Climate Downscaled Data to Support Impact Risk Assessments in Bangladesh

A guide on how to access data derived from models used in the IPCC 5th Assessment Report using the World Bank Climate Analysis Tool.
Table of Contents
Acknowledgements ........................................................................................................... 4
Section 1: Introduction to the Updated Climate Analysis Tool ........................................... 5
Section 2: Downscaling Climate Models ........................................................................... 6
  Different types of downscaling approaches (advantages and disadvantages) ......................... 7
    Dynamical Downscaling: Regional Climate Models (RCMs) ............................................... 7
    Statistical downscaling: daily bias-corrected spatial disaggregation (BCSD) ......................... 7
  Climate models downscaled .............................................................................................. 9
  Dealing with uncertainty .................................................................................................... 10
Section 3: Translating climate models into specific impacts using derivative climate metrics ........ 11
  Sector relevant climate statistics ....................................................................................... 11
Section 4: Climate downscale data access and visualization .............................................. 13
  Overview of Climate Analysis Tool powered by Climate Wizard ....................................... 13
    Accessing climate data .................................................................................................. 13
  Description of interactive tool features ............................................................................. 15
    1) Selection of Analysis Area ......................................................................................... 15
    2) Selection of Time Period: Annual or Month ............................................................... 15
    3) Selection of Climate Variable .................................................................................... 16
    4) Selection of Greenhouse Gas Representative Concentration Pathway: ....................... 16
    5) Different Types of Climate Change Analyses ............................................................ 17
    6) General Circulations Models: Ensemble Analysis ...................................................... 21
  Map and GIS Data Download .......................................................................................... 21
    Aggregated analysis: Summarizing climate change information ........................................ 22
    Monthly cycles of climate and change ........................................................................... 24
Section 5: Guiding Principles for Use of the Climate Analysis tool ..................................... 26
  ✓ Don’t look at just a single grid cell—look at regional patterns .......................................... 26
  ✓ Monsoons are difficult to model .................................................................................... 26
Section 6: Interpretation of results: Specific sectorial impacts in Northwestern Bangladesh ....... 27
  Exposure to Climate Change: Temperature and Precipitation future trends ....................... 27
  Temperature ................................................................................................................... 27
Acknowledgements
This study was commissioned by the World Bank Group, under the co-leadership of Susmita Dasgupta (Lead Environmental Economist, Environment and Energy Team, Development Research Group) and Ana E. Bucher (Climate Change Specialist, Climate Change Group). The analytical work was undertaken by the International Center for Tropical Agriculture, the CGIAR Research Program on Climate Change Agriculture and Food Security (CCAFS) under the leadership of Dr. Evan Girvetz with technical assistance from Edward Guevara and Dr. Julian Ramirez. The daily downscaled climate data using the bias-corrected spatial disaggregated approach were obtained from Dr. Bridget Thrasher from the Climate Analytics Group.

The team benefited greatly from comments received from the peer reviewers, Nagaraja Rao Harshadeep (Senior Environmental Specialist, GENDR) and Bekele Debele Negewo (Senior Water Resources Specialist, GWADR) affiliated with the World Bank.

At the World Bank, we extend our thanks to Lia C. Sieghart (Program Leader, SACBN), Johannes Zutt (Bangladesh Country Director), Herbert Acquay (Practice Manager, GENDR), Bernice K. Van Bronkhorst (Practice Manager, GSURR), and Shahpar Selim (Environmental Specialist, GSURR). We are also thankful to Elaine Wylie (Program Assistant, DECEE) for her support with contract-related logistics.

The team gratefully acknowledges the financial support provided by the Bangladesh Climate Change Resilience Fund (BCCRF), a multi-donor trust fund supported by the governments of the United Kingdom, Denmark, Sweden, Switzerland, Australia, the United States, and the European Union. This study was requested by the Government of Bangladesh and endorsed by the BCCRF Management Committee as a priority research project related to climate change and development in the region.
Section 1: Introduction to the Updated Climate Analysis Tool

Bangladesh is prone to extreme weather related disasters, especially related to floods with some areas prone to drought. Climate change has the potential to increase the magnitude and frequency of these disasters (IPCC 2012). The most recent climate models show climate change will lead to increases in the mean and extreme precipitation from the Indian summer monsoon. Integration of climate risk information in planning is now a priority for policymakers, public investment planners, environmental agencies and donors. However, it generally has been difficult for decision-makers to understand and access the most recent climate science regarding climate extreme events in the context of the country of Bangladesh, or sub-nationally in a specific province, district or village.

This initiative brings in information from the most recent General circulation models (GCMs)—also known as “global climate models”—used in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) and therefore provide the most up-to-date scientific information on future climate projections for Bangladesh. Furthermore, this project also brings value by providing GCMs at a finer spatial resolution (0.25 degrees, about 25 km) at a daily time scale and calculating metrics of climate extreme events (e.g. 5-day precipitation maximum per year). This is the first time downscaled GCMs from the IPCC AR5 will be available for planning efforts to show changes to climate extremes in Bangladesh.

This Guidance Document provides an overview of how to access and interpret downscaled future climate GCM data to support climate change impact risk assessments in Bangladesh, using the World Bank Climate Analysis Tool, powered by Climate Wizard. The tool facilitates visualization and access to future climate information at spatial and temporal scales relevant to specific climate impacts in local places. This Climate Analysis Tool web application1, a feature of the World Bank Climate Change Knowledge Portal2, calculates a set of climate statistics that show how potential extreme events are projected to change in the future. This information can help with understanding the potential climate change impacts to agriculture, water supply, fire risk, human health, urban energy demand, and among others for specific places on-the-ground. This document provides the following:

1. An understanding of how global climate models are downscaled to finer spatial and temporal scales (Section 2)
2. Basic information on how to translate changes to temperature and precipitation into specific impacts to agriculture, hydrology, human health, ecosystems, and urban energy demand, among others (see Sections 3 & 5)
3. How to use the user-friendly visualization and downloading capabilities of the World Bank Climate Analysis Tool to access relevant data for decision-makers and other users (See section 4).

