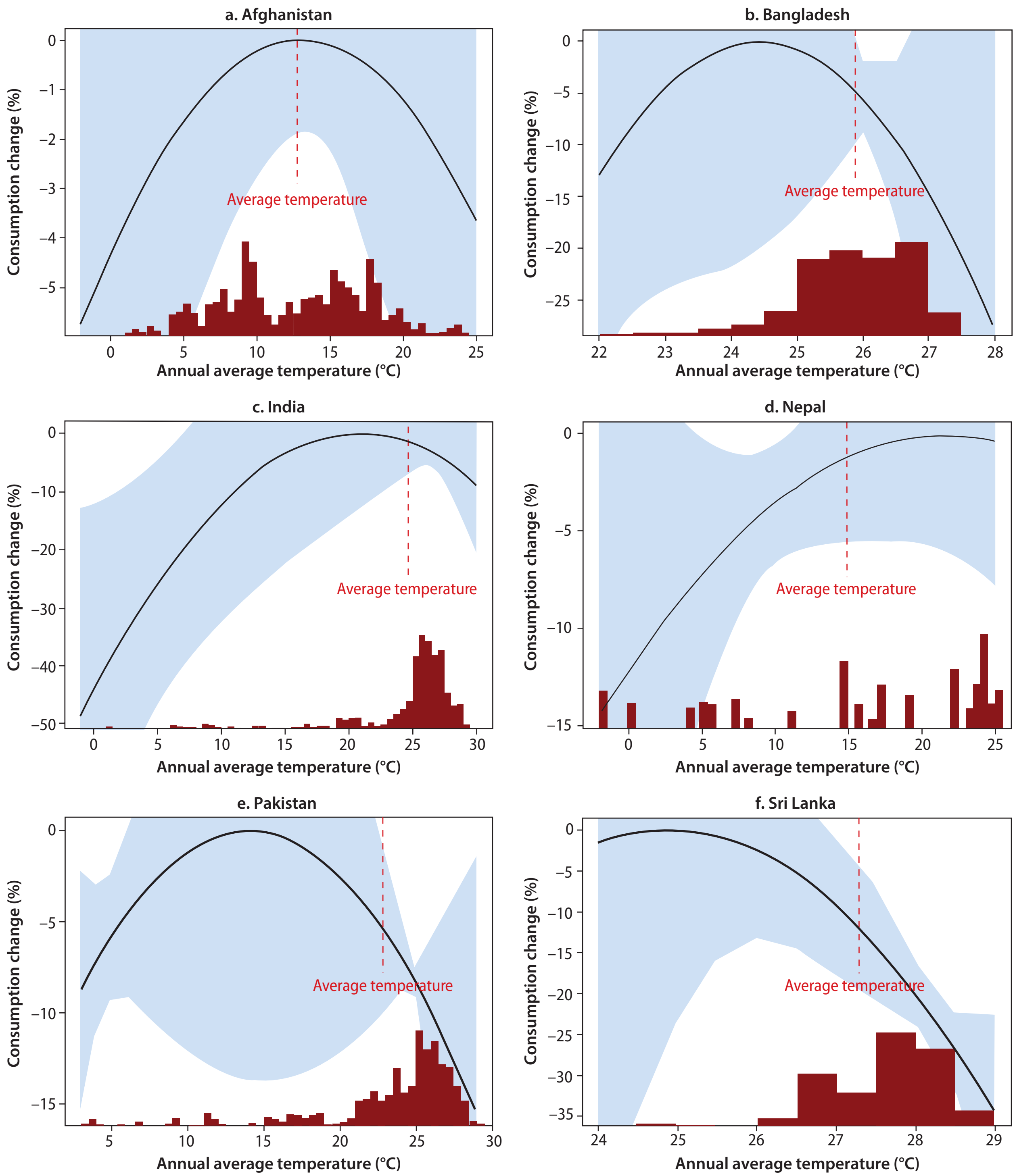
The book focuses on the impact of changes in average weather on living standards. Such changes in averages can be projected with greater confidence than changes in extreme events. Although extreme events cause major disruptions to consumption, they generally are of relatively short duration, and consumption bounces back after relief and rehabilitation efforts have been undertaken. In contrast, the effects of long-term changes in climate, such as average temperatures and precipitation patterns, are recurring and will require adaptation to overcome.

The book uses household consumption expenditures as a metric that expresses the monetary dimensions of living standards because it is objectively quantifiable. It is well understood that nonmonetary dimensions of well-being matter as well. However, the focus on per capita consumption expenditures makes the analyses in this book consistent with the literature on poverty and inequality.

There is a wide range of model formulations that could potentially be used to estimate the relationship between weather and living standards. Similar to previous studies, this research uses a reduced-form model. Reduced-form models do not make assumptions about the channels through which external factors such as weather affect living standards, and cannot provide a causal analysis. Instead, these models seek to capture the aggregate relationship between external factors and outcomes—which, in this case, are changes in average weather and living standards.

The book confirms that there is an optimal temperature range that is correlated with higher consumption expenditures relative to locations where temperatures are either hotter or colder (figure O.2). The overall relationship is similar between countries, but the optimal temperature differs. This indicates that there may be some ability for countries to adapt to long-term changes in temperature. Nationally, temperatures in Bangladesh, India, Pakistan, and Sri Lanka are already above their

FIGURE O.2 Temperature and Consumption Have an Inverted U–Shaped Relationship for Countries in South Asia



Source: Mani et al. 2018.
Note: Blue-shaded region indicates 90 percent confidence interval.

optimal values. This means that at the national level, any further increase in average temperature will have a negative effect on consumption expenditures. Temperatures in Nepal are still less than the inflection point, meaning that increases in temperatures are predicted to have positive effects on consumption. Nationally, Afghanistan is close to its optimal temperature; however, consumption expenditures are less sensitive to temperature in Afghanistan than in the other countries analyzed.

Climate Modeling and Effects

The primary driver of climate change is GHG emissions, with human-caused emissions as the major contributor. Projecting future climatic changes requires creating a scenario that projects the amount, timing, and type of future GHG emissions by human activities.

The international community has developed multiple scenarios to account for uncertainty about the path the world will take. Scenarios representing atmospheric emissions of GHGs and their associated atmospheric concentrations are referred to as RCPs. This book uses climate projections corresponding to RCPs 4.5 and 8.5. With RCPs, a higher number means greater overall emissions and atmospheric concentrations—and therefore the potential for more severe climate change.

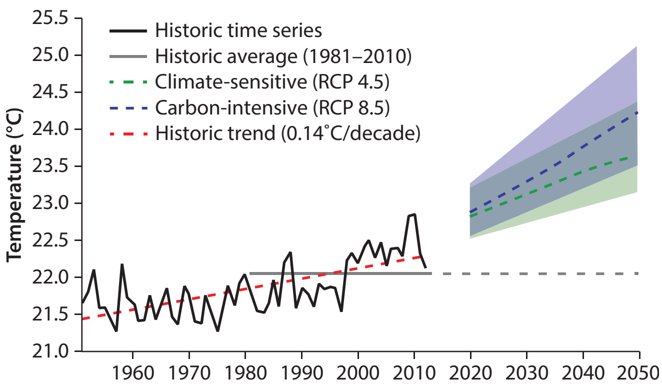
The 2015 Paris Agreement on climate change sets a target of limiting average global temperature increases to 2°C (3.6°F) relative to preindustrial conditions. RCP 4.5 represents a future in which some collective action is taken to limit GHG emissions, with global annual average temperatures increasing 2.4°C (4.3°F) by 2100. Therefore, the book labels RCP 4.5 as a "climate-sensitive" development scenario. RCP 8.5 is closer to a scenario in which no actions are taken to reduce emissions, and global annual average temperatures increase 4.3°C (7.5°F) by 2100. The book labels RCP 8.5 as a "carbon-intensive" development scenario.

Global climate models are the primary tool for projecting how a given RCP scenario will affect the Earth's climate. Climate models are designed to approximate fundamental laws of physics, modeling interactions between the atmosphere, land, and oceans. This research considers 18 global climate models covered by the Climate Model Intercomparison Project (CMIP5), and assesses their performance in reproducing historic weather patterns observed in South Asia. On the basis of this performance criterion, 11 models are selected that perform best. The research uses these 11 climate models to project long-term changes in average temperature and precipitation throughout South Asia.

The average prediction by these climate models is that annual average temperatures in South Asia will increase 1.6°C (2.9°F) by 2050 under the climate-sensitive scenario, and 2.2°C (3.9°F) under the carbon-intensive scenario. These increases are relative to 1981–2010 conditions (figure O.3).

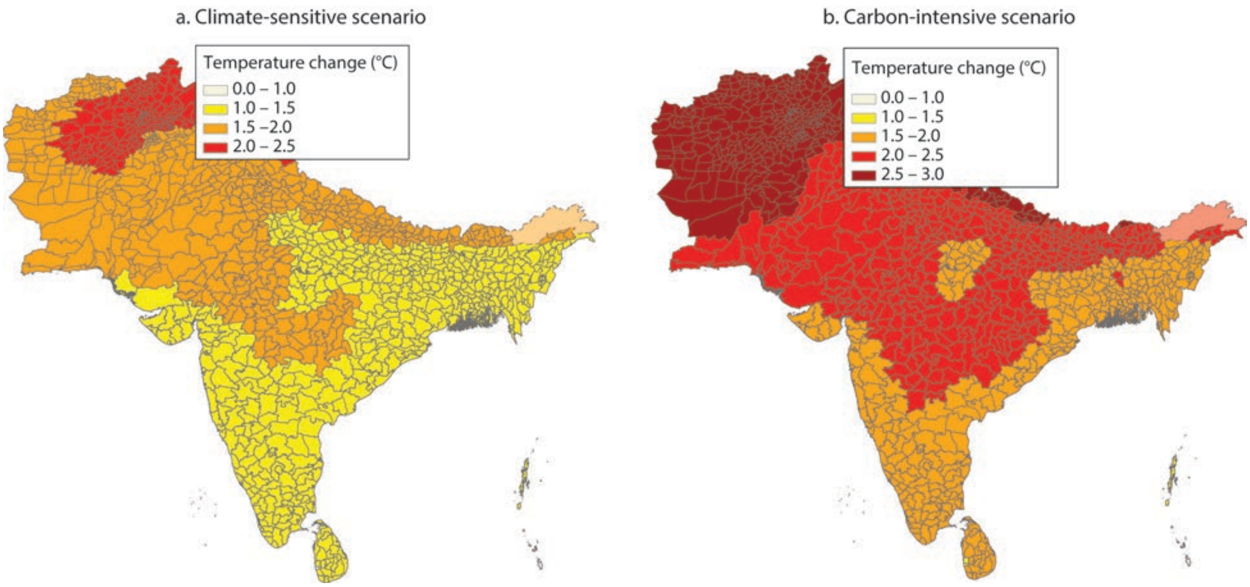
Projected changes in precipitation are highly uncertain, in part because they are heavily dependent on cloud microphysics, which are difficult to represent in current global climate models. The average climate model prediction is that average monsoon precipitation will increase 3.9 percent under the climate-sensitive scenario and 6.4 percent

FIGURE O.3 Annual Temperature Increases Are Projected to Accelerate



Sources: Mani et al. 2018; data from Harris et al. (2014) and 11 climate models.
Note: RCP = representative concentration pathway.

MAP O.2 Annual Average Temperatures Increase by 2050 Relative to 1981–2010



Source: Mani et al. 2018.
Note: Changes are for 2036 through 2065 relative to averages for 1981 through 2010.

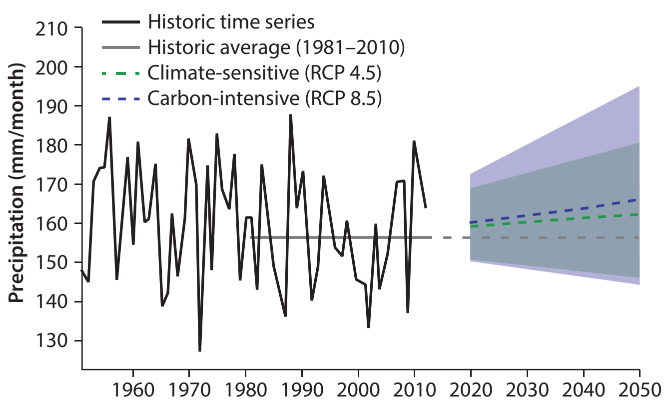
under the carbon-intensive scenario by 2050 (figure O.4).

If average precipitation increases, some areas that have historically experienced low rainfall could benefit. It is also likely that extreme precipitation events will become more common, especially because of the large simultaneous temperature increases. Extreme precipitation events would cause an increase in damage and economic disruption, whereas decreasing precipitation would result in less overall water availability in South Asia, which would reduce agricultural yields and water security in some areas (map O.2, panels a and b).

The book shows that failure to reduce GHG emissions and take measures to build climate change resilience will lead to diminished economic performance in most South Asian countries. At the same time, changes in average weather may have some benefits for Afghanistan, Nepal, and high-elevation areas of India because of their cold climates.

However, not all effects of increasing temperatures will be positive in Afghanistan, Nepal, and high-elevation areas of India. For example, people in the mountain regions rely extensively on streamflow from snow and glaciers. Warming will affect the timing and availability of water resources, which could have profound effects. In addition, mountain regions may be less resilient to natural disasters.

FIGURE O.4 Monsoon Precipitation Varies Considerably and Projections Are Uncertain



Sources: Mani et al. 2018; data from Harris et al. (2014) and 11 climate models.
Note: RCP = representative concentration pathway.

Changes in average weather are predicted to reduce living standards in Bangladesh, India, Pakistan, and Sri Lanka, relative to what they would have been with the same climate as today. By 2050, under the carbon-intensive scenario the declines are projected to be 6.7 percent for Bangladesh, 2.8 percent for India, 2.9 percent for Pakistan, and 7.0 percent for Sri Lanka.

For countries with severe hotspots—Bangladesh, India, and Sri Lanka—the negative impacts are predicted to be even greater. Translated into gross domestic product (GDP) per capita, changes in average weather are predicted to reduce income in severe hotspots by 14.4 percent in Bangladesh, 9.8 percent in India, and 10.0 percent in Sri Lanka by 2050 under the carbon-intensive scenario compared to the climate of today.

Climate effects are smaller under the climate-sensitive scenario. This finding highlights the importance of taking actions to reduce GHG emissions, and provides an additional economic justification for continuing to work toward meeting the targets established under the Paris Agreement.

Hotspots

South Asian megacities—such as Chennai, Dhaka, Karachi, Kolkata, and Mumbai—are often said to be climate hotspots because they are vulnerable to extreme events and sea-level rise, including coastal flooding and storm surges. In this book, however, hotspots are defined as areas where changes in average weather will adversely affect living standards.

Hotspots are the result of two interrelated factors: (a) the magnitude of predicted changes in average weather at the local level; and (b) the relationship between weather and living standards in that location. The magnitude of predicted changes in average weather is estimated using global climate models. The relationship between weather and living standards is estimated using country-specific household surveys and is therefore different across countries.

This diversity in the way that living standards react to changing weather conditions can be interpreted as implicitly capturing the effects of differences in institutional settings, economic structures, and policy frameworks across countries. The diversity may also reflect differing degrees of adaptive capability by households and communities to weather conditions.

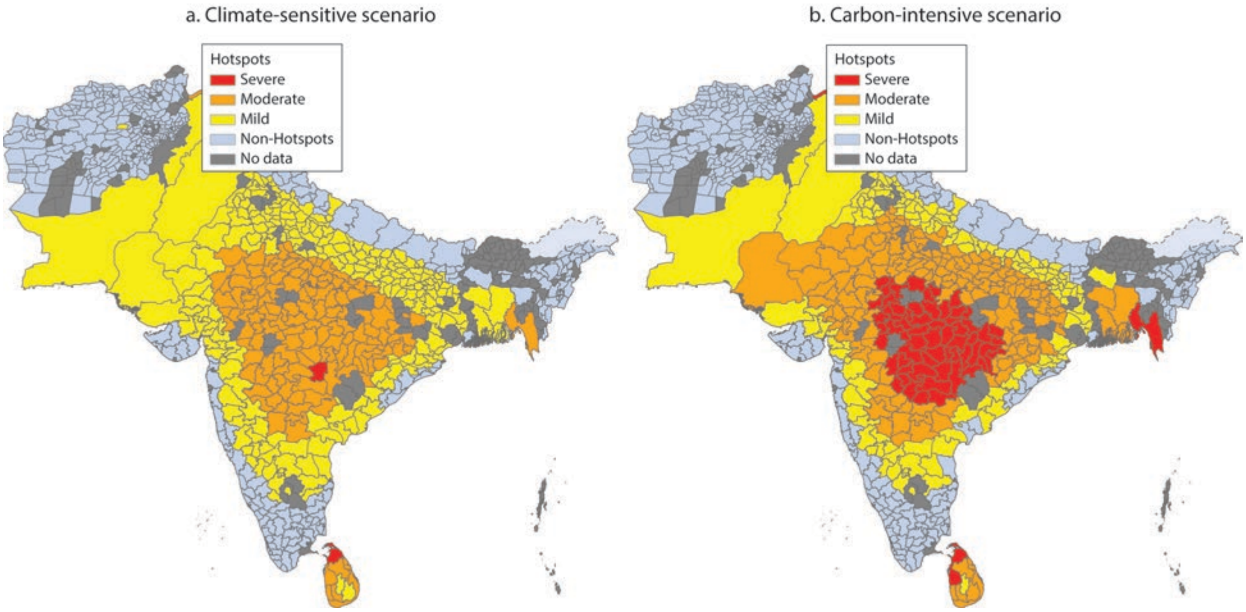
Hotspots are labeled *mild* when projected consumption spending declines by less than 4 percent, *moderate* for declines of 4 percent to 8 percent, and *severe* for declines exceeding 8 percent.

Hotspots are primarily predicted to occur in Bangladesh, India, Pakistan, and Sri Lanka. In these countries, projected changes in average weather are expected to result in an overall decrease in per capita consumption expenditures. The analyses do not include Bhutan and the Maldives because adequate climate projection data are not available.

In general, hotspots tend to be less densely populated and have poorer infrastructure, such as fewer roads, which hinder their integration with the broader society. Inland areas are predicted to be more affected by projected changes in average weather than coastal areas and mountainous regions (map O.3, panels a and b). However, there are also hotspots in some areas where precipitation is expected to increase, such as southeast Bangladesh, parts of the Kashmir Valley, and the southern tip of India.

Identifying hotspots is not as simple as finding the regions where changes in average weather are projected to be the largest. Even if climate were to change by similar magnitudes in two locations, the response would depend on the historic relationship between weather and living standards at the locations. For example, if two countries are identical except that one relies more heavily on agriculture, the magnitude of impact attributable to weather during the growing seasons can be expected to be larger in the agriculture-heavy country, all other factors held equal. The same principle applies to other pathways by which weather impacts living standards

MAP O.3 Severe Hotspots Will Cover a Significant Portion of South Asia by 2050



Source: Mani et al. 2018.

as well. For example, Ramanathapuram District in India and Jaffna District in Sri Lanka are separated by about 100 kilometers and have relatively similar weather. However, Ramanathapuram does not emerge as a hotspot in the analysis, whereas Jaffna emerges as a moderate to severe hotspot.

Under the carbon-intensive scenario, dozens of inland hotspots in the center of South Asia would shift from moderate in 2030 to severe by 2050. Coastal areas do not generally experience this additional deterioration in living standards. However, they could be negatively affected by other consequences of climate change, such as sea-level rise and a likely increase in storms and other extreme events.

Overall, more than half the region will be a hotspot by 2050 under the carbon-intensive scenario, with 45 percent of the present population of South Asia—800 million people—living in areas projected to become moderate or severe hotspots. Under the climate-sensitive scenario, the number of people affected would be 375 million, or 21 percent of the population. This finding demonstrates that mitigation efforts to minimize the effects of climate change, such as reducing GHG emissions, can positively affect living standards throughout the region.

Because climate impacts vary from region to region, the hotspots provide a blueprint for prioritizing investments and actions to build resilience. A look at where changes in average weather are predicted to impact living standards in individual countries reveals the diversity of findings from the analyses.

In Bangladesh, Chittagong Division is the most vulnerable to changes in average weather, followed by Barisal and Dhaka divisions. Chittagong is relatively more developed in terms of infrastructure compared with the national average, and is also characterized by fewer households engaged in agriculture. However, the area includes hill tracts, which are vulnerable to changes in average weather. Over the years, the Chittagong hill tracts have experienced outbreaks of vector-borne diseases and deforestation that have resulted in major landslides and the destruction of property.

In India, inland states in the central, northern, and northwestern regions emerge as the most vulnerable to changes in average weather. Chhattisgarh and Madhya Pradesh—which are predicted to have a living standards decline of more than 9 percent—are the top two hotspot states, followed by Rajasthan, Uttar Pradesh, and Maharashtra. Chhattisgarh and Madhya Pradesh are also low-income states, home to large tribal populations. Changes in average weather could therefore have important implications for poverty reduction.

In Sri Lanka, the Northern and North Western provinces emerge as the top two hotspots, followed by the much less densely populated North Central Province. The Northern Province is home to large numbers of poor and displaced people, so the effects of changes in average weather will add to these challenges. The North Western Province, in turn, is one of the driest regions of Sri Lanka.

The highly urbanized and densely populated Western Province, which includes Colombo, is also predicted to experience a living standards decline of 7.5 percent by 2050, compared with a situation without changes in average weather. This is a substantial drop, with potentially large implications for the country, given that the province contributes more than 40 percent of Sri Lanka's GDP.

In Pakistan, Sindh Province emerges as the most vulnerable hotspot, followed by Punjab. Sindh has the second-largest economy in the country. Its GDP per capita is 35 percent above the national average, and contributes around 30 percent of Pakistan's GDP. The province's highly diversified economy ranges from heavy industry and finance in and around Karachi to a substantial agricultural base along the Indus River. Punjab, which is the most densely populated province, has the largest economy in Pakistan. It contributes 53 percent of the country's GDP and is known for its relative prosperity.

Toward Greater Resilience

At the highest level, an agenda for building resilience includes sustaining economic growth and ensuring shared prosperity. Development is indeed the best adaptation strategy, since it is associated with improved infrastructure, market-oriented reforms, enhanced human capabilities, and a stronger institutional capacity to respond to the increasing threat of natural disasters. But the agenda must also include creating an incentive framework for private action, committing public resources to mitigation and adaptation, and prioritizing spending.

The full book identifies and highlights climate hotspots where communities and households are likely to be particularly vulnerable to changes in average weather. An important finding of the book is that focusing location-specific resilience-building efforts on the most vulnerable areas and population groups can reduce hotspots.

The public sector can help build resilience among these communities through actions that support adaptation, such as helping develop drought-resistant crops and providing weather forecasts and climate risk assessments. In addition, the public sector can establish a policy framework for adaptation that creates incentives for private action, including (a) regulatory and insurance instruments that convey the correct incentives for adaptation; (b) pricing and other policies that encourage the efficient use of energy, water, agriculture, and other natural resources; and (c) facilitating market access and providing fiscal incentives for research and development to exploit existing technologies or develop new ones in the energy, water-supply, agricultural, forestry, and livestock sectors.

No single set of interventions will work in all hotspots. For example, inland areas in India emerge as severe hotspots, whereas in Sri Lanka, the postconflict northern coastal areas are most vulnerable. The household characteristics of these areas also differ from one another, so interventions must be tailored to the specific context.

Understanding these diverse effects is critical to help countries design appropriate policies for building long-term resilience in communities and households.

The book investigates specific investment and policy options that countries could consider to attenuate or offset the the negative impacts of projected changes in average weather.

For Bangladesh, the analysis suggests that enhancing opportunities in the nonagricultural sector could potentially reduce the effect of changes in average weather on living standards. A 15 percent increase in nonagricultural employment would attenuate the effect of weather changes from –6.7 percent to –1.4 percent. Similarly, a 30 percent increase in the share of nonagricultural employment would not only reduce the negative effect of changes in average weather but would also result in increased living standards.

In India, the analyses discuss three options: increasing educational attainment, reducing water stress, and expanding the nonagricultural sector. The analyses predict that increasing the average educational attainment by 1.5 years would reduce the magnitude of decline in living standards from –2.8 percent to –2.4 percent. Reducing water stress by 30 percent, and increasing employment in nonagricultural sectors by the same percentage, would yield similar benefits.

In Pakistan, the analyses reveal that expanding electricity access by 30 percent above current levels would reduce the living standards burden from –2.9 percent to –2.5 percent.

In Sri Lanka, increasing the share of the nonagricultural sector by 30 percent relative to current levels would change the sign of the living standards impact from –7.0 percent to 0.1 percent. Reducing travel time to markets and increasing average educational attainment would also ease negative impacts on living standards. If implemented together, such interventions would likely yield significantly positive climate cobenefits.

In the future, economic growth and structural changes will cause people to migrate to cities, leaving behind their agricultural and other climate-sensitive practices in rural areas. Although this could potentially make more of the population climate-resilient, urban migration also will create new climate impacts. Urban populations will face a number of health risks exacerbated by events such as heat waves and flooding.

Another challenge is to ensure that resilience strategies and actions are inclusive, to avoid inequality in growth and opportunity. The projected emergence of many moderate and severe hotspots under the carbon-intensive scenario shows the need for resilience policies to target impoverished populations and highly vulnerable regions.

It is worth noting that, although fraught with risks, changes in average weather present opportunities for households, communities, and nations. Decisions about adaptation strategies, developing skills, and engaging with the communities will determine the quality of life of the next generation and beyond.

References

Harris, I. P. D. J., P. D. Jones, T. J. Osborn, and D. H. Lister. 2014. “Updated High-Resolution Grids of Monthly Climatic Observations: The CRU TS3.10 Dataset.” *International Journal of Climatology* 34 (3): 623–42.

IPCC (Intergovernmental Panel on Climate Change). 2013. *Climate Change 2013: The Physical Science Basis—Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press.

Mani, M., S. Bandyopadhyay, S. Chonabayashi, A. Markandya, and T. Mosier. 2018. *South Asia’s Hotspots: Impact of Temperature and Precipitation Changes on Living Standards*. South Asia Development Matters. Washington, DC: World Bank.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl. 2012. “An Overview of CMIP5 and the Experiment Design.” *Bulletin of the American Meteorological Society* 93 (4): 485–98.

A Vulnerable Region

1

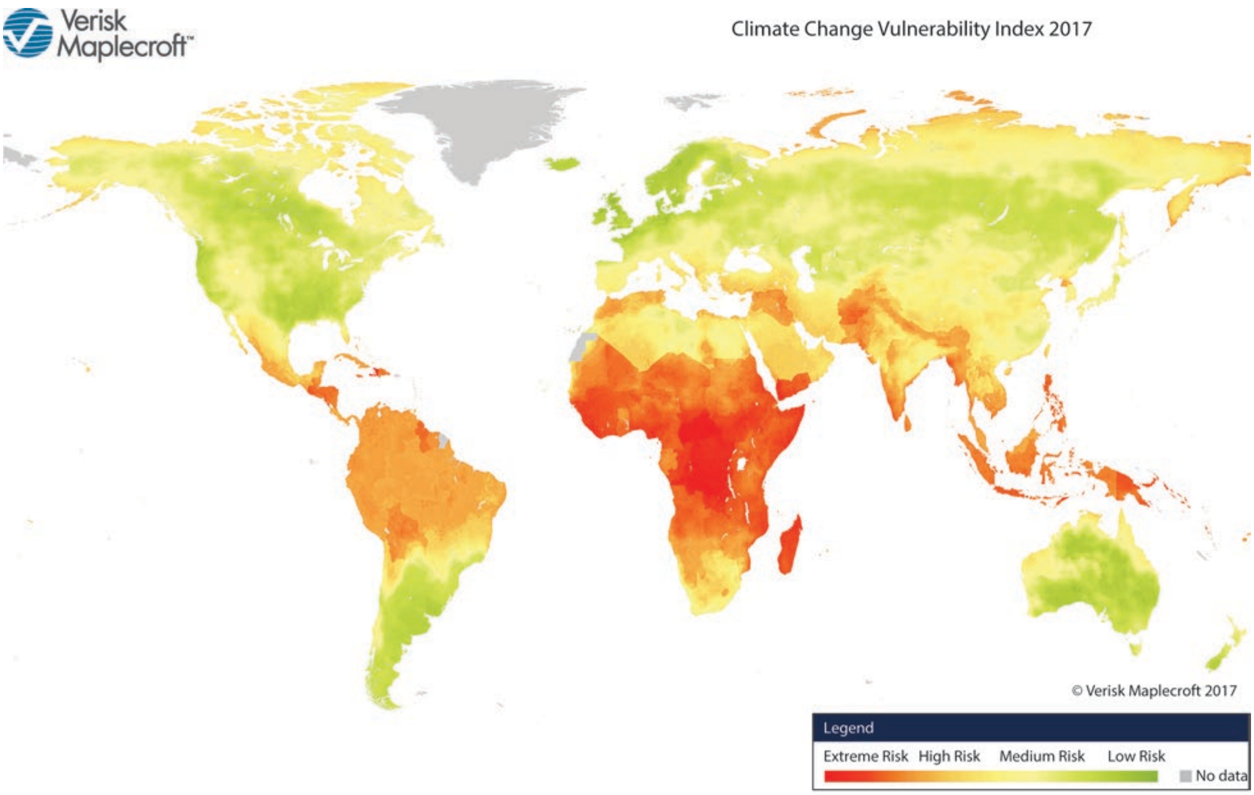
Climate change is already a pressing issue for South Asia. Temperatures have been rising across the region, and are projected to continue increasing for the next several decades under all plausible climate scenarios (IPCC 2014). Precipitation response to global emissions is more difficult to estimate. There is evidence, though, that historic precipitation patterns are changing, and that these changes will become stronger and less predictable.

South Asia is recognized as being highly vulnerable to climate variability and change (map 1.1). Increasing average temperatures and changing seasonal rainfall patterns are already affecting agriculture across the region. Low-lying Bangladesh and the Maldives are on the global front line of countries at risk for sea-level rise—a result of glacier melt induced by climate change—and increasing vulnerability to flooding and cyclones in the Indian Ocean. Major cities such as Dhaka, Karachi, Kolkata, and Mumbai—which are home to more than 50 million people and growing—face the greatest risk of flood-related damage over the next century. In addition, extreme temperature events such as the 2015 heat wave that killed more than 3,500 people also threaten the region. There are many such areas and regions in South Asia that are extremely vulnerable to climate change impacts.

The symptoms of climate change are multifaceted, including sea-level rise, shifts in average temperature and precipitation patterns, and increasing frequency of extreme events such as storms and droughts. These climatic changes have profound effects on societies, such as greater frequency of flooding events, more year-to-year variability in agriculture productivity, a greater demand for water (which may be more difficult to meet), and increased instances of heat-related medical problems. Furthermore, these and other climate change impacts will cause economic disruption in South Asia, with the effects continuing to grow over time (figure 1.1). These have been well articulated in various IPCC reports and country studies.

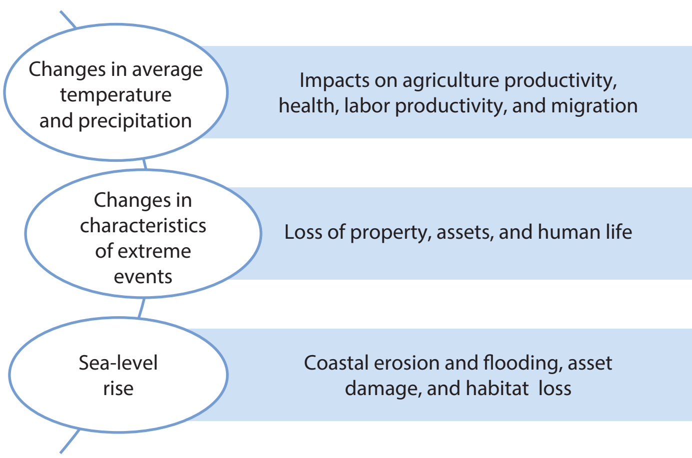
The effect of extreme events and sea-level rise is clear and well documented in the region (Bronkhorst 2012; Dasgupta and others 2015; Hallegatte and others 2017; Sanghi and others 2010). Quantification of hazard, exposure and vulnerability (which together define "climate change risk") is now a robust science; the economic consequences are extensively studied, but many uncertainties remain. Hallegatte and others (2017) move beyond asset and production losses to focus on how natural disasters affect people's well-being. By examining well-being instead of asset losses, their book provides a deeper view of natural

MAP 1.1 South Asia Remains a Region Very Vulnerable to Climate Change and Extreme Events



Source: Maplecroft Climate Vulnerability Index 2017.
Note: This index evaluates 42 social, economic, and environmental factors to assess national vulnerabilities across three core areas. These include exposure to climate-related natural disasters and sea-level rise; human sensitivity in terms of population patterns, development, natural resources, agricultural dependency, and conflicts; and assessing future vulnerability by considering the adaptive capacity of a country's government and infrastructure to combat climate change.

FIGURE 1.1 Some Manifestations of Climate Change



disasters that takes better account of people's vulnerability. With this lens, they find that poor people are significantly more impacted by natural disasters than nonpoor people.

Much of the focus related to climate change in the region has been on emergency response, including the building of cyclone shelters and coastal embankments as well as strengthening early warning systems in areas highly vulnerable to flooding, storm surges, and sea-level rise. This is an important course of action because the effects of extreme events are significant from an economic perspective. These investments help increase immediate political capital and have medium- to long-term benefits associated with reducing the adverse economic impact of future extreme events.

This book looks at the impact of long-term changes in average temperature and precipitation. "Long-term" changes in the average specifically refers to changes in the mean of 30 consecutive years of weather for a given parameter. The 30-year mean can be calculated for a specific season or to represent annual conditions. Throughout the book, "average weather" is used to refer to long-term changes in average seasonal temperature and precipitation.

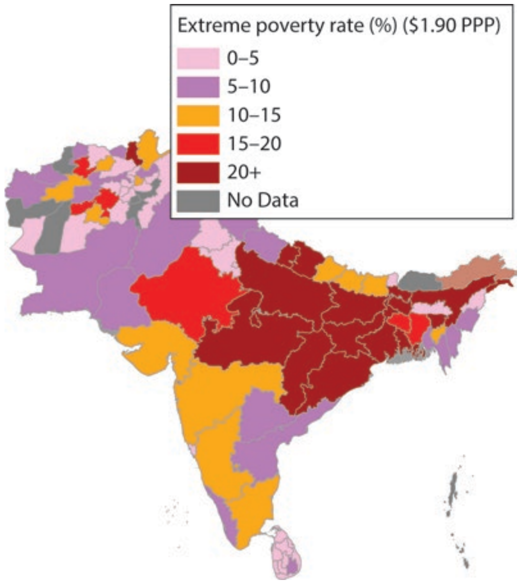
There has been little effort to understand the spatial heterogeneity of changes in average weather—specifically, increases in temperature and changes in precipitation patterns—and their implications for agricultural productivity, health, and migration. This is an important knowledge gap since increasing evidence suggests that these gradual changes are already disrupting the growing season for areas in Bangladesh, India, and Pakistan, and are causing serious health damage and productivity losses (Burke, Hsiang, and Miguel 2015). The economic implications of these changes in average weather for households and communities–and their possible thresholds or inflection points–are even less understood. This book aims to estimate these effects, focusing on changes in average weather and its impacts on household living standards across the region.

Progress So Far

The South Asia region has recently witnessed favorable economic growth and is gearing up to capitalize on opportunities provided by urbanization, economic diversification, and a young population. At the same time, the region is also home to one-third of the world's poor (map 1.2).

Countries in the region now better understand that adapting to climate change and building resilience are essential courses of action to sustain the benefits of their growing economies. They recognize climate change as a national priority and have been formulating strategies and action plans at the national and subnational levels (table 1.1). Furthermore, all countries in South Asia have pledged to contribute to global emissions reductions under the Paris Agreement through their submitted intended national contributions.[1]

MAP 1.2 South Asia Continues to Be Home to a Large Number of Poor People



Source: Household survey data (see table 3.1).
Note: PPP = purchasing power parity.

Going forward, adapting to long-term climatic shifts such as increasing temperatures and changing seasonal precipitation patterns will involve a portfolio of actions—from improving infrastructure to introducing market reforms and building household and institutional capacity. Given that such actions will incur a cost, there will inevitably be trade-offs; therefore, governments must prioritize efforts. In addition to internal resources, both international public and private funds and resources will be needed to build resilience. Decisions must be made in some cases with incomplete information, and all countries will face the dilemma of either not taking early action—with the risk of incurring very high future costs—or acting early on—when the pressure on public and private resources is intense—and eventually realizing the actions were redundant.

TABLE 1.1 Climate Change Strategies and Action Plans of Countries in South Asia

Country	National Strategy, Policy, or Action Plan	Year
Afghanistan	Intended Nationally Determined Contribution	2015
Bangladesh	Bangladesh Climate Change Strategy and Action Plan	2009
	Intended Nationally Determined Contribution	2015
Bhutan	National Adaptation Plan	2015
	Intended Nationally Determined Contribution	2015
India	National Action Plan on Climate Change	2009
	Intended Nationally Determined Contribution	2015
Maldives, The	Strategic National Action Plan for Disaster Risk Reduction and Climate Change Adaptation	2010
	Intended Nationally Determined Contribution	2015
Nepal	National Framework on Local Adaptation Plans for Action	2011
	Intended Nationally Determined Contribution	2015
Pakistan	National Climate Change Policy	2012
	Intended Nationally Determined Contribution	2015
Sri Lanka	National Adaptation Plan for Climate Change Impacts in Sri Lanka	2015
	Intended Nationally Determined Contribution	2015

The best approach is for countries to gather the existing information about the most likely causes of the problem and assess the pros and cons—costs and benefits—of alternative actions. There is, therefore, a pressing need to provide decision makers with the economic rationale for investing in resilience to changes in average weather as part of their adaptation strategies. In addition, governments require information on the types of interventions that will build resilience and the locations where the investments are most needed.

