

# **Climate Models**

This factsheet describes climate models and how they are used in climate hazard-based impact assessments.

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FACTSHEET

**Weather** refers to the state of the atmosphere at a specific time. It is usually expressed in terms of sunshine, cloudiness, humidity, rainfall, temperature, wind, and visibility. **Climate** is defined as the average weather, over a continuous period of at least 20 years. For example, the climate in Port Vila is warmer and wetter during November to April compared to May to October.

**Climate variability** refers to variations from the average climate and is driven by a range of natural processes that occur on different spatial and temporal scales. This includes systems affecting daily weather (e.g. thunderstorms, cyclones), monthly, seasonal, and annual climate (e.g. El Niño Southern Oscillation), or across decadal timescales (e.g. Pacific Decadal Oscillation), and over thousands of years (e.g. Earth's orbital variations over 20,000, 41,000 and 100,000 years).

The Earth's climate has also been changing due to global warming. Human activities like energy supply, industry, transport, buildings, agriculture and forestry have increased the concentrations of greenhouse gases in the Earth's atmosphere [1] (see <u>Greenhouse gase emissions factsheet</u>). Global average temperature has increased by 1.1 °C between 1850–1900 and 2010–2019. Global average sea level has risen, global average precipitation over land has increased, the frequency and intensity of heavy rainfall has increased, and glaciers and sea ice have retreated. The frequency and intensity of hot extremes (including heatwaves) has increased, while cold extremes have decreased [1]. These changes have caused a range of impacts including coral bleaching, changes in crop yield, increases in natural disasters, increased heat stress, coastal inundation, saltwater intrusion of aquifers, and riverine flooding.

### **Global climate models**

Ongoing increases in the amount of greenhouse gases in the atmosphere over the coming decades will cause further global warming. Global climate models (GCMs) can simulate this future global warming and associated changes in other climate variables such as precipitation and wind based on plausible scenarios for future atmospheric greenhouse gas concentrations (Figure 1; also see Greenhouse gas emissions factsheet). They do this by representing the climate system in mathematical equations, based on the laws of physics, that are solved on powerful supercomputers. Data are generated for hundreds of climate variables, over hundreds of years, over thousands of points on a grid covering the globe.

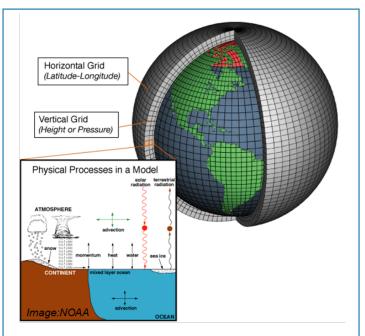


Figure 1 Schematic representation of a global climate model (Source: NOAA).

Developing, maintaining and running a GCM is a major undertaking. Dozens of research centres around the world contribute the data from their GCMs to an international project called the Coupled Model Intercomparison Project (CMIP). The previous phase of this project, Phase 5 (CMIP5), collated data from 40 GCMs [3]. These data have been used in many climate risk assessments around the world, as noted in the IPCC Fifth Assessment Report (AR5) [4]. The most recent intercomparison project, Phase 6 (CMIP6) [5], considers data from over 50 GCMs which are gradually being incorporated into risk assessments.

While all GCMs are based on the same physical laws, each GCM uses slightly different methods for representing key climate features and processes, such as cloud feedback, ice feedback, carbon cycle feedback, convection, and atmospheric chemistry. Different models are also more- or less- sensitive to changes in the atmospheric mix of gases. Therefore, each GCM has a unique simulation of past and future climates.

The performance of a GCM simulation of the past climate guides the level of confidence assigned to a simulation of the future climate, with some GCMs performing better than others (see [6]).



High-quality climate observations are required to assess climate model performance. Differences between a model simulation and observations for a common historical period are called biases. If a model has low biases for many key aspects of the climate (e.g. seasonal rainfall, or capturing the relationship between El Niño Southern Oscillation and rainfall patterns), then confidence in projections from this model is higher [7]. If a model has high biases, then confidence in its projections is lower.

There is greater confidence in projections of some variables (e.g. temperature) than others (e.g. rainfall), and greater confidence in projections over large spatial scales and long time periods (e.g. global warming over multiple decades) than for smaller spatial scales and short time periods (e.g. regional climate projections over less than ten years) [7].

Unfortunately, the size of model biases differs between different aspects of the climate (e.g. temperature and rainfall) and there is no single best model that has low biases for all aspects. Models with large biases across many performance tests may be rejected [7]. Some of the biggest biases found in GCMs are in the western Pacific. This means that confidence in some climate projections for the western Pacific region is low compared to other regions<sup>1</sup>.