1 http://climatewizard.ciat.cgiar.org/wbclimateanalysistool/
Section 2: Downscaling Climate Models

General circulation models (GCMs)—also known as “global climate models”—provide some of the best information available on future climate projections to assess potential impacts and guide climate-smart decisions about climate resilience. However, most of these models are run at very coarse horizontal resolution of 100 km or greater (>10,000 km²), limiting their utility for regional to local level decision making. In some instances, GCM information can be enhanced to better represent the conditions in specific places by using historically observed local climate information from weather stations. Local information allows for the GCMs to be downscaled to a much finer scale to improve, where possible, the resolution of climate projections. This information can be also be used to improve the future climate projections to better match observed local climate conditions—a process known as “bias-correction”. Downscaling and bias-correcting at both a finer spatial and temporal resolution can be useful to better represent the influence of topography and regional climate patterns on both the average and variation in climate, and to more accurately and completely assess future climate impacts (Girvetz et al., 2013).

Downscaling GCMs at a daily time scale is important because it is generally not the average monthly conditions that cause impacts, but rather the extreme peaks and valleys in the climate throughout the year (Figure 1), or the extreme tail of climate events (i.e., infrequent events with severe impacts). Moreover, many climate driven impacts occur as a cumulative effect of what happens at the daily time scale—for example growing degree days are often used to determine agricultural suitability—and cannot be accurately estimated from monthly data. Third, most hydrologic, agricultural, and other impact models commonly require daily climate data in order to produce results relevant to real-world decision-making.

The remainder of this section presents information about the benefits and drawbacks of two different downscaling techniques and highlights the downscaling method used by this project called “Bias-Corrected Spatial Disaggregation” (BCSD). It also discusses important issues of dealing with uncertainty in GCMs and caveats that users of the information must be aware of to properly use downscaled climate data.

Figure 1: Example of the monthly average climate during a calendar year (black line) compared to day-to-day variation (extreme hot and cold days or wet and dry days during a single calendar year).
Different types of downscaling approaches (advantages and disadvantages)

There are two commonly used methods to downscale future climate projections to finer spatial scales: *dynamical downscaling* (also referred to as “Regional Climate Models”) and *statistical downscaling* (sometimes called “empirical”).

**Dynamical Downscaling: Regional Climate Models (RCMs)**

Dynamical downscaling is a method that uses a regional climate model (RCM) and is run for a restricted area of the globe. The RCM is informed at the boundaries of the restricted area with information from a global climate model (GCM). This method has the advantage that it is based on physical laws and can, in theory, better represent localized feedbacks in response to increased greenhouse gas concentrations and global warming. This downscaling method can produce a full suite of different climate output variables from the downscaling process. However, it is computationally very demanding, making it infeasible to run on a global scale or for many different climate models. In addition, since the dynamical downscaling is connected to global climate models, errors from those models will be propagated through the downscaling—the uncertainty and errors from the GCMs will still be kept in the downscaled future climate projections.

Due to the computational complexity and difficulty in analyzing a large number of future scenarios and climate models, this project did not use dynamical downscaling, but rather used the statistical downscaling method described below.

<table>
<thead>
<tr>
<th>Dynamical Downscaling</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Based on physical laws, so should correctly represent local feedbacks in response to increasing GHG.</strong></td>
<td><strong>Computationally very demanding</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Produces a full suite of climate output variables.</strong></td>
<td><strong>Generally preserves biases (errors) from the driving GCM—“garbage-in, garbage-out”</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Most GCM simulations don’t save output needed for dynamical downscaling</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Difficult to downscale a large number of future climate projections</strong></td>
</tr>
</tbody>
</table>

**Statistical downscaling: daily bias-corrected spatial disaggregation (BCSD)**

Statistical downscaling (also called empirical downscaling) is a commonly used method for downscaling because of the relative ease of application and the flexibility of the method for different applications. Due to this wide use, statistical downscaling methods have been well tested and validated in many environments, and has been found to be useful for many different applications (Wood et al. 2004, Maraun 2012).
The daily timescale Bias-corrected Spatial Disaggregation (BCSD) statistical downscaling method can downscale multiple global climate models (GCMs). BCSD has been applied over regional and continental domains in many different climates, including, the Northeastern U.S., the Western U.S., Latin America, and Africa (Barnett et al. 2008, Hayhoe et al. 2008, Girvetz et al. 2009, Maurer et al. 2009, Beyene et al. 2010). The BCSD method has also been applied to examine climate change impacts on diverse sectors including agriculture, hydropower and energy, water resources, wildfire, air quality and public health, and ecosystem responses (Hayhoe et al. 2004, Cayan et al. 2007). The wide applicability of BCSD across different spatial and temporal scales and use in different impacts studies makes it unique among statistical downscaling methods, and appropriate for the current effort.

See Appendix 1 for a complete description of the technical approach.