A Road Map for Climate-Resilient Development

This book identifies climate hotspots, defined as locations that will be adversely affected by changes in average weather. The book does not focus on short-term manifestations of climate change, such as extreme events, or slow onset events, such as glacier melt or sea-level rise. However, the analysis does capture some long-term effects of changes in extreme temperature and precipitation (box 1.1). Overall, the analysis builds on the existing well-documented work on emergency response and disaster preparedness with a view to inform long-term development planning, public sector programs, and public and private sector projects.

The book uses granular spatial information from the World Bank's South Asia Spatial Database and national household surveys to understand the characteristics of hotspots at the household and district levels. The information will be useful from a national perspective (for example, when designing a social welfare program) as well as a local one (for example, determining which investments would be most needed in each community, accounting for local socioeconomic characteristics and climate-related risks). Detailed analyses are carried out for Afghanistan, Bangladesh, India, Nepal, Pakistan, and Sri Lanka—the South Asian countries for which the necessary household survey and climate data are available.

The objective is to investigate the spatial patterns of historic and projected changes in average weather across South Asia and their effects on living standards. To this end, the book attempts to answer three specific questions related to changes in average weather:

- What changes in average temperature and precipitation will occur in different locations across South Asia?
- How will these changes affect living standards?

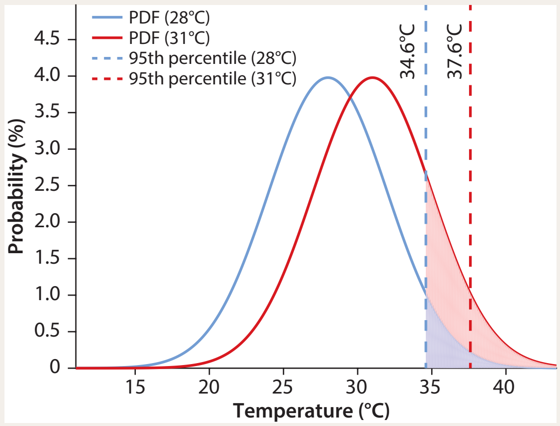
BOX 1.1 Why Do Changes in the Average Weather Matter?

The term *climate change* refers to changes in the frequency or magnitude of weather. Climate change therefore encapsulates a wide variety of phenomena, including changes in average temperature and precipitation and changes in the frequency or severity of extreme events (such as tropical storms or heat waves). Often, much of the attention related to climate change is on extreme events and sea-level rise, which are more immediately visible through the profound effects these events have on communities. From a long-term perspective, both changes in the average weather and extreme events matter.

In many cases, changes in extreme events can be explained through changes in average weather. As a practical example, over the past 30 years there has been an increasing number of heat-related deaths in South Asia and around the world. The increase has been driven by more frequent, longer, and more intense heatwaves during the summer. While heatwaves are an extreme event, their changes are explained well through analyzing shifts in the average distribution of temperature (McKinnon and others 2016). Similarly, the analyses in this book, which focus on shifts in average weather, are able to capture some changes in extreme events.

The concept that changing averages can capture changes in extreme weather is demonstrated visually in figure B1.1.1. In this figure, it is supposed that the average temperature of a location is 28°C (represented by the blue solid line) and that climate change shifts the mean temperature +3°C (represented by the red solid line). Assuming the shape of the underlying probability distribution remains constant, this shift would increase the likelihood that temperature exceeds 34.6°C (the assumed 95th percentile of the 28°C distribution) by 13 percent. This increased likelihood is represented by the red-shaded area.

FIGURE B1.1.1 Increased Average Temperature Causes Increased Likelihood of Extreme Heat Events



Source: World Bank calculations.
Note: The blue-shaded region represents the probability that the 95th percentile will be exceeded for the normal distribution having a mean of 28°C, and the red-shaded region represents the additional probability of exceedance for this magnitude event when the normal distribution is shifted such that the mean is 31°C. The standard deviation used to produce these probability distribution functions is 4°C. PDF = probability distribution function.

Any rise in the average temperature could thus potentially lead to a rise in the number of days that are extremely hot. This increase in heat has repercussions for a myriad of sectors, including health, farming, and energy systems. More extreme heat raises the risk of heat-related illnesses, such as heat exhaustion, and allows insects to move into new areas, potentially increasing the spread of vector-borne diseases. It could also stress crops accustomed to a milder climate and worsen drought conditions. In addition, extreme heat is associated with air stagnation, which could trap pollutants and worsen respiratory illnesses such as asthma. Similarly, shifting the average of the precipitation distribution would mean a greater likelihood of no precipitation or extreme precipitation, corresponding to an increasing likelihood of droughts or flooding, respectively.

- What are the characteristics of the places and people most affected by these changes?

Understanding answers to these important questions will help countries and communities build resilience to changes in average weather in the region through the following:

- Designing interventions across locations that address the challenges posed by higher temperatures and uncertain long-term precipitation patterns
- Helping local communities design social protection programs that can build climate resilience given the current spatial distribution of poverty through a location-specific focus
- Highlighting the costs, trade-offs, and opportunities for countries to build climate resilience while realizing their growth potentials

The rest of this book is structured as follows: chapter 2 provides an overview of historic climate trends in the region, as well as future projections, using extensive and sophisticated climate modeling; chapter 3 provides an analytical framework linking changes in average weather and living standards by estimating their effects on household consumption; chapter 4 identifies future climate-induced hotspots at the national and local levels; and chapter 5 provides policy recommendations.

Note

1. At the Paris climate conference (Conference of Parties [COP21]) in December of 2015, 195 countries reached the world's most significant agreement to address climate change since the issue first emerged as a major political priority decades ago. Countries committed to keep global temperatures from rising more than 2°C by 2100, with an ideal target of keeping temperature rise less than 1.5°C.

References

Bronkhorst, V. B. 2012. "Disaster Risk Management in South Asia: A Regional Overview." Working Paper 76302, World Bank, Washington, DC.

Dasgupta, S., A. Zaman, S. Roy, M. Huq, S. Jahan, and A. Nishat. 2015. *Urban Flooding of Greater Dhaka in a Changing Climate: Building Local Resilience to Disaster Risk*. Directions in Development. Washington, DC: World Bank.

Hallegatte, S., A. Vogt-Schilb, M. Bangalore, and J. Rozenberg. 2017. *Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters*. Washington, DC: World Bank.

IPCC (Intergovernmental Panel on Climate Change). 2014. "Climate Change 2014: Synthesis Report; Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change." IPCC, Geneva.

Maplecroft Climate Vulnerability Index 2017. http://www.maplecroft.com/about/news/ccvi.html.

McKinnon, K. A., A. Rhines, M. P. Tingley, and P. Huybers. 2016. "The Changing Shape of Northern Hemisphere Summer Temperature Distributions." *Journal of Geophysical Research: Atmospheres* 121 (15): 8849–68.

Sanghi, A., S. Ramachandran, A. de la Fuente, M. Tonizzo, S. Sahin, and B. Adam. 2010. *Natural Hazards, Unnatural Disasters : The Economics of Effective Prevention*. Washington, DC: World Bank.

Increasingly Hot 2

Temperatures have been rising in most parts of the globe, and South Asia is no exception (IPCC 2013). These temperature increases are going to continue, with some variation based on location and the level of global collective action taken to limit greenhouse gas (GHG) emissions. As outlined in chapter 1, these changes will have varied consequences. Preparing for climate change impacts is critical and requires understanding projections of changes over the horizons useful to planners. For this purpose, this chapter outlines the diverse historic climatic conditions across South Asia and develops estimates of future changes based on an ensemble of the most suitable climate models.

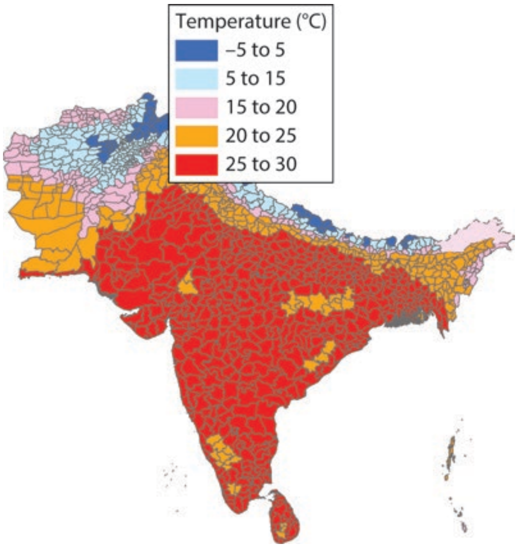
Highly Diverse Climate

The geography of South Asia is extremely varied. This, combined with regional circulation patterns, leads to a highly diverse climate across the region. The glaciated northern parts—punctuated by the Himalayas, Karakoram, and Hindu Kush mountains—have annual average temperatures at or below freezing (map 2.1). These areas, which contain small villages, are much less densely populated because of the harsh conditions. In contrast, much of the Indian subcontinent has average temperatures of 25°C to 30°C, resulting in a climate that is already uncomfortably hot much of the year. Both the hot and cold extremes are challenging for human well-being.

Precipitation patterns are similarly diverse, with portions of the region receiving as little as 100 mm of average annual precipitation and others receiving nearly 5,000 mm (map 2.2). The South Asian monsoon typically occurs during the months of June through September and is the most important climatic feature in terms of effect on the region's people. During the premonsoon season, temperatures are typically the highest of any point during the year. The onset of monsoon rains quickly reduces temperatures to more comfortable levels and brings much of the year's water, which facilitates agriculture. These water resources are close to fully used in many parts of South Asia, resulting in strong agricultural productivity (though not at its full potential), but with high vulnerability to changes in water supply or demand.

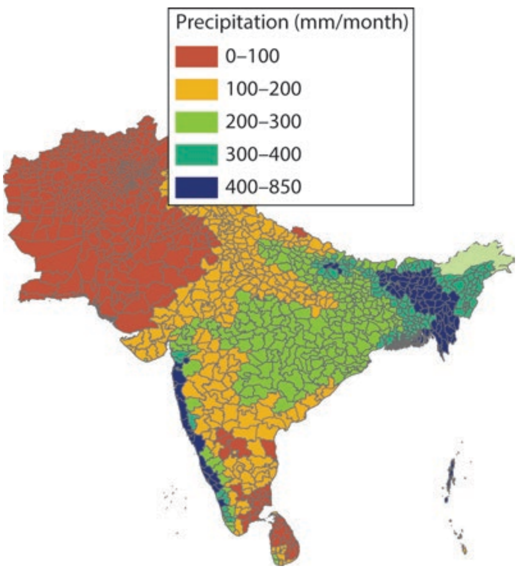
Too much water delivered too suddenly can cause significant damage. For example, swaths of South Asia have experienced several catastrophic tropical storms and flooding. Bangladesh is highly susceptible to flooding because much of the country is close to sea level and because the Ganges River and the Brahmaputra River—two of South Asia's three great rivers—drain through the country.

MAP 2.1 Temperatures Vary Significantly across South Asia



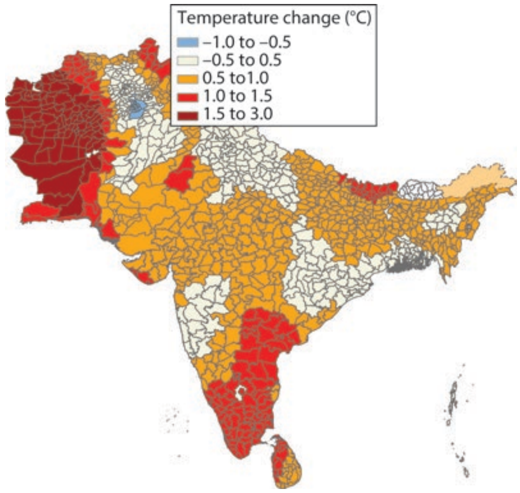
Source: Harris and others 2014 (Climate Research Unit TS 2.24).
Note: Annual average for 1981 through 2010.

MAP 2.2 Average Monsoon Precipitation in South Asia Generally Increases from West to East



Source: Harris and others 2014 (Climate Research Unit TS 2.24).
Note: Average monsoon precipitation for 1981 through 2010.

MAP 2.3 Temperatures Have Been Increasing in Most of South Asia



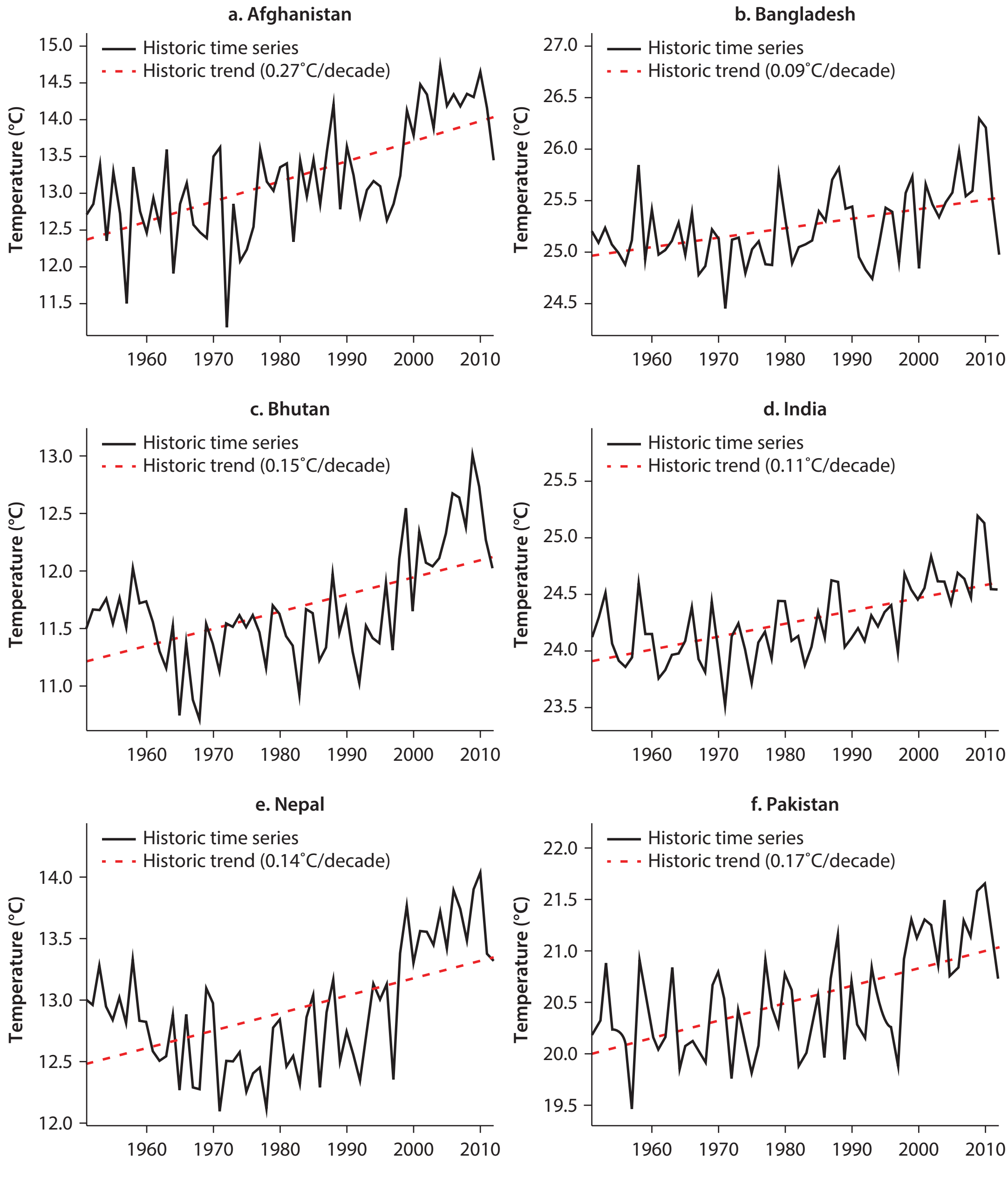
Source: Harris and others 2014 (Climate Research Unit TS 2.24).
Note: Linear trend in average annual temperature from 1951 through 2010. Areas showing 0°C change include locations where trends are not statistically significant.

Unambiguous Historic Temperature Increases

Average annual temperatures throughout many parts of South Asia have increased significantly, but unevenly, in recent decades. Western Afghanistan and southwestern Pakistan have experienced the largest increases, with annual average temperatures rising by 1.0°C to 3.0°C from 1950 to 2010 (map 2.3). Southeastern India, western Sri Lanka, northern Pakistan, and eastern Nepal have all also experienced increases of 1.0°C to 1.5°C over the same time frame. Although the precise magnitude of these estimated historic temperature changes varies depending on the time frame and the observational data set, the fact that temperature changes have been occurring is unambiguous (figure 2.1, panels a through g).

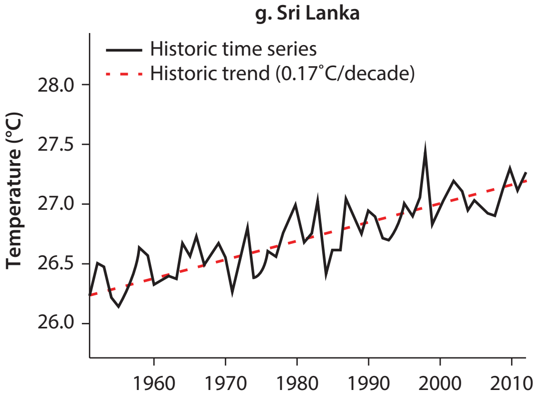
Changes in average precipitation are much harder to detect because of large year-to-year and interdecadal variability. From 1950 through 2010, statistically significant trends of increasing monsoon precipitation are found for parts of eastern Afghanistan and central Pakistan, and decreasing monsoon precipitation for Uttaranchal and Uttar Pradesh in India, but no statistically significant trends for other regions (map 2.4). Consequently, there are contradictory scientific findings regarding if and how precipitation is changing based on analysis of station records. For example,

FIGURE 2.1 Unambiguous Temperature Trends in South Asia



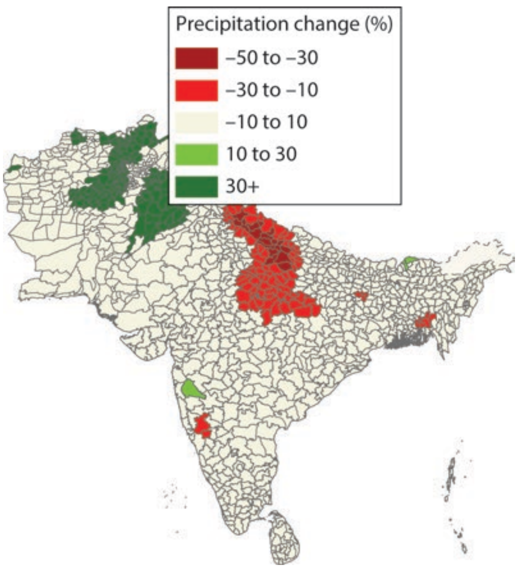
(continues next page)

FIGURE 2.1 Unambiguous Temperature Trends in South Asia (continued)



Source: Calculations based on CRU TS 3.22 (Harris and others 2014).

MAP 2.4 No Overall Monsoon Precipitation Trends for Most of South Asia



Source: Harris and others 2014 (Climate Research Unit TS 2.24).
Note: The change in monsoon precipitation is based on a linear trend in the average monsoon precipitation from 1951 through 2010. Areas showing zero percent change include locations where trends are not statistically significant.

on the basis of daily station records, Abbas and others (2014) do not identify any statistically significant precipitation time trends in Pakistan, whereas Basistha, Arya, and Goel (2009) find an increasing trend in monsoon precipitation for the Indian Himalayas from 1902 through 1964 and a decreasing trend from 1965 through 1980. Other studies that are based on station records have found increasing monsoon precipitation trends in some parts of India and decreasing trends in others (Kumar and others 1992; Pal and Al-Tabbaa 2009; Roy and Balling 2004). The primary reasons for differences between these aforementioned results and those presented in this book are the data sets, time frames, and statistical tests used in the analyses.

There is more robust evidence for changes in monsoon wet and dry spells and overall weakening caused by human activities. For most regions in South Asia, the monsoon patterns have remained constant (similar to the findings in map 2.4). However, the core region (western and central India) has experienced increases in both intensity of extreme wet periods and the frequency of dry periods (Singh and others 2014). The precise set of reasons for these changes is not known. It has been shown, though, that one contributing factor is an increase in the concentration of human-produced aerosols in the region. These aerosols have caused an overall drying (or weakening) of the monsoon in recent decades (Bollasina, Ming, and Ramaswamy 2011; Singh 2016).

Projecting Future Climate

Climate change refers to long-term deviations in the strength or frequency of weather events relative to a historic baseline. There are many important aspects of the climate that may change, including for example:

- 30-year average annual or seasonal temperatures at a given location
- Number or average strength of tropical storms
- Timing of the onset of the monsoon rains
- Frequency of droughts

Each of the aforementioned types of climatic changes has been observed in recent decades.

The primary driver of current climate changes is GHG emissions. The addition of human-emitted GHGs into the atmosphere has several effects, including raising temperature through the greenhouse effect. The greenhouse effect is well understood and agreed on by the scientific community. The basic principle of the greenhouse effect is that more GHGs in the atmosphere lead to more heat being trapped by the climate system. This trapped heat transfers to many parts of the Earth system, resulting in warmer air temperatures, warmer oceans, and melting glaciers and ice sheets. This means that the response of long-term average air temperatures to release of GHGs is also well understood and agreed on. Although there are many sources of GHGs, it is also well documented and agreed on that emissions from human sources are the primary contributor driving recent observed changes in climate (IPCC 2013).

Projecting future climatic changes requires creating a scenario that represents future conditions, including the amount, timing, and type of emissions by human activities. Multiple scenarios are developed to account for uncertainty about the path that the world will take. The socioeconomic dimensions of each scenario are referred to as shared socioeconomic pathways (SSPs) (O'Neill and others 2014), and the scenarios representing atmospheric emissions of greenhouse gases (GHGs) are referred to as representative concentration pathways (RCPs) (Taylor, Stouffer, and Meehl 2012).

Climate models are the primary tools for projecting how a given RCP scenario will affect the Earth's climate. Climate models are designed to approximate fundamental laws of physics (for example, conservation of energy, mass, and momentum) and interactions among the atmosphere, land, cryosphere, and oceans. The goal is to capture all the relevant processes governing the Earth's climate. In practice, these models have certain deficiencies, such as not correctly accounting for cloud processes (Rosenfeld and others 2014). The relative strengths and weaknesses of climate models mean that they can more accurately project change in long-term temperature, but they are much less able to project extreme events and long-term changes in precipitation. These relative degrees of uncertainty are borne out in the analysis throughout this book.

Of the several existing RCPs, this book uses climate projections corresponding to RCPs 4.5 and 8.5. Conceptually, a higher number associated with an RCP corresponds to a scenario with greater overall emissions and potential for more severe climate change.

The landmark global Paris Agreement, in which countries came together to agree to limit GHG emissions, set a target of holding temperature increases at 2°C relative to preindustrial conditions. The climate change scenario corresponding to the Paris Agreement would be even less than RCP 4.5, which represents a future in which some collective action is taken to limit GHG emissions and global annual average temperatures increase by 2.4°C (range of 1.7°C to 3.2°C) by 2100 relative to preindustrial levels. RCP 8.5 is closer to a scenario in which no actions are taken to reduce emissions and global annual average temperatures increase by 4.3°C (range of 3.2°C to 5.4°C) by 2100 relative to preindustrial levels. Because RCP 4.5 depends on taking collective action, this book refers to it as the climate-sensitive scenario; because RCP 8.5 corresponds to emitting significant carbon dioxide (and other GHGs), this book refers to it as the carbon-intensive scenario.

The range of projected global temperature increases and precipitation changes cited in the previous paragraph stems from differences between the approximately 45 climate models used in the IPCC's Fifth Assessment Report (IPCC 2013). In this book, climate projections for South Asia are based on the

11 climate models which have publicly available data and perform best for South Asia, as described in the following section.

Selecting Appropriate Climate Models

It is well accepted that projecting future changes to climate should be conducted using multiple climate models. The reason is that although all models have imperfections, they do not always have the same imperfections, and random errors will tend to cancel. Although a multimodel approach is preferred, adding poorly performing models degrades the quality of the information. Therefore, model selection is important to developing climate projection scenarios and assessing uncertainty.

Of the approximately 45 climate models participating in the Climate Model Intercomparison Program (CMIP5), 18 were evaluated for this book because they had publicly available monthly output for the required historic and projection simulations (see the list of models assessed and selected in table B.1). The climate models were examined for their ability to replicate the observed characteristics of the regional climate (see the more detailed explanation of model assessment in appendix D). The two metrics used to assess model performance are spatial pattern correlation and regionally aggregated root mean squared error (RMSE).

A high spatial pattern correlation is desirable because it suggests that models capture the right climate processes responsible for that pattern (that is, spatial pattern of mean climate, variability, or trend). A low RMSE is desirable because it suggests that model response to the relevant climate processes is more accurate. The aforementioned metrics were calculated for each model's ability to reproduce the long-term mean, standard deviation, and trend in temperature and precipitation relative to gridded observational data.

Not all observational data sets are of equal quality, and errors and uncertainties in observations are inescapable. Several observational data sets were considered as possible representation of the "true" historical climate. The principal data sets were Aphrodite v1101, a daily gridded data set for monsoon Asia, and CHIRPS v2.0, a daily gridded data set available globally. These two data sets were compared with the daily gridded data set of the Indian Meteorological Department (IMD), whose data set is considered to be the most spatially and temporally consistent, but is available only over India. Therefore, the IMD data were used to determine which regionally available data set performs best for South Asia, on the basis of agreement over India. Overall, the Aphrodite data set best matches the spatial pattern and local magnitudes of the IMD data, particularly with respect to variability, trends, and precipitation extremes. Aphrodite is therefore used to assess the climate model performance.

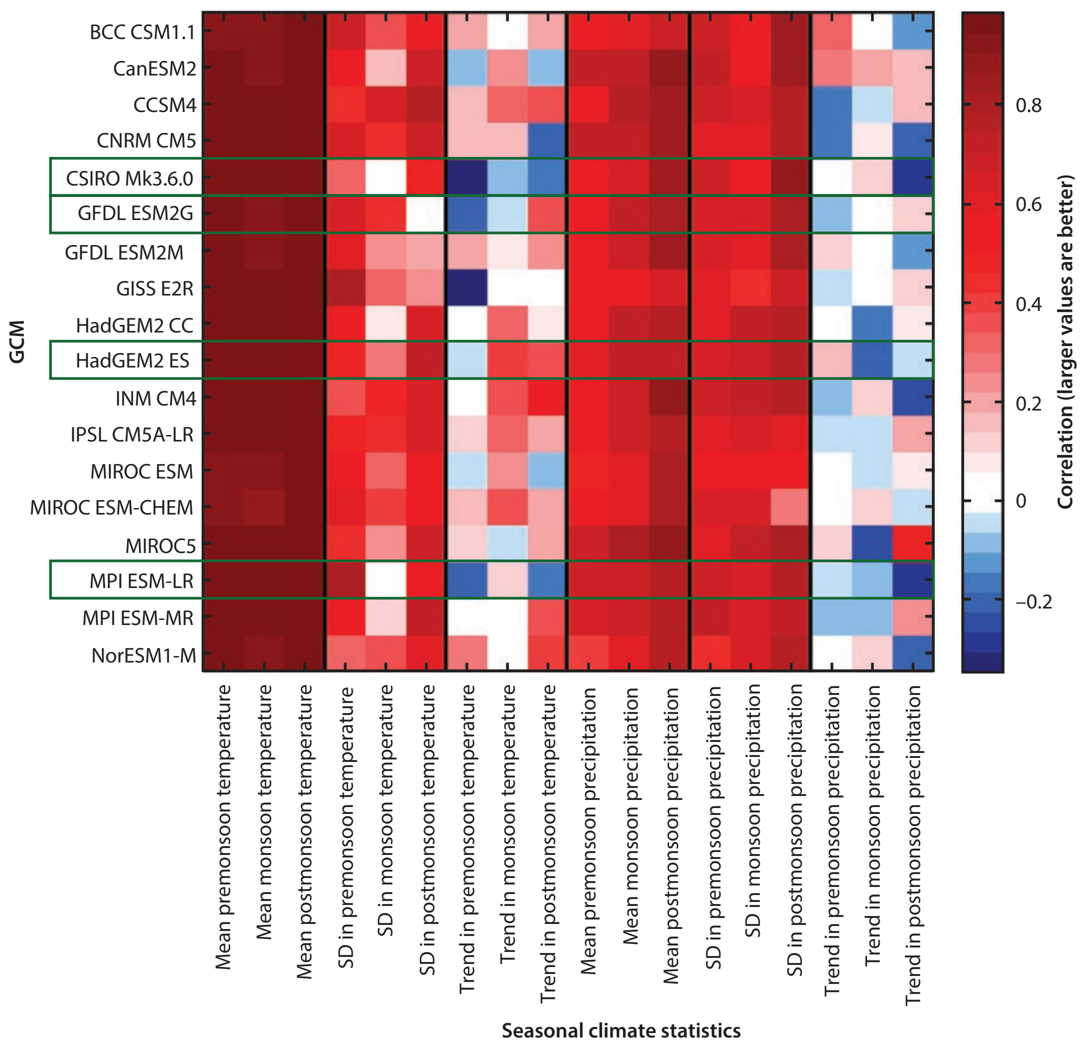
The performance of each of the 18 climate models is displayed in figure 2.2, panels a and b. In general, the models better reproduce the spatial patterns of long-term average climate and year-to-year standard deviation compared with the spatial pattern of multiyear trends; however, the climate models better reproduce regionally aggregated trends than long-term average climate or year-to year variability. In general, though, the climate models better reproduce the regionally aggregated climate than the spatial pattern of climate within South Asia. The method of model selection was to eliminate those with the worst performance. Four models—CSIRO Mk3.6.0, GFDL ESM2G, HadGEM2 ES, and MPI ESM-LR—were eliminated because of particularly poor spatial correlation performance. Three models—GISS E2R, INM CM4, and MIROC5—were eliminated because of particularly poor regionally aggregated performance (see appendix D for more details). Therefore, of the 18 climate models assessed, 11 were selected for projecting conditions in South Asia (figure 2.2).

These 11 selected climate models are used to form ensemble climate projections for the climate-sensitive and carbon-intensive scenarios. The three metrics calculated for each ensemble are the multimodel mean (MMM), low, and high. The MMM is the average of all 11 model values at each location and time frame. The ensemble low and high are the values from the climate model that projects the minimum or maximum future climate aggregated over the country for each climate parameter and season (or on an annual basis). A different climate model can be selected as the low or high ensemble member for each country and each season.

Ensemble climate model projections of the MMM, low, and high values are estimated for each district for all countries in South Asia. Climate projections are calculated for annual (January through December), premonsoon (March through May), monsoon (June through September), and postmonsoon (October through February) seasons. Each projection is a 30-year average centered on the target year. The hotspot analysis is conducted for the two climate projection time frames shown in table 2.1.

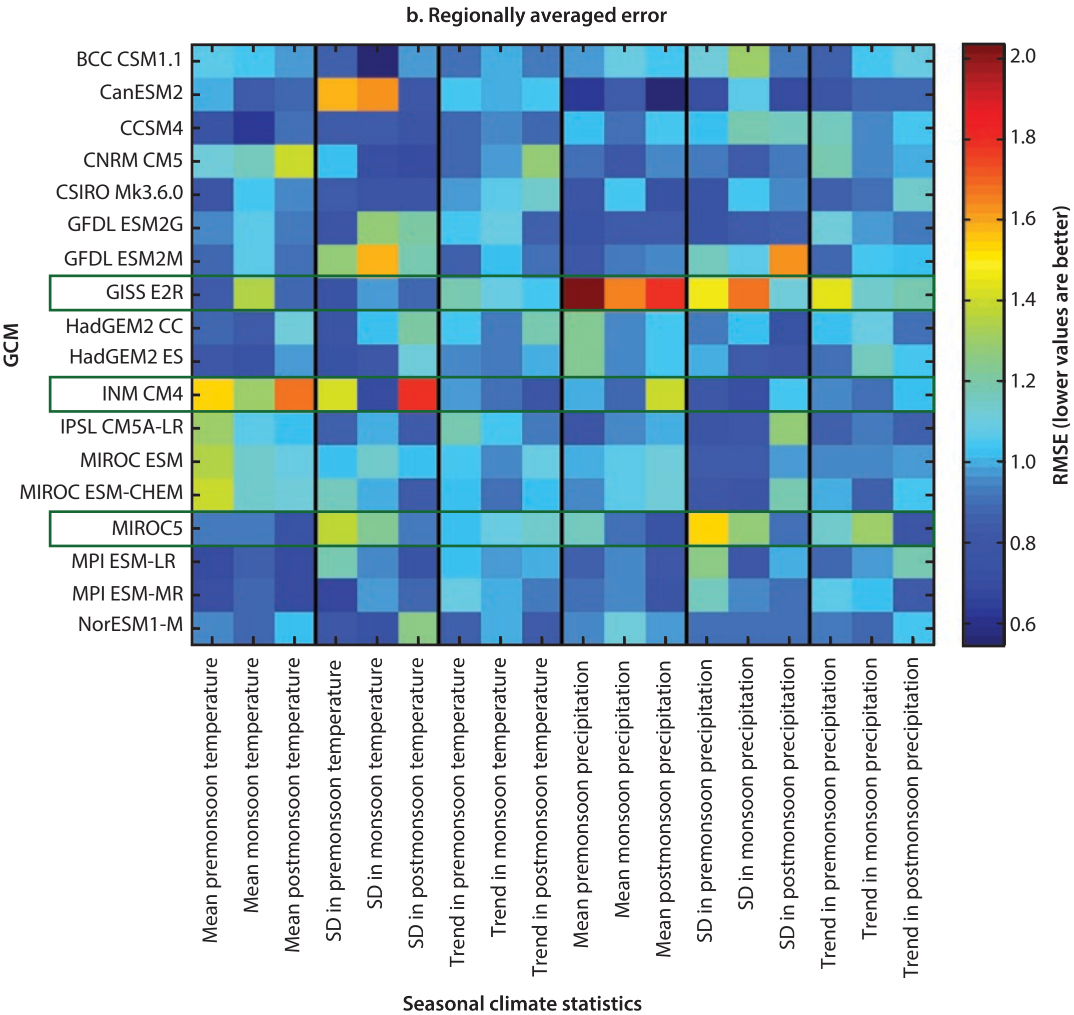
FIGURE 2.2 An Illustration of Model Selection Criteria

a. Spatial pattern reproduction



(continues next page)

FIGURE 2.2 An Illustration of Model Selection Criteria (continued)



Note: Green rectangles indicate the four climate models that were eliminated because of low spatial pattern correlations and the three climate models that were eliminated because of large RMSE values (see appendix D for more details on model selection). RMSE = root mean squared error; SD = standard deviation.

TABLE 2.1 Results from Climate Model Projections for Two Future Time Frames

Target year	Definition
2030	Midpoint of projected climate values for 2016 through 2045
2050	Midpoint of projected climate values for 2036 through 2065

South Asia Continues to Get Hotter

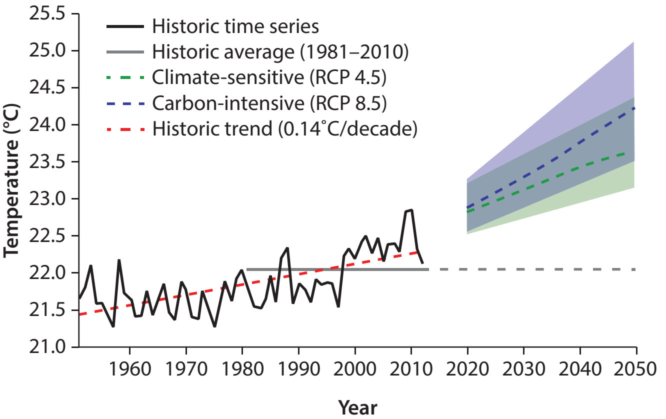
Annual average temperatures in South Asia are projected to increase 1.6°C (with a range of 1.0°C to 2.3°C) under the climate-sensitive scenario and 2.2°C (range is 1.5°C to 3.1°C) under the carbon-intensive scenario by 2050, relative to 1981–2010 (figure 2.3). Although the uncertainty range is notable, the magnitude of the projected temperature increases is larger than the uncertainty. This indicates high confidence that temperatures in South Asia will continue increasing under both the climate-sensitive and carbon-intensive scenarios.

Unlike temperature, projected changes in precipitation are very uncertain (figure 2.4).

One reason for the high degree of uncertainty is that precipitation patterns highly depend on cloud microphysics, which is difficult to represent in current climate models. The projected MMM change in average monsoon precipitation is ±3.9 percent under the climate-sensitive scenario and ±6.4 percent under the carbon-intensive scenario (the range of projections is negative 6.9 percent to positive 25.2 percent, depending on the climate model and scenario). This large range represents a risk for South Asia. If average precipitation increases, some areas that have historically experienced low precipitation could benefit. At the same time, it is also likely that extreme precipitation events would become more common under a scenario of increasing precipitation patterns, especially because of the large temperature increases. Extreme precipitation events would cause an increase in damage. Decreasing precipitation would result in less overall water availability in South Asia, which would also cause problems for people and agricultural yields.