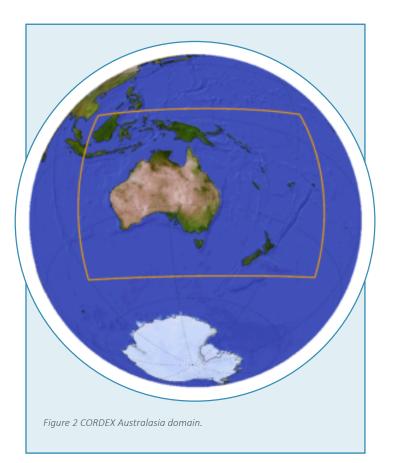
The Van-KIRAP project has identified a set of GCMs that perform well over the western tropical Pacific region. They give a range of plausible future climates that could be used in risk assessments [8]. Climate change projections for 14 Pacific countries, including Vanuatu, are available from the <u>Regional Climate Consortium for Asia and the Pacific.</u>

While the large-scale patterns of the future climates are plausible, there is no fine-scale detail in these projections (e.g. differing climates between towns that are 50 km apart). This is because the number of data points across the globe is limited by the available computer power to run the model. Even with powerful supercomputers, the horizontal spacing of data points is typically 150 km. Hence, GCMs don't fully include the local influence of important surface features (e.g. mountains, coastlines and vegetation). GCMs also have difficulty simulating extreme weather events, such as thunderstorms and tropical cyclones. To address these limitations, "downscaling" techniques can be used.

### **Dynamical downscaling**

Dynamical downscaling involves running a Regional Climate Model (RCM) that focuses available computer power over a limited region, rather than over the whole globe. This allows the spacing of data points to be reduced to around 10–50 km or less. The result is a better representation of many regional weather and climate phenomena, especially over regions of complex terrain [1]. However, some local phenomena such as land-sea breezes, mountain winds, cold fronts and extreme rainfall can only be realistically represented at a resolution of less than 10 km. Another limitation of this technique is that the RCM is driven at its boundary by information from a GCM, so the RCM will inherit biases in the broad-scale climate simulated by the GCM [1]. Therefore, GCMs with small biases are usually chosen for downscaling. An alternative approach is to use a "stretched grid" model, such as CSIRO's Cubic Conformal Atmospheric Model (CCAM), that simulates the entire globe but has a greater density of the data points over the region of interest than elsewhere.

The <u>Coordinated Regional Downscaling Experiment</u> (CORDEX) is an international science project that is advancing downscaling through regional partnerships. It aims to compare downscaling results in 14 regional "domains" around the world, including Australasia. The Australasian domain covers part of the western Pacific region (Figure 2). For CORDEX, selected CMIP5 GCMs have been downscaled at 25 km resolution from 1950–2100. CMIP6 GCMs are being downscaled to around 12.5–25 km resolution.



## Application-ready data

Because of model biases and limited spatial resolution, climate model data sets cannot be directly used in climate change impact assessments. 'Application-ready' data can be generated for this purpose. There are two main methods of doing this:

- Use observed data for a recent historical 'baseline' period (e.g. 1986–2005) and then adjust these data to represent the future climate (e.g. for 2046–2065). The adjustments are based on climate changes between the future and historical period simulated by GCMs or RCMs or a stretched grid model.
- 2. Use bias-adjusted data simulated by GCMs or RCMs or a stretched grid model. Adjustments to the model data to reduce biases are derived from the difference between the simulated historical climate and the observed historical climate. The adjustments are applied to the simulated future climate data.

Each method has strengths and weaknesses. The Van-KIRAP project employs method 1 with the advantage that it is relatively simple to implement, and it incorporates historical climate data that are widely used by stakeholders. This can be important for establishing historical climate-impact relationships that can be used in future climate impact assessments. A weakness of method 1 is that the historical sequence of weather events is repeated in the future climate and potential changes in weather sequences are not accounted for.

<sup>&</sup>lt;sup>1</sup>Important model biases for the Pacific region include: Sea surface temperatures: West Pacific Warm Pool and equatorial 'cold tongue' can be the wrong shape, and the cold tongue is generally too strong in models [1].

Rainfall: South Pacific Convergence Zone and Inter-Tropical Convergence Zone can be too strong and there is a tendency for the SPCZ to be too zonal (horizontal) and can extend too far eastward [9, 10].

While method 2 allows for different weather sequences in future, not all impact-relevant biases can be corrected for, the biasadjustments may be large, interannual variability may be overestimated, the spatial patterns may be too smooth [1], and the bias-corrected historical data are not widely used by stakeholders (ee <u>Climate projections for use in impact assessments factsheet</u>).