<table>
<thead>
<tr>
<th><strong>Bias-corrected Spatial Disaggregation (BCSD) Downscaling</strong></th>
<th><strong>Advantages</strong></th>
<th><strong>Disadvantages</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Computationally not very demanding</td>
<td>• Produces results for only a few variables (usually Temperature and Precipitation)</td>
</tr>
<tr>
<td></td>
<td>• Does not require special output from the GCM</td>
<td>• Accuracy limited by availability of gridded observations</td>
</tr>
<tr>
<td></td>
<td>• Can be applied to large ensembles of GCM simulations, allowing quantification of consensus.</td>
<td>• Relationships derived from observations assumed to apply in the future, this is not true where local feedbacks important</td>
</tr>
<tr>
<td></td>
<td>• Can include correction of GCM biases (errors)</td>
<td>• Bias correction derived in historical period is assumed to apply in the future.</td>
</tr>
<tr>
<td></td>
<td>• Produces results on a uniform spatial grid</td>
<td>• Results for projected temperature changes have no fine detail, due to a consequence of preserving trends from the GCM</td>
</tr>
<tr>
<td></td>
<td>• Preserves long-term trends from the GCM</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Allows GCM to simulate changes in variability</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Can produce monthly or daily results</td>
<td></td>
</tr>
</tbody>
</table>
Climate models downscaled

This project provides data from 17 GCMs developed for the IPCC AR5 (CMIP5 Archive) run across two Representative Concentration Pathways (RCPs 4.5 and 8.5). Table 1 below lists the specific GCMs used by this project. All of these GCMs were downscaled to a 0.25 degree resolution (around 25 by 25 km grid cell) for the time period of 1950-2099. These data were downscaled using bias correction-spatial disaggregation (BCSD) methods described above and in Appendix 1, and was used previously within the Climate Knowledge Portal and Climate Analysis Tool.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Lead Research Center</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC-CSM1.1</td>
<td>Beijing Climate Center, China Meteorological Administration</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>College of Global Change and Earth System Science, Beijing Normal University</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
</tr>
<tr>
<td>CCSM4</td>
<td>National Center for Atmospheric Research</td>
</tr>
<tr>
<td>CESM1-BGC</td>
<td>National Science Foundation, Department of Energy, National Center for Atmospheric Research</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>Geophysical Fluid Dynamics Laboratory</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td>Geophysical Fluid Dynamics Laboratory</td>
</tr>
<tr>
<td>INM-CM4</td>
<td>Institute for Numerical Mathematics</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>Institut Pierre-Simon Laplace</td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>Institute Pierre-Simon Laplace</td>
</tr>
<tr>
<td>MIROC5</td>
<td>Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>Same as MIROC5</td>
</tr>
<tr>
<td>MIROC-ESM-CHEM</td>
<td>Same as MIROC5</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max Planck Institute for Meteorology (MPI-M)</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td>Max Planck Institute for Meteorology (MPI-M)</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>Meteorological Research Institute</td>
</tr>
</tbody>
</table>

Table 1: List of 17 downscaled GCMs from the CMIP5 archives that are a part of the World Bank Climate Analysis Tool.

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3 Representative Concentration Pathways were developed for the IPCC Fifth Assessment Report. RCP 4.5 represents a low greenhouse gas emissions development pathway scenario, whereas RCP 8.5 represents a high greenhouse emission scenario and development pathway that might lead to a 4°C increase in future temperature change. For more information see: http://sedac.ipcc-data.org/ddc/ar5_scenario_process/RCPs.html

**Dealing with uncertainty**

Users of these datasets should be aware that downscaling come with inherent drawbacks and, the use of such dataset for decision making actions should be carefully scrutinized. Three major considerations should be recognized:

1. The accuracy of the downscaling is limited by both the accuracy of the GCMs as well as the accuracy of the gridded historic weather data used to inform the downscaling process. In the case of Bangladesh, there are very few weather stations with a sufficiently long time series of data (e.g. >20 years), which limits the accuracy of individual grid cells.

2. The relationships derived from current and past observations are assumed to apply in the future, and this is not completely true where localized climatic events are very important—this may be the case for Bangladesh, especially in relation to monsoon patterns and the ability of models to project its future changes.

3. The bias-correction derived in the historical time period is assumed to apply in the future, which is likely generally true, but does not incorporate changes to local and regional weather patterns.

Despite these caveats statements, statistical downscaling is used in many applications and is one of the most commonly used approaches for better understanding future climate change impacts at the national and sub-national scale (Girvetz et al, 2009; Abatzoglou and Brown, 2012). Users must note that the historical period simulated by downscaled GCMs will statistically match the observations from local weather stations. The sequencing of years, however, will not correspond to local observations, since GCMs are not constrained to reproduce the exact timing of natural climate variations, such as the past occurrences of El Niño-southern Oscillation events. That is, on average, the mean and variance of climate from the GCMs and observations for the historic baseline period will closely match, but any given day, month or year (e.g. in 1979) will not match between the GCMs and the observations.
Section 3: Translating climate models into specific impacts using derivative climate metrics

Decision-makers need information targeted to specific types of climate risks such as flooding, drought, and storm surges and their impact on water supply, agriculture, human health, and urban energy demand, among others. Information about average temperature and precipitation change can be useful in some instances, but will be of particular interest if it can be used directly to inform the development of climate adaptation responses.

This project provides a valuable contribution to other existent information about future temperature and precipitation change by providing a set of 10 “derivative climate metrics” from the daily downscaled climate dataset. These metrics include, among others, the growing degree days, the hottest day of each year, and the most amount of rain that falls in a 5-day period each year (please see Tables 2 and 3). The calculation of derivative climate metrics allow for a more insightful way to interpret climate impacts to specific sectors. These metrics can be interpreted as surrogates of climate risks to agriculture, water supply, human health, energy-demand, and ecosystem resilience as described below.

Sector relevant climate statistics
To better understand the utility of these climate metrics on interpreting risks, they can be classified based on their relationship with a specific sector or service, such as agriculture productivity, water supply, flood risk, human health, energy demand, and ecosystem resilience. For example:

- **Crop productivity** relies on many different climate factors including total precipitation, growing degree days, consecutive dry days, average low and high temperatures.
- **Water supply** is focused on three precipitation variables: total precipitation—quantifying average water input into the system; and two measures of dryness and drought conditions—consecutive dry days.
- **Flood risk** is driven by rainfall average, measures of wet day rainfall and short term maximum rainfall intensities.
- **Human health** focuses on temperature stress (hot and cold) to people: hottest and coldest single day temperature.
- **Energy demand** incorporates heating and cooling demand using heating and cooling degree days.
- **Ecosystem resilience** to climate change is complex and so incorporates many different aspects including total precipitation, dry conditions, extreme hot and cold temperatures, and growing degree days.
Table 2: Temperature-based derivative climate metrics calculated from daily downscaled future climate projections.