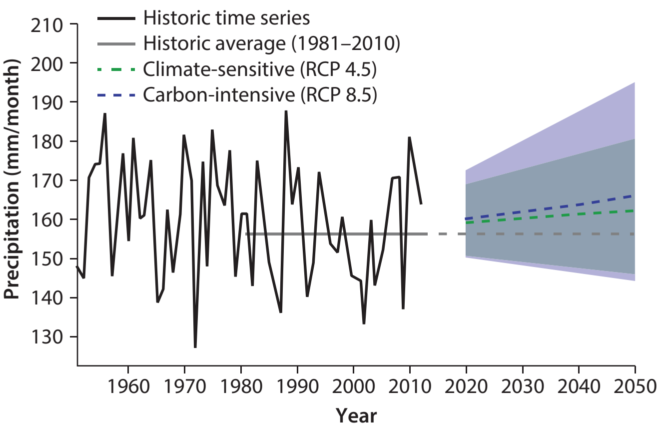
The patterns of temperature change are not evenly distributed throughout South Asia (box 2.1 and map 2.5, panels a and b). Under the climate-sensitive scenario, temperatures are projected to increase the most for the Hindu Kush and Karakoram mountains. Under the carbon-intensive scenario, the MMM climate model projection is for annual average temperatures to increase 2.5°C to 3.0°C for Afghanistan, the portion of Pakistan neighboring Afghanistan, the Karakoram mountains, and the Himalayas, relative to 1981–2010 values. Part of the reason for this spatial pattern of large temperature increases is that these regions will lose substantial snow and ice cover under these climate scenarios. For example, Mosier (2015) finds that snowfall will decrease more in the Hindu Kush mountains than the Karakoram or Himalaya mountains. Snow and ice help to regulate air temperatures because they reflect solar radiation and regulate air temperatures through the melting process. Snow and ice also store water, which gets released during the hottest portions of the year. Therefore, losing these important natural water reservoirs results in feedback that enhances climate change and affects water availability.

FIGURE 2.3 Historic Trends in Annual Temperature Increases Are Projected to Increase



Sources: Harris and others 2014 (Climate Research Unit TS 2.24); 11 climate models cited in box 2.1.
Note: The black line indicates yearly annual temperature, the gray line indicates average annual temperature from 1981 through 2010, the dashed purple line indicates multimodel mean under the carbon-intensive scenario, the dashed green line represents multimodel mean under the climate-sensitive scenario, and the shaded areas indicate range of results based on 11 climate models for each scenario.

FIGURE 2.4 Monsoon Precipitation Varies Considerably Year to Year, and Projections Are Highly Uncertain



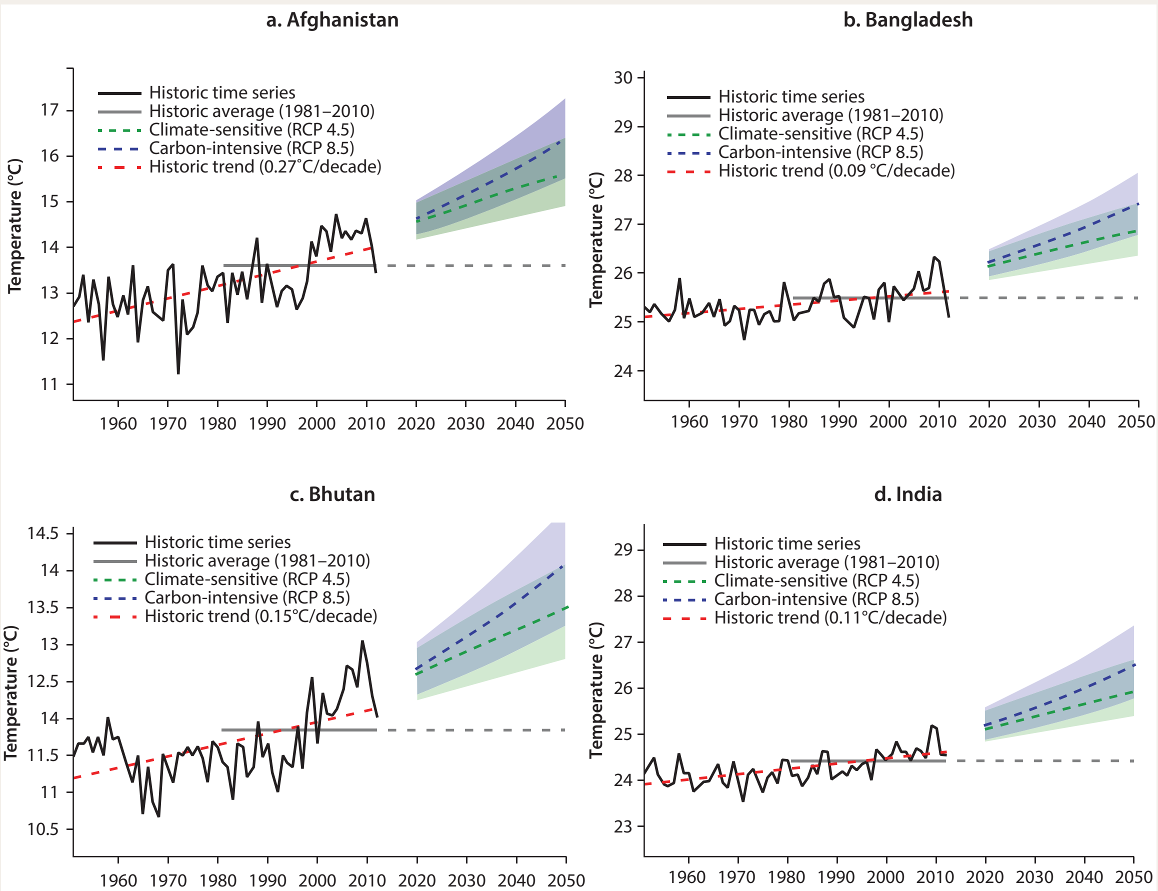
Sources: Harris and others 2014 (Climate Research Unit TS 2.24); 11 climate models cited in box 2.1.
Note: The black line indicates yearly monsoon precipitation, the gray line indicates average monsoon precipitation from 1981 through 2010, the dashed purple line indicates multimodel mean under the carbon-intensive scenario, the dashed green line represents multimodel mean under the climate-sensitive scenario, and the shaded areas indicate range of results based on 11 climate models for each scenario.

In South Asia, temperatures are projected to increase the least along the coastal areas of India, Bangladesh, and Sri Lanka because the oceans help to moderate the temperature. Temperature increases in these areas are still 1.0°C to 1.5°C under the climate-sensitive

BOX 2.1 Understanding Historic and Projected Temperatures for Each Country

Temperature patterns vary considerably throughout South Asia. This means that in a given year, temperatures may be hotter than average in one part of the region but cooler than average in a different part. It also means that the trends are nonuniform. These attributes do not decrease the ability to make projections about future climate, but they do demonstrate the importance of spatially analyzing climate change. At the national level, historic temperature trends are lowest for Bangladesh (0.09°C per decade), India (0.11°C per decade), Nepal (0.14°C per decade), and Bhutan (0.15°C per decade). Trends are the highest for Afghanistan (0.27°C per decade), Pakistan (0.17°C per decade), and Sri Lanka (0.17°C per decade) (figure B2.1.1, panels a through g).

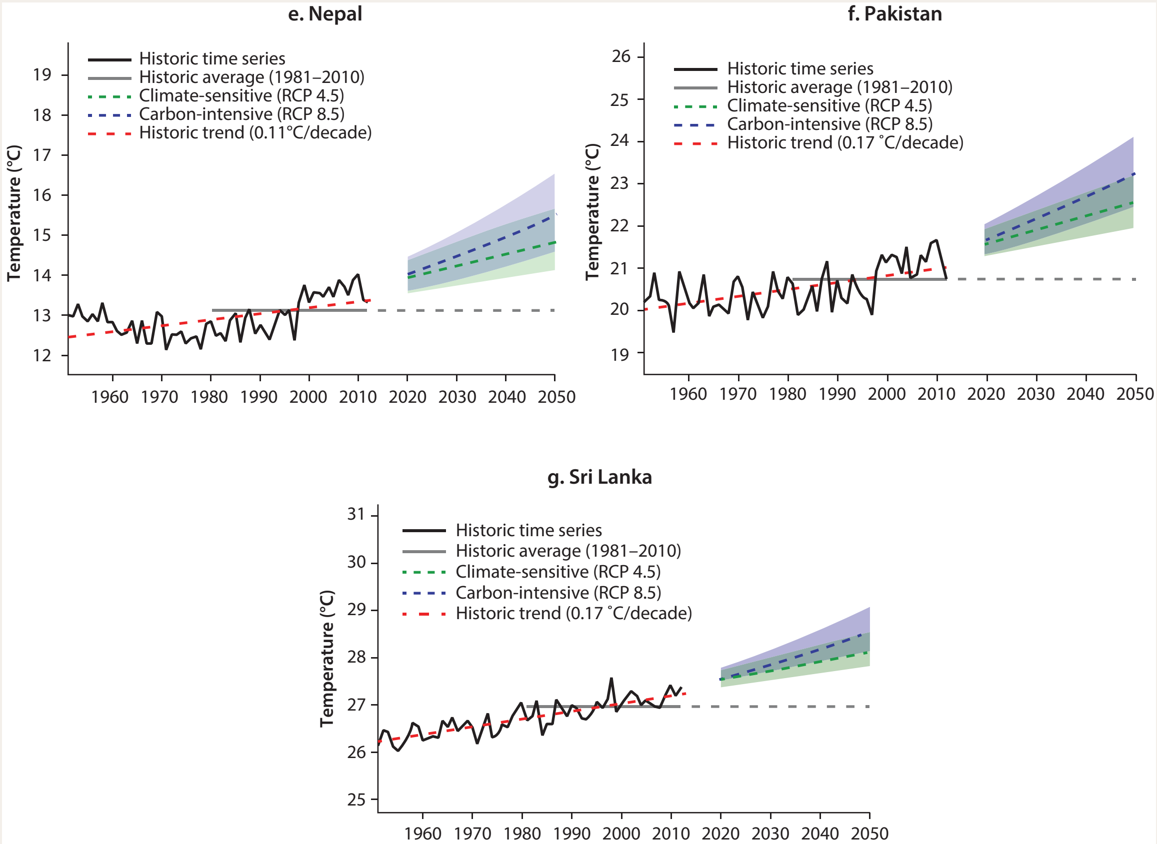
FIGURE B2.1.1 Annual Temperatures Are Increasing for All Countries, but the Rate of Change Varies



(continues next page)

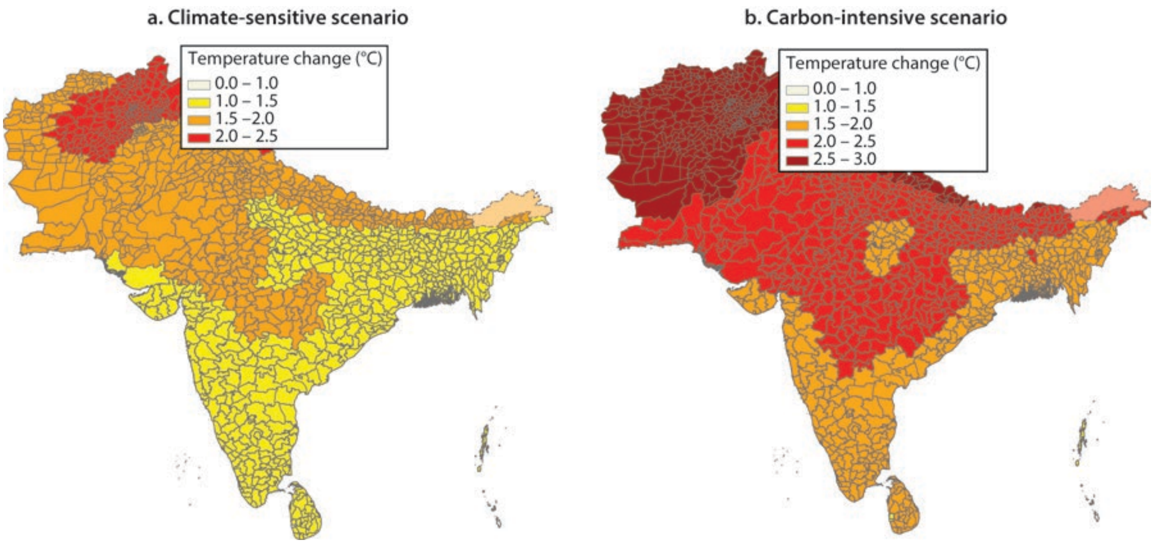
BOX 2.1 Understanding Historic and Projected Temperatures for Each Country (continued)

FIGURE B2.1.1 Annual Temperatures Are Increasing for All Countries, but the Rate of Change Varies (continued)



Sources: Harris and others 2014 (Climate Research Unit TS 2.24); 11 climate models cited in box 2.1.
Note: The black line line indicates yearly annual temperature, the gray line indicates average annual temperature from 1981 through 2010, the dashed purple line indicates multimodel mean under the carbon-intensive scenario, the dashed green line represents multimodel mean under the climate-sensitive scenario, and the shaded areas indicate 100 percent confidence interval based on 11 climate models for each scenario.

MAP 2.5 Annual Average Temperature Is Projected to Continue Increasing Dramatically under the Climate-Sensitive and Carbon-Intensive Scenarios



Sources: Harris and others 2014 (Climate Research Unit TS 2.24); 11 climate models cited in box 2.1.
Note: Changes are by 2050 (average for 2036 through 2065) relative to 1981 through 2010 averages (figure 2.1).

scenario and 1.5 to 2.0°C under the carbon-intensive scenario by 2050, relative to 1981 through 2010.

References

Abbas, F., A. Ahmad, M. Safeeq, S. Ali, F. Saleem, H. M. Hammad, and W. Farhad. 2014. "Changes in Precipitation Extremes over Arid to Semiarid and Subhumid Punjab, Pakistan." *Theoretical and Applied Climatology* 116 (3–4): 671–80.

Basistha, A., D. S. Arya, and N. K. Goel. 2009. "Analysis of Historical Changes in Rainfall in the Indian Himalayas." *International Journal of Climatology* 29 (4): 555–72.

Bollasina, M. A., Y. Ming, and V. Ramaswamy. 2011. "Anthropogenic Aerosols and the Weakening of the South Asian Summer Monsoon." *Science* 334 (6055): 502–5.

Harris, I. P. D. J., P. D. Jones, T. J. Osborn, and D. H. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations—The CRU TS3.10 Dataset." *International Journal of Climatology* 34 (3): 623–42.

Kumar, K. R., G. B. Pant, B. Parthasarathy, and N. A. Sontakke. 1992. "Spatial and Subseasonal Patterns of the Long-Term Trends of Indian Summer Monsoon Rainfall." *International Journal of Climatology* 12 (3): 257–68.

Mosier, T. M. 2015. "Characterizing Linkages Between the Climate, Cryosphere, and Impacts on Run-of-River Hydropower in Data-Sparse Mountain Environments." PhD dissertation, Oregon State University, Corvallis.

O'Neill, B. C., E. Kriegler, K. Riahi, K. L. Ebi, S. Hallegatte, T. R. Carter, R. Mathur, and D. P. van Vuuren. 2014. "A New Scenario Framework for Climate Change Research: The Concept of Shared Socioeconomic Pathways." *Climatic Change* 122 (3): 387–400.

Pal, I., and A. Al-Tabbaa. 2009. "Trends in Seasonal Precipitation Extremes—An Indicator of 'Climate Change' in Kerala, India." *Journal of Hydrology* 367 (1): 62–69.

Rosenfeld, D., S. Sherwood, R. Wood, and L. Donner. 2014. "Climate Effects of Aerosol-Cloud Interactions." *Science* 343 (6169): 379–80.

Roy, S., and R. C. Balling. 2004. "Trends in Extreme Daily Precipitation Indices in India."

International Journal of Climatology 24 (4): 457–66.

Singh, D. 2016. "South Asian Monsoon: Tug of War on Rainfall Changes." *Nature Climate Change* 6 (1): 20.

Singh, D., M. Tsiang, B. Rajaratnam, and N. S. Diffenbaugh. 2014. "Observed Changes in Extreme Wet and Dry Spells during the South Asian Summer Monsoon Season." *Nature Climate Change* 4 (6): 456.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl. 2012. "An Overview of CMIP5 and the Experiment Design." *Bulletin of the American Meteorological Society* 93 (4): 485–98.

Climate and Living Standards

3

The climate is changing and will continue to do so over the coming decades under a range of emissions scenarios, but what effect will this have on living standards? Addressing this question requires understanding the relationship between today's weather and living standards and then extrapolating this relationship to look at future climatic conditions. "Living standards" encapsulate a broad set of conditions that can be expressed both monetarily and nonmonetarily. For example, a family's type of housing is easy to express monetarily, although the sense of well-being received from that housing cannot be easily expressed in monetary terms. This book uses consumption expenditures as a metric for overall living standards because it encapsulates the monetary dimensions of living standards and is objectively quantifiable. There are strong precedents for using consumption expenditures as a proxy for living standards, although it should be acknowledged that it is an imperfect approximation.

The most direct (and popular) measures of living standards in the literature are income and consumption. In general terms, *income* refers to the earnings from productive activities and current transfers, whereas *consumption* refers to resources used. Consumption is usually measured by looking at household expenditures from household-level surveys.[1] There has been a long-standing debate in the literature on whether income or consumption is a better measure of standards of living. Especially for low-income countries, a strong case has been made for preferring consumption expenditures, based on both conceptual and practical considerations (Deaton and Grosh 2000). Expenditures are supposed to better reflect "long-term" or "permanent" income and are from this point of view considered to be a better measure of economic well-being (Atkinson 1987).

In the poverty literature, the standard way to determine whether a household is poor is to compare its daily expenditures per capita to a minimum consumption threshold, or poverty line (Chatterjee and others 2016; Haughton and Khandker 2009). In his seminal work on poverty measurements, Deaton (2005) fervently argues that although consumption measures are limited in their scope, they are nevertheless a central component of any assessment of living standards. Consumption expenditures per capita are used extensively at the World Bank to produce poverty diagnostics for countries, including mapping poverty (Li and Rama 2016). These poverty maps succinctly represent average household expenditures per capita in real terms across space, at a disaggregated level.

Building on theories of consumption, they use household surveys—whose samples are small but rich in information—to estimate the relationship between household expenditures per capita and household characteristics. The set of characteristics considered are those that can also be found in population censuses. The estimated relationship is then used to predict household per capita expenditures at varying spatial levels, based on local household characteristics as reported by population censuses (Demombynes and others 2002; Elbers, Lanjouw, and Lanjouw 2003).

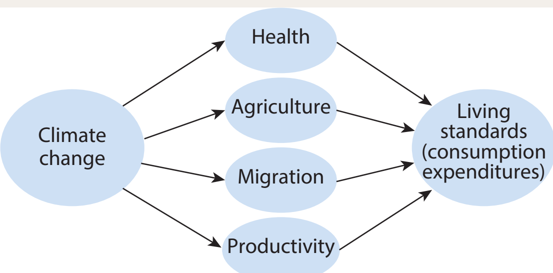
Using this understanding of current living standards, the next step is to estimate the link between climate change and consumption expenditures (see box 3.1). The two main categories of model formulations for estimating living standards are structural and reduced-form. Structural models seek to represent the causal relationships between inputs and outputs, which in this case are climate and consumption expenditures, respectively. Structural models can capture the basic relationships that govern an interaction, but they tend to also be highly uncertain in real-world situations because of the complex nature of the causal relationships. As an example, a structural model may contain an equation to estimate agricultural yield as a function of weather, but it likely would not capture the psychological effects of multiple poor yield years on a farmer.

This book builds and extends this knowledge base by delving into the relationship between changes in average weather—long-term seasonal average temperature and precipitation—and consumption expenditures. Like many previous studies, the analysis here uses a reduced-form model to estimate the relationship between weather and consumption expenditures.

BOX 3.1 How Climate Change Affects Consumption Expenditures

A changing climate can affect consumption expenditures in many diverse ways (see figure B3.1.1 for a conceptual representation of some of the pathways). For example, increasing temperatures combined with shifting precipitation patterns can dampen agricultural productivity, leading to a decline in consumption expenditures for households dependent on agriculture.

FIGURE B3.1.1 Climate Change and Living Standards Are Linked through a Diverse Set of Pathways



Increasing temperatures and wet conditions can increase the propagation of vector-borne and other infectious diseases, resulting in lost productivity and income. Similarly, extreme heat days are generally correlated with declining productivity of workers, especially in areas that are already warm. A changing climate can force people out of their traditional professions, resulting in individuals taking up occupations not suitable for their skills and earning less income.

Extreme events also cause major disruptions to consumption. For example, individuals may consume less, either because they have no savings and their work is disrupted, or because they know they need to use their resources carefully for recovery efforts. In many cases these individual disaster responses are of relatively short duration and consumption rebounds after relief and rehabilitation efforts. In contrast, the effects of changing average weather will be slow-moving and persistent.

Reduced-form models do not make assumptions about the way a system works, but instead seek to capture the aggregate relationship between the inputs and outputs. Therefore, reduced-form models tend to have greater predictive capability than structural models under a wider set of conditions. However, because reduced-form models do not represent the underlying causal relationships, they do not capture fundamental changes to a given system. This is particularly problematic when a relationship includes a threshold response. For example, over the baseline period of 1981 through 2010, climate change may not have caused very significant migrations, but it is likely that climate change induced migrations will occur in the future if conditions become too adverse. In addition, it is likely that a community will have greater resources to recover from a single shock, compared with a series of independent shocks. Such thresholds and cumulative effects cannot be adequately captured using a reduced-form model, such as that used in this book. Despite these limitations, reduced-form models are the best means for assessing the linkages between living standards and climate because these relationships are not adequately represented in current structural models and reduced-form models explain the maximum amount of variation in the data.

Accumulated Knowledge

A growing set of research explores the relationship between weather or climate and human activities. Many of these studies use reduced-form models. Studies differ primarily in the effect that they seek to quantify and level of aggregation. Aggregation refers to whether a variable is reflective of conditions at a single point (such as a single person or family) or is representative of a larger group (such as a province or country).

Many studies have estimated the relationship between weather or climate and societies at the national level. Several identify a negative relationship between increasing temperatures and gross domestic product (GDP) (DARA 2012; Ahmed and Suphachalasai 2014; OECD 2015). There is also evidence of a negative effect of climate change, especially extreme events, on GDP growth (Brown and others 2013; Burke, Hsiang, and Miguel 2015; Dell, Jones, and Olken 2012; Hsiang and Jina 2014; Moore and Diaz 2015). Other studies have identified negative effects of climate change on health, agriculture, and labor productivity (Auffhammer and Schlenker 2014; Deschenes 2014; Mani and Wang 2014; Heal and Park 2015; WHO 2015).

At the local level, studies have investigated effects of climate change on household living standards. Verner (2010) examines the relationship between climate change and income in Latin America using municipality-level data, and finds a mixed set of relationships between temperature and income. For Bolivia, Brazil, and Peru, the relationship is clearly an inverted *U* (that is, higher temperatures are good to a point, and then cause harm); in Chile, the relationship is more or less inverse; and in Mexico, the relationship is not statistically significant. Skoufias, Katayama, and Essama-Nssah (2012) find that climate change will lower agricultural productivity and increase food prices, but expect these changes to be offset by reductions in poverty and economic growth rates. In contrast, Hallegatte and others (2016), in *Shock Waves*, find that economic growth can play a major role in determining future poverty levels, but that an additional 100 million people could end up in poverty by 2030 because of climate change without such growth, including 42 million in India.

Existing studies have looked at an array of economic impacts. Hallegatte and others (2017), in *Unbreakable*, focus on the current effects of natural disasters across all income groups (they make no projections) and find that such events account for varying losses in consumption across the world. In South Asia, losses are estimated at 0.3 percent in Sri Lanka, 0.4 percent in India, 0.9 percent in Pakistan, 1.6 percent in Nepal, and 3.5 percent in Bangladesh. Jacoby, Rabassa, and Skouas (2011) investigate the effects of rural consumption levels in India and estimate that because of climate change, rural households will face a loss of between 6 percent and 11 percent by 2040.

This book adds to this accumulated knowledge through a combination of granularity and region-specific climate change analyses. The research here uses the household as the fundamental unit of analysis. The household results are then aggregated to the district or province level to appropriately represent the distribution of households in the given political administrative unit. The book focuses on effects of changes in average precipitation and temperature because changes in the average can be projected with greater confidence than changes in extreme events.

Analytical Framework

Much of the accumulated knowledge uses reduced-form models to estimate the relationship between weather or climate and a given activity. Many of these reduced-form models include both linear and quadratic weather or climate factors (Burke, Hsiang, and Miguel 2015; Mendelsohn, Nordhaus, and Shaw 1994; Schlenker and Roberts 2009). The fundamental reason is that linear terms capture only a single trend estimate, which does not account for the impact of spatial differences in the current climate. Also, there are often optimal climates, which can be captured in a quadratic model, but not a linear one. Intuitively this is clear: too little or too much precipitation causes problems, and excessively cold and excessively hot temperatures affect many important activities (box 3.2).

The analysis here includes seasonal weather in the model because many human activities in South Asia are seasonal (Massetti, Mendelsohn, and Chonabayashi 2016). The model also includes a set of household, district, and geospatial characteristics, which are chosen because they are only weakly correlated with climate and they potentially help explain variations in consumption expenditures.

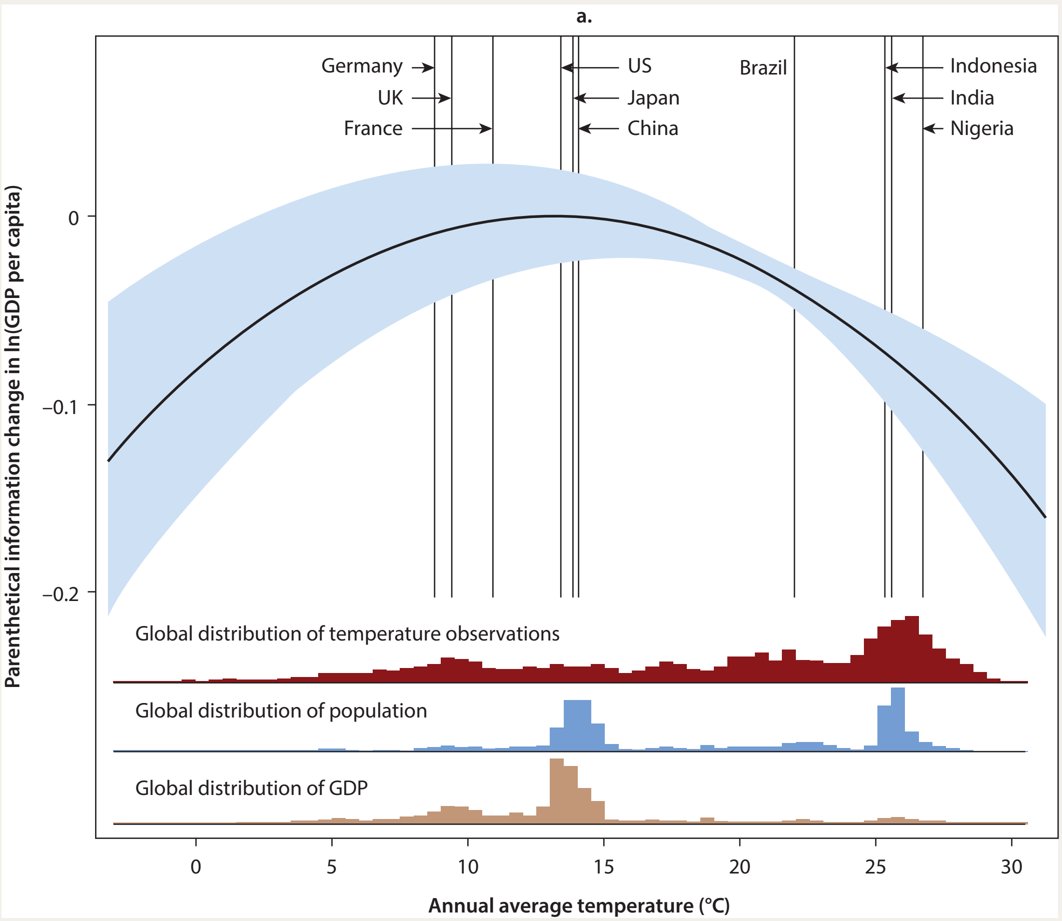
BOX 3.2 The Quadratic Relationship between Climate and Economy

Burke, Hsiang, and Miguel (2015) investigate the relationship between climate and the economy by looking at the effect of annual average temperature on productivity. They find that country-level economic production is smooth, nonlinear, and concave with respect to temperature, with an optimal temperature of 13°C (figure B3.2.1). Productivity in countries with average temperatures lower than 13°C is estimated to benefit until the optimal value is reached. This model is produced using data from many countries and is therefore driven by average relationships. Their model does not allow different optimal temperatures (corresponding to unique adaptive capacities) for individual countries. Whereas significant global economic production is clustered near the estimated temperature optimum, individual communities and countries exhibit similar—but unique—nonlinear responses to temperature. In their model, low-income tropical countries exhibit larger responses mainly because they are hotter on average, not because they are poorer. Although there is suggestive evidence that upper-income countries might be somewhat less affected by temperature, their response is statistically indistinguishable from low-income countries at all temperatures.

(continues next page)

BOX 3.2 The Quadratic Relationship between Climate and Economy (continued)

FIGURE B3.2.1 Impacts of Temperature on Productivity Are Well Explained Using a Quadratic Model



Source: Burke, Hsiang, and Miguel 2015.
Note: Blue-shaded region indicates 90 percent confidence interval.

After extensive investigations, the reduced-form model chosen for the analysis is:

$$\begin{aligned} Y_{hit} = \alpha + \sum_{j\in(s,m,w)} & (\beta_{1j} temp_{it}^{j} + \beta_{2j} temp_{it}^{j^2} \\ & + \beta_{3j} rain_{it}^{j} + \beta_{4j} rain_{it}^{j^2}) \\ & + \beta_5 X_{hit} + \beta_6 W_i + \tau_t + u_{hit} \end{aligned} \qquad \text{(Eq 3.1)}$$

where h refers to the household surveyed, i refers to the district, t refers to the survey year, Y is the log of average real annual household consumption expenditures, $temp_{it}$ is mean seasonal temperature for the survey year t in district i, $rain_{it}$ is mean seasonal precipitation for the survey year t in district i, X_{hit} is a vector of control variables, W_i is a vector of district characteristics, and τ is a vector of dummy variables representing each survey year; j takes the values s, m, and w representing premonsoon (March through May), monsoon (June through September), and postmonsoon (October through February) seasons, respectively. The selection of control variables is discussed in the "Control Variable Selection" section later in this chapter.

The reduced-form relationship is estimated using equation (3.1) separately for Afghanistan, Bangladesh, India, Nepal, Pakistan, and Sri Lanka, using all years of available survey data for each country (see the survey information in table 3.1). The relationship is estimated using seasonal weather contemporaneous to the household survey. Impacts of changes in average weather are then estimated by applying the empirical relationship to 30-year average seasonal climate projections corresponding to the ensemble multimodel mean (MMM) under the climate-sensitive and carbon-intensive scenarios for 2030 and 2050; 2030 and 2050 refer to average climate from 2016–2045 and 2036–2065, respectively (see chapter 2). The historic baseline is established through applying the estimated relationship to the most recent available year of household surveys for each country and the corresponding 30-year seasonal climate (that is, if the most recent survey year is 2011, then the baseline climate is 1981 through 2010).

These predicted consumption changes assume that only the average weather changes between the baseline and 2030 or 2050. That is, all household, district, and socioeconomic characteristics are held constant. Although this may appear to be an unreasonable assumption, it is impossible to know how household size, dependency ratio, and other demographic characteristics will change over the coming decades. Shared socioeconomic pathway (SSP) scenarios can be used to estimate changes at the national level, but equation (3.1) is implemented at the household level, and there is very high uncertainty translating national scenarios to individual households. It is certain that, on average, education, electricity, road, and market access will improve in the future. The net extent of these opposing effects (that is, development versus negative climate change impacts) would depend on the growth and development policies of respective countries. The corresponding qualification is that the results represent the effects of projected climate change if it were to happen today.

Data Sources

Annual household consumption expenditures (the proxy for living standards) and several household characteristics used as control variables are obtained from country-specific household surveys (table 3.1). These household surveys are designed to represent conditions at different levels of administrative aggregation, which vary between countries. For example, survey data for Pakistan are designed to represent provincial conditions, whereas survey data for India are designed to represent district conditions. Several control variables are paired with the household survey data and tested for suitability (table 3.2).

Historic weather and climate are derived from the Climate Research Unit Time-Series (CRU TS) 3.22 monthly precipitation and

TABLE 3.1 Household Surveys in South Asia

	Afghanistan	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Name	ALCS	HIES	NSS	NLSS	PSLM	HIES
Years	2008, 2012	2000, 2005, 2010	2004, 2009, 2011	2003, 2010	2001, 2004, 2005, 2007, 2010, 2011	2006, 2009, 2012
Representative administrative unit	District	Division	District	Region	Province	Province

Note: Survey names are ALCS (Afghanistan Living Conditions Survey), HIES (Household Income Expenditure Survey), NSS (National Sample Survey), PSLM (Pakistan Social and Living Standard Measurement), and NLSS (Nepal Living Standard Survey). The survey results for Nepal are representative at the provincial level, but five regions are used to represent results in this book.

TABLE 3.2 Variables Considered for Household, District, and Geospatial Differences

	Household	District	Geospatial
Variables	Access to electricity; age of head of household; agriculture household; dependency ratio; education of head of household; female-headed household; household size; rural household	Population density; road density; seasonality of water availability; travel time to market; water availability; water stress	Distance to coast; elevation; latitude; longitude
Sources	Survey data	Spatial Database for South Asia; Aqueduct data set by the World Resources Institute (Gassert and others 2013); GoN (2013); Uchida and Nelson (2008)	WorldClim Digital Elevation Model (Hijmans and others 2005)

temperature data (Harris and others 2014). These data are available from 1901 through 2013 at a spatial resolution of 0.5 degrees (each grid cell is square in geographic coordinates, with a side length of approximately 55 kilometers at the equator). The CRU TS data set is produced by statistically interpolating available station records to a uniform grid. Therefore, in regions where station observations are sparse or climate variability is large, CRU tends to contain greater uncertainty. However, in this book, as in many other studies, CRU is used as a reference data set (that is, the uncertainty is ignored).[2] Climate projections are produced from the ensemble of climate model simulations described in chapter 2. District-level climate is calculated by area-weighting the gridded CRU TS and climate model ensemble projections. The premonsoon season is defined as March through May, the monsoon season is defined as June through September, and the postmonsoon season is defined as October through February. These season definitions are consistent with agricultural seasons within the region.

Two Methodological Challenges

Two challenges to the empirical estimation of the net relationship between climate change and consumption are selecting appropriate control variables and determining the most appropriate model structure. The challenges stem from the fact that many household-level variables tend to be correlated with weather or climate. For example, a household's decision on where to live may be influenced by climatic conditions. Similarly, a farmer's decision on when to plant a crop will depend greatly on the weather patterns observed in the preceding years. The extent to which changes in average weather are appropriately captured in a model requires carefully considering the set of modeling choices.

Control Variable Selection

This analysis uses a variant of the time-series research design that relies on different cohort samples over time in the same region (similar to the design used by Maccini and Yang 2008). In this context, it might be tempting to control for all observable and potentially confounding factors. Although well intentioned, such an approach can introduce bias into the coefficients describing the effect of climate on living standards, because these controls may themselves affect the climate. For example, elevation may cause households to make certain decisions, but elevation also impacts surface air temperature. Therefore, if elevation were included in equation (3.1), it would not be possible to determine the portion of the modeled impact due to household choices caused by elevation versus temperature. Such an effect is termed a *bad control* (Angrist and Pischke 2008) and is undesirable in this setting because climatic variables may affect many of the socioeconomic factors commonly included as control variables.

TABLE 3.3 Control Variables for Each Country

Country	Controls
Afghanistan	Rural household, household size, dependency ratio, age of head, female-headed household, access to electricity, years of education, agriculture household, baseline water stress, latitude, blue water availability, seasonal variability of water availability, inverse square of distance to coast, primary road density, access to market, population density
Bangladesh	Rural household, agricultural household, household size, dependency ratio, age of head, female-headed household, access to electricity, years of education, baseline water stress, elevation, blue water availability, primary road density, population density
India	Rural household, agricultural household, household size, dependency ratio, age of head, female-headed household, access to electricity, years of education, baseline water stress, blue water availability, seasonal variability of water availability, inverse square of distance to coast, primary road density, population density
Nepal	Rural household, agricultural household, household size, dependency ratio, age of head, female-headed household, access to electricity, years of education, baseline water stress, blue water availability, seasonal variability of water availability, population density
Pakistan	Rural household, agricultural household, household size, dependency ratio, age of head, female-headed household, access to electricity, years of education, baseline water stress, blue water availability, seasonal variability of water availability, inverse square of distance to coast, population density
Sri Lanka	Rural household, agricultural household, household size, dependency ratio, age of head, female-headed household, access to electricity, years of education, baseline water stress, access to market

Note: Selected control variables have a correlation of less than 0.5 with all seasonal climate values for the given country.

Unfortunately, removing a bad control can introduce bias into the results. Taking the example of elevation, eliminating this parameter from equation (3.1) causes any effects of elevation to be manifest in the temperature parameter, because temperature and elevation are highly correlated. Therefore, there may be biases from including controls and biases from excluding controls. Since the household survey data used in this analysis are not a true panel data set, but rather include samples within a given region in different years, one can argue for the use of some controls to reduce the chance that the results will be biased because of the exclusion of potentially important characteristics.

To minimize the problem of bad controls, the analysis here uses controls that are weakly correlated with the climate indicators. Specifically, each control variable selected must have a correlation coefficient of less than 0.5 with all climate variables for the country being modeled (Booth, Niccolucci, and Schuster 1994; Dormann and others 2013; Elith and others 2006; Suzuki, Olson, and Reilly 2008; Tabachnick and Fidell 1996). Country characteristics and geographic setting influence the correlation between a specific control variable and climate indicator. Thus, there are some differences in selected control variables between the six countries (see table 3.3). As subsequently discussed, the analysis also tests correlation thresholds of 0.3 and 0.7 to assess the robustness of the findings.