#### Caveats

Climate model simulations are affected by uncertainties from three main sources:

- 1. Future greenhouse gas emissions scenarios
- 2. Regional climate responses to each emissions scenario
- 3. Natural climate variability

The combined range of uncertainty is given by the blue arrow in Figure 3. The regional climate response for high emissions (pink arrow) and low emissions (green arrow) includes the range of natural climate variability (black arrow).

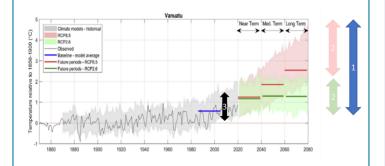


Figure 3 Annual average temperature change in Vanuatu relative to 1850–1900 derived from observations (solid grey line) and simulated by CMIP5 GCMs for the past (grey shaded band) and the future (pink shaded band for high emissions, green shaded band for low emissions). Thick horizontal lines show the average of all GCMs in 20-year periods: 1986–2005, 2021–2040, 2041–2060 and 2081–2100. The arrows indicate (1) total range of uncertainty, (2) climate response uncertainty due to different emissions pathways, and (3) uncertainty due to natural climate variability. Source: [11].

Regarding future greenhouse gas emissions, the scenarios are similar up to 2040, but beyond 2040 there is significant uncertainty as the emissions scenarios diverge. This is because of different assumptions about future demographic changes, socio-economic development, energy use, land use, and associated changes in greenhouse gases and air pollution (see <u>Greenhouse gas emissions factsheet</u>).

Regarding regional climate change, climate models have limitations at regional scales. While downscaled projections can provide high-resolution information, the data may include regional biases, especially at local scales. The numerical precision of these data must not be confused with accuracy. Downscaled projections from CMIP5 climate models should be considered plausible, rather than precise, based on the best available information. Data from a new set of CMIP6 GCMs are currently being evaluated. Some of these GCMs will eventually be downscaled in the CORDEX-2 experiment. Over the coming decade, it is hoped that a paradigm-shift in the performance of GCMs and RCMs will enable simulations with much finer resolution, smaller biases, and higher confidence [12].

Regarding natural climate variability, this is a factor that can strongly influence short-term trends and extreme events. Natural variability is hard to predict. Observed climate trends over recent decades may be the best choice to inform climate trends over the next decade. Climate model simulations can inform trends beyond the next decade (see <u>Climate variability explainer</u>).

### References

- IPCC, Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. 2021. Available from: <u>https://www.ipcc.ch/ report/sixth-assessment-report-working-group-i/</u>
- IPCC, Summary for Policymakers. Synthesis of IPCC Sixth Assessment Report. 2023. Available from: <u>https://</u> www.ipcc.ch/report/sixth-assessment-report-cycle/
- 3. Taylor, K.E., R.J. Stouffer, and G.A. Meehl, An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 2012. 93(4): p. 485-498.
- IPCC, Climate Change 2013: The Physical Science Basis. 2013. Available from: <u>https://www.ipcc.ch/report/ar5/wg1/</u>
- O'Neill, B.C., et al., The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, 2016. 9(9): p. 3461-3482.
- Grose, M.R., et al., Assessment of the CMIP5 global climate model simulations of the western tropical Pacific climate system and comparison to CMIP3. *International Journal of Climatology*, 2014.
- CSIRO and BoM, Climate Change in Australia Technical Report. 2015, CSIRO: Melbourne, Australia. Available from: <u>http://climatechangeinaustralia.gov.au/</u>
- 8. CSIRO and SPREP, 'NextGen' Projections for the Western Tropical Pacific: Current and Future Climate for Vanuatu. 2021, CSIRO: Melbourne, Australia.
- Brown, J.R., et al., South Pacific Convergence Zone dynamics, variability and impacts in a changing climate. *Nature Reviews Earth & Environment*, 2020. 1(10): p. 530-543.
- Brown, J.R., A.F. Moise, and R.A. Colman, The South Pacific Convergence Zone in CMIP5 simulations of historical and future climate. *Climate Dynamics*, 2013. 41(7-8): p. 2179-2197.
- 11. CSIRO and SPREP, Climate hazard-based impact assessments for the Pacific: A step-by step guide on climate change related impact assessments for sectors. 2022, CSIRO: Melbourne, Australia. Available from: <u>https://www. rccap.org/climate-hazard-based-impact-assessment/</u>
- **12.** Fiedler, T., et al., Business risk and the emergence of climate analytics. *Nature Climate Change*, 2021. 11(2): p. 87-94.