<table>
<thead>
<tr>
<th>Long Name</th>
<th>Variable</th>
<th>Units</th>
<th>Description</th>
<th>Annual</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Low Temperature</td>
<td>tasmin</td>
<td>°C</td>
<td>Monthly mean of daily minimum temperatures</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Average High Temperature</td>
<td>tasmax</td>
<td>°C</td>
<td>Monthly mean of daily maximum temperatures</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Hottest Temperature</td>
<td>txx</td>
<td>°C</td>
<td>Maximum temperature for the month and year</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Coldest Temperature</td>
<td>tnn</td>
<td>°C</td>
<td>Minimum temperature for the month and year</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Growing Degree Days</td>
<td>gd10</td>
<td>days</td>
<td>Growing degree days, for Tavg, sum of degrees</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>&gt; 10°C for each day, but month and year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooling Degree Days</td>
<td>cd18</td>
<td>days</td>
<td>Cooling degree days, calculated with 18°C base</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>temperature, by month and year</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Precipitation-based derivative climate metrics calculated from daily downscaled future climate projections.

<table>
<thead>
<tr>
<th>Long Name</th>
<th>Variable</th>
<th>Units</th>
<th>Description</th>
<th>Annual</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Precipitation</td>
<td>pr</td>
<td>mm</td>
<td>Total precipitation for the month and year</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Consecutive Dry Days</td>
<td>cdd</td>
<td>days</td>
<td>largest number of consecutive dry days (with daily pr&lt;1mm) per year</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Number of Wet Days</td>
<td>r02</td>
<td>days</td>
<td>Number of wet days (with precipitation &gt; 0.2mm/day), per month and year</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>5 Day Rainfall</td>
<td>r5d</td>
<td>mm</td>
<td>Maximum 5-day precipitation total per year</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>
Section 4: Climate downscaled data access and visualization

As a result of this initiative, all analyzed downscaled climate data was compiled for visualization and access through the Climate Analysis Tool. The online application (See landing page snapshot below) allows anyone to explore and access latest set of downscaled future climate and projected impacts in Bangladesh. This World Bank Climate Analysis Tool can be accessed at: http://climatewizard.ciat.cgiar.org/wbclimateanalysis TOOL/.

Overview of Climate Analysis Tool

Accessing climate data
In order to visualize available climate data for Bangladesh, a first step is to select the future time period of interest (compared to a historic baseline time period of 1961-1999).
(1) 2010-2039 (approximating 2025);
(2) 2040-2069 (approximating 2055); and
(3) 2070-2099 (approximating 2085). Please see snapshot below
Once you have selected a particular timeframe, relevant climate data will be accessible through an interactive online interphase. The figure below shows an overview of the different options available in the Climate Analysis Tool. This includes: (1) Analysis Area; (2) Climate Variable; (3) Measurement type; (4) General Circulation Model (or Ensemble of them all); (5) Time period (annual or specific month); and (6) Representative Concentration Pathway Emissions Scenario. These options are described in further depth in the next pages.
Description of interactive tool features

1) Selection of Analysis Area
Six spatial analysis areas are provided in the Climate Analysis Tool for the Bangladesh region. Users are prompted to select one from the pull down menu:

- Territory of Bangladesh;
- Northwest region of Bangladesh (vulnerable to drought and flood);
- Northeast region of Bangladesh (vulnerable to flash flood);
- Western coastal region (vulnerable to cyclone);
- Central coastal region (vulnerable to cyclone);
- Eastern coastal region (vulnerable to cyclone);

2) Selection of Time Period: Annual or Month
Climate change can be assessed over an entire year or for a specific month for all variables, except for consecutive dry days and 5-day rainfall - which can only be assessed annually. The selection of a specific month can be important for looking at impacts during particular vulnerable times of the year. For example, it might be important to look at change in total rainfall or consecutive dry days during the start of the growing season. Or it might be important to look at the change in average high temperature during hottest months of the year to assess potential heat stress.

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5 Please note that when GIS data or graphics are downloaded from the Tool, the file name will contain a number that signifies annual or the specific month. Annual is coded with the number 14, while January is 1, February is 2, March is 3, and so on.
3) Selection of Climate Variable
There are 12 derivative climate metrics available as part of this application—seven temperature-based climate metrics, and 5 precipitation-based climate metrics. Different climate variables are important for assessing different types of climate impacts—drought, flood, heat stress, energy use, etc. The section on “Translating climate models into specific impacts: derivative climate metrics” in Section 2 above, gives an overview of how different climate variables are relevant to different sectors of society, and a description of how they were calculated.

4) Selection of Greenhouse Gas Representative Concentration Pathway:
Two greenhouse gas Representative Concentration Pathways are provided in the Climate Analysis Tool—RCP 4.5 (lower concentration) and RCP 8.5 (higher concentration). They describe four possible climate futures depending on how much greenhouse gases are emitted over the next 85 years (Figure 3). All of these are considered possible, although we are currently on the track of the highest RCP 8.5. Reduced greenhouse gas concentrations under RCP 4.5 are possibly, but would take a global effort with substantial reductions in greenhouse gas emissions.