Absorbed Climate Effects

There are many district, provincial, and national characteristics that are not available in curated data sets. For example, there is little quantifiable data on differences in governmental policies or implementation of policies across districts or provinces. The omission of these unobserved or unobservable characteristics can result in omitted variable bias.[3] An empirical method for eliminating omitted variable bias is inclusion of fixed effects in the reduced-form model. Models with fixed effects address this challenge by empirically accounting for spatial differences in predictions.

A challenge to using a model with fixed effects is that the climate data are aggregated to the district level. This can cause unexpected interactions between any included fixed effects and the model's sensitivity to climate. Thus, fixed effects used to correct for omitted variable bias could result in biasing climate coefficient estimations as they absorb the effects of the district-level climate.

An alternative formulation could be to use a model with provincial fixed effects. While this method is better suited to the current analysis than district fixed effects, it can also be problematic because climates of neighboring districts within a given province are typically highly correlated. Thus, models using district- or province-level fixed effects can both lead to biased estimates.

Another potential issue with models including fixed effects is that the unobserved variables accounted for by the formulation may also be highly correlated with climate. Therefore, introducing fixed effects may lead to the same control variable correlation problems discussed in the preceding section. Despite these concerns, the present analysis includes a variant of the reduced-form model using provincial fixed effects to test the robustness of the findings (appendix B, table B.3).

Temperature Inflection Points

The first step in the analysis is to understand the conceptual relationship between temperature and consumption expenditures. For this exercise, equation (3.1) is modified to include only annual temperature (that is, seasonality and precipitation are removed):

$$Y_{bit} = \alpha + \beta_1 temp_{it} + \beta_2 temp_{it}^2 + \beta_3 rain_{it} + \beta_{4j} rain_{it}^2) + \theta_s t + \theta_{s2} t^2 + \mu_s + \tau_t + u_{bit} \quad \text{(Eq 3.2)}$$

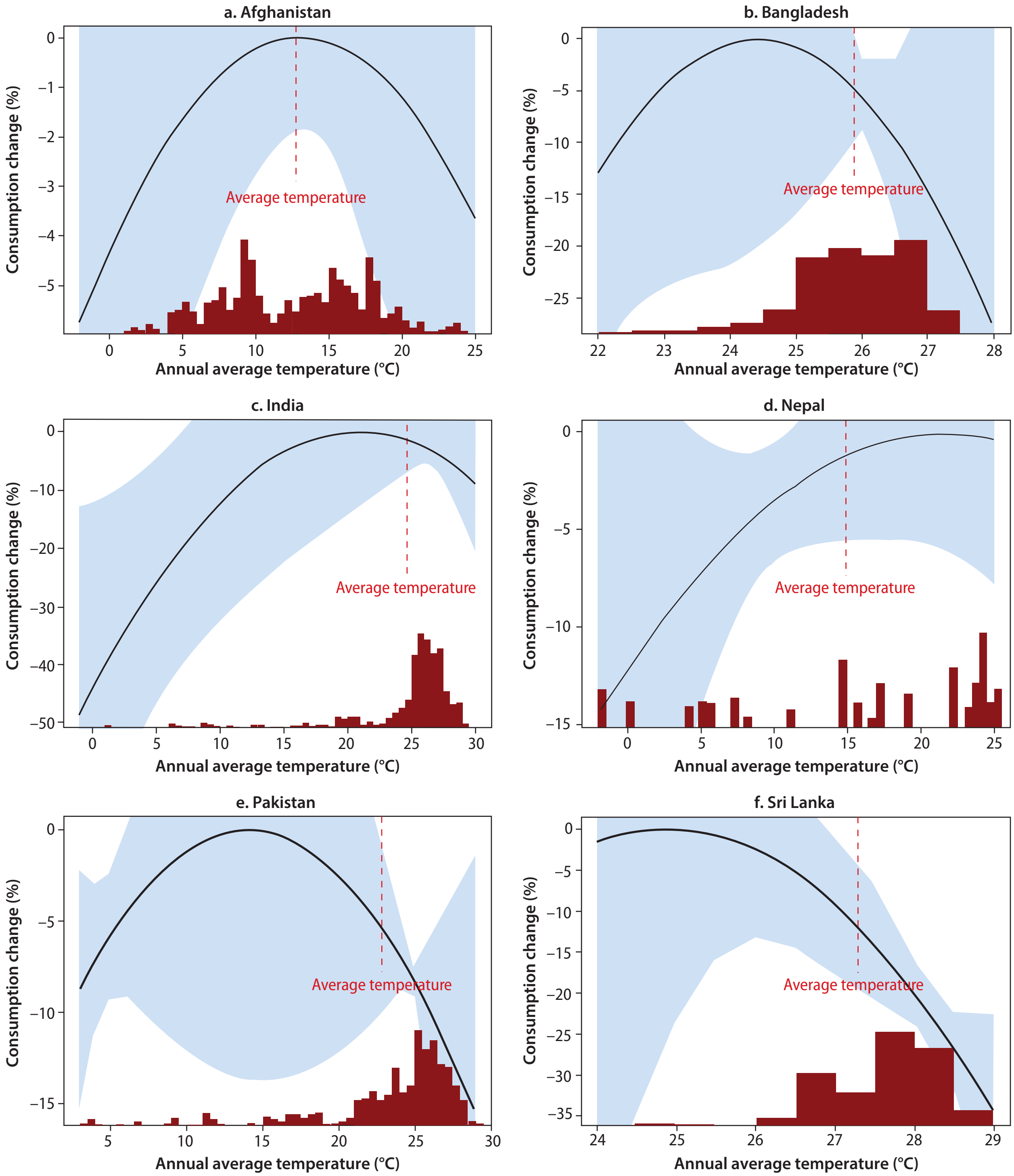
where h refers to the household surveyed; i refers to the district; t refers to the survey year; Y is the log of average real annual household consumption expenditures; $temp_{it}$ is mean annual temperature for the survey year t in district i; $rain_{it}$ is mean annual precipitation for the survey year t in district i; $\theta_s t + \theta_{s2} t^2$ is country-specific time trend, which accounts for slowly changing factors within a district or province such as demographic shifts and institutional capacity; μ is a province dummy variable; and τ is a vector of dummy variables representing each year of survey.

The reason for simplifying the relation is to ascertain how reasonable the overall modeled relationship appears and identify possible temperature thresholds (“inflection points”). As clearly demonstrated by Burke, Hsiang, and Miguel (2015) (box 3.1), temperature and productivity have an inverted U–shaped relationship. That is, temperatures that are both too cold and too hot result in lower productivity. Burke, Hsiang, and Miguel (2015) use national-level average data for countries around the world. It is important to confirm if a similar relationship between temperature and consumption expenditures holds at the subnational level for individual countries in South Asia. To do this analysis, equation (3.2) is implemented using annual contemporaneous temperatures to estimate household consumption expenditures. The results confirm that each country in South Asia has the expected inverted U–shaped relationship to temperature (figure 3.1, panels a through f).

Although the overall relationship is similar across countries, the precise temperature inflection point—the point at which a marginal change in temperature results in no change to consumption—differs by country. For Bangladesh, India, Sri Lanka, and Nepal, the inflection points are in the expected range of 24°C to 27°C; in Pakistan, the model finds the inflection point to be 14°C. These temperature inflection points matter in the context of the current climate conditions.

Nationally, Bangladesh, India, Pakistan, and Sri Lanka are already past their temperature inflection points. This intuitively makes sense given that these four countries have a warm climate. This means that at the national level, any further increase in average temperature will have a net negative effect on consumption expenditures. Temperatures in Afghanistan and Nepal are still less than the inflection point, meaning that increases in temperatures are predicted to have a net positive effect on consumption. This can be also expected because Nepal overall has a cold climate and could potentially benefit from a warmer temperature.

FIGURE 3.1 Temperature and Consumption Have an Inverted U–Shaped Relationship for Countries in South Asia



Source: World Bank calculations.
Note: Blue-shaded region indicates 90 percent confidence interval.

It should be noted, however, that the effects of increases in temperature will be heterogeneous throughout each country, with some areas benefiting slightly from small increases in temperature and other areas being severely harmed. Temperatures can increase by several degrees Celsius in much of Nepal and the mountainous areas of India and Pakistan before these areas pass their temperature inflection points. For Bangladesh, Sri Lanka, the southern and central portions of India, and Pakistan—where temperatures are already relatively hot—the levels of climate change projected under both the climate-sensitive and carbon-intensive scenarios will have negative effects on consumption.

National-Level Empirical Findings

Since the results obtained based on equation (3.2) (representing effects of annual temperature) are similar in form to those obtained in other studies (for example, Burke, Hsiang, and Miguel 2015), one can conclude that the household and climate data for South Asia are expressing the previously documented relationship between climate and living standards. Therefore, equation (3.1) (representing effects of seasonal precipitation and temperature) is implemented to provide a better understanding of the nuanced relationship between climate and living standards in South Asia; regression coefficients based on equation (3.1) are provided in appendix B, table B.2). The analytical framework is then used to estimate the effect of projected changes in average weather on living standards. The framework is implemented at the household level and then aggregated into national predictions through weighting the household-level results. Using this methodology, one can estimate aggregate effects of changes in average weather by 2030 and 2050 under the climate-sensitive and carbon-intensive climate change scenarios. These estimates come with some caveats, as explained in the "Analytical Framework" and "Two Methodological Challeges" sections earlier in this chapter. To summarize a few of the limitations, the results are based on an empirical model that does not directly account for any adaptation to climate change and assumes that multiple independent shocks do not have cascading negative effects, resulting in larger overall negative effects.

The analysis finds that changes in average weather will have a negative effect on living standards in Bangladesh, India, Pakistan, and Sri Lanka, but a positive effect on living standards in Afghanistan and Nepal (table 3.4). Although the magnitude of the results varies on the time frame and climate scenario, the qualitative findings are consistent. As seen in the analysis of temperature changes in chapter 2, the results under the climate-sensitive and carbon-intensive scenarios are very similar for 2030, but they diverge substantially by 2050, with the carbon-intensive scenario being more extreme. The Maldives and Bhutan are not considered in the economic analysis within this book because the required household survey and climate data are not available or adequate for these countries.

TABLE 3.4 Changes in Average Weather Predicted to Have Mostly Negative Effects under Both Scenarios

Time frame	2030		2050	
Scenario	**Climate-sensitive**	**Carbon-intensive**	**Climate-sensitive**	**Carbon-intensive**
Afghanistan	5.1	5.8	8.3	11.9
Bangladesh	−1.3	−2.3	−2.9	−6.7
India	−1.3	−1.5	−2.0	−2.8
Nepal	2.1	2.3	3.2	4.1
Pakistan	−1.3	−1.5	−2.0	−2.9
Sri Lanka	−3.2	−3.7	−4.9	−7.0

Source: World Bank calculations.
Note: The model described by equation (3.1) is implemented for two time frames (2030 and 2050) and two projection scenarios (climate-sensitive and carbon-intensive). The national-level results are aggregated from the household predictions. Percentage change is calculated relative to the historic baseline.

The results do not include effects of extreme event shocks, natural disasters, or changes in water resources (for example, because of overwithdrawal of groundwater, glacier melt, or changes in snowpack).[4] To highlight this caveat, it is well understood that coastal areas—for example, Bangladesh—will experience strong negative effects from sea-level rise and a probable increase in the severity of storms, neither of which is captured in the results. Similarly, mountain areas are known to be highly vulnerable to increases in natural disasters, which are not considered. Consequently, the results should be interpreted as complementary to existing studies that capture the effect of extreme events on household living standards (for example, Hallegatte 2017). The findings are also more or less consistent with the findings of other recent studies for the region (table 3.5).

The finding that effects of changes in average weather increase with time and are stronger under the carbon-intensive scenario highlights the benefits of taking actions to reduce greenhouse gas (GHG) emissions. Actions to limit GHG emissions are commonly referred to as mitigation, or those that reduce the net carbon footprint. The predominant international accord for achieving emissions reductions is the 2015 Paris Climate Agreement. The results provide a further line of economic reasoning for continuing to work toward the emissions targets established under the Paris Agreement.

The positive modeled effects of changes in average weather on living standards in Afghanistan and Nepal may be explained by the countries' historic climates: Afghanistan is a very water-limited country and the mean climate change projection is for an increase in precipitation. In addition, much of Afghanistan and all of Nepal are historically very cold, which means that temperature increases may have some positive benefits. These results are consistent with global findings, showing that climate change may cause

TABLE 3.5 Comparison between This Book's Results and Those of Other Studies in the Same Time Frame

	Climate events studied	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Hallegatte (2017) Δ consumption[a]	Disasters	−3.5	−0.4	−1.6	−0.9	−0.3
Hallegatte (2016) total Δ income	Temp. and prec. changes, disasters	−4.2	−4.5	−3.0	−4.0	−2.7
Disasters		*−1.2*	*−0.6*	*−0.3*	*−0.5*	*−0.5*
Other		*−3.0*	*−3.9*	*−2.7*	*−3.6*	*−2.2*
Ahmed and Suphachalasai (2014) (ADB) Δ GDP	Temp. and prec. changes, sea-level rise	−2.0	−1.8	−2.2	n.a.	−1.2
DARA (2012) Δ GDP	Temp. and prec. changes, disasters, sea-level rise	−6.4	−4.3	−2.7	−4.2	−7.2
Jacoby, Rabassa, and Skouas (2011) Δ rural consumption	Temp. and prec. changes	n.a.	−5.0	n.a.	n.a.	n.a.

Source: World Bank calculations.
Note: GDP = gross domestic product; n.a. = not applicable.
a. Focuses only on extreme events.

BOX 3.3 Why the Positive Results for Nepal Are Not an Anomaly

The findings presented in table 3.4 suggest a net positive effect of changes in average weather on Nepal, whereas the rest of South Asia (except Afghanistan) is projected to be adversely affected. Although this may be surprising, the differentiated effect of climate across regions and countries has been well documented in the literature.

Burke, Hsiang, and Miguel (2015) find that productivity in cold countries increases as annual temperature increases. This result continues until the temperature increases pass an optimum inflection point, after which further temperature increases result in negative marginal effects on productivity. Although Burke, Hsiang, and Miguel (2015) find that much of the global economic production is clustered near the estimated temperature optimum, both upper-income and low-income countries exhibit similar nonlinear responses to temperature. The results of Burke, Hsiang, and Miguel (2015) are based on pooling all countries together, and therefore they estimate a single temperature inflection point. This book finds unique inflection points for each country, indicating that adaptation to climate change is possible.

Similarly, Mendelsohn and Reinsborough (2007) find that the climate responses of Canada and the United States are similar but statistically different, even though the two countries are neighbors. Comparing the marginal effects of climate change, they find that Canadian agriculture is unaffected by warmer temperatures, and would benefit from more precipitation. U.S. farms, on the other hand, are much more sensitive to higher temperatures and benefit relatively less from increased precipitation. The authors conclude that these marginal results are anticipated given that Canadian farms are generally cooler and drier than American farms.

A growing literature describes a positive relationship between climate and the economy in Nepal, consistent with the findings of this book. Joshi, Lall, and Luni (2011) assess the effect of observed climate variables on yields of major food crops in Nepal—rice, wheat, maize, millet, barley, and potatoes—based on a regression model for historical (1978–2008) climate and food crop yield data. Although the temperature increased by 0.7°C during the period, there are no significant trends in precipitation patterns. The study finds that during this period, (a) the growth in the yield of most food crops is positive; (b) increases in summer rain and maximum temperature contribute positively to rice yields; (c) increases in summer rain and minimum temperature have positive effects on potato yields; (d) increases in summer rain and maximum temperature adversely affect the yield of maize and millet; and (e) increases in winter rain and temperature have a positive effect on wheat and barley yields.

Acharya and Bhatta (2013) model climate change and its effect on the agricultural value addition, taking into consideration annual agricultural gross domestic product (AGDP), rainfall, temperature, seeds, and fertilizer distribution data for the 36 years from 1975 to 2010. Although annual average temperatures show an increasing trend during this period, precipitation trends are mostly mixed. The findings are that (a) rainfall has a significant positive effect on AGDP; (b) one unit of rainfall causes agricultural output to increase by 9.6 percent; (c) since the AGDP contribution to the GDP is high in Nepal, the authors infer that more rainfall will result in a higher GDP growth rate; and (d) although increases in temperature may also affect AGDP, the authors find the relationship to be statistically insignificant.

Poudel and Shaw (2016) explore the effects of climate change on major crop yields in the mountainous parts of Nepal using a regression model between 30 years of historical climate data and yield records for food crops. Their climate analysis shows an increase in temperature of approximately 0.02°C to 0.07°C per year (varying by season) and a mixed trend in precipitation.

(continues next page)

BOX 3.3 Why the Positive Results for Nepal Are Not an Anomaly (continued)

During this period rice yields increase by 4.7 kilograms per hectare per year, maize yields increase by 16.0 kilograms per hectare per year, and wheat yields increase by 26.8 kilograms per hectare per year. Over the same period millet yields increase steadily, but barley yields decrease. While these results indicate correlation rather than causation, they are consistent with the results found in this book.

Dhakal, Sedhain, and Dhakal (2016) study the effect of climate change and adaptation practices on agriculture in the Rautahat District of central Nepal by analyzing temperature, rainfall, soil moisture, and agriculture surveys. Their study uses primary data on crop production collected through household surveys and information on crop production adaptation practices collected through focus group discussions, interviews, and direct observations. Over their 30-year study period, annual average rainfall in the area decreases 10.21 millimeters per year and annual mean temperature increases 0.02°C per year. During this period, yields of rice, maize, wheat, sugarcane, potatoes, and pulses all have an increasing trends. The surveys and focus group discussions suggest that farmers achieved these increases using climate change adaptation measures. The measures included using high-yielding varieties of crops, enhanced irrigation systems, switching to hybrid seeds, and increasing pesticide use.

productivity increases in colder parts of the world (Burke, Hsiang, and Miguel 2015; Mendelsohn and Reinsborough 2007). These results for Nepal are consistent with some of the literature (box 3.2). The positive results for Afghanistan and Nepal do not provide a complete picture of climate change effects in these locations, though. For example, other studies that project negative climate change effects for Nepal include a greater emphasis on extremes, including water scarcity and escalating electricity prices (Ahmed and Suphachalasai 2014), which are not captured in this book.

The results for Afghanistan should be viewed with some skepticism because of the low density of meteorological stations for much of the country's history and the associated unknown quality of the spatially aggregated climate data used in this book. In Afghanistan, there are only two stations that report climate observations to the international community. Further, these two stations have significant gaps in their observations and the data quality is not known. These factors have the potential to create spurious statistical results, such as the historical temperature cooling trends evident in chapter 2 (figure 2.3). For these and potentially other reasons, the reduced-form model relating seasonal weather to consumption expenditures in Afghanistan has a much lower predictive ability than the models for other countries examined (appendix B, table B.2).

Dealing with Uncertainty

The three main sources of uncertainty in the findings produced using equation (3.1) are the precision of the empirical model, differences in climate projections between climate models, and unknown future socioeconomic conditions. Empirical modeling errors are represented by the standard error, which is a widely used metric for representing modeling confidence and is standard in the econometrics literature. Another category of model error is epistemic, which relates to deficiencies in the model's ability to capture processes and responses. These errors relate to the caveats discussed in the "Analytical Framework" and "Two Methodological Challenges" sections in this chapter, but are not possible to represent quantitatively. Considering only the

MMM climate scenario, the prediction uncertainty stemming from uncertainty in the empirical model is statistically different from zero for all countries and all future climate projections except Nepal (figure 3.1, panels a through f). This finding is consistent with the results shown in table 3.4.

The robustness of the model predictions is checked by estimating similar empirical models, using different control variables and including provincial fixed effects (see discussion in the "Temperature Inflection Points" section of this chapter). Four alternative control variable specifications are implemented: (a) with "all" control variables; (b) a correlation threshold of 0.7; (c) a correlation threshold of 0.3; and (d) with no control variables. These alternate specifications produce results that are qualitatively similar but with slightly reduced estimates of the effects of weather on consumption (see appendix B, table B.3). Estimations using provincial fixed effects tend to reduce the sensitivity of living standards to changes in average weather. For example, estimates for Pakistan under the carbon-intensive scenario by 2050 change from –2.9 percent to –0.9 percent when provincial fixed effects are included.

There is substantial uncertainty in projecting how the climate, especially precipitation, will respond to atmospheric GHG concentrations (as shown in chapter 2). The main findings in this book are based on the MMM for an ensemble of 11 climate models selected for use in this study. Uncertainty in modeling how the climate will respond to a specific emissions scenario is evaluated using four combinations of climate models:

- Low temperature and low precipitation
- Low temperature and high precipitation
- High temperature and low precipitation
- High temperature and high precipitation

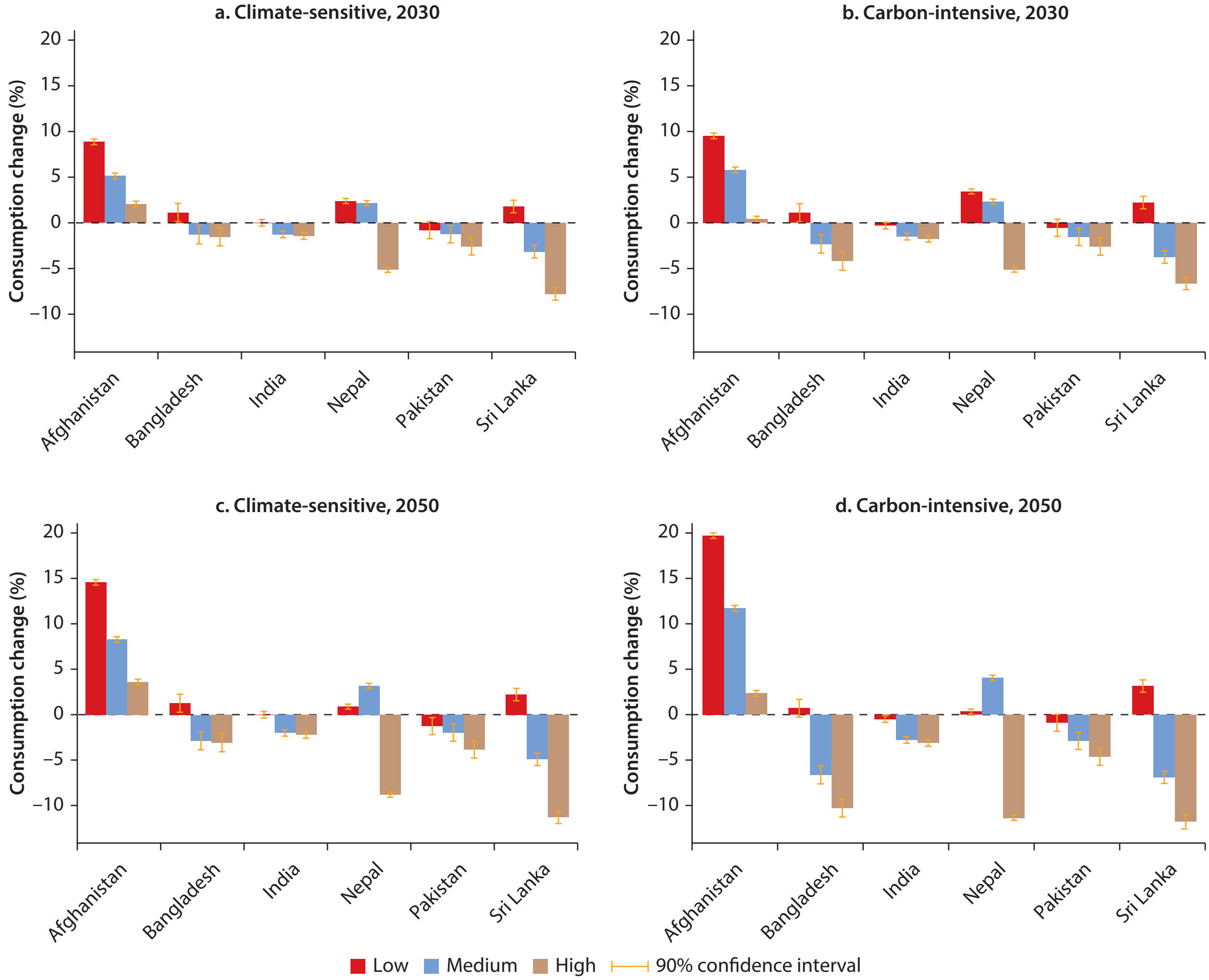
From these four climate uncertainty estimates, the two that represent the highest and lowest effects are chosen to bracket the uncertainty due to climate models. This is an overrepresentation of the climate modeling uncertainty because it is based on 100 percent confidence intervals, which could include outliers.

Uncertainty regarding which emissions trajectory will manifest is represented through providing results for both the climate-sensitive and carbon-intensive scenarios. Highlighting this cause of uncertainty provides perspective on the ability of the global community to impact future well-being.

The climate model and econometric estimation uncertainties add nuance to the main empirical findings (figure 3.2). For example, under the climate-sensitive scenario, the modeling uncertainties include the possibility that effects in 2030 will be positive for all six countries (figure 3.1, panels a through f). The magnitude of these positive effects decreases for all countries except Nepal from 2030 to 2050 and from the climate-sensitive to carbon-intensive scenarios. Most of the positive living standards responses in figure 3.2 correspond to model predictions using the high precipitation ensemble member. Given that climate model projections of precipitation are highly uncertain (figure 2.3), this highlights a challenge in using climate models to make predictions about relationships involving precipitation, and an area in which more research is needed to fundamentally improve climate model simulations.

One could argue that the main findings are not valid because of the possibility that a climate projection estimate exists for which the effects would be positive. This view would be shortsighted because it ignores the equally likely possibility that effects will be very strong and negative (the "high" case in figure 3.2, panels a through d). For example, under the high case, which generally corresponds to model predictions using the high temperature and low precipitation ensemble members, average weather impacts on consumption expenditures would be approximately –11 percent for Bangladesh, –13 percent for Nepal, and –12 percent for Sri Lanka. These results are much worse than the MMM results. Furthermore, it is well accepted that MMM scenarios are more likely than any of the climate model end member projections (that is, high or low in figure 3.2). Therefore, the living standards effects based on the MMM climate projections are also the most likely.

FIGURE 3.2 Uncertainties of the Predicted Consumption Changes Arise from Differences between Climate Models and Economic Modeling



Source: World Bank calculations.
Note: The "medium" bar refers to results based on the MMM climate model projection. "High" and "low" depict uncertainty based on choice of climate model. Confidence intervals indicate econometric model uncertainty estimated using a robust standard error formulation.

Notes

1. There is an argument that consumption expenditures exclude consumption that is not based on market transactions. But given the difficulties associated with collecting information on these nonmarket values, consumption expenditures are often used as a best proxy for household living standards.
2. For example, CRU TS data are used to assess the historic performance of climate models in many studies referenced in the Intergovernmental Panel on Climate Change's *Fifth Assessment Report* (IPCC 2013).
3. Omitted variable bias is the effect on model prediction of not including a characteristic that explains significant differentiation between samples in a data set.

4. Some effects of high temperatures or levels of precipitation may have been captured if the years of survey have such temperature or precipitation. But the surveys are usually selected to take place outside such periods, so the extent to which they are covered is limited.

References

Acharya, S. P., and G. R. Bhatta. 2013. "Impact of Climate Change on Agricultural Growth in Nepal." NRB Working Paper 15, Research Department, Nepal Rastra Bank, Kathmandu.

Ahmed, M., and S. Suphachalasai. 2014. "Assessing the Costs of Climate Change and Adaptation in South Asia." Asian Development Bank, Mandaluyong City, Philippines.

Atkinson, A. 1987. "On the Measurement of Poverty." *Econometrica* 55: 749–64.

Angrist, J. D., and J. S. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Auffhammer, M., and W. Schlenker. 2014. "Empirical Studies on Agricultural Impacts and Adaptation." *Energy Economics* 46: 555–61.

Booth, G. D., M. J. Niccolucci, and E. G. Schuster. 1994. "Identifying Proxy Sets in Multiple Linear Regression: An Aid to Better Coefficient Interpretation." US Department of Agriculture, Forest Service, Intermountain Research Station, Ogden, UT.

Brown, C., R. Meeks, Y. Ghile, and K. Hunu. 2013. "Is Water Security Necessary? An Empirical Analysis of the Effects of Climate Hazards on National-Level Economic Growth." *Philosophical Transactions of the Royal Society* 371: 1–19.

Burke, M., S. M. Hsiang, and E. Miguel. 2015. "Global Non-Linear Effect of Temperature on Economic Production." *Nature* 527 (7577): 235–39.

Chatterjee, U., R. Murgai, A. Narayan, and M. Rama. 2016. *Pathways to Reducing Poverty and Sharing Prosperity in India*. Washington, DC: World Bank.

DARA. 2012. "Climate Vulnerability Monitor (2nd edition): A Guide to the Cold Calculus of a Hot Planet." DARA. http://daraint.org/climate-vulnerability-monitor/climate-vulnerability-monitor-2012/data.

Deaton, A. 2005. "Measuring Poverty in a Growing World (or Measuring Growth in a Poor World)." *Review of Economics and Statistics* 87 (1): 1–19.

Deaton, A., and M. Grosh. 2000. *Designing Household Survey Questionnaires for Developing Countries: Lessons from Ten Years of LSMS Experience*. Washington, DC: World Bank.

Dell, M., B. F. Jones, and B. A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4 (3): 66–95.

Demombynes, G., C. Elbers, J. Lanjouw, P. Lanjouw, J. Mistiaen, and B. Özler. 2002. "Producing an Improved Geographic Profile of Poverty: Methodology and Evidence from Three Developing Countries." WIDER Discussion Paper 2002/39, UNU-WIDER Helsinki.

Deschenes, Olivier. 2014. "Temperature, Human Health, and Adaptation: A Review of the Empirical Literature." *Energy Economics* 46: 606–19.

Dhakal, S., G. K. Sedhain, and S. C. Dhakal. 2016. "Climate Change Impact and Adaptation Practices in Agriculture: A Case Study of Rautahat District, Nepal." *Climate* 4 (4): 63.

Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J. R. G. Márquez, B. Gruber, B. Lafourcade, P. J. Leitão, T. Münkemüller, C. McClean, P. E. Osborne, B. Reineking, B. Schröder, A. K. Skidmore, D. Zurell, and S. Lautenbach. 2013. "Collinearity: A Review of Methods to Deal with It and a Simulation Study Evaluating Their Performance." *Ecography* 36 (1): 27–46.

Elbers, C., J. O. Lanjouw, and P. Lanjouw. 2003. "Micro-Level Estimation of Poverty and Inequality." *Econometrica* 71 (1): 355–64.

Elith, J., C. H. Graham, R. P. Anderson, M. Dudík, S. Ferrier, A. Guisan, R. J. Hijmans, F. Huettmann, J. R. Leathwick, A. Lehmann, J. Li, L. G. Lohmann, B. A. Loiselle, G. Manion, C. Moritz, M. Nakamura, Y. Nakazawa, J. M. Overton, A. T. Peterson, S. J. Phillips, K. Richardson, R. Scachetti-Pereira, R. E. Schapire, J. Soberón, S. Williams, M. S. Wisz, and N. Zimmermann. 2006. "Novel Methods Improve Prediction of Species' Distributions from Occurrence Data." *Ecography* 29: 129–51.

Hallegatte, S., M. Fay, M. Bangalore, T. Kane, and L. Bonzanigo. 2016. *Shock Waves: Managing the Impacts of Climate Change on Poverty*. Washington, DC: World Bank.

Hallegatte, S., C. Green, R. J. Nicholls, and J. Corfee-Morlot. 2013. "Future Flood Losses in Major Coastal Cities." *Nature Climate Change* 3 (9): 802–6.

Hallegatte, S., A. Vogt-Schilb, M. Bangalore, and J. Rozenberg. 2017. *Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters*. Washington, DC: World Bank.

Harris, I. P. D. J., P. D. Jones, T. J. Osborn, and D. H. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations—The CRU TS3.10 Dataset." *International Journal of Climatology* 34 (3): 623–42.

Haughton. J., and S. Khandker. 2009. *Handbook on Poverty and Inequality.* Washington, DC: World Bank.

Heal, G., and J. Park. 2015. "Goldilocks Economies? Temperature Stress and the Direct Impacts of Climate Change." NBER Working Paper 21119, National Bureau of Economic Research, Cambridge, MA.

Hsiang, S. M., and A. S. Jina. 2014. "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones." NBER Working Paper 20352, National Bureau of Economic Research, Cambridge, MA.

IPCC (Intergovernmental Panel on Climate Change). 2013. *Climate Change 2013: The Physical Science Basis—Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press.

Jacoby, H. G., M. Rabassa, and E. Skoufias. 2011. "Distributional Implications of Climate Change in India." Policy Research Working Paper 5623, World Bank, Washington, DC.

Joshi, N. P., M. K. Lall, and P. Luni. 2011. "Effect of Climate Variables on Yield of Major Food-Crops in Nepal—A Time-Series Analysis." *Journal of Contemporary India Studies: Space and Society* 1: 19–26.

Li, Y., and M. Rama. 2016. "Households or Locations? Cities, Catchment Areas and Prosperity in India." Policy Research Working Paper 7473, World Bank, Washington, DC.

Mani, M., and L. Wang. 2014. "Climate Change and Health Impacts: How Vulnerable Is Bangladesh and What Needs to Be Done." World Bank, Washington, DC.

Massetti, E., R. Mendelsohn, and S. Chonabayashi. 2016. "How Well Do Degree Days over the Growing Season Capture the Effect of Climate on Farmland Values?" *Energy Economics* 60: 144–50.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review* 84 (4): 753–71.

Mendelsohn, R., and M. Reinsborough. 2007. "A Ricardian Analysis of US and Canadian Farmland." *Climate Change* 81: 9–17.

Moore, F. C., and D. B. Diaz. 2015. "Temperature Impacts on Economic Growth Warrant Stringent Mitigation Policy." *Nature Climate Change* 5: 127–31.

OECD (Organisation for Economic Co-operation and Development). 2015. *The Economic Consequences of Climate Change*. Paris: OECD.

Poudel, S., and R. Shaw. 2016. "The Relationships between Climate Variability and Crop Yield in a Mountainous Environment: A Case Study in Lamjung District, Nepal." *Climate* 4 (13).

Schlenker, W., and M. J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences* 106 (37): 15594–8.

Skoufias, E., R. S. Katayama, and B. Essama-Nssah. 2012. "Too Little Too Late: Welfare Impacts of Rainfall Shocks in Rural Indonesia." *Bulletin of Indonesian Economic Studies* 48 (3): 351–68.

Suzuki, N., D. H. Olson, and E. C. Reilly. 2008. "Developing Landscape Habitat Models for Rare Amphibians with Small Geographic Ranges: A Case Study of Siskiyou Mountains Salamanders in the Western USA." *Biodiversity and Conservation* 17 (9): 2197–218.

Tabachnick, B. G., and L. S. Fidell. 1996. *Using Multivariate Statistics*. New York: HarperCollins.

WHO (World Health Organization). 2015. *Quantitative Risk Assessment of the Potential Effects of Climate Change on Health*. Geneva: WHO.

Mapping Hotspots 4

Although climate change is occurring throughout South Asia (chapter 2), the effects of these changes are expected to be heterogeneous. For example, long-term temperature increases are predicted to have a positive effect on household living standards in Nepal, even though the aggregate effects will be negative for Bangladesh, India, Pakistan, and Sri Lanka (chapter 3). The effects of changes in average weather–long-term average seasonal temperature and precipitation–on household living standards also vary by household and location within countries, resulting in some hotspots—that is, locations predicted to be negatively affected by changes in average weather. As a result, understanding the granularity—the spatial locations and distributions—of climate impacts on living standards is necessary to understand the challenges faced in these locations and to design appropriate interventions.

What Is a Hotspot?

In this book, a *hotspot* is defined as a location where changes in average weather will have a negative effect on living standards (the model is described in chapter 3). The model linking changes in average weather and living standards is implemented at the household level. These results are then aggregated at the district, province, or national levels to determine aggregate effects. The use of the term *hotspot* predominantly refers to the impact of changes in average weather aggregated to the district level in each of the six countries for which survey data are available. To qualify the magnitude of a hotspot, the predicted changes in living standards are calculated in per capita percentage terms and defined in three hotspot levels: mild, moderate, and severe (see definitions in table 4.1).

South Asian megacities such as Chennai, Dhaka, Karachi, Kolkata, and Mumbai are often identified as being climate hotspots or vulnerable to extreme events and sea-level rise, including coastal flooding and storm surges. The hotspots defined in this book only account for changes in average weather and therefore are complementary to locations categorized as hotspots as a result of the effects of extreme events and sea-level rise.

Hotspots are the result of two interrelated factors: (a) the magnitude and seasonality of climate change; and (b) the relationship between climate and living standards at a given location. Since the model used to predict hotspots is unique for each country in

TABLE 4.1 Hotspot Labels and Definitions

Hotspot label	Definition
Severe	Living standards decline of more than 8 percent
Moderate	Living standards decline of 4 percent to 8 percent
Mild	Living standards decline of 0 percent to 4 percent

Note: Hotspots are locations where living standards are negatively affected by changes in average weather.

South Asia, the relationship between changes in average weather and living standards varies between countries. This means that the model implicitly captures the effects of differences in policies or regulations between countries as well as some degree of inherent adaptive capability by households and communities to changes in average weather.

Identifying hotspots is not as simple as identifying the regions where changes in average weather are projected to be the largest. Even if climate were to change by similar magnitudes in two locations, the response (including whether the locations become hotspots) depends on the historic relationship between climate and living standards at the two locations. For example, if two countries are identical except that one relies more heavily on agriculture for household income, the magnitude of the coefficients for climate variables during the growing season(s) are expected to be larger in the agriculture-heavy country, all other factors held equal. Therefore, the emergence of hotspots should vary relatively smoothly within a given country, but may include discontinuities across borders of different countries.