Figure 3: The graph the “Radiative Forcing”—a measure of climate change effect—of the different RCPs over this century—from van Vuuren et al (2011) The Representative Concentration Pathways: An Overview. Climatic Change, 109 (1-2), 5-31. The light grey area captures 98% of the range in previous Integrated Assessment Modeling (IAM) scenarios, and dark grey represents 90% of the range.
5) Different Types of Climate Change Analyses

Under the Measurement option, different types of climate analysis measurements can be reviewed as maps within the tool:

- **Future Average**: average climate value during future time period (does not represent change)
- **Historic Average**: average climate value during historic baseline time period 1961-1990 based on the bias-corrected and downscaled GCMs
- **Change in Future**: amount of change between historic baseline average climate value and future average climate value
- **Recurrence Interval**: How much more often extreme events will occur in the future than occurred in the past.

Please see below detailed description of how they are calculated.

**Average climate**

The mean of each climate variable is calculated across either monthly or annual time domains (user-specified) for one of three future time periods (2010-2039, 2040-2069, and 2070-2099).

Mean calculations are only performed within user-specified polygon boundaries (hereafter referred to as the “area”). The calculation can be expressed as:

Spatial equation (map) \( \bar{x}_i = \{mean(x)\}_{T,i} \)

Non-spatial equation (table) \( \bar{x} = mean(\bar{x}_i) \)

where \( \bar{x}_i \) and \( \bar{x} \) (spatial and non-spatial means) are summarized across the time domain set, \( T \), and pixel set, \( i \). The non-spatial mean aggregates all pixels within the user-specific area, and therefore describes the area as a whole.

A spatially resolved example is provided for the maximum 5-day precipitation of the year across Bangladesh comparing the average for 1961-1990 to the average for 2070-2099 (See Figure 3 below). Note how much greater the 5-day precipitation maximum is projected to be by 2070-2099 compared to the historic baseline.
Figure 3: Maps of historic (1961-1990) and future projected (2070-2099) 5-day maximum precipitation during the year for Bangladesh (RCP 8.5). The darker blue colors represent greater 5-day annual maximum precipitation, the green colors represent lower 5-day maximum precipitation.

Information can also be aggregated and graphed over time to show year-to-year variability. For example, Figure 4 shows how the high temperature of the hottest day of the year for each year over time during both 1961-1990 and 2070-2099. The black line in Figure 4 shows the average of the 17 GCMs, while the dashed black line shows the historic average value, and the dashed grey lines represent the minimum and maximum value over the historic time period. The graph on the right shows that the future average year in 2085 is over 40 C, which is hotter than ever happened historically.

Figure 4: Hottest daily temperature of the year in Bangladesh for 1961-1990 (left) and 2040-2069 (right) for RCP 8.5. The grey dashed lines represent the lowest and high temperature years for any of the 17 GCMs over the historic time period, the black dashed line is the historic average.
Departure change analysis

The departure (or difference) of each climate variable is calculated as the difference between future and historic periods. The historic period is always 1961-1990 and the future period can be defined as either 2010-2039, 2040-2069, or 2070-2099.

Spatial equation (map):

\[ \delta_i = \bar{x}_{i,F} - \bar{x}_{i,P} \]

Non-spatial equation (table):

\[ \delta = \bar{x}_F - \bar{x}_P \]

where \( \delta_i \) and \( \delta \) (spatial and non-spatial departures) are simply the differences of the future and past means, \( \bar{x}_F \) and \( \bar{x}_P \) respectively. The spatial departure, \( \delta_i \), is calculated at every pixel, \( i \), and the non-spatial departure, \( \delta \), is calculated from the past and future means in the summary table. Figure 5 gives an example of a map of ‘Change in the Future’—the change in the coldest day per year for a single climate model in 2070-2099 as compared to the historic period of 1961-1990.

![Figure 5: Map of change in coldest day per year (TNN) for the GFDL_esm2g climate model RCP 8.5 for 2070-2099. Note this is only a single climate model, and an ensemble of multiple climate models is suggested to be used (see section below on “Ensemble Analysis”)]
**Future recurrence interval**

The recurrence interval statistic describes how often the climate in a future average year would have been expected to happen in the past. In other words, answering the question “In our recent historic climate (e.g. 1961-1990), how often did we experience events that we expect to be commonplace in the future”. For example, a recurrence interval value of 10 means that events that occurred only once every 10 years during the recent past (1961-1990) will be expected to happen every other year in the future. With temperature increase, by the end of the

Spatial equation (for creating map):

\[
fpoi = \frac{\{rank(\bar{x}_{i,f})\}_p}{Np + 1}
\]

\[
fr_i = \begin{cases} 
fpoi \geq 0.5; & \frac{1}{1 - fpoi} \\
fpoi < 0.5; & \frac{1}{fpoi}
\end{cases}
\]

Non-spatial equation (for creating table):

\[
fpo = \frac{\{rank(\bar{x}_f)\}_p}{Np + 1}
\]

\[
fri = \begin{cases} 
fpo \geq 0.5; & \frac{1}{1 - fpo} \\
fpo < 0.5; & \frac{1}{fpo}
\end{cases}
\]

where \(fpo\) is the future probability of occurrence; \(\bar{x}_{i,f}\) is the median of the future set at each pixel, \(i\); \(p\) is the past set; \(N_p\) is the sample size of the past set; and \(fri\) is the future recurrence interval. The non-spatial recurrence interval is calculated like the recurrence interval at each pixel in the spatial calculation, except that the climate variable is spatially averaged (\(\bar{x}_f\)) before finding the median across the future set (\(\bar{x}_{i,f}\)). The maximum recurrence interval possible is 30 because there are only 30 years in the past set. If \(\bar{x}_{i,f}\) or \(\bar{x}_f\) are outside the range of values of the past set, a value of 31 is assigned. It denotes a scenario where the median future event was not experienced within the 30-year historic period (i.e., a “novel” climate, Figure 6).

**Figure 6:** Map showing the change in recurrence interval of the 2070-2099 median ensemble model for total precipitation. This shows the extreme high annual precipitation that historically occurred only once every 3-5 years (light blue), 5-10 years (medium blue), or 10-30 years (dark blue) during 1961-1990, is projected to be the precipitation amount in a normal year in 2085.
6) General Circulations Models: Ensemble Analysis
Climate change analysis becomes more complex for the future than the past because there is not one time-series of climate, but rather many future projections from different GCMs run with a range of CO$_2$ emissions scenarios (Hartmann et al. 2013). It is important not to analyze only one GCM for any given emission scenario, but rather to use ensemble analysis to combine the analyses of multiple GCMs and quantify the range of possibilities for future climates under different emissions scenarios. There are many approaches for doing ensemble analysis ranging from simple averaging approaches to more complex and computationally intensive probability estimation approaches (Dettinger 2006, Araújo and New 2007).

Quantile ensembles
The multiple climate model maps are combined together using a simple, yet informative non-parametric quantile-rank approach that maps out the 0 (minimum), 20, 40, 50 (median), 60, 80, and 100th (maximum) percentiles. The range of a climate variable across the different ensembles shows you the range in the climate models for that variable.

Ensembles can be interpreted differently for temperature versus precipitation. For temperature, all models agree that mean temperatures will increase everywhere in the world, so the ensemble shows you different magnitudes of temperature increase. However for precipitation, all models often do not agree on the direction of change, much less the magnitude in either direction. Ensemble analysis can be used to understand the distribution of climate models, look for climate model agreement, and identify the range of future climate projections. A spatially-resolved example of an ensemble analysis is given for change in consecutive dry days by 2081-2100 under the A2 emissions scenario.

Map and GIS Data Download
The following data and reference material can be downloaded from the links on the upper left of the World Bank Climate Analysis Tool:

- “Map Image” provides a PNG graphic of the map currently shown in the Climate Analysis Tool map viewer.
- “GIS data” provides data in ASCII grid format, which can be loaded directly into ArcGIS or other GIS programs (e.g. QGIS).
- “Full Statistics Table” provides a tabular summary for each GCM (see further description below).
- “Ensemble Table” provides a tabular summary for the ensemble of all GCMs (see further description below).
- “Complete Download” provides a complete download of all data
Aggregated analysis: Summarizing climate change information

The mapping tool is useful for showing how climate change is spatially variable across Bangladesh. However, an aggregated analysis is useful for summarizing climate change over an entire area (e.g. whole country, region, or watershed) as a single value. This tool includes 6 regions:

i. Territory of Bangladesh;
ii. Northwest region of Bangladesh (vulnerable to drought and flood);
iii. Northeast region of Bangladesh (vulnerable to flash flood);
iv. Western coastal region (vulnerable to cyclone);
v. Central coastal region (vulnerable to cyclone);
vi. Eastern coastal region (vulnerable to cyclone);

All of the climate change statistics described above in the section “Different Types of Climate Change Analyses”—average (mean), change between past and future (departure), and frequency recurrence interval (FRI)—are calculated based on the average climate over the entire area (e.g. Bangladesh Country Boundary) to give the user a calculation of how the area is changing on average. This allows for easier interpretation and for developing climate planning scenarios for that area. Figure 7 below shows an example for all of Bangladesh—this table can be downloaded from the WB Climate Analysis Tool by clicking on “Full Statistics Table” in the upper left of the website.

![Table with climate change statistics](image-url)
Figure 7: This table shows the climate metric values averaged over the entire Bangladesh Area periods 1961-1990 and 2070-2099. The Departure value represents change in the future: the difference between the aggregate means Past Average and Future Average. The recurrence interval relates the future average condition to the frequency of climate extremes in the past (e.g., what happened once every 10 years in the past is projected to every other year in the future.

Aggregated analyses can analyze the ensemble of multiple climate models. A second table is provided for this purpose and is downloaded from the Web Application by clicking on “Ensemble Table” in the upper left. Table 8, for example, shows the range of the GCM future climate projections for the 6 different focus areas in Bangladesh using a multi-model ensemble. For each “Area”, “Variable”, “Month”, and greenhouse gas Representative Concentration Pathway “RCP”, the values are given for the different quantiles of the ensemble ranging from the “lowest change (minimum)”, to the “median change (50%)”, to the “highest change (maximum)”.

Figure 8: Ensemble table downloaded from the WB Climate Analysis Tool.
Monthly cycles of climate and change
Climate does not change the same during all months of the year, but often has a pattern of change, with some months having greater changes than others. For example, looking at maps of change in precipitation for each month of the year show that the greatest increases are projected to occur during rainy season May-August, with the exception of some areas in the south and east which are projected to decrease in precipitation during June (Figure 9). Precipitation decreases are projected to occur mostly during the start and end of the wet season (April and October) and in some areas during the dry season (Figure 9).

Figure 9: Maps of all months during the year showing differences in the projected precipitation change (ensemble average of all GCMs) during in approximately 2025 for RCP 8.5.