The Carbon-Intensive Scenario Leads to More Severe Hotspots

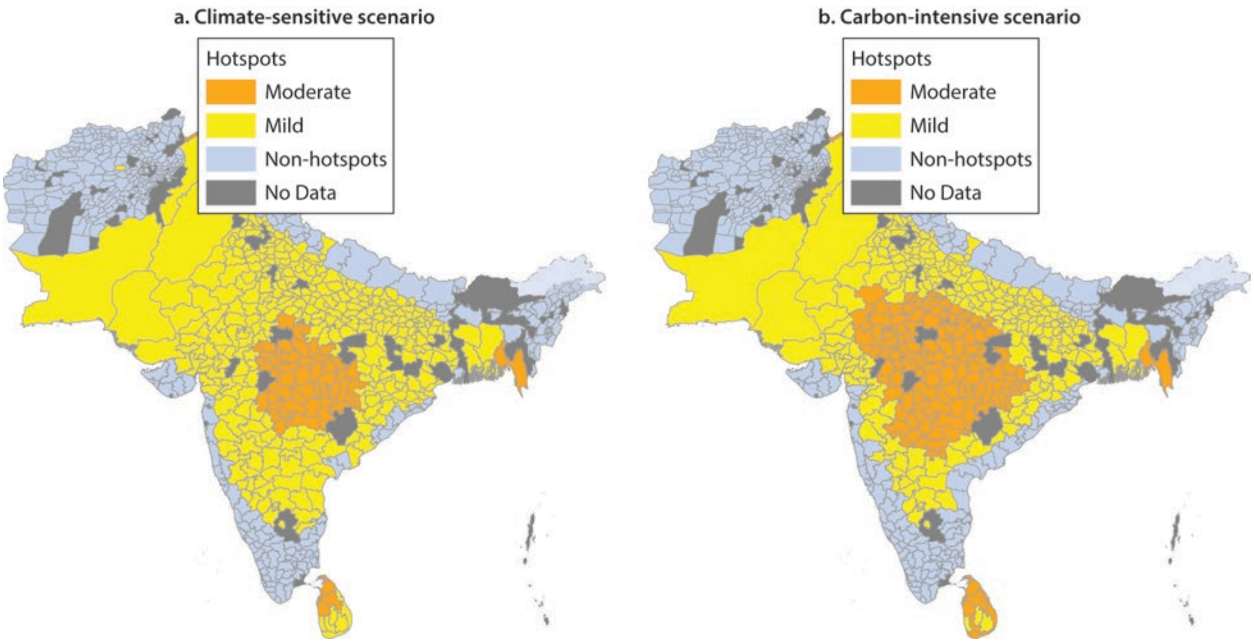
The precise effects of changes in average weather on living standards vary depending on the climate change scenario, model, and time frame. However, a general theme is that the larger the magnitude of climate changes—either from looking further into the future or a more extreme scenario—the higher the number and greater the severity of hotspots (maps 4.1, panels a and b, and 4.2). This indicates that efforts to decrease the development of hotspots—for example, through global mitigation of climate change or location-specific hotspot interventions—can positively affect living standards throughout the region.

Even by 2030 most locations in South Asia are predicted to become mild or moderate hotspots (map 4.1). The overall picture of the region is that of concentric rings, with the outer ring (the coastal areas of India and districts in the mountains along the northern border of South Asia) not emerging as hotspots, whereas the areas closer to the center of India are more affected. In a broad sense, therefore, low-lying inland areas appear to be more fragile to changes in average weather than regions along the coast or in the mountains, where the historic climate is relatively cold. However, coastal areas are susceptible to rising oceans, stronger storms, and other climate-related effects (see box 4.1 for a further exploration of these issues). The pattern of hotspots does not appear to correspond significantly to major river basins in a manner not explained by differences between countries (appendix C, maps C.7 and C.8).

The predictions for 2030 are very similar between the climate-sensitive and carbon-intensive scenarios (map 4.1, panels a and b). The reason for the similarity is that the cumulative emission differences of the climate-sensitive and carbon-intensive scenarios take time to accumulate and result in different magnitudes of climate change. The climate change scenarios diverge around 2050, with effects beginning to level off under the climate-sensitive scenario (IPCC 2013). Under the carbon-intensive scenario, climate changes continue accruing through the end of the century.

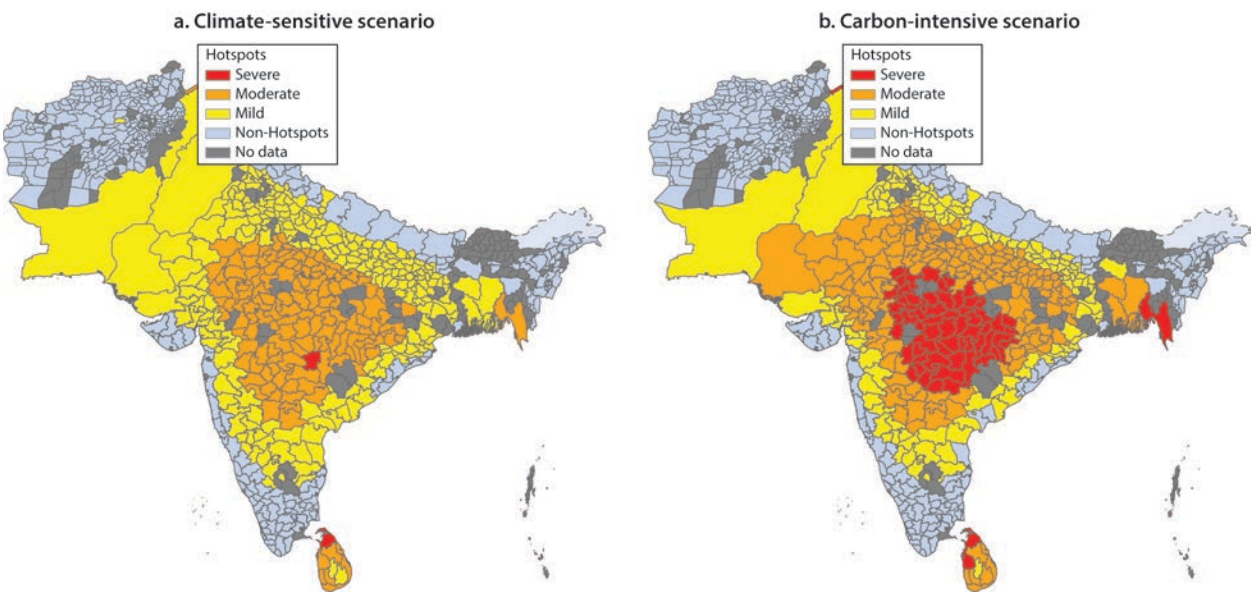
By 2050, many severe hotspots emerge under the carbon-intensive scenario, while the climate-sensitive scenario primarily contains moderate hotspots (map 4.2, panels a and b). Under the carbon-intensive scenario,

MAP 4.1 Mild and Moderate Hotspots Are Prevalent Throughout South Asia by 2030



Source: World Bank calculations.
Note: These results are based on the mean of the 11 climate model ensemble used in this book.

MAP 4.2 Moderate and Severe Hotspots Cover a Significant Portion of South Asia by 2050



Source: World Bank calculations.
Note: Achieving the climate-sensitive scenario (panel a) would mostly prevent the emergence of severe hotspots through 2050, compared to the carbon-intensive scenario (panel b). These results are based on the mean of the 11 climate models used in this book. Grey areas are those where insufficient data are available.

BOX 4.1 Will Mountain and Coastal Areas Benefit from Climate Change?

The hotspots analyses conducted in this book predict that many mountains and coastal areas will not be negatively affected by changes in average weather. This is not the same as finding that these areas will benefit overall from climate change. For example, the predictions do not account for specific aspects of climate change that will have negative effects. The following is a breakdown of general negative dimensions of climate change that are not accounted for in the analysis.

Mountain Areas

Climate change will likely affect the frequency of natural disasters in mountain areas (Chen and others 2010; Keiler, Knight, and Harrison 2010; Stoffel and Huggel 2012). This includes increasing the likelihood of events such as landslides and glacier lake outburst floods. Such events can have devastating effects, such as—in extreme instances—destroying entire villages.

Climate change will have devastating effects on biodiversity in mountain areas (Bellard and others 2012; Chakraborty and Newton 2011; Siraj and others 2014; Xu and others 2009). This means that the natural ecosystems that people in mountains are accustomed to will potentially change more rapidly than communities and lifestyles are able to adapt. For example, certain pests and disease vector organisms will flourish, causing a negative effect on agriculture.

Climate change will affect the timing and stability of snow and glacier melt (Immerzeel, Van Beek, and Bierkens 2010; Miller, Immerzeel, and Rees 2012; Xu and others 2009). These changes will affect all communities that rely on freshwater resources originating in mountain headwaters. The effects, however, will be strongest in and around the mountains. In mountain communities where all water resources come from melting snow and glaciers, the effects could be devastating to personal well-being and agriculture.

Coastal Areas

Climate change is leading to rising sea levels (Asuncion and Lee 2017; Hallegatte and others 2013; Nicholls and others 2007). This is an existential threat to several coastal areas in South Asia, including all of the Maldives, significant portions of Bangladesh, and selected regions of coastal India. Rising sea levels can submerge certain areas and worsen storm surges, leading to more flooding during extreme weather events.

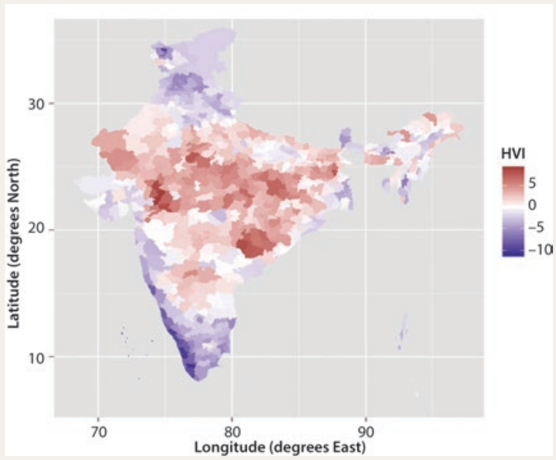
Climate change will likely increase the severity of tropical storms, which will increase damages in affected coastal areas (Mendelsohn and others 2012). Because of the large natural variability of extreme storm events, no conclusive statistical evidence exists indicating that they will become more frequent in the future. However, there is a good physical basis for predicting that storm events will at least become stronger, if not more frequent. The main reason is that sea surface temperatures are warming. Warmer oceans mean there is more energy available to fuel storms once they materialize. Cities in coastal areas are also rapidly growing around the world. This increases potential economic damage from a storm event of a given magnitude, since there is simply more property in the storm's path.

moderate and severe hotspots are predominantly in central India, northern Sri Lanka, and southeastern Bangladesh. The overall pattern of hotspots predicted for 2050 under both scenarios is similar to that for 2030, with inland areas predicted to be more affected than coastal or mountain areas. The spatial pattern of these hotspots predictions is very similar to the recent estimate of heat vulnerability in India (box 4.2).

BOX 4.2 Heat Vulnerability Index for India

High heat vulnerability index districts are those for which a larger portion of individuals experience heat-related medical incidents. Interestingly, districts with high heat vulnerabilities are not necessarily those with the highest temperatures (map B4.2.1 compared to map 2.1). One reason for this is that people have the capacity to adapt to changes in their environment, and this capacity is a by-product of their environment. Therefore, the most vulnerable are those with low adaptive capacities and sufficient temperatures to trigger a health problem. Azhar and others (2017) also find that districts with high heat vulnerability index values are less urbanized, have lower literacy rates, have less access to water and sanitation, and have fewer household amenities.

MAP B4.2.1 Central India Is the Most Vulnerable to Heat



Source: Azhar and others 2017.
Note: Larger values indicate high vulnerability.

Mountainous regions do not emerge as hotspots under this analysis because these regions are the coldest; therefore, some degree of warming may be beneficial for them. That does not mean that climate change will always have positive effects in these zones (see box 4.1). For example, the economies of these mountain regions rely extensively on streamflow from snow and glaciers. Warming will affect the timing and availability of these water resources, which could have profound effects (Bolch and others 2012; Immerzeel, Van Beek, and Bierkens 2010). In addition, mountain regions are often highly vulnerable to natural disasters.

Although the conditions leading to hotspots vary within countries and across the region, the estimated effects are unambiguous: approximately 800 million people in South Asia today live in locations that could become moderate or severe hotspots by 2050 under the carbon-intensive scenario (table 4.2). This is equivalent to 45 percent of the region's population. Under the climate-sensitive scenario, the number of people affected is 375 million—or 21 percent of the population. These numbers do not account for Bhutan or the Maldives, which will also be affected by climate change. The solutions will vary based on the location and country contexts, but clearly this is a challenge that must be addressed.

Hotspots Tend to Have Less Infrastructure and Services

Hotspots tend to have less infrastructure and worse integration with the broader society (table 4.3, appendix C, maps C.1 through C.6). For example, the average household residing in a severe hotspot by 2050 under the carbon-intensive scenario has an average road density of 1.5 kilometers (per 10 square kilometers of area) compared with the overall density of 2.1 kilometers of road.

TABLE 4.2 Millions of South Asians Are Living in Areas Projected to Become Hotspots

Hotspot category	Afghanistan	Bangladesh	India	Nepal	Pakistan	Sri Lanka	South Asia
Severe	0.0	26.4	148.3	0.0	0.0	3.6	178.4
Moderate	0.0	107.9	440.9	0.0	48.7	14.9	612.4
Mild	0.0	20.4	399.9	0.0	144.5	2.6	567.4
Total population	34.7	163.0	1,324.2	29.0	193.2	21.2	1,765.2

Sources: World Bank calculations based on WDI (population data); World Bank 2016.
Note: Estimates are based upon the carbon-intensive scenario by 2050. Data show that around 800 million people live in moderate or severe hotspots.

TABLE 4.3 Locational Characteristics, by Hotspot Category

Country	Hotspot category / overall	Households (%)	Living standards change (%)	Average road density (km/10 km^2)	Average population (per km^2)	Travel time to market (hours)
Afghanistan	Severe	0.1	−10.4	0.0	1.0	36.3
Afghanistan	Moderate	n.a.	n.a.	n.a.	n.a.	n.a.
Afghanistan	Mild	n.a.	n.a.	n.a.	n.a.	n.a.
Afghanistan	Overall	100.0	11.9	2.9	951.6	5.2
Bangladesh	Severe	16.2	−14.4	6.1	1,043.1	2.2
Bangladesh	Moderate	66.2	−6.4	6.1	1,539.1	1.9
Bangladesh	Mild	12.5	−1.5	4.4	795.7	1.7
Bangladesh	Overall	100.0	−6.7	5.8	1,320.6	2.0
India	Severe	11.2	−9.8	0.8	231.3	2.7
India	Moderate	33.3	−5.6	1.7	1,005.8	2.1
India	Mild	30.2	−2.3	1.6	1,119.1	2.7
India	Overall	100.0	−2.8	1.6	840.7	2.7
Pakistan	Moderate	25.2	−4.6	0.7	205.1	3.1
Pakistan	Mild	74.8	−2.4	1.6	448.4	3.7
Pakistan	Overall	100.0	−2.9	1.4	387.0	3.6
Sri Lanka	Severe	17.2	−10.5	10.4	254.6	2.6
Sri Lanka	Moderate	70.3	−7.1	13.2	865.8	2.5
Sri Lanka	Mild	12.4	−4.0	19.5	451.7	2.6
Sri Lanka	Overall	100.0	−7.0	13.5	708.9	2.6
South Asia	Severe	11.6	−10.2	1.6	335.6	3.3
South Asia	Moderate	32.6	−5.6	2.1	987.1	2.1
South Asia	Mild	32.9	−2.3	2.2	990.2	2.9
South Asia	Overall	100.0	−3.2	2.1	831.3	2.8

Source: World Bank calculations.
Note: Under the carbon-intensive scenario in 2050. n.a. = not applicable.

Severe hotspots are also less densely populated than average (319 people per square kilometer for hotspots, compared with 829 people per square kilometer overall). Moreover, these population, infrastructure, and integration differences hold for Bangladesh, India, Pakistan, and Sri Lanka individually. In India and Pakistan, water-stressed areas will also be more adversely affected compared with the national average. Travel time to market is not related in any clear way to the severity of hotspots. Although this is based on observing the correlation and not attributing any causality, one could potentially look more deeply at other social and economic characteristics of these hotspots to see whether better services and infrastructures would reduce the effect of climate change on living standards.

The Most Vulnerable Households

Changes in average weather will affect households to different degrees. Although the hotspot analysis investigates the overall relationship between household living standards and changes in average weather throughout the region, understanding the characteristics of vulnerable households can be informative for developing targeted policies. The results discussed in this section are for 2050 hotspots predictions under the carbon-intensive scenario.

Taking all households in South Asia together, those that are most affected by changes in average weather are less likely to be headed by a woman (table 4.4). This result appears to be driven mainly by India (7.4 percent headed by a woman in severe hotspots, compared with 10.8 percent overall) and Pakistan (2.1 percent in severe hotspots, compared with 10.2 percent overall). In Bangladesh, the households that will be the most affected are more likely to be headed by a woman (9.9 percent, compared with 7.6 percent), whereas the likelihood is approximately equal in Nepal and Sri Lanka. This needs further analysis, but could occur because female-headed households find it harder to survive and move out of severely affected areas.

In all countries except Bangladesh, the households most affected by changes in average weather are more likely to be engaged in agriculture as their main livelihood (table 4.4). This is particularly important to note because agriculture will be affected by climate change in multiple ways not accounted for by the analysis. For example, higher temperatures increase the likelihood of droughts, which can have devastating effects on crops, yet these types of events are not fully captured in the methodology.

The relationship between hotspots and agriculture varies between countries. For South Asia as a whole, the heads of 46.9 percent of the households in severe hotspots derive their primary income from agriculture, compared

TABLE 4.4 Characteristics of the Most Affected Households Compared with National Averages

Country	Severe / overall	Living standards change (%)	Female-headed household (%)	Agriculture head (%)	Education of head of household (years)	Electricity (%)
Afghanistan	Severe	−10.4	0.0	70.0	2.7	0.0
Afghanistan	Overall	11.9	0.7	31.2	3.2	27.0
Bangladesh	Severe	−12.9	8.2	27.4	4.2	60.3
Bangladesh	Overall	−6.7	7.6	39.1	3.9	54.9
India	Severe	−9.8	7.4	51.0	5.7	91.3
India	Overall	−2.8	10.8	39.8	5.7	79.8
Nepal	Severe	n.a.	n.a.	n.a.	n.a.	n.a.
Nepal	Overall	4.1	26.7	52.6	3.8	70.0
Pakistan	Severe	n.a.	n.a.	n.a.	n.a.	n.a.
Pakistan	Overall	−2.9	10.2	24.0	5.3	13.6
Sri Lanka	Severe	−9.7	22.9	26.1	8.5	88.2
Sri Lanka	Overall	−7.0	22.5	28.6	8.3	90.6
South Asia	Severe	−10.2	7.6	48.6	5.5	86.1
South Asia	Overall	−3.2	10.7	38.0	5.4	69.6

Source: World Bank calculations.
Note: Under the carbon-intensive scenario in 2050. n.a. = not applicable.

with 38.1 percent overall (table 4.4). This pattern exists in India, Nepal, Pakistan, and Sri Lanka, whereas the reverse pattern is seen in Bangladesh. Because this is based on observed correlation, one cannot attribute any causality between the socioeconomic characteristics of households and climate vulnerability. However, one can safely say that climate adds another dimension to the existing vulnerability of households living in hotspots.

Country Hotspots

A strength of this hotspot analysis is being able to explain the spatial dimensions of changes in average weather effects on living standards throughout South Asia. This section lists the most affected states or provinces and districts for Afghanistan, Bangladesh, India, Nepal, Pakistan, and Sri Lanka, and describes some of the relevant country context.

County context matters in terms of the development of hotspots (maps 4.1, panels and b, and 4.2). For example, Ramanathapuram District in India and Jaffna District in Sri Lanka are separated by only about 100 kilometers, meaning that their climates are relatively similar. Yet Ramanathapuram does not emerge as a hotspot, whereas Jaffna emerges as a moderate to severe hotspot (depending on the time horizon and climate change scenario). Given that the underlying regression model is empirical, the modeled relationship implicitly reflects the aggregate differences in how climate affects household living standards in the two countries.

Bangladesh

In Bangladesh, Chittagong Division emerges as the most vulnerable to changes in average weather, followed by Barisal and Dhaka divisions (table 4.5). Chittagong is relatively more developed in terms of infrastructure compared with the national average and is characterized by fewer households in which the head of the household is engaged in agriculture. It is relatively densely populated, with a greater number of female-headed households compared with the national average. Seven of the 10 top hotspot districts are in Chittagong Division, with Cox's Bazar predicted to experience the largest negative effects (table 4.6).

Although low-lying coastal areas in Chittagong have received a lot of attention in Bangladesh due to weather events, hill tracts in Chittagong also emerge as vulnerable to changes in average weather. Over the years, the hill tracts have become hotspots for outbreaks of vector-borne diseases. In addition, deforestation and hill-cutting have affected the hill slopes considerably, resulting recently in major landslides and destruction of property. Cox's Bazar has gone through a major environmental upheaval in recent years and is now also embroiled in a social crisis due to the influx of Rohingya refugees from neighboring Myanmar. Chittagong city, which emerges as the third-most-vulnerable city in Bangladesh, is also the second-largest city in the country. It is the busiest seaport in the region and a major economic hub, attracting strong inflows of foreign investment to produce apparel, decommission ships, and refine oil. Going forward, climate vulnerability will have huge economic implications for the growing city.

India

States in the central, northern, and northwestern parts of India emerge as the most vulnerable to changes in average weather. Chhattisgarh and Madhya Pradesh, which are predicted to experience a decline in living standards of more than 9 percent, are the top two hotspot states, followed by Rajasthan, Uttar Pradesh, and Maharashtra (table 4.7). In addition to being poverty hotspots, Chhattisgarh and Madhya Pradesh are home to large tribal populations. Coastal areas in India receive a lot of attention due to extreme storms and flooding. However, here the inland areas emerge as hotspots due to changes in average weather.

Seven out of the top 10 most affected hotspot districts belong to the Vidarbha region of Maharashtra State, with

TABLE 4.5 Predicted Change in Living Standards and Characteristics of Divisions in Bangladesh

Division	Share of households(%)	Living standards change (%)	Average length of road in km/10 km^2	Average population density per km^2	Travel time to market (hours)	Water availability	Female-headed household (%)	Agriculture head (%)	Years of education	Electricity (%)
Chittagong	16.2	−14.4	6.1	1,043.1	2.2	31.3	10.0	34.4	4.2	58.5
Barisal	6.0	−7.4	8.5	680.6	4.1	34.4	6.4	31.8	4.1	39.4
Dhaka	32.9	−6.9	7.1	2,330.9	1.5	0.4	6.9	29.0	4.3	67.5
Khulna	13.1	−6.7	3.7	686.0	2.3	0.7	6.1	44.7	3.9	54.8
Rajshahi	14.2	−4.6	5.2	851.9	1.6	1.9	7.1	53.0	3.4	52.7
Rangpur	12.5	−1.5	4.4	795.7	1.7	1.0	7.0	54.8	3.7	30.7
Sylhet	5.1	0.8	4.4	645.7	2.5	3.5	12.6	36.1	2.9	44.9
Overall	100.0	−6.7	5.8	1,320.6	2.0	7.9	7.6	39.1	3.9	54.9

Source: World Bank calculations.
Note: Under the carbon-intensive scenario in 2050.

TABLE 4.6 Predicted Change in Living Standards and Characteristics of the Top 10 District Hotspots in Bangladesh

District	Division	Share of households (%)	Living standards change (%)	Average length of road in km/10 km^2	Average population density per km^2	Travel time to market (hours)	Water availability	Female-headed household (%)	Agriculture head (%)	Years of education	Electricity (%)
Cox's Bazar	Chittagong	0.9	−20.2	8.3	812.9	2.7	5.8	7.6	43.5	2.6	25.9
Bandarban	Chittagong	1.1	−18.4	1.9	73.6	4.5	3.4	8.5	55.4	2.8	39.0
Chittagoun	Chittagong	4.8	−18.1	6.7	1,395.4	1.6	55.5	10.7	14.7	5.9	79.3
Rangamati	Chittagong	1.1	−15.8	1.3	91.9	3.6	1.9	10.7	54.8	4.0	29.1
Noakhali	Chittagong	1.3	−14.8	4.9	926.4	2.3	62.0	6.9	38.9	3.7	44.9
Feni	Chittagong	0.8	−13.5	8.0	1,312.6	1.5	3.1	9.4	33.8	4.8	72.0
Khagrachhari	Chittagong	1.0	−12.6	6.0	190.3	3.2	2.1	7.2	42.6	3.4	43.3
Barguna	Barisal	0.9	−12.5	4.3	524.3	5.7	0.9	5.8	30.2	4.3	22.6
Bagerhat	Khulna	1.1	−12.0	3.2	368.1	3.6	1.2	5.6	35.2	4.5	36.8
Satkhira	Khulna	1.3	−11.5	2.7	490.3	3.1	1.9	5.4	42.9	4.6	41.4
Overall		100.0	−6.7	5.8	1,320.6	2.0	7.9	7.6	39.1	3.9	54.9

Source: World Bank calculations.
Note: Under the carbon-intensive scenario in 2050.

TABLE 4.7 Predicted Change in Living Standards and Characteristics of the 10 Most Affected States in India

State	Share of households	Living standards change (%)	Average length of road in km/10 km^2	Average population density per km^2	Travel time to market (hours)	Water availability	Female-headed household (%)	Agriculture head (%)	Years of education	Electricity (%)
Chhattisgarh	2.1	−9.4	1.0	212.7	2.9	0.3	6.3	60.7	5.5	89.5
Madhya pradesh	5.7	−9.1	1.0	237.0	2.6	0.4	6.0	48.5	5.4	88.4
Rajasthan	5.9	−6.4	0.7	229.4	2.6	0.1	9.4	36.8	4.8	82.7
Uttar Pradesh	15.8	−4.9	1.4	801.3	1.9	0.9	10.5	42.9	5.1	51.7
Maharashtra	10.0	−4.6	1.0	325.6	2.7	0.4	9.4	40.3	7.1	94.2
Jharkhand	2.0	−4.6	1.6	482.4	2.0	3.5	8.2	30.6	5.2	74.3
Haryana	2.1	−4.3	2.3	480.5	2.6	0.2	7.4	36.2	6.6	96.6
Andhra Pradesh	10.2	−3.4	2.1	1,831.3	2.6	2.3	14.3	41.2	5.2	98.2
Punjab	1.8	−3.3	2.1	464.6	3.5	0.2	12.4	23.5	5.7	98.6
Chandigarh	0.1	−3.3	5.1	4,529.6	1.5	0.1	6.2	0.2	8.9	97.9
Overall	100.0	−2.8	1.6	840.7	2.7	2.0	10.8	39.8	5.7	79.8

Source: World Bank calculations.
Note: Under the carbon-intensive scenario in 2050.

TABLE 4.8 Predicted Change in Living Standards and Characteristics of the Top 10 District Hotspots in India

District	State	Share of household(%)	Living standards change (%)	Average length of road in km/10 km^2	Average population density per km^2	Travel time to market (bours)	Water availability	Female-headed household (%)	Agriculture head (%)	Years of education	Electricity (%)
Chandrapur	Maharashtra	0.2	−12.4	1.2	161.6	1.7	3.1	8.7	50.6	6.8	84.6
Bhandara	Maharashtra	0.1	−11.9	0.8	219.7	2.5	0.3	5.3	51.9	7.2	93.1
Gondiya	Maharashtra	0.1	−11.8	0.8	215.9	2.5	0.2	9.5	51.2	7.0	96.6
Wardha	Maharashtra	0.1	−11.8	0.5	172.0	2.6	0.1	9.8	53.1	8.3	93.6
Nagpur	Maharashtra	0.5	−11.7	0.2	379.9	2.3	0.1	7.7	17.7	8.8	97.2
Raj Nandagaon	Chhattisgarh	0.1	−11.4	1.5	153.0	3.8	0.1	1.8	59.2	4.4	98.0
Durg	Chhattisgarh	0.3	−11.4	0.5	314.4	2.3	0.2	10.6	43.7	7.1	94.3
Hoshangabad	Madhya Pradesh	0.1	−11.3	1.3	144.1	3.6	0.6	0.2	40.0	5.8	91.2
Yavatmal	Maharashtra	0.3	−11.1	0.3	169.3	2.3	0.1	4.4	67.7	5.4	83.0
Garhchiroli	Maharashtra	0.1	−11.1	0.8	61.8	2.5	7.7	9.1	74.0	5.1	81.1
Overall		100.0	−2.8	1.6	840.7	2.7	2.0	10.8	39.8	5.7	79.8

Source: World Bank calculations.
Note: Under the carbon-intensive scenario in 2050.

the remaining three districts located in Chhattisgarh and Madhya Pradesh (table 4.8).

Sri Lanka

The Northern and North Western provinces of Sri Lanka emerge as the top two hotspots, followed by the much less densely populated North Central Province (table 4.9). Northern Province is home to a large number of poor and displaced people. The effects of climate change will add a challenge to this long-term recovery. The highly urbanized and densely populated Western Province, which includes Colombo, is also predicted to experience a 7.5 percent decline in living standards by 2050. This has huge economic implications for the country, especially since the province contributes more than 40 percent of Sri Lanka's gross domestic product (GDP).

Among the districts, Jaffna emerges as the top hotspot, followed by Puttalam in North Western Province and Mannar and Kilinochchi in Northern Province (table 4.10). Given that 5 of the 10 most vulnerable districts of Sri Lanka are in Northern Province, changes in average weather and vulnerability must be considered for future planning and development activities there. Gampaha, which is among the 10 most vulnerable districts, is also the second-most-populous district in the country and was declared one of the worst-affected districts in the recent droughts.

Pakistan

Sindh Province emerges as the most vulnerable hotspot in Pakistan, followed by Punjab (table 4.11). Sindh has the second-largest economy, with a per capita GDP of US$1,400, which is 35 percent more than the national average. The province has a highly diversified economy ranging from heavy industry and finance centered in and around Karachi to a substantial agricultural base along the Indus River. Changes in average weather will add another dimension to the future growth of Sindh, given its high vulnerability.

Punjab Province, which is the most densely populated province, is also the second-most vulnerable. Punjab has the largest economy in Pakistan (contributing 53.3 percent of Pakistan's GDP), and overall has the lowest rate of poverty of all the provinces. However, the prosperity is unevenly distributed throughout the province, with the northern portion being relatively well off economically and the southern portion among the most impoverished in the country. Long-term climate vulnerability has implications for both growth and poverty reduction for Punjab.

Hyderabad District in Sindh emerges as the top hotspot followed by the districts of Mirpur Khas and Sukkur (table 4.12). Some of the densely populated cities in Punjab, including Lahore, Multan, and Faisalabad, emerge among the top 10 hotspot districts. This highlights the importance of addressing changes in average weather in the economically important Punjab and Sindh provinces.

Nepal

The Mid-Western, Western, and Far-Western development regions of Nepal will benefit the most from changes in average weather (table 4.13). Almost all districts in the Mid-Western Development, Western Development, and Far-Western Development regions are at relatively high altitudes and are part of the trans-Himalayan corridor. The more densely populated Eastern Development and Central Development regions will benefit less from changes in average weather because they are at lower altitudes and currently have temperatures closer to the optimum.

Mugu, Rasuwa, Solukhumbu, and Taplejung districts will be negatively affected by changes in average weather (table 4.14). The rest of the districts in Nepal are predicted to experience either neutral or positive effects from warming and change in long-term precipitation patterns. In contrast, Nepal is considered extremely fragile to natural disasters and extreme climate events.

TABLE 4.9 Predicted Change in Living Standards and Characteristics of Provinces in Sri Lanka under the Carbon-Intensive Scenario in 2050

Province	Share of households (%)	Change in living standards (%)	Average length of road in (km/10 km^2)	Average population density (per km^2)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Years of education	Electricity (%)
Northern	4.9	−11.2	9.3	264.8	2.5	0.1	21.0	34.7	8.0	65.8
North Western	12.3	−10.3	10.9	250.6	2.6	0.5	22.9	30.5	8.2	89.5
North Central	6.5	−8.0	5.2	98.8	2.8	0.3	23.4	50.	7.9	87.4
Western	28.0	−7.5	18.1	1,764.8	1.1	0.5	21.5	8.8	9.6	97.8
Eastern	7.4	−7.2	4.3	124.8	3.3	0.3	23.3	27.9	7.1	81.4
Southern	12.3	−7.1	13.1	446.7	3.2	0.6	23.4	34.7	8.0	94.9
Sabaragamuwa	9.7	−6.8	13.0	341.6	3.9	0.6	20.4	38.6	7.8	89.3
Uva	6.4	−4.6	11.1	176.6	4.5	0.2	21.1	53.4	7.3	83.9
Central	12.4	−4.0	19.5	451.7	2.6	0.1	25.0	32.0	7.9	92.9
Overall	100.0	−7.0	13.5	708.9	2.6	0.4	22.5	28.6	8.3	90.6

a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

TABLE 4.10 Predicted Change in Living Standards and Characteristics of the Top 10 District Hotspots in Sri Lanka under the Carbon-Intensive Scenario in 2050

District	Province	Share of households (%)	Change in living standards (%)	Average length of road in (km/10 km^2)	Average population density (per km^2)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Years of education	Electricity (%)
Jaffna	Northern	2.7	−11.9	13.4	433.0	1.6	0.1	22.4	30.3	8.2	76.2
Puttalam	North Western	4.0	−10.4	8.1	196.0	2.8	0.4	23.9	31.3	7.5	86.5
Manar	Northern	0.4	−9.8	2.9	41.1	3.6	0.1	14.0	51.7	7.7	71.0
Kilinochchi	Northern	0.5	−9.5	6.9	89.0	3.8	0.1	14.1	38.6	7.7	26.1
Kurunegala	North Western	8.3	−9.4	12.2	276.8	2.5	0.5	22.5	30.1	8.6	91.0
Trincomalee	Eastern	1.8	−9.3	3.3	107.6	3.0	0.2	23.4	23.8	7.6	78.8
Gampaha	Western	11.3	−8.9	28.2	1,401.2	0.8	0.7	23.0	6.9	9.5	97.9
Kegalle	Sabaragamuwa	4.2	−8.7	16.9	427.6	3.8	0.4	24.4	26.2	8.4	90.7
Mullaitivu	Northern	0.4	−8.3	2.6	41.0	4.5	0.1	19.4	53.3	7.0	35.0
Vavuniya	Northern	0.8	−8.3	4.9	76.6	3.0	0.1	25.4	27.2	7.9	71.4
Overall		100.0	−7.0	13.5	708.9	2.6	0.4	22.5	28.6	8.3	90.6

a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

TABLE 4.11 Predicted Change in Living Standards and Characteristics of Provinces in Pakistan under the Carbon-Intensive Scenario in 2050

Province	Share of households (%)	Change in living standards (%)	Average length of road in (km/10 km²)	Average population density (per km²)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Years of education	Electricity (%)
Sind	25.2	−4.6	0.7	205.1	3.1	0.9	3.9	19.0	6.6	8.0
Punjab	59.0	−2.6	1.6	464.3	2.4	0.9	11.9	26.6	4.9	17.4
Khyber Pakhtukhwa	12.9	−1.7	1.6	455.6	9.1	0.2	16.5	21.4	4.3	9.2
Baluchistan	2.8	−1.3	0.1	79.5	7.1	0.0	0.7	25.2	4.5	5.6
Overall	100.0	−2.9	1.4	387.0	3.6	0.8	10.2	24.0	5.3	13.6

a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

TABLE 4.12 Predicted Change in Living Standards and Characteristics of the Top 10 District Hotspots in Pakistan under the Carbon-Intensive Scenario in 2050

District	Province	Share of households (%)	Change in living standards (%)	Average length of road in (km/10 km²)	Average population density (per km²)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Years of education	Electricity (%)
Hyderabad	Sindh	4.3	−6.0	0.0	175.5	3.9	0.4	1.3	31.1	4.5	2.8
Mirpur Khas	Sindh	2.3	−5.7	0.0	151.2	4.6	0.0	2.2	41.8	3.9	1.8
Sukkur	Sindh	6.9	−4.1	0.1	183.0	3.7	0.9	2.7	20.2	6.7	5.8
Larkana	Sindh	11.8	−4.0	1.5	239.2	2.2	1.4	6.0	9.5	7.9	12.3
Bahawalpur	Punjab	5.4	−3.2	0.1	187.8	4.3	0.6	7.8	49.6	2.6	2.6
Faisalabad	Punjab	8.2	−2.8	2.7	581.6	1.6	0.1	11.4	30.4	5.2	7.8
Lahore	Punjab	4.3	−2.7	2.5	1,088.2	1.4	0.4	9.0	21.2	4.5	3.1
Multan	Punjab	8.1	−2.6	0.9	506.7	1.6	0.0	8.4	39.7	3.7	28.6
Dera Ghazi Khan	Punjab	4.9	−2.6	0.5	197.5	3.9	2.3	10.6	35.0	3.2	36.7
Sargodha	Punjab	9.0	−2.5	2.5	232.9	2.4	4.0	10.9	17.8	5.1	15.4
Overall		100.0	−2.9	1.4	387.0	3.6	0.8	10.2	24.0	5.3	13.6

a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

TABLE 4.13 Predicted Change in Living Standards and Characteristics of Regions in Nepal under the Carbon-Intensive Scenario in 2050

Region	Share of households (%)	Change in living standards (%)	Average length of road in (km/10 km²)	Average population density (per km²)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Yeras of education	Electricity (%)
Eastern	23.5	3.5	0.9	297.8	10.4	2.6	24.7	58.8	3.7	69.1
Centeral	35.6	3.9	1.8	843.7	7.8	0.9	21.2	44.9	4.1	78.9
Far-Western	8.6	4.4	0.0	124.4	11.6	1.8	34.6	53.1	3.7	51.8
Western	19.8	4.5	1.4	223.2	10.8	0.7	34.3	54.1	4.0	78.8
Mid-Western	12.4	4.9	0.5	126.6	8.5	0.7	28.7	60.2	3.1	45.0
Overall	100.0	4.1	1.2	441.5	9.4	1.3	26.7	52.6	3.8	70.0

a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

TABLE 4.14 Predicted Change in Living Standards and Characteristics of the Top 10 District Hotspots in Nepal under the Carbon-Intensive Scenario in 2050

District	Region	Share of households (%)	Change in living standards (%)	Average length of road in (km/10 km²)	Average population density (per km²)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Years of education	Electricity (%)
Solukhumbu	Eastern	0.5	−1.2	0.8	29.3	11.1	0.2	22.0	52.1	2.3	53.3
Mugu	Mid-Western	0.2	−0.8	0.0	13.7	25.5	0.0	0.0	66.7	4.4	0.0
Rasuwa	Central	0.2	−0.7	2.0	23.3	10.4	0.1	0.0	72.7	2.3	0.0
Taplejung	East	0.2	−0.6	0.5	27.9	12.3	127.1	16.7	66.7	3.6	0.0
Sankhuwasabha	East	0.9	0.0	1.2	36.6	8.8	0.2	25.2	61.6	4.0	69.9
Dolakha	Central	1.0	0.3	1.2	69.3	8.4	0.1	30.2	70.1	2.6	87.3
Bajhang	Far-Western	0.7	0.8	0.0	46.3	12.8	0.0	19.6	64.0	4.2	0.0
Sindhupalchok	Central	1.1	1.4	2.0	92.5	10.4	0.2	32.5	59.8	2.0	96.3
Darchula	Far-Western	0.5	2.1	0.1	47.2	9.8	10.0	21.7	43.5	4.5	43.5
Gorkha	West	1.2	2.2	1.0	64.1	18.3	0.2	43.1	72.2	2.7	66.9
Overall		100.0	4.1	1.2	441.5	9.4	1.3	26.7	52.6	3.8	70.0

a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

Afghanistan

Only Wakhan District in northeastern Afghanistan is projected to emerge as a hotspot by 2050 under either climate scenario (table 4.15). The districts with the least positive effects of climate change are spread throughout the country, with many in the central, mountainous portions of the country (for example, in Bamyan, Wardak, and Ghazni provinces). The spatial pattern of climate change effects is similar at the provincial level, with many of the least positively affected provinces being in the Hindu Kush mountains (table 4.16).