It is also important to assess the range GCMs for each month. This is difficult to do with maps, but the ensemble table shown above in Figure 8 can allow us to create a graph showing the range of GCM projections for each moth. By loading the ensemble table into a spreadsheet, it is possible to a graph each of the quantiles of the ensemble—minimum GCM, 10 percentile, 20 percentile, etc. (Figure 10).
Figure 10: Showing the projected changes in the single coldest temperature recorded per month during 2070-2099 for RCP 8.5. Each line represents a different quantile of the ensemble—minimum, 10\textsuperscript{th} percentile, 20\textsuperscript{th} percentile, etc. Note the strong pattern throughout the year with greater increases projected in October – March (most models ranging between 2 and 8 °C increase), and the lowest coldest temperature increases during June and July (most models projecting 1.5 to 5 °C increase).
Section 5: Guiding Principles for Use of the Climate Analysis tool
The Climate Analysis tool provides easy access to a wide range of future climate model information, but as with any modelling of the future, it must be used properly. It is critical for users of this tool to familiarize themselves with the strengths and limitations of future climate projections. Here are two major issues to consider for the region:

☑️ Don’t look at just a single grid cell—look at regional patterns
These climate data are derived from global climate models and as such the result of a single grid cell must be interpreted cautiously. It is best to look at an area around the single grid cell to see if the patterns of change are consistent or if there is large variation from grid cell to grid cell. Assessing regional patterns in climate change is important for understanding if climate change is consistent for the area or if climate change varies regionally. If there is significant variation within the region, then values taken from a single grid cell should be interpreted with caution.

Often climate change will have different patterns for different areas. Temperature change across Bangladesh is not constant. Looking at regional patterns can provide information on what parts of the country are projected to experience the greatest amount of climate change.

☑️ Monsoons are difficult to model
GCMs historically have had difficulty modeling monsoons. However, the most recent IPCC Fifth Assessment Report states that there is growing evidence of improved skill of climate models in reproducing monsoons (Hartmann et al. 2013). This report also states that monsoons are likely increase in area and intensity during the 21st century, with monsoon onset dates becoming earlier or not to change much and monsoon retreat dates are very likely to delay, resulting in lengthening of the monsoon season. This is consistent with the data in the World Bank Climate Analysis Tool monthly precipitation change maps shown above (Figure 9).
Section 6: Example of results

Specific sectorial impacts for Northwestern Bangladesh

Exposure to Climate Change: Temperature and Precipitation future trends

Temperature
By 2025 under RCP 8.5 greenhouse gas emissions, the daily high temperature in Northwestern Bangladesh is projected to increase by approximately 1.1 °C and by 2085 the daily high is projected to be 3.8 °C (as high as 5.5 °C) hotter. By 2050 more than 75% of climate models project the high temperature to increase over 2 °C. The IPCC and other scientists have stated that temperature increases over 1-2 °C constitutes “dangerous climate change” (IPCC, 2007). This has major implications for human health, agriculture, and energy demand with these hot daily temperatures.

Precipitation
Precipitation in Northwestern Bangladesh is projected to increase the greatest during the middle of the rainy season in June-September (Figure 12). During this time the majority of climate models agree on increasing precipitation in 2025, 2055 and 2085 under both of the greenhouse gas emissions scenarios. With further time in the future and higher greenhouse gas emissions the magnitude of change is higher, but the number of climate models that agree stays approximately the same, with 80-100% of the climate models agree on increasing precipitation during some months. By 2080, during June-August precipitation is projected to be more than 30% greater than historically. However, during the dry season November through April (light colored bars), precipitation is projected to change very slightly or even decrease. This pattern of the wet months getting wetter and the dry months getting drier will have negative implications for agriculture, flooding and timing of water supply.

Figure 11: Box plot showing the range of GCM projections of change in daily high temperature by 2025, 2055 and 2085 for the RCP 8.5 greenhouse gas emissions. The black bar is the median, boxes represent the 25th and 75th percentiles.

Figure 12: Graph of percent change in precipitation over months in 2085 for RCP 8.5. Darker colored bars represent months with historically greater average precipitation.
Impacts on Agriculture
Increasing temperatures will increase the number of growing degree days over time, increasing by over 15% by 2055 and by about 25% in 2085 (Figure 13). Although this change might result in positive impacts for some local crops, the accompanying increased high temperatures could cause heat stress and increased evapotranspiration. This will lead to increased water demand for water and soil moisture stress. Heat stress is a major issue with many crops including wheat and rice, and could reduce yields even with increasing growing degree days.

Impacts on Disaster Risks: Flooding
Based on climate models results, there is high agreement among models that the 5-day maximum rainfall amount per year will increase by around 20% in by 2025, and could be as great as a 40% increase (Figure 14). By 2085, the majority of climate models project the increase to be approximately 40% and could be higher than a 70% increase. Moreover, the majority of climate models show that the 5-day extreme precipitation around 2085 will be similar to what only used to occur once every 5-10 years historically.

This is in agreement with the graph in Figure 12 above showing that precipitation during the wettest season is projected to increase by over 30% during the time of year with the greatest precipitation (July & August).

Figure 13: Box plot showing the range of GCM projections of percent change in growing degree days by 2025, 2055 and 2085 for the RCP 8.5 greenhouse gas emissions. The black bar is the median, boxes represent the 25th and 75th percentiles.

Figure 14: Box plot showing the range of GCM projections of percent change in 5-day precipitation maximum by 2025, 2055 and 2085 for the RCP 8.5 greenhouse gas emissions. The black bar is the median, boxes represent the 25th and 75th percentiles.
Impacts on Human Heat Stress and Cooling Energy Demand

Cooling degree days provides a measure of the cumulative energy demand to cool a building to a comfortable level. By 2025, the amount of cooling degree days is projected to increase by over 15% compared to historical times (Figure 15). By 2055, the increase is projected to be over 30%. By 2085, it is projected to increase by over 45%, and possibly higher than 60%.

In the absence of air conditioning or other cooling, this will be an impact on human well-being and health. The chart on the bottom shows the projected increase in the single hottest day of the year. The projected increase by 2085 is projected to be over 4 °C and could be as high as 6.5 °C, which could have major implications for human and livestock heat stress.