The lack of infrastructure in the most affected districts and provinces is staggering (tables 4.15 and 4.16). For example, whereas 27 percent of people in Afghanistan overall have access to electricity, between 0 and 5 percent have access in these areas; the extremely low density of paved primary roads (0 kilometers in many districts) and long average travel time to markets (more than 36 hours in Wakhan District) is similarly profound.

Nonmonetary Indicators of Well-Being

Although the focus of the book has been on living standards—as measured through consumption expenditures—there are also nonmonetary effects of climate change on well-being (Carleton and Hsiang 2016). A growing literature links changes in temperature and precipitation patterns to increasing crime rates, civil conflict, intergroup riots, migration, and mortality (box 4.3). It is possible that these could be triggered by monetary effects such as negative rain shocks that lower income, which, in turn, increase the likelihood of violence. Nonmonetary effects could be a complement to living standards measures that focus on income and expenditures. This is especially relevant as the climate hotspots identified in the book could also potentially become hotspots for crime, violence, and civil conflict.

TABLE 4.15 Predicted Change in Living Standards and Characteristics of the Top 10 Most Affected Districts in Afghanistan under the Carbon-Intensive Scenario in 2050

District	Province	Household (%)	Change in living standards (%)	Average length of road in (km/10 km²)	Average population density (per km²)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Years of education	Electricity (%)
Wakhan	Badakhshan	0.0	−10.4	0.0	1.0	36.3	3.0	0.0	70.0	2.7	0.0
Bamyan City	Bamyan	0.3	2.2	0.0	32.0	7.3	0.3	0.6	39.2	2.5	0.0
Nawur	Ghazni	0.3	2.8	0.0	16.0	10.2	0.7	0.0	40.0	5.9	0.0
Shighnan	Badakhshan	0.0	2.8	0.0	9.0	11.8	2.1	0.0	70.0	7.2	0.0
Yakawlang	Bamyan	0.2	2.8	0.0	10.0	13.9	0.2	0.0	47.4	1.9	0.0
Shibar	Bamyan	0.1	2.9	0.0	18.0	9.1	0.0	1.5	37.9	1.2	0.0
Hisa-i-Awali-Bihsud	Wardak	0.3	3.0	0.0	18.0	6.8	0.2	0.0	81.5	4.0	0.0
Markazi Bihsud	Wardak	0.6	3.1	0.0	26.0	6.7	1.1	0.5	54.6	4.4	0.0
Kohistanat	Sari Pul	0.2	3.3	0.0	11.0	8.5	0.4	0.0	21.1	1.0	4.1
Ajristan	Ghazni	0.2	3.3	0.0	16.0	11.3	0.0	0.0	49.3	1.5	0.0
Overall		100.0	11.9	2.9	951.6	5.2	0.5	0.7	31.2	3.2	27.0

a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

TABLE 4.16 Predicted Change in Living Standards and Characteristics of the Top 10 Province Hotspots in Afghanistan under the Carbon-Intensive Scenario in 2050

Province	Household (%)	Change in living standards (%)	Average length of road in (km/10 km²)	Average population density (per km²)	Travel time to market (hours)	Water availability[a]	Female household head (%)	Agriculture head (%)	Years of education	Electricity (%)
Bamyan	1.4	3.2	0.0	25.6	9.8	0.3	0.5	46.1	1.7	0.2
Ghor	2.8	4.5	0.0	15.2	6.3	0.1	0.2	72.9	0.9	4.2
Wardak	2.7	4.7	1.1	48.6	6.4	1.0	0.1	61.2	7.0	2.3
Panjshir	0.6	5.2	0.0	39.9	17.3	0.0	0.1	25.2	7.8	1.8
Daykundi	1.7	5.4	0.0	21.8	8.8	0.0	3.1	41.4	1.3	0.3
Ghazni	5.2	5.6	1.5	112.6	6.7	0.1	0.0	31.3	5.0	5.0
Logar	1.7	6.4	1.1	91.2	5.2	0.1	0.5	48.7	6.3	1.2
Paktika	1.4	6.7	0.0	28.9	6.3	0.1	0.4	25.2	4.4	0.8
Kapisa	1.6	7.1	0.0	356.4	5.1	0.0	0.7	16.4	4.8	0.4
Paktya	1.8	7.2	0.7	82.5	4.5	0.7	0.0	29.2	3.0	2.5
Overall	100.0	11.9	2.9	951.6	5.2	0.5	0.7	31.2	3.2	27.0

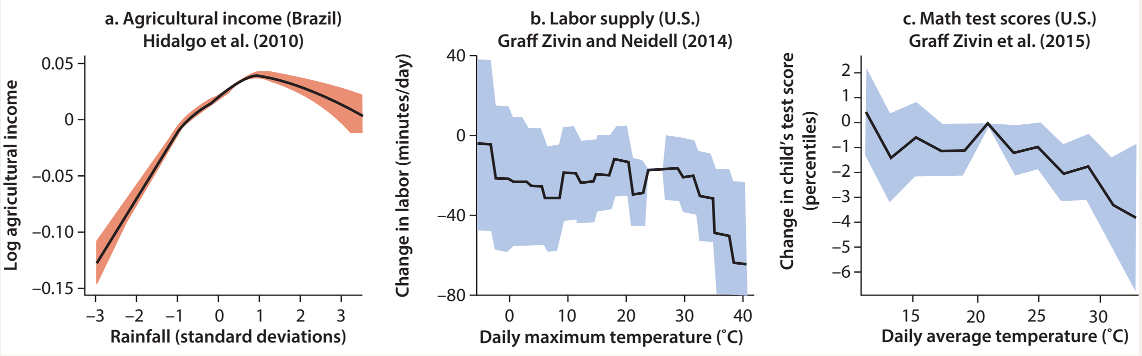
a. "Water availability" refers to the ratio of surface water use to groundwater use. A large value is good because it indicates that water use is more likely to be sustainable.

BOX 4.3 Other Dimensions of Hotspots: Tracking Nonmonetary Effects of Climate Change

Although the focus of this book has been on documenting declining living standards from climate change, there is now a growing body of research that is attempting to capture adverse human dimensions of climate change, including increased incidences of suicides, violent crimes, civil conflict, and riots (Carleton 2017; Carleton and Hsiang 2016; and figure B4.3.1, panels a through f). Through a meta-analysis of the literature, Hsiang, Burke, and Miguel (2013) find strong causal evidence linking climatic events to human conflict across a range of spatial and temporal scales and across all major regions of the world. They find the magnitude of climate's influence is substantial: for each 1°C increase in long-term average temperatures or one standard deviation increase in extreme rainfall, interpersonal violence rises by 4 percent and the frequency of intergroup conflict rises by 14 percent. Because locations throughout the inhabited world are expected to warm 2°C to 4°C by 2050, the researchers argue that the amplified rates of human conflict could represent a large and critical impact of anthropogenic climate change. The relationship between climate change and conflict is an active area of research, and several groups are currently trying to reproduce the results of Hsiang, Burke, and Miguel (2013).

Analysis of crime, agriculture, and weather data from India from 1971 to 2000 shows that drought and heat exert a strong effect on virtually all types of crimes, with the effect on property crimes being greater than for violent crimes (Blakeslee and Fishman 2017). This relationship is relatively stable over three decades of economic development. They also find the effects of income shocks on crime are highly nonsymmetric: although negative agriculture shocks consistently lead to increases in crime, positive agriculture shocks do not result in a decline in crime. The researchers conclude that despite the effects that accompany economic growth—higher incomes, greater access to consumption-smoothing instruments, and reduced susceptibility of agriculture to climatic variability—there is little evidence that crime has become less responsive to extreme rainfall than it was before the improvements. This may be taken as evidence that despite India's remarkable gains in human and economic development, the poorest members of society continue to remain highly vulnerable to aggregate economic shocks.

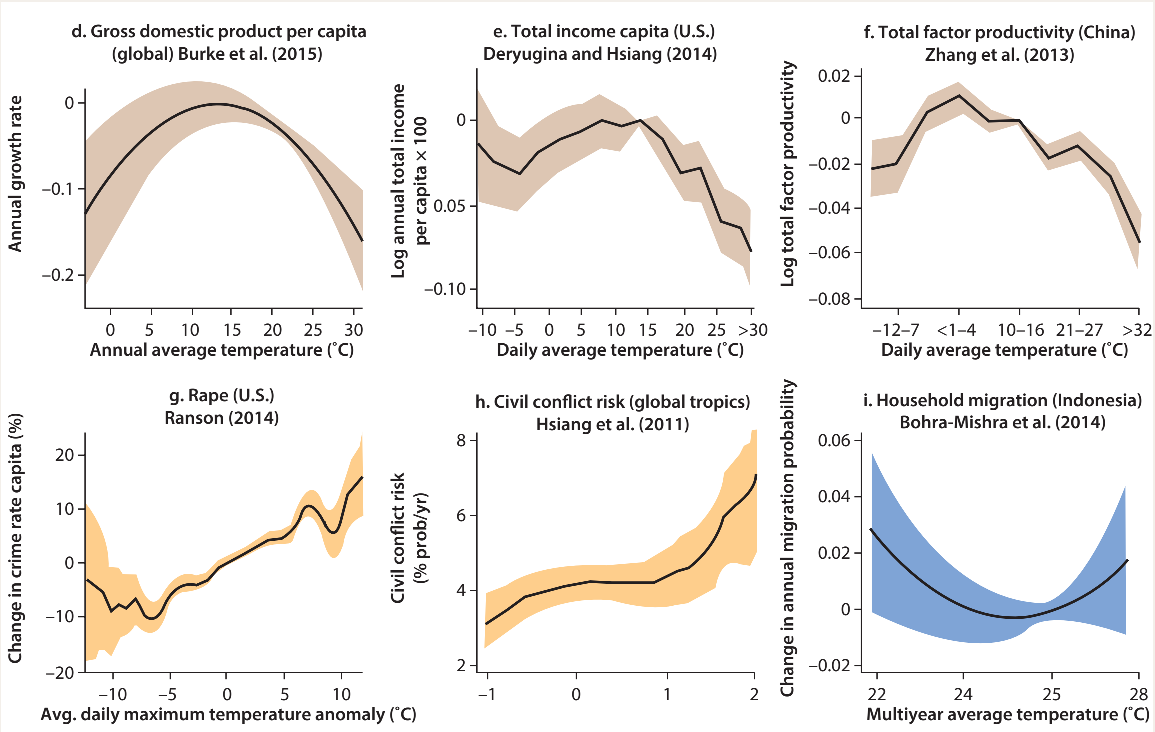
FIGURE B4.3.1 Climate Has Diverse Monetary and Nonmonetary Effects on Well-Being



(continues next page)

BOX 4.3 Other Dimensions of Hotspots: Tracking Nonmonetary Effects of Climate Change (continued)

FIGURE B4.3.1 Climate Has Diverse Monetary and Nonmonetary Effects on Well-Being (continued)



Source: Carleton and Hsiang 2016.

References

Asuncion, R. C., and M. Lee. 2017. "Impacts of Sea-Level Rise on Economic Growth in Developing Asia." ADB Economics Working Paper Series 507, Asian Development Bank, Manila. https://www.adb.org/sites/default/files/publication/222066/ewp-507.pdf.

Azhar, G., S. Saha, P. Ganguly, D. Mavalankar, and J. Madrigano. 2017. "Heat Wave Vulnerability Mapping for India." *International Journal of Environmental Research and Public Health* 14 (4): 357.

Bellard, C., C. Bertelsmeier, P. Leadley, W. Thuiller, and F. Courchamp. 2012. "Impacts of Climate Change on the Future of Biodiversity." *Ecology Letters* 15 (4): 365–77.

Blakeslee, D. S., and R. Fishman. 2017. "Weather Shocks, Agriculture, and Crime: Evidence from India." *Journal of Human Resources* 52 (3).

Bolch, T., A. Kulkarni, A. Kääb, C. Huggel, F. Paul, J. G. Cogley, H. Frey, J. S. Kargel, K. Fujita, M. Scheel, S. Bajracharya, and M. Stoffel. 2012. "The State and Fate of Himalayan Glaciers." *Science* 336 (6079): 310–14.

Carleton, T. A. 2017. "Crop-Damaging Temperatures Increase Suicide Rates in India." *PNAS* 114 (33): 8746–51.

Carleton, T. A., and S. Hsiang. 2016. "Social and Economic Impacts of Climate." *Science* 353 (6304).

Chakraborty, S., and A. C. Newton. 2011. "Climate Change, Plant Diseases and Food Security: An Overview." *Plant Pathology* 60 (1): 2–14.

Chen, Y., C. Xu, Y. Chen, W. Li, and J. Liu. 2010. "Response of Glacial-Lake Outburst Floods to Climate Change in the Yarkant River Basin on Northern Slope of Karakoram Mountains, China." *Quaternary International* 226 (1): 75–81.

Hallegatte, S., C. Green, R. J. Nicholls, and J. Corfee-Morlot. 2013. "Future Flood Losses in Major Coastal Cities." *Nature Climate Change* 3 (9): 802–6.

Harris, I. P. D. J., P. D. Jones, T. J. Osborn, and D. H. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations—The CRU TS3.10 Dataset." *International Journal of Climatology* 34 (3): 623–42.

Hsiang, S. M., M. Burke, and E. Miguel. 2013. "Quantifying the Influence of Climate on Human Conflict." *Science* 341.

Immerzeel, W. W., L. P. Van Beek, and M. F. Bierkens. 2010. "Climate Change Will Affect the Asian Water Towers." *Science* 328 (5984): 1382–5.

IPCC (Intergovernmental Panel on Climate Chante). 2013. *Climate Change 2013: The Physical Science Basis: Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. edited by T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley. Cambridge: Cambridge University Press. doi:10.1017/CBO97811 07415324.

Keiler, M., J. Knight, and S. Harrison. 2010. "Climate Change and Geomorphological Hazards in the Eastern European Alps." *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences* 368 (1919): 2461–79.

Mendelsohn, R., K. Emanuel, S. Chonabayashi, and L. Bakkensen. 2012. "The Impact of Climate Change on Global Tropical Cyclone Damage." *Nature Climate Change* 2 (3): 205–9.

Miller, J. D., W. W. Immerzeel, and G. Rees. 2012. "Climate Change Impacts on Glacier Hydrology and River Discharge in the Hindu Kush-Himalayas: A Synthesis of the Scientific Basis." *Mountain Research and Development* 32 (4): 461–7.

Nicholls, R. J., P. P. Wong, V. R. Burkett, J. O. Codignotto, J. E. Hay, R. F. McLean, S. Ragoonaden, and C. D. Woodroffe. 2007. "Coastal Systems and Low-Lying Areas." In *Climate Change 2007: Impacts, Adaptation and Vulnerability*, edited by M. L. Parry, O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson, 315–56. Cambridge: Cambridge University Press.

Siraj, A. S., M. Santos-Vega, M. J. Bouma, D. Yadeta, D. R. Carrascal, and M. Pascual. 2014. "Altitudinal Changes in Malaria Incidence in Highlands of Ethiopia and Colombia." *Science* 343 (6175): 1154–58.

Stoffel, M., and C. Huggel. 2012. "Effects of Climate Change on Mass Movements in Mountain Environments." *Progress In Physical Geography* 36 (3): 421–39.

World Bank. 2016. World Development Indicators Database, World Bank, Washington, DC.

Xu, J., R. E. Grumbine, A. Shrestha, M. Eriksson, X. Yang, Y. U. N. Wang, and A. Wilkes. 2009. "The Melting Himalayas: Cascading Effects of Climate Change on Water, Biodiversity, and Livelihoods." *Conservation Biology* 23 (3): 520–30.

Toward Greater Resilience

5

Climate change is one of the most significant threats facing the world today. The adverse impacts of climate change are affecting all countries, especially developing countries, including persistent drought and extreme weather events, rising sea levels, and coastal erosion, and further threatening food security, water, energy and health, and more broadly efforts to eradicate poverty and achieve sustainable development. The global nature of the problem calls for the widest possible cooperation by all countries and their participation in an effective and appropriate international response. Also, it is critical to continue mobilizing financing from a variety of sources, public and private, bilateral and multilateral, including innovative sources of finance. Given the critical importance of resilience to addressing climate change impact and risk, what type of strategies and actions can be adopted at all levels to make sure that resilience is incorporated and mainstreamed in international and national planning and budgeting processes, as well as informing investment and development cooperation strategies and decisions?

Using extensive climate and household-level data, this book shows the effects of changes in average weather—long-term changes in average seasonal temperature and precipitation—to be significant, but with substantial variations across South Asia. Hotspots are expected to be less severe if countries implement their national strategies and the Paris Agreement's goal of limiting average global temperature increases to 2°C is achieved. In contrast, hotspots are expected to be more severe if the Paris Agreement fails, leading to a future climate more consistent with the carbon-intensive scenario. Under the carbon-intensive scenario, the effects to living standards will be widespread throughout the region: more than 800 million people, or 45 percent of the region's current population, live in locations projected to become moderate to severe climate hotspots because of changes in average weather by 2050 (table 4.1). Furthermore, living standards of more than 80 percent of the overall population could be adversely affected.

From a public policy perspective, these granular findings point to the importance of the geographical, political, and household context in developing interventions to assist people living in climate hotspots. For example, some inland areas in India emerge as severe hotspots, whereas in Sri Lanka, the postconflict northern coastal areas are most vulnerable. The household characteristics of these areas also differ from one another, as do the characteristics of the locations themselves, so the interventions must be tailored to the specific context. This granular analysis can also inform decision making on the locations and households most in need of resources.

TABLE 5.1 Changes in Average Weather Projected under the Carbon-Intensive Scenario Will Disproportionately Impact Severe Hotspots

	Bangladesh	India	Sri Lanka
Entire country with no climate change (GDP per capita in PPP$)	13,365	21,148	28,632
Entire country under the carbon-intensive climate scenario (GDP per capita in PPP$)	12,470	20,555	26,628
Change for entire country due to carbon-intensive climate scenario (%)	–6.7	–2.8	–7.0
Severe hotspots with no climate change (GDP per capita in PPP$)	13,231	21,782	29,491
Severe hotspots under the carbon-intensive climate scenario (GDP per capita in PPP$)	11,326	19,647	26,394
Change for severe hotspots under the carbon-intensive climate scenario (%)	–14.4	–9.8	–10.5

Source: Calculations based on World Development Indicators, SSPs, and results in chapters 3 and 4. See explanation of calculations in Appendix E.
Notes: Only the countries where severe hotspots are projected to emerge are shown. Severe hotspots correspond to those identified in chapter 4 under the carbon-intensive scenario by 2050. Methodology described in appendix E. GDP = gross domestic product; PPP = purchasing power parity; SSP = shared socioeconomic pathway. Dollars are US dollars.

Money Worth Spending

The findings of this book suggest that good development outcomes are the best adaptation: investing in skills, health, knowledge, better infrastructure, and a more diversified economy should reduce climate hotspots at the household, district, and country levels. This supports earlier conclusions on the importance of growth in reducing the potential negative effects of climate change (Hallegatte and others 2016; Skoufias, Katayama, and Essama-Nssah 2012).

The climate hotspots presented in this book will impact future gross domestic product (GDP). Underlying each of the climate scenarios is a shared socioeconomic pathway (SSP) scenario, which includes projections of national-level GDP and many other macroeconomic variables (O'Neill and others 2014; descriptions provided in appendix E). Cast in terms of GDP projections, the hotspots predicted under the carbon-intensive climate scenario will reduce projected per capita GDP 6.7 percent in Bangladesh, 2.8 percent in India, and 7.0 percent in Sri Lanka by 2050 compared to a scenario in which further climate change does not occur (table 5.1).

The estimated GDP losses are even greater for the regions identified in this book as severe hotspots (table 5.1). By 2050 in these areas, per capita GDP is predicted to be 14.4 percent lower in Bangladesh than without further climate change, 9.8 percent lower in India, and 10.5 percent lower in Sri Lanka.

TABLE 5.2 Changes in Average Weather Projected under the Carbon-Intensive Scenario Will Reduce Total GDP

	Loss of GDP by 2050 (US$, billions)	
Country	Severe hotspots	Entire country
Bangladesh	58.7	171.1
India	403.9	1,177.8
Sri Lanka	12.2	49.9

Source: Calculations based on World Development Indicators, SSPs, and results in chapters 3 and 4.
Notes: Only countries where severe hotspots are projected to emerge are shown. Severe hotspots correspond to those identified in chapter 4 under the carbon-intensive scenario by 2050. Methodology described in appendix E. Includes population changes corresponding to SSPs (see description in appendix E) and per capita calculations in table 5.1. GDP = gross domestic product; SSP = shared socioeconomic pathway.

Thus, the most affected hotspot regions in Bangladesh, India, and Sri Lanka would disproportionately suffer, unless bolstered with additional growth.

The national decreases in living standards as a result of changes in average weather are substantial and tend to be concentrated in the severely affected regions (table 5.2). The costs of inaction expressed as amount of total GDP losses in severe hotspots are significant—US$59 billion in Bangladesh, US$404 billion in India, and US$12 billion in Sri Lanka by 2050 under the carbon-intensive scenario. The total costs for the entire countries are even larger—US$171 billion in Bangladesh, US$1,178 billion in India, and US$50 billion in Sri Lanka by 2050 under the carbon-intensive scenario. As discussed in the following section, this potential damage can be reduced through good development policies, even if the carbon-intensive climate change scenario manifests.

Reducing Hotspots in Vulnerable Communities and Vulnerable Households

Reducing hotspots could involve a portfolio of actions aimed at making affected places and the households located in them more resilient. Potential actions include improving infrastructure, introducing market reforms, and building individual and institutional capacity. In this context, some of the difficult questions that governments often grapple with are: Which interventions are most warranted? Where? And when?

The hotspot analysis provides some interesting insights on locations that are particularly vulnerable to changes in average weather. In the case of India, the top hotspots are not often talked about as being particularly vulnerable to climate change, but are frequently identified as critical from a development perspective. For example, central India—including states such as Madhya Pradesh, Chhattisgarh, Rajasthan, and Uttar Pradesh—emerges as being highly vulnerable to changes in average weather. These states are also home to many poor and tribal people. In contrast, coastal areas in India—often identified as being most vulnerable to extreme events and sea-level rise—are found to be relatively more resilient to changes in average weather compared with nearby areas in Sri Lanka.

This book underscores how the vulnerability of communities and households to climate risks depends on local, social, and economic factors. To explain the implications of changes in average weather, the book helps identify the factors that increase both vulnerability and resilience to changes in average weather. Although not necessarily causal, these elements can be important indicators, and understanding them can help shape policies and programs to strengthen communities and households, and their capacities to adapt. Vulnerability factors (for example, elevation, education, electricity access, and water stress) also increase the likelihood that a household or community will experience negative outcomes. The benefits from continued investments in basic infrastructure—such as improving access to electricity or density of primary roads (as identified in the literature)—could outweigh the climate-related loss in living standards for households that lack access to these infrastructure services. Similarly, technological advances, coupled with expanded irrigation systems, work to make agriculture less sensitive to climate change in the long-term (Taheripour and others 2016).

The analysis suggests that the risks associated with changes in average weather can increase over time when combined with poverty, lack of education, and poorly maintained infrastructure. Table 5.3 shows the profiles of the most resilient households relative to the overall country profiles.[1] Resilient households are those that face smaller reductions in living standards from changes in average weather. In India, for example, such households have higher levels of education and enjoy higher rates of electrification. The impact of changes in average weather could presumably be attenuated if the less resilient households acquired the characteristics of their more resilient counterparts.

Policy Agenda

Although increasing temperatures and changing precipitation patterns present unique and sometimes hard-to-predict challenges, households, communities, and governments can take actions to improve resilience. Decisions about investment in adaptation strategies, development of human skills, and engagement options with communities will significantly affect this generation and the next generation's quality of life. With more knowledge about how these changes will affect communities and households, especially poor and vulnerable populations, governments will be better able to design policies and interventions that best serve specific segments of society. Targeting resources efficiently to the most vulnerable communities and groups should be a priority. The

TABLE 5.3 Profile of the Top 10 Percent Resilient Households

Country	Top 10 percent / overall	Living standards change (%)	Average length of road in km / 10 km^2	Average population density per km^2	Travel time to market (hours)	Water availability	Female-headed household (%)	Agriculture head (%)	Years of education	Electrification (%)
Afghanistan	Top 10%	17.1	3.8	713.3	3.6	0.4	1.5	30.8	2.6	37.5
Afghanistan	Overall	11.9	2.9	951.6	5.2	0.5	0.7	31.2	3.2	27.0
Bangladesh	Top 10%	0.9	5.7	680.3	2.9	3.0	7.6	44.6	3.5	39.2
Bangladesh	Overall	−6.7	5.8	1320.7	2.0	7.9	7.6	39.1	3.9	54.9
India	Top 10%	4.4	2.2	596.9	3.1	0.8	17.9	28.0	6.5	91.8
India	Overall	−2.8	1.6	840.7	2.7	2.0	10.8	39.8	5.7	79.8
Nepal	Top 10%	6.5	0.5	125.0	9.5	0.2	34.0	61.2	3.2	36.2
Nepal	Overall	4.1	1.2	441.5	9.4	1.3	26.7	52.6	3.8	70.0
Pakistan	Top 10%	−1.3	0.6	181.9	11.8	0.1	13.8	26.8	4.4	7.9
Pakistan	Overall	−2.9	1.4	387.0	3.6	0.8	10.2	24.0	5.3	13.6
Sri Lanka	Top 10%	−2.9	22.2	437.8	3.4	0.2	22.7	38.8	7.5	91.4
Sri Lanka	Overall	−7.0	13.5	708.9	2.6	0.4	22.5	28.6	8.3	90.6
South Asia	Top 10%	3.6	2.6	553.2	4.1	0.9	16.6	30.1	5.9	76.2
South Asia	Overall	−3.2	2.1	831.3	2.8	2.3	10.7	38.0	5.4	69.6

Source: World Bank calculations.

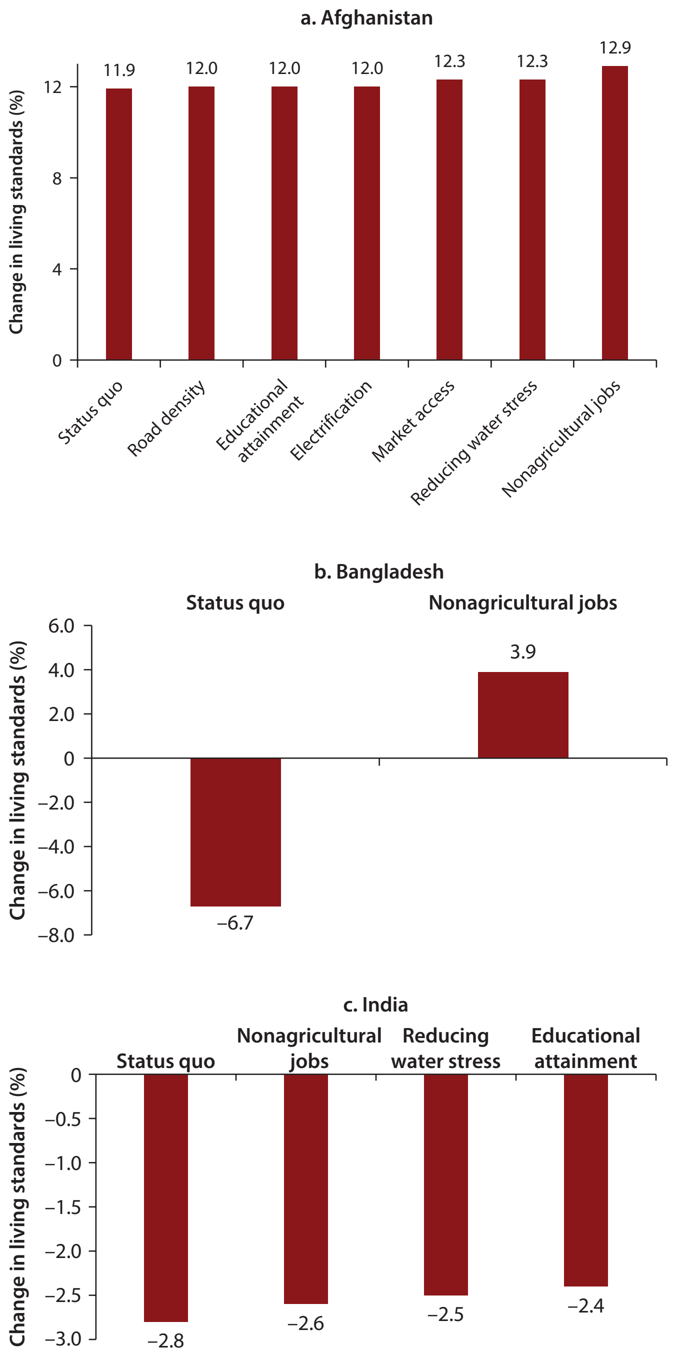
measures that reduce climate hotspots also have strong overall development benefits. Therefore, policy makers should think of these investments as win-win decisions that can sustainably break the downward spiral of poverty and inequality, at the same time driving growth and sustainable development.

The book identifies and highlights climate hotspots where communities and households are likely to be particularly vulnerable to changes in average weather. The positive effects of reducing hotspots can be amplified through efforts focused on the most vulnerable locations and population groups. The hotspot analysis undertaken here can better inform policy through refining our understanding of the underlying reasons that people in specific hotspot areas are particularly vulnerable.

Of the six countries investigated, living standards are predicted to be adversely affected by changes in average weather in four: Bangladesh, India, Pakistan, and Sri Lanka. Afghanistan and Nepal are estimated to benefit from these changes in average weather. The broader growth-and-development agenda includes investing in human capital (such as through education) and infrastructure (such as through electrification and construction of roads). The questions then arise: What are the co-benefits of these strategies for climate resilience? What effect would a given policy have in a specific setting? Using the analysis from chapters 3 and 4, this book investigates investment and policy options that countries could consider to reduce the negative consequences of changes in average weather under the carbon-intensive climate scenario (figure 5.1, panels a through f; see appendix A for a description of the methodology used). Although all policies may not work for all the countries, the analysis here illustrates promising avenues that could be explored at the national and subnational levels.

Several development interventions could assist Afghanistan in leveraging projected increases in temperature and changes in

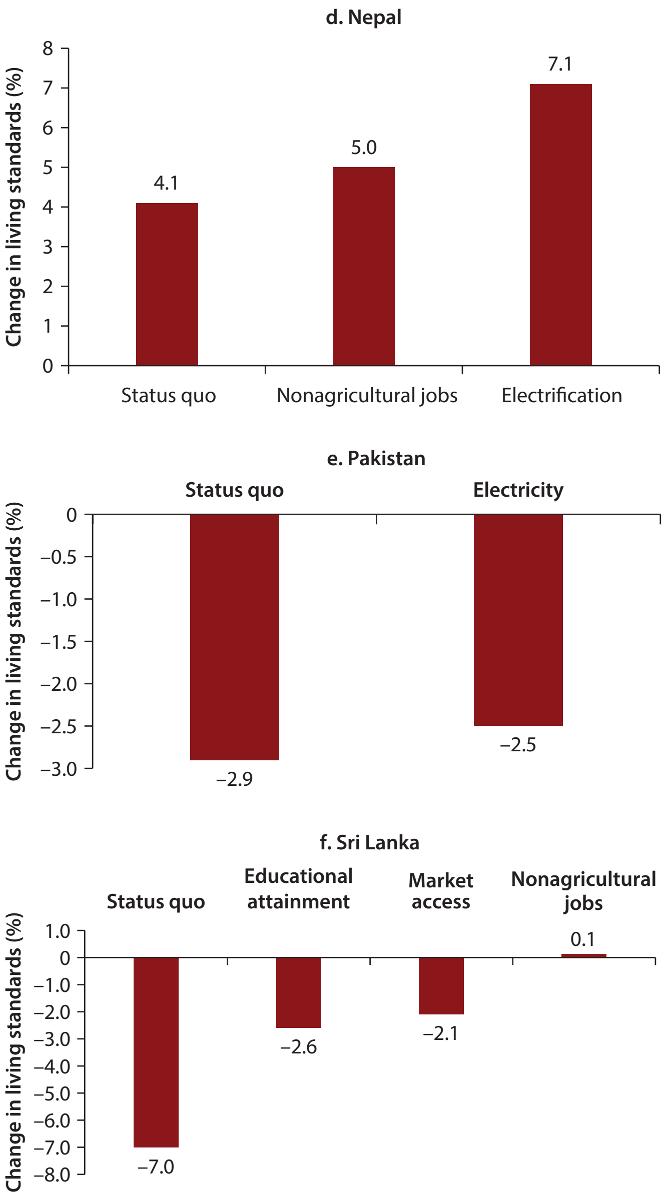
FIGURE 5.1 Good Development Outcomes Reduce Hotspots
(Effects of Various Interventions on Living Standards in South Asia under the Carbon-Intensive Scenario, by 2050)



(continues next page)

FIGURE 5.1 Good Development Outcomes Reduce Hotspots (continued)

(Effects of Various Interventions on Living Standards in South Asia under the Carbon-Intensive Scenario, by 2050)



Source: World Bank calculations.
Note: Impacts of interventions are estimated using the method described in appendix A. 15% and 30% increases in market access are defined as 1.5% and 3% decreases in travel time to major cities, respectively.

precipitation (figure 5.1a): (a) increasing access to electricity; (b) reducing water stress; and (c) providing nonagricultural employment opportunities. Based on the correlations observed today, increasing access to electricity by 30 percent could reduce negative impacts on living standards by roughly 1 percent, whereas the other two aforementioned development strategies would each provide a 0.4 percent benefit. Improving education and primary road density are also projected to weakly—but positively—increase net improvements from changes in average weather.

For Bangladesh, the analysis suggests that enhancing nonagricultural employment opportunities could potentially reduce the living standards burden of changes in average weather (figure 5.1b). A 15 percent increase in nonagricultural employment opportunities would lead to a reduction in the impact of average weather changes on living standards from −6.7 percent to −1.4 percent. Similarly, a 30 percent increase in nonagricultural employment would not only negate all the negative effects of changes in average weather but also result in a 3.9 percent increase in living standards.

In India, the analysis identifies three possible avenues to offset the effects of changes in average weather, including improving educational attainment, reducing water stress, and improving nonagricultural employment opportunities (figure 5.1c). The analysis predicts that increasing the average educational attainment by 30 percent (or 1.5 additional years of schooling) would reduce the impact of changes in average weather on living standards from −2.8 percent to −2.4 percent. Reducing water stress and enhancing nonagricultural employment by 30 percent could yield similar benefits. Therefore, multiple actions could be taken simultaneously to maximally reduce hotspots. Conversely, these results also indicate that the wrong policy actions or worsening water stress could exacerbate the effects of changes in average weather on living standards.

Although the analysis indicates that Nepal will on average benefit from changes in average weather, the country can further leverage climatic changes (figure 5.1d). The analysis shows that living standards increase when there is access to electricity and nonagricultural employment opportunities. Based on the findings, increasing access to electricity by 30 percent could improve living standards by approximately 3 percent. Although warming temperatures may open up more areas for agriculture, the analysis highlights that people must have access to nonagricultural job opportunities to leverage the effects of changes in average weather for maximum increases in living standards.

In Pakistan, the analysis reveals that expanding electrification by 30 percent could reduce the impact of average weather on living standards from –2.9 percent to –2.5 percent (figure 5.1e). Thus, electrification alone may not completely overcome the negative effects of changes in average weather on living standards. This indicates that additional analysis could be warranted to better understand how to prevent the emergence of hotspots within the country.

For Sri Lanka, the policy choices considered include enhancing education, improving market access, and increasing nonagricultural employment (figure 5.1f). The analysis suggests that increasing nonagricultural employment by 30 percent relative to current levels could entirely eliminate the burden of changes in average weather on living standards; the overall impact would shift from –7 percent to 0.1 percent. On the other hand, reducing time traveled to the market by 3 percent and increasing eductional attainment by 30 percent would respectively change the impact on living standards from –7 percent to –2.1 percent and –2.6 percent, respectively. If these interventions were implemented together, living standards would most likely increase under the climate change scenario.

These national-level policy choices may mask some of the subtle regional differences in terms of the benefits. In Pakistan, for example, increasing education may reduce hotspots in some regions, even though the effect is not significant at the national level. This analysis therefore should be taken as an illustration of an array of various complementary policy and investment choices available for decision makers.

Resilience in communities and households can also be built through policies that enable effective private actions on adaptation. Examples include boosting research and development on new technologies, such as drought-resistant crops, or providing weather forecasts and climate risk assessments that can leverage adaptive actions. In addition, the government can play a key role through establishing the policy framework for adaptation, which sets the incentives for private action. This could include (a) regulatory and insurance instruments that convey the correct incentives for adaptation; (b) pricing and other policies that encourage efficient use of energy, water, agriculture, and other natural resources; and (c) facilitating market access and providing fiscal incentives for research and development to exploit existing technologies or develop new ones in the energy, water-supply, agricultural, forestry, and livestock sectors.

Hotspots tend to have lower living standards compared to the national average. In this respect, it seems right to conclude that changes in average weather will hurt poor households disproportionately and therefore increase poverty and inequality. While this is true on average, the granularity of the analysis in this book provides a more nuanced profile of the households that stand to lose the most. As seen in table 5.3, in Nepal and Sri Lanka, the top 10 percent of the resilient households are more rural than the average household in the country. In a relatively large country like India, poor and rich households are spread evenly across all climate zones. Therefore, poor households living in cooler areas may in fact benefit from changing average weather compared with those living in warmer areas. It should be noted, however, that this book investigates only changes in average weather, not differences in climate variability or shocks caused by extreme events. The reason for the focus on changes in the averages is that changes in the variability are not as well captured in the current generation of climate models. As shown by Hallegatte and others (2017), natural disasters tend to affect poor households the most.

In the future, economic growth and structural changes will lead people to migrate from rural areas to cities, leaving behind many of their agricultural and other climate-sensitive practices. Although this could potentially make the migrants more climate-resilient, it may also create new climate risks. For example, urban populations will face several health risks exacerbated by climate change, such as heatwaves (enhanced by heat island effects) and flood-related challenges. To the extent that economic growth is noninclusive and certain segments of the population are left behind, there is always a danger that climate change will deepen poverty in some parts of the region. These results, along with suggested costs of inaction, point in the direction of resilience policies that are more targeted toward poorer populations and areas and households that have high vulnerability.

Note

1. Table 5.3 compares the overall impacts of climate change with those for the 10 percent most resilient households. Table 4.2 does the same for the 10 percent least resilient households. Thus, the two tables provide a complementary picture of the effects at the two ends of the scale.

References

Hallegatte, S., M. Fay, M. Bangalore, T. Kane, and L. Bonzanigo. 2016. *Shock Waves: Managing the Impacts of Climate Change on Poverty*. Washington, DC: World Bank.

Hallegatte, S., A. Vogt-Schilb, M. Bangalore, and J. Rozenberg. 2017. *Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters*. Washington, DC: World Bank.

Harris, I. P. D. J., P. D. Jones, T. J. Osborn, and D. H. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations—The CRU TS3.10 Dataset." *International Journal of Climatology* 34 (3): 623–42.

O'Neill, B. C., E. Kriegler, K. Riahi, K. L. Ebi, S. Hallegatte, T. R. Carter, R. Mathur, and D. P. van Vuuren. 2014. "A New Scenario Framework for Climate Change Research: The Concept of Shared Socioeconomic Pathways." *Climatic Change* 122 (3): 387–400.

Skoufias, E., R. S. Katayama, and B. Essama-Nssah. 2012. "Too Little Too Late: Welfare Impacts of Rainfall Shocks in Rural Indonesia." *Bulletin of Indonesian Economic Studies* 48 (3): 351–68.

Methodology for Policy Cobenefits A

Extra resources made available through specific policies of governments and nongovernmental organizations may facilitate the mitigation of the risks of changes in average weather on living standards. Six variables that can be influenced by policy actions are considered: (a) nonagricultural households, (b) households' access to electricity, (c) years of education of the head of the household, (d) baseline water stress, (e) primary road density, and (f) access to market. The impact of these was explored using a variant of the model specification provided in equation (3.1).

Agricultural households (in general) and rain-fed agriculture (in particular) are most susceptible to changes in average weather. Policies that help households move from agriculture to nonagricultural occupations may help mitigate the ill effects of changes in average weather on living standards. Similarly, access to electricity may help in coping with long-term increases in average temperature. If household heads have more education, then they may be better equipped to deal with changes in average weather. This would be in addition to the direct effects of higher education on living standards, through higher income. Policies that improve water use efficiency and reduce baseline water stress in a district may make households in that district more resilient to changes in average weather. Last, improving primary road density and access to markets may make new resources available to households, which might allow better protection against changes in average weather.

Not all policy-relevant variables could be analyzed in the context of all the countries since the country-specific models include only the variables that are weakly correlated with the seasonal climate indicator variables with a correlation coefficient of less than 0.5. For example, access to market fails the weak correlation criterion in all the countries except Sri Lanka. Similarly, primary road density is used only in Bangladesh and India, because this policy-relevant variable is highly correlated with seasonal climate indicators in other countries.

To analyze how policy-relevant variables mediate the effects of changes in average weather on living standards, the original equation (3.1) is rewritten with a few changes in notation, leading to equation (A.1). In equation (3.1) household variables are denoted by X; here, they are denoted as H. Similarly, originally district and locational variables in equation (3.1) are W; here, they are denoted as L:

$$Y_{hit} = \alpha + \sum_{j\in(s,m,w)} (\beta_{1j} temp_{it}^{j} + \beta_{2j} temp_{it}^{j^2} + \beta_{3j} rain_{it}^{j} + \beta_{4j} rain_{it}^{j^2}) + \beta_5 H_{hit} + \beta_6 L_i + \tau_t + u_{hit} \quad \text{(Eq. A.1)}$$

The main equation can be rewritten as follows:

$$Y_{hit} = \alpha + \alpha W_{it} + \beta X_{hit} + \tau_t + u_{hit} \quad \text{(Eq. A.2)}$$

where:

$$\alpha W_{it} = \sum_{j\in(s,m,w)} \begin{pmatrix} \beta_{1j} temp_{it}^{j} + \beta_{2j} temp_{it}^{j^2} \\ + \beta_{3j} rain_{it}^{j} + \beta_{4j} rain_{it}^{j^2} \end{pmatrix}$$

and

$$\beta X_{hit} = \beta_5 H_{hit} + \beta_5 L_i$$

To capture the interaction between the policy actions and effects of changes in average weather on living standards, let X_{hit}^{POL} be one of these six policy variables described above (that is, $POL = 1, 2\ldots6$). Then up to six interaction models, one for each POL, are estimated for each country. The interaction model is represented as:

$$Y_{hit} = \alpha + \alpha W + \beta X_{hit} + \gamma X_{hit}^{POL} W_{it} + \tau_t + u_{hit} \quad \text{(Eq. A.3)}$$

Note that γ is a vector of coefficients for interactions with each of the seasonal and quadratic components of W.

These interaction models—and associated marginal changes in consumption expenditure—are computed as:

$$\frac{\Delta Y_i}{\Delta W_i} = \gamma I X_i^{POL},$$

where I is an identity vector of the dimension of γ. In other words:

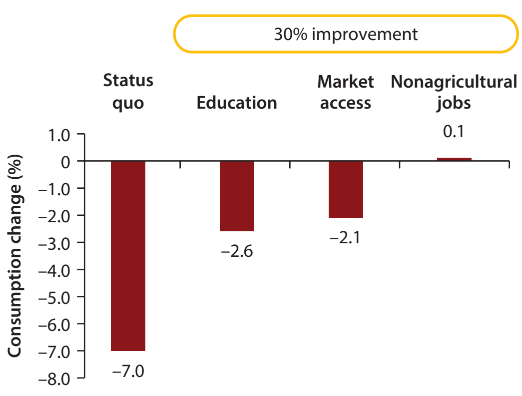
$$\frac{\Delta Y_i}{\Delta W_i} = X_i^{POL} \sum_{j=1}^{12} \gamma_j$$

This captures only the additional effects of the policy-relevant variables on changes in living standards because of changes in average weather. Because it is expected that an increase in any of the policy-relevant variables will improve the resilience of households and help them better cope with long-term changes in average weather, the marginal effects on consumption, $\Delta Y_i/\Delta W_i$, are expected to be positive. These positive effects are expected to be in addition to the main benefits of improving any of the policy-relevant variables, such as education, for consumption. The main benefits, which can be substantial, are not included in this analysis.

To understand the marginal effects of policy relevant variables on changes in consumption stemming from changes in average weather, the effects are plotted around the mean predicted changes in consumption and the respective average policy-relevant indicator (see figure A.1).

To plot more than one policy variable on the X axis, the indicators are rescaled to be in the range of 0 to 100 (for example, $Rescaled\ X_{hit}^{POL} = \frac{[X_{hit}^{POL} - Min]}{[Max - Min]}$). Here, all variables (termed "development outcomes") are improved by 30 percent to calculate their impact on living standards in the context of average changes in precipitation and temperature. The only exception is "market access," which is only increased by 3 percent.

FIGURE A.1 Effects of Development Outcomes on Hotspots in Sri Lanka under the Carbon-Intensive Scenario by 2050



Source: World Bank calculations.
Note: Impacts of interventions are estimated using the method described in this appendix. 15% and 30% increases in market access are defined as 1.5% and 3% decreases in travel time to major cities, respectively.

Supplementary Tables B

More than 40 climate models have been developed and used by scientists around the world in the CMIP5 climate modeling experiment to help understand the Earth's climate system (Taylor, Stouffer, and Meehl 2012). Of these models, the climate output needed for the analysis in this book is publicly available for 18 (names given in table B.1). These 18 climate models are assessed as described in appendix D. Eleven of the climate models are selected as best representing climate conditions best in South Asia. These 11 models are used throughout the report to project future climate conditions.

TABLE B.1 18 Climate Models Assessed

Climate model	Included	Reference
ACCESS1.0	Yes	Bi and others 2013
BCC CSM1.1	Yes	Wu and others 2008
CanESM2	Yes	Arora and others 2011
CCSM4	Yes	Gent and others 2011
CNRM CM5	Yes	Voldoire and others 2012
CSIRO Mk3.6.0	No	Rotstayn and others 2012
GFDL ESM2G	No	Freidenreich and others 2004
GFDL ESM2M	Yes	Freidenreich and others 2004
GISS E2R	No	Schmidt and others 2014
HadGEM2 CC	Yes	Collins and others 2011
HadGEM2 ES	No	Collins and others 2011
INM CM4	No	Volodin and others 2010
IPSL CM5A-LR	Yes	Dufresne and others 2013
MIROC ESM	Yes	Watanabe and others 2011
MIROC ESM-CHEM	Yes	Watanabe and others 2011
MIROC5	No	Watanabe and others 2010
MPI ESM-LR	No	Giorgetta and others 2013
MPI ESM-MR	Yes	Giorgetta and others 2013
NorESM1-M	Yes	Kirkevåg and others 2013

Note: The models are the subset of those participating in CMIP5 that include publicly available simulations for the historical, RCP 4.5, and RCP 8.5 experiments.

Table B.2 shows the regression results for the reduced-form model in equation (3.1). The estimated coefficients from this model are used to predict the changes in consumption expenditures resulting from the long-term changes in average weather in table 3.4.

Table B.3 shows the results of a robustness test for changes in consumption expenditures under different model specifications using different sets of control variables and with and without provincial fixed effects. The selection of control variables is based on different correlation coefficient threshold criteria.

TABLE B.2 Regression Results Used for Consumption Predictions

	Afghanistan	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Summer temperature	0.311***	–0.469***	0.302***	0.109***	0.077***	0.604
	(0.028)	(0.1100)	(0.0130)	(0.0360)	(0.0100)	(0.4220)
Summer temperature squared	–0.008***	0.009***	–0.006***	–0.001*	–0.001***	–0.017**
	(0.001)	(0.0020)	(0.0002)	(0.0010)	(0.0002)	(0.0070)
Summer precipitation	0.001*	0.0004*	–0.001***	0.005***	0.0001	–0.002***
	(0.001)	(0.0002)	(0.0001)	(0.0010)	(0.0004)	(0.0004)
Summer precipitation squared	0.00002***	0.0000	0.00001***	–0.00003***	0.00001***	0.00000***
	(0.00000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Monsoon temperature	–0.330***	–0.328	–0.124***	–0.023	–0.174***	–0.426**
	(0.027)	(0.2860)	(0.0140)	(0.0800)	(0.0110)	(0.1980)
Monsoon temperature squared	0.005***	0.005	0.003***	0.001	0.002***	0.010***
	(0.001)	(0.0050)	(0.0002)	(0.0020)	(0.0002)	(0.0030)
Monsoon precipitation	–0.017***	–0.001***	–0.0002***	0.002***	–0.001***	0.001
	(0.001)	(0.0003)	(0.0001)	(0.0010)	(0.0001)	(0.0004)
Monsoon precipitation squared	0.0001***	0.00000***	0.00000***	–0.00000**	0.00000***	–0.00000**
	(0.00001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Winter temperature	–0.037***	1.210**	–0.193***	–0.119***	0.040***	0.064
	(0.009)	(0.4990)	(0.0100)	(0.0350)	(0.0060)	(0.3920)
Winter temperature squared	0.005***	–0.028**	0.005***	0.001*	–0.001***	0.003
	(0.001)	(0.0110)	(0.0002)	(0.0010)	(0.0002)	(0.0070)
Winter precipitation	0.003	–0.001	0.0004**	0.031**	–0.001**	–0.004***
	(0.002)	(0.0020)	(0.0002)	(0.0130)	(0.0010)	(0.0010)
Winter precipitation squared	–0.00005**	0.00002	–0.00001***	–0.001*	0.0000	0.00000***
	(0.00002)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)
Rural household	0.016	0.044***	–0.046***	–0.044***	–0.172***	–0.145***
	(0.011)	(0.0080)	(0.0060)	(0.0150)	(0.0040)	(0.0070)
Household size	–0.033***	–0.050***	–0.068***	–0.060***	–0.054***	–0.117***
	(0.001)	(0.0020)	(0.0010)	(0.0030)	(0.0010)	(0.0020)
Dependency ratio	–0.102***	–0.126***	–0.101***	–0.120***	–0.072***	–0.058***
	(0.003)	(0.0060)	(0.0020)	(0.0060)	(0.0020)	(0.0040)
Age of household head	0.001***	0.007***	0.005***	0.008***	0.004***	0.004***
	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0001)	(0.0002)
Female-headed household	–0.066***	0.080***	0.047***	0.206***	0.199***	–0.001
	(0.025)	(0.0140)	(0.0060)	(0.0150)	(0.0070)	(0.0070)
Household has electricity	0.110***	0.227***	0.189***	0.293***	0.171***	0.258***
	(0.012)	(0.0080)	(0.0050)	(0.0130)	(0.0050)	(0.0070)
Years of education of head	0.018***	0.042***	0.045***	0.054***	0.035***	0.059***
	(0.001)	(0.0010)	(0.0004)	(0.0010)	(0.0004)	(0.0010)
Agricultural household	–0.023***	0.021***	–0.046***	–0.062***	0.135***	–0.059***
	(0.006)	(0.0070)	(0.0040)	(0.0120)	(0.0040)	(0.0060)
Baseline water stress	–0.159***	1.356***	0.022***	–0.362**	–0.001	0.080*

(continues next page)

TABLE B.2 Regression Results Used for Consumption Predictions (continued)

	Afghanistan	Bangladesh	India	Nepal	Pakistan	Sri Lanka
	(0.032)	(0.1660)	(0.0050)	(0.1500)	(0.0010)	(0.0410)
Latitude	−0.089***	n.a.	n.a.	n.a.	n.a.	n.a.
	(0.007)	n.a.	n.a.	n.a.	n.a.	n.a.
Elevation	n.a.	0.0004**	n.a.	n.a.	n.a.	n.a.
	n.a.	(0.0002)	n.a.	n.a.	n.a.	n.a.
Water availability normalized	0.001	0.0004**	−0.0001	0.001**	−0.005***	n.a.
	(0.002)	(0.0001)	(0.0002)	(0.0010)	(0.0010)	n.a.
Water availability seasonal variability	−0.103**	n.a.	0.023**	0.175***	0.03	n.a.
	(0.047)	n.a.	(0.0090)	(0.0610)	(0.0180)	n.a.
Coast distance inverse squared	−203,172.200***	n.a.	0.00004	n.a.	38.497***	n.a.
	(26,586.490)	n.a.	(0.0003)	n.a.	(13.4370)	n.a.
Road density: primary	0.010***	−0.001	0.008***	n.a.	n.a.	n.a.
	(0.002)	(0.0020)	(0.0010)	n.a.	n.a.	n.a.
Market access	−0.00000	n.a.	n.a.	n.a.	n.a.	−0.001***
	(0.00002)	n.a.	n.a.	n.a.	n.a.	(0.0001)
Population density: 2010	−0.00003***	0.00004***	0.00002***	0.00004***	0.00004***	n.a.
	(0.00000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	n.a.
Constant	13.113***	4.136	5.926***	4.593***	8.577***	6.614***
	(0.292)	(4.5510)	(0.1340)	(0.6530)	(0.1070)	(1.3400)
Observations	38,579	19,508	240,206	9,600	75,635	55,639
R^2	0.188	0.38	0.446	0.558	0.43	0.349
Adjusted R^2	0.188	0.379	0.446	0.557	0.429	0.349
Residual standard error	5.669 (df = 38549)	21.776 (df = 19480)	20.069 (df = 240177)	15.598 (df = 9574)	13.970 (df = 75604)	8.174 (df = 55614)
F statistic	308.672*** (df = 29; 38549)	442.151*** (df = 27; 19480)	6,908.214*** (df = 28; 240177)	482.813*** (df = 25; 9574)	1,897.374*** (df = 30; 75604)	1,242.781*** (df = 24; 55614)

Source: World Bank calculations.
Note: Dependent variable: *ln consumption.* Robust standard errors are in parentheses. Models include survey year dummies.
$^{*}p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.

TABLE B.3 Changes in Consumption from Base Year 2011 to 2030 and 2050 for Climate-Sensitive and Carbon-Intensive Scenarios from Model Specifications
Percent

Model specification			Climate in 2030		Climate in 2050	
Provincial fixed effect	Correlation threshold	Country	Climate-sensitive	Carbon-intensive	Climate-sensitive	Carbon-intensive
No	0.3	Afghanistan	4.9	5.6	8.0	11.38
No	0.3	Bangladesh	−2.3	−3.7	−4.9	−10.4
No	0.3	India	−1.3	−1.5	−2.0	−2.9
No	0.3	Nepal	2.0	2.1	3.1	3.8
No	0.3	Pakistan	−1.3	−1.5	−2.0	−2.9
No	0.3	Sri Lanka	1.6	1.7	2.8	3.9
No	0.5	Afghanistan	5.1	5.8	8.3	11.9
No	0.5	Bangladesh	−1.3	−2.3	−2.9	−6.7

(continues next page)

TABLE B.3 Changes in Consumption from Base Year 2011 to 2030 and 2050 for Climate-Sensitive and Carbon-Intensive Scenarios from Model Specifications (continued)
Percent

Model specification			Climate in 2030		Climate in 2050	
Provincial fixed effect	Correlation threshold	Country	Climate-sensitive	Carbon-intensive	Climate-sensitive	Carbon-intensive
No	0.5	India	−1.3	−1.5	−2.0	−2.8
No	0.5	Nepal	2.1	2.3	3.2	4.1
No	0.5	Pakistan	−1.3	−1.5	−2.0	−2.9
No	0.5	Sri Lanka	−3.2	−3.7	−4.9	−7.0
No	0.7	Afghanistan	5.1	5.8	8.3	11.9
No	0.7	Bangladesh	−4.2	−7.3	−10.0	−21.7
No	0.7	India	−0.5	−0.6	−0.7	−1.1
No	0.7	Nepal	2.7	3.0	4.1	5.4
No	0.7	Pakistan	−1.3	−1.6	−2.0	−3.0
No	0.7	Sri Lanka	−0.9	−0.6	−0.8	0.3
No	All controls	Afghanistan	3.7	4.2	6.1	8.8
No	All controls	Bangladesh	0.7	−1.2	−0.9	−6.8
No	All controls	India	1.2	1.4	1.7	2.4
No	All controls	Nepal	2.2	2.3	3.2	3.9
No	All controls	Pakistan	−2.4	−2.9	−3.7	−5.4
No	All controls	Sri Lanka	−0.5	0.0	0.0	1.5
No	No control	Afghanistan	7.4	8.3	12.1	17.3
No	No control	Bangladesh	12.5	15.6	20.7	32.1
No	No control	India	−2.0	−2.2	−3.0	−4.1
No	No control	Nepal	5.4	5.1	8.2	9.5
No	No control	Pakistan	1.7	2.2	2.7	4.1
No	No control	Sri Lanka	5.6	5.7	8.9	11.6
Yes	0.3	Afghanistan	5.6	6.3	9.1	12.9
Yes	0.3	Bangladesh	−0.7	−1.5	−2.6	−7.5
Yes	0.3	India	−1.5	−1.9	−2.4	−3.5
Yes	0.3	Nepal	4.1	4.9	5.9	8.8
Yes	0.3	Pakistan	−0.3	−0.5	−0.5	−0.9
Yes	0.3	Sri Lanka	−9.4	−9.4	−11.1	−12.4
Yes	0.5	Afghanistan	5.5	6.2	8.8	12.6
Yes	0.5	Bangladesh	0.0	−0.6	−1.2	−4.9
Yes	0.5	India	−1.5	−1.8	−2.3	−3.3
Yes	0.5	Nepal	4.9	5.9	7.1	10.8
Yes	0.5	Pakistan	−0.3	−0.5	−0.5	−0.9
Yes	0.5	Sri Lanka	−9.0	−9.0	−10.9	−12.3
Yes	0.7	Afghanistan	5.5	6.2	8.8	12.6
Yes	0.7	Bangladesh	−2.6	−4.4	−7.7	−17.6

(continues next page)

TABLE B.3 Changes in Consumption from Base Year 2011 to 2030 and 2050 for Climate-Sensitive and Carbon-Intensive Scenarios from Model Specifications (continued)
Percent

Model specification			Climate in 2030		Climate in 2050	
Provincial fixed effect	Correlation threshold	Country	Climate-sensitive	Carbon-intensive	Climate-sensitive	Carbon-intensive
Yes	0.7	India	−0.9	−1.1	−1.5	−2.2
Yes	0.7	Nepal	7.4	8.9	10.5	15.4
Yes	0.7	Pakistan	0.1	0.0	0.1	−0.1
Yes	0.7	Sri Lanka	−7.3	−7.2	−8.5	−8.9
Yes	All controls	Afghanistan	4.2	4.8	6.9	9.9
Yes	All controls	Bangladesh	−1.9	−3.3	−5.3	−12.3
Yes	All controls	India	−1.4	−1.7	−2.2	−3.2
Yes	All controls	Nepal	3.9	4.0	5.7	6.9
Yes	All controls	Pakistan	−3.9	−4.8	−5.9	−8.4
Yes	All controls	Sri Lanka	−6.1	−6.0	−7.2	−7.6
Yes	No control	Afghanistan	7.7	8.7	12.7	18.1
Yes	No control	Bangladesh	15.1	19.2	24.1	37.2
Yes	No control	India	−3.5	−4.0	−5.4	−7.4
Yes	No control	Nepal	2.9	3.3	5.8	9.1
Yes	No control	Pakistan	−1.0	−1.2	−1.6	−2.3
Yes	No control	Sri Lanka	−12.3	−12.6	−14.2	−16.1

Source: World Bank calculations.
Note: "Correlation threshold" is a threshold used for a correlation coefficient of control variables with all climate variables.

References

Arora, V. K., J. F. Scinocca, G. J. Boer, J. R. Christian, K. L. Denman, G. M. Flato, and W. J. Merryfield. 2011. "Carbon Emission Limits Required to Satisfy Future Representative Concentration Pathways of Greenhouse Gases." *Geophysical Research Letters* 38 (5).

Bellouin, N., J. Rae, A. Jones, C. Johnson, J. Haywood, and O Boucher. 2011. "Aerosol Forcing in the Climate Model Intercomparison Project (CMIP5) Simulations by HadGEM2-ES and the Role of Ammonium Nitrate." *J. Geophys. Res.*, 116, D20206, doi:10.1029/2011JD016074, 2011.

Bi, D., M. Dix, S. J. Marsland, S. O'Farrell, H. A. Rashid, P. Uotila, A. C. Hirst, E. Kowalczyk, M. Golebiewski, A. Sullivan, H. Yan, N. Hannah, C. Franklin, Z. Sun, P. Vohralik, I. Watterson, X. Zhou, R. Fiedler, M. Collier, Y. Ma, J. Noonan, L. Stevens, P. Uhe, H. Zhu, S. M. Griffies, R. Hill, C. Harris, and K. Puri. 2013. "The ACCESS Coupled Model: Description, Control Climate and Evaluation." *Australian Meteorological and Oceanographic Journal* 63 (1): 41–64.

Collins, W. J., N. Bellouin, M. Doutriaux-Boucher, N. Gedney, P. Halloran, T. Hinton, . . ., and G. Martin. 2011. "Development and Evaluation of an Earth-System Model-HadGEM2." *Geoscientific Model Development* 4 (4): 1051.

Dufresne, J. L., M. A. Foujols, S. Denvil, A. Caubel, O. Marti, O. Aumont, Y. Balkanski, S. Bekki, H. Bellenger, R. Benshila, S. Bony, L. Bopp, P. Braconnot, P. Brockmann, P. Cadule, F. Cheruy, F. Codron, A. Cozic, D. Cugnet, N. de Noblet, J. P. Duvel, C. Ethé, L. Fairhead, T. Fichefet, S. Flavoni, P. Friedlingstein, J. Y. Grandpeix, L. Guez, E. Guilyardi, D. Hauglustaine, F. Hourdin, A. Idelkadi,

J. Ghattas, S. Joussaume, M. Kageyama, G. Krinner, S. Labetoulle, A. Lahellec, M. P. Lefebvre, F. Lefevre, C. Levy, Z. X. Li, J. Lloyd, F. Lott, G. Madec, M. Mancip, M. Marchand, S. Masson, Y. Meurdesoif, J. Mignot, I. Musat, S. Parouty, J. Polcher, C. Rio, M. Schulz, D. Swingedouw, S. Szopa, C. Talandier, P. Terray, N. Viovy, and N. Vuichard. 2013. "Climate Change Projections Using the IPSL-CM5 Earth System Model: From CMIP3 to CMIP5." *Climate Dynamics* 40 (9-10): 2123–65.

Freidenreich, S. M., S. T. Garner, R. G. Gudgel, C. T. Gordon, and I. M. Held. 2004. "The New GFDL Global Atmosphere and Land Model AM2–LM2: Evaluation with Prescribed SST Simulations." *Journal of Climate* 17: 4641–73.

Gent, P. R., G. Danabasoglu, L. J. Donner, M. M. Holland, E. C. Hunke, S. R. Jayne, and P. H. Worley. 2011. "The Community Climate System Model Version 4." *Journal of Climate* 24 (19): 4973–91.

Giorgetta, M. A., J. Jungclaus, C. H. Reick, S. Legutke, J. Bader, M. Böttinger, V. Brovkin, T. Crueger, M. Esch, K. Fieg, K. Glushak, V. Gayler, H. Haak, H. D. Hollweg, T. Ilyina, S. Kinne, L. Kornblueh, D. Matei, T. Mauritsen, U. Mikolajewicz, W. Mueller, D. Notz, F. Pithan, T. Raddatz, S. Rast, R. Redler, E. Roeckner, H. Schmidt, R. Schnur, J. Segschneider, K. D. Six, M. Stockhause, C. Timmreck, J. Wegner, H. Widmann, K. H. Wieners, M. Claussen, J. Marotzke, and B. Stevens. 2013. "Climate and Carbon Cycle Changes from 1850 to 2100 in MPI-ESM Simulations for the Coupled Model Intercomparison Project Phase 5." *Journal of Advances in Modeling Earth Systems* 5 (3): 572–97.

Kirkevåg, A., T. Iversen, Ø. Seland, C. Hoose, J. E. Kristjánsson, H. Struthers, A. M. L. Ekman, S. Ghan, J. Griesfeller, E. D. Nilsson, and M. Schulz. 2013. "Aerosol–Climate Interactions in the Norwegian Earth System Model—NorESM1-M." *Geoscientific Model Development* 6 (1): 207–44.

Rotstayn, L. D., S. J. Jeffrey, M. A. Collier, S. M. Dravitzki, A. C. Hirst, J. I. Syktus, and K. K. Wong. 2012. "Aerosol-and Greenhouse Gas-Induced Changes in Summer Rainfall and Circulation in the Australasian Region: A Report Using Single-Forcing Climate Simulations." *Atmospheric Chemistry and Physics* 12 (14): 6377.

Schmidt, G. A., M. Kelley, L. Nazarenko, R. Ruedy, G. L. Russell, I. Aleinov, M. Bauer, S. E. Bauer, M. K. Bhat, R. Bleck, V. Canuto, Y. Chen, Y. Cheng, T. L. Clune, A. Del Genio, R. de Fainchtein, G. Faluvegi, J. E. Hansen, R. J. Healy, N. Y. Kiang, D. Koch, A. A. Lacis, A. N. LeGrande, J. Lerner, K. K. Lo, E. E. Matthews, S. Menon, R. L. Miller, V. Oinas, A. O. Oloso, J. P. Perlwitz, M. J. Puma, W. M. Putman, D. Rind, A. Romanou, M. Sato, D. T. Shindell, S. Sun, R. A. Syed, N. Tausnev, K. Tsigaridis, N. Unger, A. Voulgarakis, M. Yao, and J. Zhang. 2014. "Configuration and Assessment of the GISS ModelE2 Contributions to the CMIP5 Archive." *Journal of Advances in Modeling Earth Systems* 6 (1): 141–84.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl. 2012. "An Overview of CMIP5 and the Experiment Design." *Bulletin of the American Meteorological Society* 93 (4): 485–98.

Volodin, E. M., N. A. Dianskii, and A. V. Gusev. 2010. "Simulating Present-Day Climate with the INMCM4.0 Coupled Model of the Atmospheric and Oceanic General Circulations." *Izvestiya, Atmospheric and Oceanic Physics* 46 (4): 414–31.

Watanabe, M., T. Suzuki, R. O'ishi, Y. Komuro, S. Watanabe, S. Emori, T. Takemura, M. Chikira, T. Ogura, M. Sekiguchi, K. Takata, D. Yamazaki, T. Yokohata, T. Nozawa, H. Hasumi, H. Tatebe, and M. Kimoto. 2010. "Improved Climate Simulation by MIROC5: Mean States, Variability, and Climate Sensitivity." *Journal of Climate* 23 (23): 6312–35.

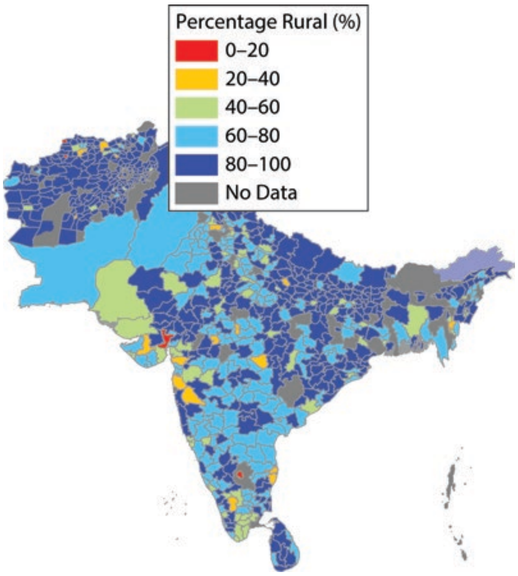
Watanabe, S., T. Hajima, K. Sudo, T. Nagashima, T. Takemura, H. Okajima, T. Nozawa, H. Kawase, M. Abe, T. Yokohata, T. Ise, H. Sato, E. Kato, K. Takata, S. Emori, and M. Kawamiya. 2011. "MIROC-ESM 2010: Model Description and Basic Results of CMIP5-20c3m Experiments." *Geoscientific Model Development* 4 (4): 845.

Wu, T., R. Yu, F. Zhang, Z. Wang, M. Dong, L. Wang, X. Jin, D. Chen, and L. Li. 2010. "The Beijing Climate Center Atmospheric General Circulation Model: Description and Its Performance for the Present-Day Climate." *Climate Dynamics* 34 (1): 123–47.

Supplementary Maps

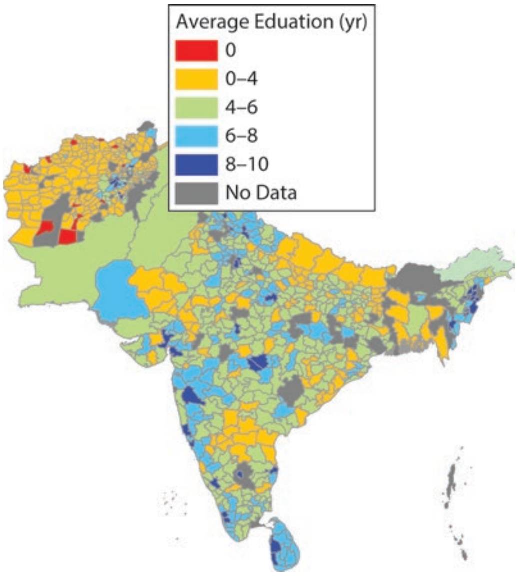
C

MAP C.1 Percentage of People in Each Administrative Unit Who Live in Rural Environments



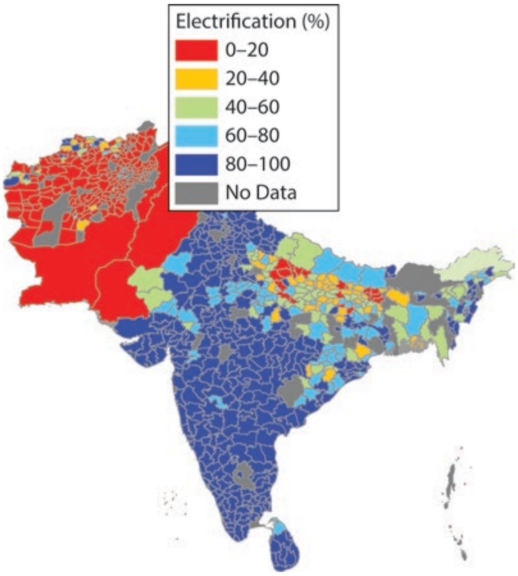
Source: Based on household data referenced in table 3.2.
Note: This classification is based on the most recent year of survey data available, as outlined in table 3.1.

MAP C.2 Average Years of Education of the Head of Household in Each Administrative Unit



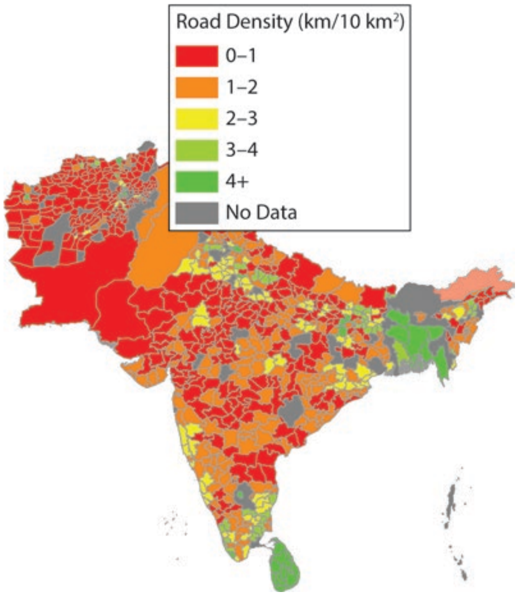
Source: Based on household data referenced in table 3.2.
Note: This classification is based on the most recent year of survey data available, as outlined in table 3.1.

MAP C.3 Percentage of People in Each Administrative Unit Who Have Access to Electricity



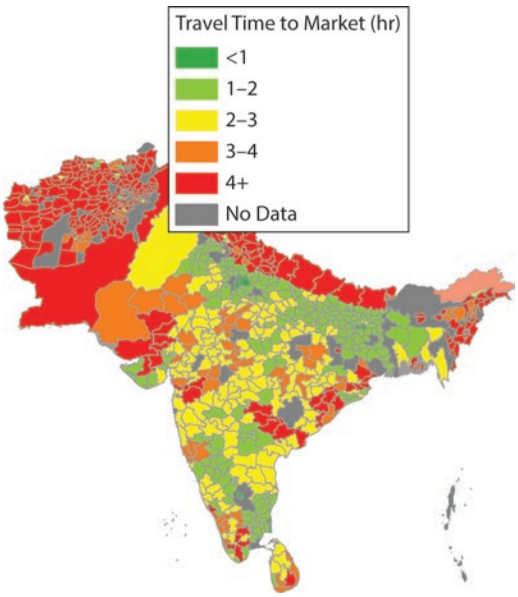
Source: Based on household data referenced in table 3.2.
Note: This classification is based on the most recent year of survey data available, as outlined in table 3.1.