Summary

In summary, it is clear that precipitation patterns will change and temperatures will increase in northwestern Bangladesh. Even as soon as 2025, the region will likely have significant impacts across all sectors. Precipitation is projected to increase during the wettest time of the year, whereas the precipitation during the dry season is projected to change little or decrease slightly. This shows likely impacts to agriculture from plant heat stress, dry season moisture stress, and flooding. A projected increase in the 5-day precipitation maximum shows high potential for increased risk of flash flooding, which is known to be a historic risk in northwestern Bangladesh. Projected temperature increases will very likely increase energy demand for cooling (where people have cooling), and increase heat will increase heat stress vulnerability to humans and livestock.
References


Appendix 1: Downscaling Methodology

Adapted from Girvetz, et al (2013)

The downscaling method used was a daily-timescale variant of a method known as Bias Correction/Spatial Downscaling (BCSD) that has been widely applied to produce monthly downscaled quantities based upon monthly GCM results. The monthly version of the method is described by Wood et al. (2002 and 2004). Further documentation can be found online at http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/dcpInterface.html. As with any statistical downscaling method, some assumption of stationarity is needed. For the technique used in this study it is assumed that the processes shaping the climate at the fine grid scale during the historical period will continue to govern local climate features in the future, which may not always be the case. Past work has shown that the statistical BCSD method as implemented here performs comparably to dynamical downscaling approaches, at least when assessing hydrologic impacts of climate change.

A daily variant, which produced daily timescale downscaled results based upon daily timescale GCM results, is described by Abatzoglou and Brown (Abatzoglou and Brown 2012). This daily downscaling is not to be confused with temporal disaggregation, which produces daily values based upon monthly GCM results and some questionable assumptions. Here we used a daily variant of the BCSD that is similar to that of Abatzoglou and Brown (2012), but which was developed independently.

The downscaling and bias-correction was done using historical observed daily gridded observations. The base meteorological data consists of daily time-series for the period of 1950 through 2005 of precipitation, maximum temperature and minimum temperature. Monthly station data from a variety of sources (including the Global Historical Climatology Network (GHCN) version 2 data) were compiled and gridded to a resolution of 0.25-degree over all global land areas. The daily variability of precipitation, maximum and minimum temperature was constructed using other global daily datasets, which were scaled to match the monthly values.

Bias-correction

The bias correction step is performed independently for each day of the year (January 1 through December 31). For each day, we based the bias correction on results from the reference period within +/- 15 days of the day in question. For example, for February 20 (the 51st day of the year), the bias correction is based upon results from days 51 - 15 = 36 through 51 + 15 = 66, for all 40 years in the reference period (i.e. a total of 40*31 days). That is, the bias correction for February 20 is determined by comparing reference period results from days 36 through 66 in the GCM to results from the same set of days in observations. Using these data, the bias correction process itself is the same quantile mapping approach described in the references cited above.

Trend Preservation

A potential hazard of the bias correction process is that it cannot distinguish between year-to-year variability and an underlying trend (such as from increasing greenhouse gases)—these both create an
increased range of values. Thus, bias correction of data with an underlying trend would tend to artificially adjust variability downwards. This would not only produce incorrect interannual variability in the bias-corrected results, but also tend to remove the underlying trend. To avoid these tendencies, we remove any underlying trend from the results before bias correction, and add it in again afterwards. This ensures that the bias correction adjusts the interannual variability properly, and that trends in the bias corrected results are the same as before bias correction. Because the downscaling step does not alter trends, either, this implies that trends in our BCSD results are the same as in the original GCM results. This realizes an important principle, namely that the GCM is the best source of information about long-term trends; hence bias correction and downscaling should preserve those trends.

The trend preservation process involves the following steps:
   a. Calculate monthly means for all data;
   b. Calculate monthly climatologies for 1950-2005; i.e. the mean of all Januaries, the mean of all Februaries, etc;
   c. Calculate monthly anomalies relative to the climatologies described above;
   d. Calculate the 9-year running mean of anomalies for each month (this is the "trend");
   e. Set the trend to zero during 1961-1999;
   f. Subtract the trend from each day in the month in question;
   g. Perform bias correction on detrended results;
   h. Add trend removed in step (f) to the detrended results.

All climate models listed in Table 1 were downscaled to a 0.25 degree resolution and daily time scale for the years 1950-2099.
Appendix 2: Methods for calculating derivative metrics

Adapted from Girvetz et al. 2013

To be consistent with past efforts calculating similar extreme climate statistics, we used the source code developed and distributed by the Max Plank Institute (MPI) for Meteorology. The code is a set of commands wrapped into a package called the Climate Data Operators, Version 1.5.0 (March 2011). All source code can be obtained at the MPI site [https://code.zmaw.de/projects/cdo/files](https://code.zmaw.de/projects/cdo/files).

We calculated a suite of 12 statistics using daily downscaled GCM output, with most of these statistics being widely used for many years in the climate community for characterizing extreme events (Karl et al. 1999, Easterling et al. 2003). Typical values, for historic periods, of many statistics are illustrated by Fritch et al. (Frich et al. 2002).

In the tables above, the calculation of each statistic is described, and some more complete descriptions are in the literature (von Engelen et al. 2008, Schulzweida et al. 2011). Many of these statistics have been used to characterize observed historical climate and its changes (Alexander et al. 2006). For most statistics the detailed calculation is obvious from the description, though some statistics require additional detail.

For statistics based on values for multi-day periods (consecutive dry days, most amount of rain in a 5 day period), the meaningfulness of these statistics at the monthly level becomes compromised, because the length of the period being assessed (for example, 5 days) becomes large relative to the length of the period being assessed (e.g., a 30-day month). This would cause problems when, for instance, a 5-day dry period spans the 1st of a month, which would then be divided into two shorter dry periods which would not show up as a 5-day dry period. Thus, for these statistics, only annual values are included in our database.

Heating and cooling degree days were calculated using a base temperature of 18 °C (65 °F) following the Encyclopedia of World Climatology (Oliver, 2005). Growing degree days were calculated using a base temperature of 10 °C with no upper threshold used.