MAP C.5 Average Density of Roads



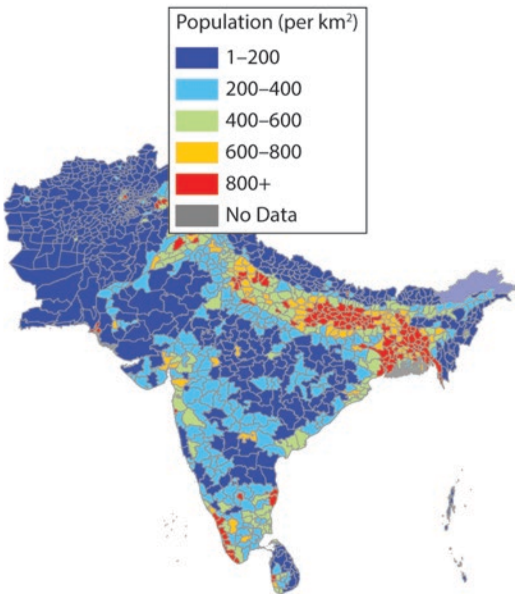
Source: Based on district data referenced in table 3.2.
Note: This classification is based on the most recent year of survey data available, as outlined in table 3.1.

MAP C.4 Average Travel Time to Market in Hours



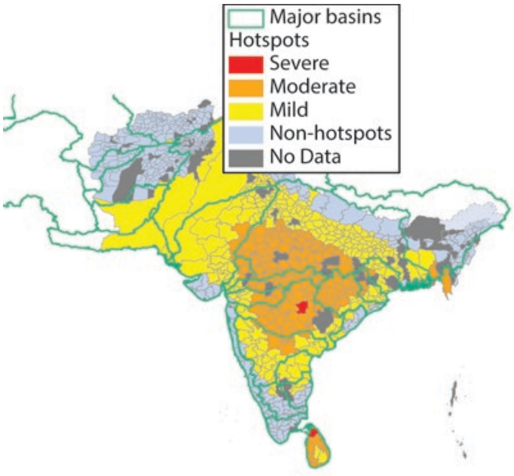
Source: Based on district data referenced in table 3.2.
Note: This classification is based on the most recent year of survey data available, as outlined in table 3.1.

MAP C.6 Average Population Density per Square Kilometer



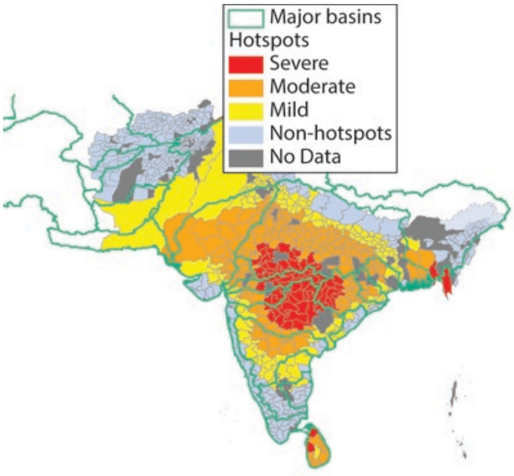
Source: Based on household data referenced in table 3.2.
Note: This classification is based on the most recent year of survey data available, as outlined in table 3.1.

MAP C.7 Climate-Sensitive Scenario by 2050: Hotspots Do Not Clearly Overlap with Major Basins



Source: Based on household data referenced in table 3.2.
Note: Same as map 4.2, but with basin boundaries.

MAP C.8 Carbon-Intensive Scenario by 2050: Hotspots Do Not Clearly Overlap with Major Basins



Source: Based on household data referenced in table 3.2.
Note: Same as map 4.2, but with basin boundaries.

Climate Model Selection

D

Multimodel approaches to estimate future climate are superior compared to approaches using individual models. The reason is that multimodel mean is typically more representative than any individual model. Additionally, the multimodel ensemble can be used to estimate uncertainty. The conceptual basis for this approach is that although all models have imperfections, they do not always have the same imperfections. For multimodel approaches to perform as expected, each of the included models must perform adequately by itself. Although it is difficult to identify the best-performing model, it is often possible to identify the models that do not perform as well as the others and to discard those. This is the approach taken here.

This book evaluates 18 Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models (Taylor, Stouffer, and Meehl 2012) that have publicly available simulation output for the historic period, RCP 4.5 and RCP 8.5 (appendix B, table B.1). The region used for evaluation includes Afghanistan, Bhutan, Bangladesh, India, Maldives, Nepal, Pakistan, and Sri Lanka. The evaluation is conducted for three seasons based on the monsoon:

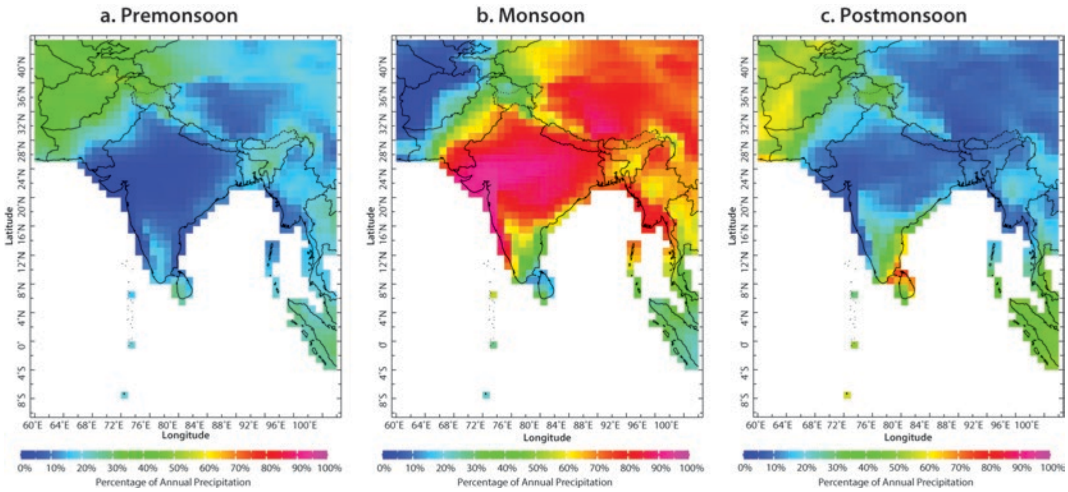
- Premonsoon: March through May
- Monsoon: June through September
- Postmonsoon: October through February

The monsoon is the most important climatic feature of the region because it regulates the seasonality of temperature and brings the rain that allows agriculture to thrive in many locations with the region. The seasonal fractions of annual average precipitation in each season are presented in map D.1, panels a through c. This confirms that most precipitation occurs during the monsoon season for most of South Asia. However, this is not uniformly the case because Afghanistan, Sri Lanka, Southwestern Pakistan, and Southeastern India receive significant portions of their precipitation during the postmonsoon season.

The performance of climate models is assessed using spatial pattern correlation and root mean squared error (RMSE). A high pattern correlation suggests that models adequately capture the underlying climate processes controlling that pattern. A low RMSE suggests that the model represents the correct amplitude of response to the relevant climate processes.

The baseline climatological period for all mean and standard deviation calculations is 1981 through 2000. All the trend calculations, however, are performed based on the longest common period between models and observations. In the case of precipitation, the trends are also normalized to a 30-year

MAP D.1 Percentage of Annual Precipitation Contained in the Study Seasons



Source: Yatagai and others 2012 (Aphrodite v 1101).
Note: Based on average conditions during 1981 through 2000.

period and compared as a change in percentage terms.

Choice of Observations

The climate models are compared to an observational data set over a common historic period. This provides a direct comparison of how the climate models represent actual climate. Several observational data sets are considered as possible representation of the true historical climate. The principal data sets are Aphrodite v1101, a daily gridded data set for monsoon Asia (Yatagai and others 2011), and CHIRPS v2.0, a daily gridded data set available globally (Funk and others 2015).

These two data sets are compared with the Indian Meteorological Department (IMD) daily gridded data set (Rajeevan and others 2006) to determine which one is most preferred for the South Asian analysis. It is determined that overall, the Aphrodite data better match the spatial pattern and local magnitudes of the IMD data, particularly with respect to variability, trends, and precipitation extremes.

For temperature extremes, Aphrodite data do not contain maximum and minimum temperatures, which are important for the calculation of those extremes. Furthermore, comparison of representations of extreme events in observational data sets such as IMD (Rajeevan and others 2006), Berkeley Earth (Rohde and others 2013), and HADEX2 (Donat and others 2013) indicates that there are large discrepancies between observational estimates of extremes. Therefore, there is not a strong quantitative basis against which to compare climate model representations of extremes. As noted in chapter 2, there is also substantial disagreement between climate models in terms of their representation of extremes. These are the two primary reasons that this book focuses on long-term mean climate and does not investigate extreme events.

Weather Measurements Are Uneven across South Asia

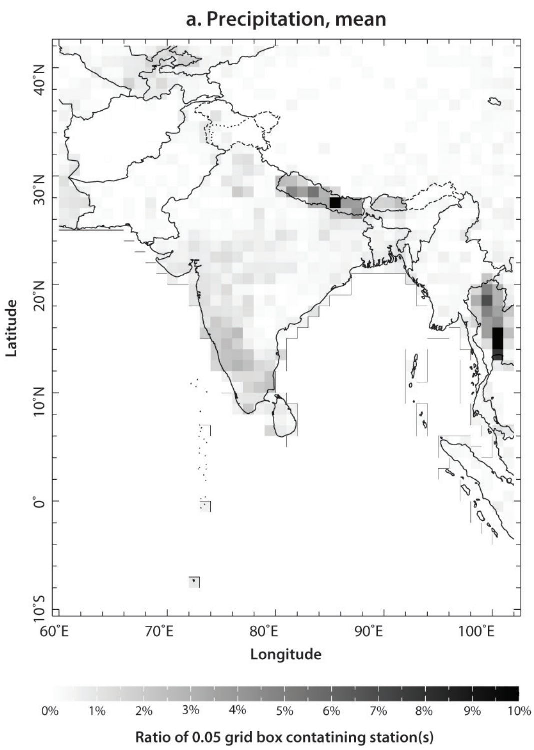
Map D.2 shows the number of weather stations contributing data to the Aphrodite data set. The density of stations contributing to the calculation of precipitation is relatively good across the region, particularly over India, Bangladesh, and Nepal. Afghanistan effectively has no stations contributing precipitation measurements. Temperature measurements are sparser for most countries, except Nepal, but this should be sufficient because temperature has a more stable regional structure (map D.2). Afghanistan is again notably data poor. The Maldives does not have station data provided for temperature in Aphrodite, and it is challenging to isolate for the models given that land-sea masks in most models would consider these small islands as ocean grid points.

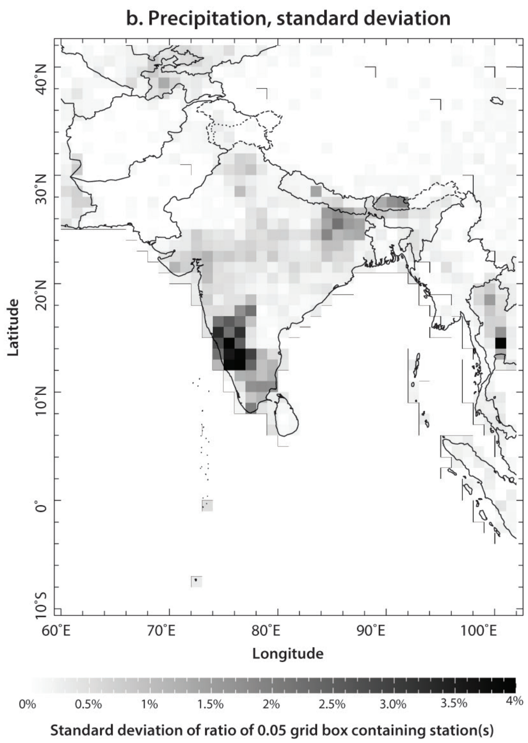
Precipitation station measurements are more temporally complete relative to temperature measurements (maps D.3). The spatial pattern in map D.3 is similar to that in map D.2, with India, Bangladesh, and Nepal having the most complete records for precipitation. For temperature, Nepal appears to have the most thorough coverage, though the stations reporting for India also appear to be consistent over time.

Comparison of Climate Models to Aphrodite

Aphrodite is used as the observational data set for evaluating the historic performance of climate models. Prior to comparison, Aphrodite is regridded to a 1-degree spatial resolution. Each climate model is used

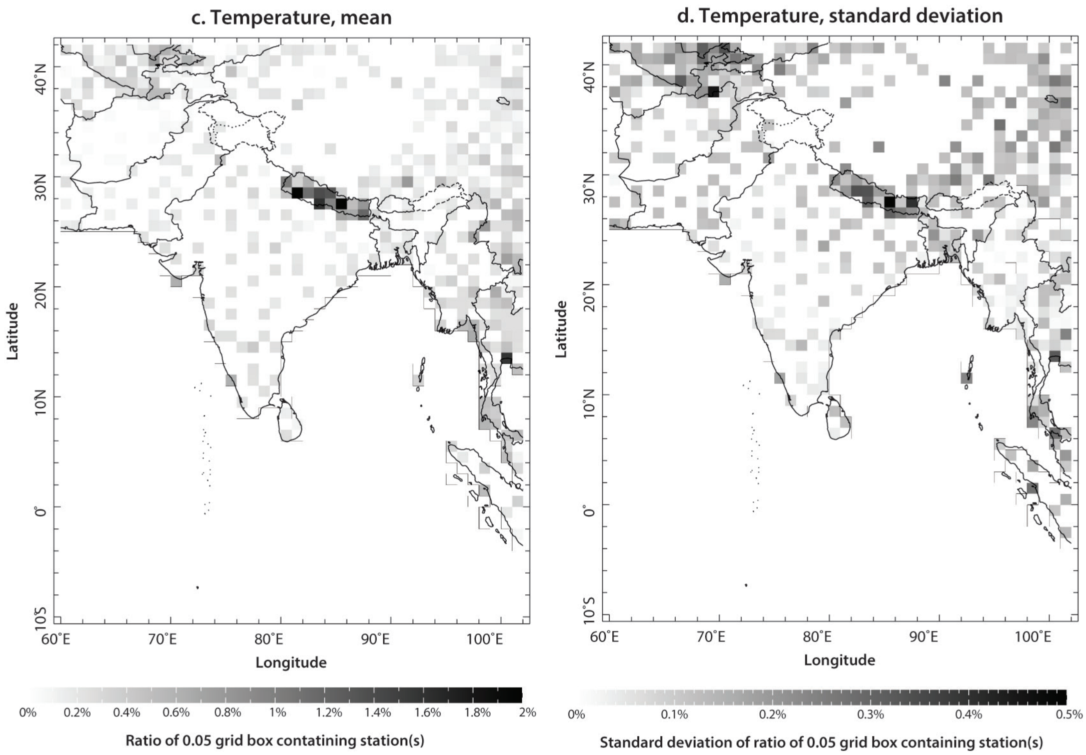
MAP D.2 Spatial Density of Station Measurements' Contribution to the Aphrodite Data Set, 1981 through 2000





(continues next page)

MAP D.2 Spatial Density of Station Measurements' Contribution to the Aphrodite Data Set, 1981 through 2000 (continued)



Sources: Yatagai and others 2011 ("rstn" variable in Aphrodite v1101 data set, for precipitation); v1204R1 (for temperature).
Note: Values are presented as the percentage of 0.05 degrees latitude/longitude grid boxes contained in a 1 degree latitude/longitude grid box. The highest value, 100 percent, would indicate that there is a station in each of the 400 0.05 degree boxes contained in a single 1 degree grid box. Therefore, an average of four stations (or four 0.05 degree boxes) would appear as an average of 1 percent. Standard deviation indicates the temporal variation in availability of station measurements within each grid cell.

at its original latitude/longitude resolution. The quantitative summary of this analysis is present in table 2.2.[1]

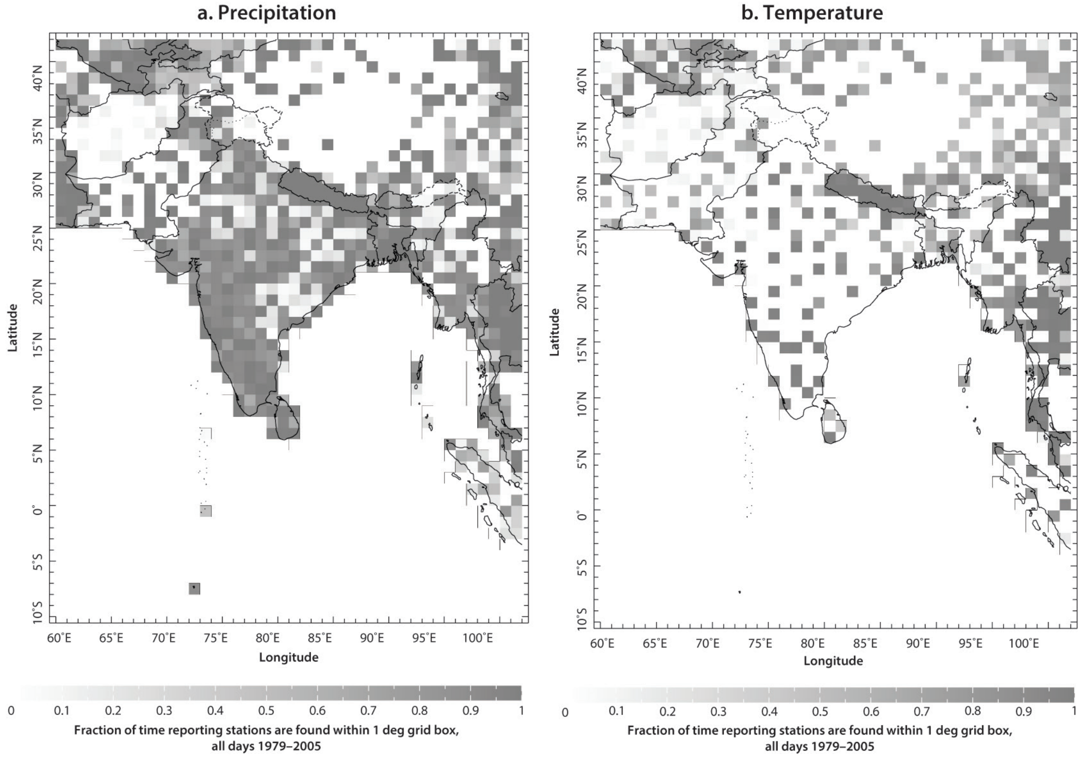
Temperature

March through May (Premonsoon)

For the premonsoon season (March through May), all of the climate models (or GCMs) capture the main spatial features of the mean temperature field, including the sharp gradient created by the Himalaya mountains and a relatively cooler west Indian coast because of the Western Ghats. Other fine-scale details are not properly represented, mainly because of the relatively coarse resolution of the GCMs. Most models simulate colder conditions over Nepal than are observed. Some models tend to overestimate temperatures in northeast India, Bangladesh, and Bhutan, such as CSIRO Mk3.6.0, and GISS E2R; others, such as INM CM4, have a cooler bias over most of India. Exploration of the year-to-year variability (characterized by standard deviation) indicates an even larger disagreement between observations and GCMs.

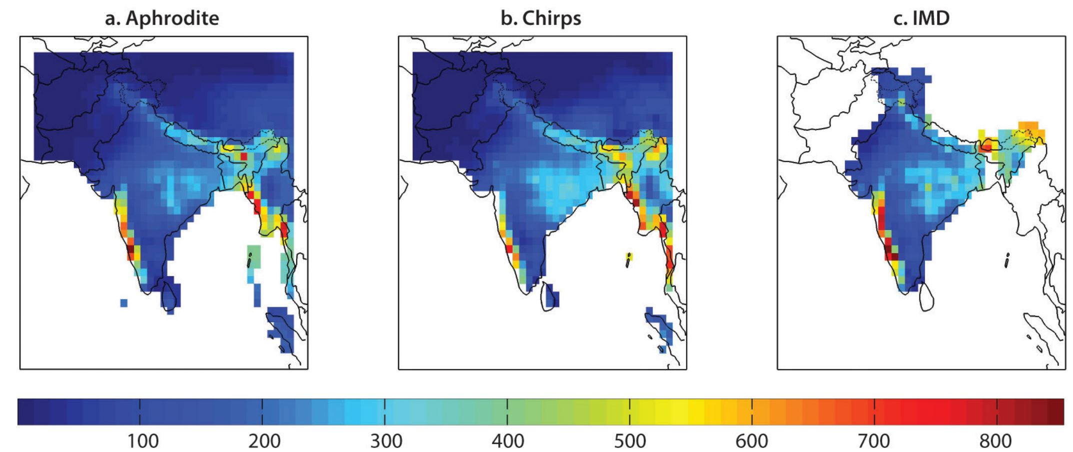
The temperature variability tends to be overestimated throughout the study region. The observations suggest that most of the variability occurs over Pakistan, Afghanistan, and northwest India, and decreases sharply toward the south. However, this region is not well covered by station observations

MAP D.3 Seasonal and Temporal Consistency of Station Measurements' Contribution to the Aphrodite Data Set, 1979 through 2005



Source: Yatagai and others 2011 ("rstn" variable in Aphrodite v1101 data set).
Note: Fraction of daily station data reported for each year during the period 1979 through 2005. Spatial explanation of grid cell configuration is the same as with map D.2.

MAP D.4 Average Monsoon Precipitation, 1981 through 2000



Sources: Funk and others 2015 (CHIRPS); Rajeevan and others 2006 (IMD); Yatagai and others 2011 (Aphrodite).

(maps D.2 and D.3). A large dispersion is seen among GCMs, both in the intensity of the variability and the location of its maximums. With the exception of CSIRO Mk3.6.0, they all overestimate variability in the study region.

The pattern of observed temperature trends for March through May shows a lot of small-scale details, probably because of the complex topography of the study region. A slight warming signal dominates, interrupted by a cooling region along the mountain ranges to the north of the study region. A stronger warming is observed just north of Nepal. The GCMs are unable to reproduce the observed trend pattern, though many of them exhibit reasonable magnitudes of temperature change in the study countries. Most are dominated by a warming through much of the study region, and the most extreme cases are the IPSL, CM5A-LR, and MPI ESM-MR models.

June through September (Monsoon)

During the monsoon season (June through September), the average temperatures over the study region yield a more complex pattern than seen in March through May, with more regional characteristics such as a cooler west coast, to the west of the Western Ghats, which correlates with the increased precipitation in that area. The GCMs tend to have a more widespread minimum in the whole southern portion of the peninsula, probably because of the resolution of the simulated topographies. In addition, some models have very strong warm biases in the northern part of India and extending into Pakistan, such as GISS E2R and CSIRO Mk3.6.0.

The year-to-year variability for July through September is similar in magnitude to that in March through May, but slightly larger for central India. The sharp difference in the temperature variability between Afghanistan and Pakistan might be due to the complex topography of that region, but also may be due to the lack of station data over Afghanistan. Most GCMs show notable differences with the observed pattern, with very large overestimations of the temperature variability in north India. CanESM2 and the two GFDL models are the more extreme cases.

The observed trend pattern for July through September is very similar to that of March through May, suggesting that a weak cooling occurred over 1961–2005. Most models show a slightly larger cooling trend in most of the domain than is observed, with the HadGEM2 and MIROC5 models being the most extreme.

October through February (Postmonsoon)

For the postmonsoon season (October through February), the models exhibit a range of differences in the spatial pattern of mean temperatures. Most models include a strong bias of cooler temperatures over the northern portion of the study region, with the HaDGEM2 and INM CM4 as the worst performers. The GCMs also differ considerably on both the intensity and the patterns of variability. Most of the models tend to overestimate the magnitude of the variability throughout the study region.

The observed trend pattern for October through February temperatures is very similar to the one observed for the two previous seasons. Most of the models, though not all, again tend to overestimate the cooling trends slightly. A couple of the models (the worst performers are IPSL and MPI ESM-MR) show overall warming and fail to represent the cooling trend associated with the mountain ranges at the north of the study region.

Precipitation

March through May (Premonsoon)

Precipitation is a very challenging variable for climate models to capture, and is also affected by the complex topography and circulation of the region. The premonsoon season (March through May) is very dry over the study region, with the exception of the southwesternmost tip of India and Sri Lanka and the topography to the north and northeast of the domain. The GCMs capture the main structures of the

March through May field, but fail to represent the small-scale details, particularly over southwest India, probably because of their deficient representations of topography.

For the year-to-year variability (quantified by the standard deviation), the differences between observations and GCMs are most notable along the Himalayan region and in southern India. Many models also show weakened variability compared with the observations along much of coastal India and over Bangladesh.

The trends for March through May show very small values for most of the region. In the southern part of the region, there is a dipolar structure that includes both a drying trend in southwest India and wettening trend over Sri Lanka. Some other significant wettening trends are present near Bangladesh, Bhutan, and Nepal. No GCM captures these localized details that are seen in the observation data. In terms of percentage change, which considers the trends relative to the local magnitude of the rainfall, the GCMs exhibit obvious differences from the observed trends.

June through September (Monsoon)

The agreement between the Aphrodite and GCM simulation mean values is much better for the monsoon season (June through September), despite differences in the small-scale details due to topography. Some models—such as GFDL and MIROC ESM—overestimate the precipitation over most of central, southern, and eastern India. Also, few GCMs capture the localized rainfall maximum over the western coast of India.

For the standard deviation, only some models—such as CCSM4, HadGEM, MIROC5, MPI, and NorESM—simulate the structure of the observed variability, which shows some resemblance to the mean rainfall pattern.

The observed monsoon trend is noisy and weak, with localized drying over southernmost India and wettening over Sri Lanka. The GCMs also have weak and noisy patterns of trend in this season. Models showing more coherent patterns of trend—such as GFDL ESM2G, GISS ER, and HadGEM2—are likely the more unreliable.

October through February (Postmonsoon)

During the postmonsoon season (October through February), the wettest conditions are found over the southernmost parts of India and Sri Lanka. Many of the GCMs show a distinct dry bias over this seasonally wet area.

As in the previous seasons, many of the models overestimate the year-to-year variability, particularly over northern India and Nepal. Some models—such as CCSM4, GFDL ESM2M, and INM CM4—overestimate precipitation across nearly the entire region.

The wettening over Sri Lanka is the main feature of the trend field, with weaker increases seen in central India. The CCSM4 model is the only one that reproduces this wettening feature over Sri Lanka to a similar degree as found in the observations. The BCC model shows the most extreme trends over India, which are not consistent with the observations. Cast as a percentage, the model and observed trends show very little agreement in the pattern or magnitude of changes.

Summary of Climate Model Selection: Interpretation of Figure 2.2

In general, all the climate models tend to overestimate the year-to-year variability. They also tend to overestimate the precipitation trends and underestimate the temperature trends in the main monsoon season (June through September) over most of the study region.

Figure 2.2 summarizes the regionally integrated measures of pattern correlation (figure 2.2, panel a) and RMSE (figure 2.2, panel b) as a single number for each model, season, and variable. The displayed RMSE values have been normalized by the average magnitude in each column, in order to plot the values with a more uniform color scale. It is noted, however, that the magnitude of errors in the trend fields, especially the temperature trends, are typically larger than for the mean or standard deviation.

Higher pattern correlations and lower RMSE values indicate better model performance. It is generally preferable to have models that do a fair job overall, rather than an excellent job in a few selected instances and terrible performance in other instances.

Examination of figure 2.2, panel a, confirms many of the statements made in the preceding discussion. The observed pattern of the mean seasonal climate is generally well represented by the models, even if the magnitudes may differ. Although the pattern of standard deviation in precipitation may be well captured by the models, several models do a poor job. In particular, CSIRO Mk3.6.0, HadGEM2 CC, and MPI ESM-LR all have a near-zero correlation to the spatial pattern of the observations. These models have a weakly positive to strongly negative pattern correlation for trend in both temperature and precipitation. GFDL ESM2G does a particularly poor job of reproducing the pattern of temperature and precipitation trends.

Figure 2.2 B highlights the relative magnitude of regionally aggregated errors, rather than the spatial pattern of errors. Particularly notable are the large errors in the precipitation fields of GISS E2R and the temperature fields of INM CM4. MIROC 5 shows relatively larger errors overall. These three models do not perform well in their patterns of variability and change either.

Of the 18 CMIP5 models available for this study (appendix B, table B.2), seven models—CSIRO Mk3.6.0, GFDL ESM2G, GISS-E2R, HadGEM2 ES, INM CM4, MIROC5, and MPI ESM-LR—were excluded from the climate model ensemble. The reasons for exclusion are those provided in the preceding paragraphs. The remaining 11 models are used to formulate the MMM, low, and high values used throughout this book.

Note

1. The analysis in this section was provided by the International Research Institute for Climate and Society at Columbia University. Further details of its analysis are available upon request.

References

Donat, M. G., L. V. Alexander, H. Yang, I. Durre, R. Vose, R. J. H. Dunn, and B. Hewitson. 2013. "Updated Analyses of Temperature and Precipitation Extreme Indices since the Beginning of the Twentieth Century: The HadEX2 Dataset." *Journal of Geophysical Research: Atmospheres* 118 (5): 2098–118.

Funk, C., P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, S. Shukla, G. Husak, J. Rowland, L. Harrison, A. Hoell, and J. Michaelsen. "The Climate Hazards Infrared Precipitation with Stations: A New Environmental Record for Monitoring Extremes." *Scientific Data* 2: 150066.

Harris, I., P. D. Jones, T. J. Osborn, and D. H. Lister. 2014. "Updated High-Resolution Grids of Monthly Climatic Observations—The CRU TS3.10 Dataset." *International Journal of Climatology* 34 (3), 623–42.

Rajeevan, M., J. Bhate, J. D. Kale, and B. Lal. 2006. "High Resolution Daily Gridded Rainfall Data for the Indian Region: Analysis of Break and Active Monsoon Spells." *Current Science*, 296–306.

Rohde, R., R. Muller, R. Jacobsen, S. Perlmutter, A. Rosenfeld, J. Wurtele, and S. Mosher. 2013. "Berkeley Earth Temperature Averaging Process." *Geoinformatics & Geostatistics: An Overview* 13: 20–100.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl. 2012. "An Overview of CMIP5 and the Experiment Design." *Bulletin of the American Meteorological Society* 93 (4): 485–98.

Yatagai, A., K. Kamiguchi, O. Arakawa, A. Hamada, N. Yasutomi, and A. Kitoh. 2012. "APHRODITE: Constructing a Long-Term Daily Gridded Precipitation Dataset for Asia Based on a Dense Network of Rain Gauges." *Bulletin of the American Meteorological Society* 93 (9): 1401–15.

Calculating Gross Domestic Product Based on Shared Socioeconomic Pathways and Hotspots Results

E

The calculations in tables 5.1 and 5.2 use predicted changes in population and gross domestic product (GDP). The predictions used for these properties are calculated as the average of values associated with shared socioeconomic pathway 1 (SSP1), SSP3, and SSP5 in the International Institute for Applied Systems Analysis (IIASA) database, developed in coordination with the OECD (see the description of SSPs in the following section).

Methods used to calculate values in table 5.1 are:

- Row 1—GDP estimates for the "entire country with no climate change" are calculated as the average of GDP projections in SSP1, SSP3, and SSP5. It is assumed that percentage changes in GDP per capita are equal to percentage changes in consumption expenditures per capita.
- Row 2—GDP estimates for the "entire country under the carbon-intensive climate scenario" are calculated such that percentage decreases in GDP are equivalent to corresponding decreases in consumption expenditures per capita for that year (see chapter 3 for consumption expenditures estimate details).
- Row 3—Percentage changes in GDP for the "entire country due to the carbon-intensive climate scenario" are equivalent to national-level impacts of climate change on consumption expenditures per capita (table 3.4). This assumes that percentage changes in consumption expenditures per capita are equal to percentage changes in GDP per capita.
- Row 4—GDP estimates for "severe hotspots with no climate change" are derived by calculating the portion of estimated historic baseline consumption expenditures in severe hotspots relative to the entire country and using this proportion to scale the SSP GDP projections (row 1 of table 5.1). It is assumed that the ratio of per capita GDP in the two areas is the same as the ratio of per capita consumption in the two areas.
- Row 5—GDP estimates for "severe hotspots under the carbon-intensive climate scenario" are calculated by assuming that reductions in consumption expenditures per capita within severe hotspots will be equivalent to reductions in GDP per capita, given the estimated proportion of historical baseline GDP generated in areas projected to become severe hotspots (row 4 of table 5.1).
- Row 6—GDP estimates of "change for severe hotspots under the carbon-intensive climate scenario" are calculated as the percentage difference between rows 5 and 4.

TABLE E.1 Population Projections for Countries with Severe Hotspots
Millions

	Severe hotspots		Entire country	
Country	2016	2050	2016	2050
Bangladesh	26.4	30.8	163.0	190.1
India	148.3	189.2	1,324.2	1,689.3
Sri Lanka	3.6	3.9	21.2	23.2

Source: O'Neill and others 2014.
Note: Severe hotspots correspond to those identified to occur under the carbon-intensive scenario by 2050. Projections of population growth are based on the country-level average of SSP1, SSP3, and SSP5. Population in severe hotspots by 2050 under the carbon-intensive scenario is projected to remain in the same proportion to the total as it is today. SSP = shared socioeconomic pathway.

The total GDP losses in table 5.2 are the product of population projection estimates and projected changes in per capita GDP (table 5.1). The total GDP estimates in table 5.2 assume that population grows as predicted by the average of SSP1, SSP3, and SSP5 (table E.1). The SSP scenarios estimate population changes only for the entire country. Population changes for severe hotspots are calculated by assuming that the national-level population change projections apply evenly across the country and using these projections to scale observed population during the historic baseline period.

Note on Shared Socioeconomic Pathway Scenarios

A shared socioeconomic pathway (SSP) is essentially a storyline describing a future development scenario (O'Neill and others 2014). There are five SSPs produced and agreed on by the international community and used by the IPCC.[1] Each of the SSPs includes three drivers, projected in five-year intervals at the country level: (a) overall population growth, (b) urban population growth, and (c) economic growth. These parameters vary between SSP narratives and country.

The SSPs exist in parallel with the RCP emissions scenarios. Multiple SSPs can lead to a given RCP since different socioeconomic changes can result in similar greenhouse gas (GHG) concentrations.

Three SSPs used in chapter 5 of this book are:

- **SSP 1, sustainability.** This pathway is characterized by reduced inequality globally, and within countries, as low-income countries develop at a rapid rate and a high level of education is achieved globally. The low global population growth present in the scenario is associated with consumption oriented toward low-energy intensity goods, partly enabled by fast-paced and environmentally friendly technological development. Reduced fossil fuel dependency and rapid clean energy technological development are concurrent with high levels of environmental awareness. Environmental governance is successful at achieving globally implemented agreements. The Millennium Development Goals are achieved within the next decade or two.
- **SSP 3, fragmentation.** This world is fragmented into marginalized and poor regions, countries struggling to maintain their living standards, and pockets of moderate wealth. There is little progress toward achieving the Millennium Development Goals, lowering energy and material intensity consumption, or reducing fossil fuel dependency. Inequalities between countries and populations are increasing. Economic growth is slowed by low levels of investment in education and clean technologies, along with policies oriented toward security and barriers to trade. Population growth is high and drives up emissions. Global governance is weak and international aid is low, leaving some populations vulnerable to climate change.
- **SSP 5, conventional development.** This pathway illustrates a world where conventional development (economic growth and pursuit of self-interest in a liberalized world) is perceived as the solution to social and economic challenges. As a result, fossil fuel dependency deepens and mitigation challenges are high. The Millennium Development Goals are attained, and robust economic growth, engineered solutions, and highly managed

ecosystems provide a certain level of adaptive capacity.

Note

1. For details, see https://secure.iiasa.ac.at/web-apps/ene/SspDb/dsd?Action=htmlpage&page=about.

Reference

O'Neill, B. C., E. Kriegler, K. Riahi, K. L. Ebi, S. Hallegatte, T. R. Carter, R. Mathur, and D. P. van Vuuren. 2014. "A New Scenario Framework for Climate Change Research: The Concept of Shared Socioeconomic Pathways." *Climatic Change* 122 (3): 387–400.

ECO-AUDIT

Environmental Benefits Statement

The World Bank Group is committed to reducing its environmental footprint. In support of this commitment, we leverage electronic publishing options and print-on-demand technology, which is located in regional hubs worldwide. Together, these initiatives enable print runs to be lowered and shipping distances decreased, resulting in reduced paper consumption, chemical use, greenhouse gas emissions, and waste.

We follow the recommended standards for paper use set by the Green Press Initiative. The majority of our books are printed on Forest Stewardship Council (FSC)–certified paper, with nearly all containing 50–100 percent recycled content. The recycled fiber in our book paper is either unbleached or bleached using totally chlorine-free (TCF), processed chlorine–free (PCF), or enhanced elemental chlorine–free (EECF) processes.

More information about the Bank's environmental philosophy can be found at http://www.worldbank.org/corporateresponsibility.

green press INITIATIVE

South Asia Development Matters

South Asia is highly vulnerable to climate change. Average temperatures have been rising throughout the region, and rainfall has become more erratic. These changes are projected to continue accruing over the coming decades.

South Asia's Hotspots: The Impact of Temperature and Precipitation Changes on Living Standards is the first book of its kind to provide granular spatial analysis of the long-term impacts of changes in average temperature and precipitation on one of the world's poorest regions.

South Asia's Hotspots finds that higher temperatures and shifting precipitation patterns will reduce living standards in communities across South Asia—locations that the book terms "hotspots." More than 800 million people in South Asia currently live in communities that are projected to become hotspots under a carbon-intensive climate scenario. Global action to reduce greenhouse gas emissions will reduce the severity of hotspots.

Diverse and robust development is the best overall prescription to help people in hotspots. The book also suggests actions tailored to each country in the region—such as increasing employment in nonagricultural sectors, improving educational attainment, and expanding access to electricity—that would offset the declines in living standards associated with hotspots.

South Asia's Hotspots complements previous studies detailing the impacts of sea-level rise and extreme events on the people of South Asia. Together, these bodies of work create a sound analytical basis for investing in targeted policies and actions to build climate resilience throughout the region.

www.worldbank.org/SouthAsiaHotspots

ISBN 978-1-4648-1155-5
90000
9 781464 811555
SKU 211155

WORLD BANK GROUP