ECMWF COPERNICUS NOTE

Copernicus Climate Change Service

Guidance Sheet No. 4

Climate modelling and data sources

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1. Introduction

Climate modelling are important for risk assessment as they can give an idea of the evolution of the climate variables (e.g. temperature, rainfall, wind) based on some hypothesis on human gas emission. However, climate models have been designed to study behaviour of the atmosphere at large scales, not to make predictions or for impacts and adaptation studies at local scale. Depending on the climate model, certain variables are better simulated. Therefore, it is important to consider the climate model that we want to use depending on its resolution and on its performance.

2. What is a climate model?

- A model is a representation of a real system under some hypothesis. It helps us understand the processes that drives the system and project its evolution and consequences with an accuracy depending on the complexity of the model and knowledge of the real system.
- Global climate and its processes cannot be fully reproduced in by a physical model, therefore numerical models are essential to understand the climate and its changes.
- Climate models, also called GCMs (General Circulation Models), represents the interactions between energy and matter in the ocean, atmosphere and land surface using mathematical equations.
- In order to solve these equations, the globe is divided into cells by a 3-dimensionnal grid. Time is also divided into time steps. Equations are solved in each cell and share information with their neighbours between each time step.
- Initial conditions represent the climate forcing. In order to test the forcing and the accuracy of the model, they are run backwards in time and compare results to observations and other models.
- The calculations are run repeatedly with different forcing in order to understand the role of each variable in the processes. These calculations are very expensive in terms of computing resources and need supercomputers to run.

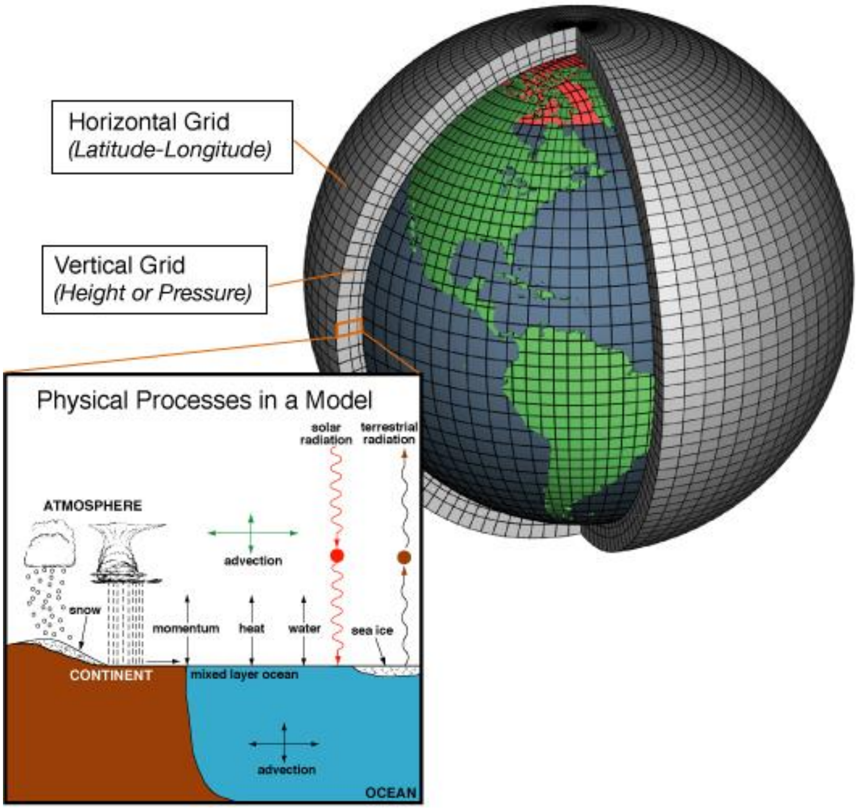

Figure 1 – Concepts used in climate models (NOAA, 2018)

3. What is a climate scenario

Climate scenarios are predictions of greenhouse gas emissions by human activities. The scenarios used by the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) in 2014 are the RCPs (Representative Concentration Pathway). Four scenarios (RCPs 2.6, 4.5, 6.0 and 8.5) have been predicted depending on how human activities will evolve from very high (RCP8.5) to very low (RCP2.5) concentrations of greenhouse gases. The numerical value represents the concentrations in 2100. Climate models are then run using these scenarios of gas emission and give us projections of climate variables (e.g. evolution of the global average temperature in Figure 2)

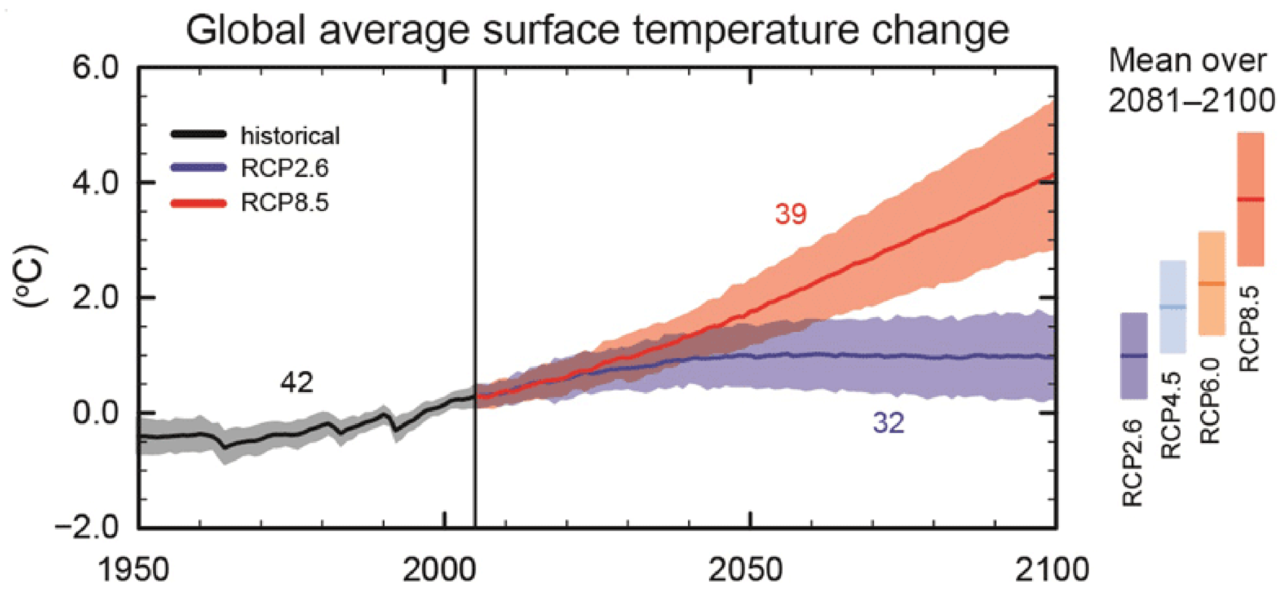

Figure 2 - Global average surface temperature change (from CoastAdapt, www.coastadapt.com.au)

4. How to use a climate model

Uncertainty arises from several sources in climate modelling (Figure 3), the most dominant being that around the RCP climate scenarios. Climate models available are Global Climate Models (GCMs) with a low resolution or Regional Climate Models (RCMs) which are applicable to a specific region. An RCM will usually take GCM output as boundary conditions. To study the performance and forcing of climate models, it would be recommended to use climate projection data from several GCM/RCM models, and perhaps several runs from the models, each started with slightly different initial conditions. In that way, the analyst can assess the level of uncertainty in the climate data.

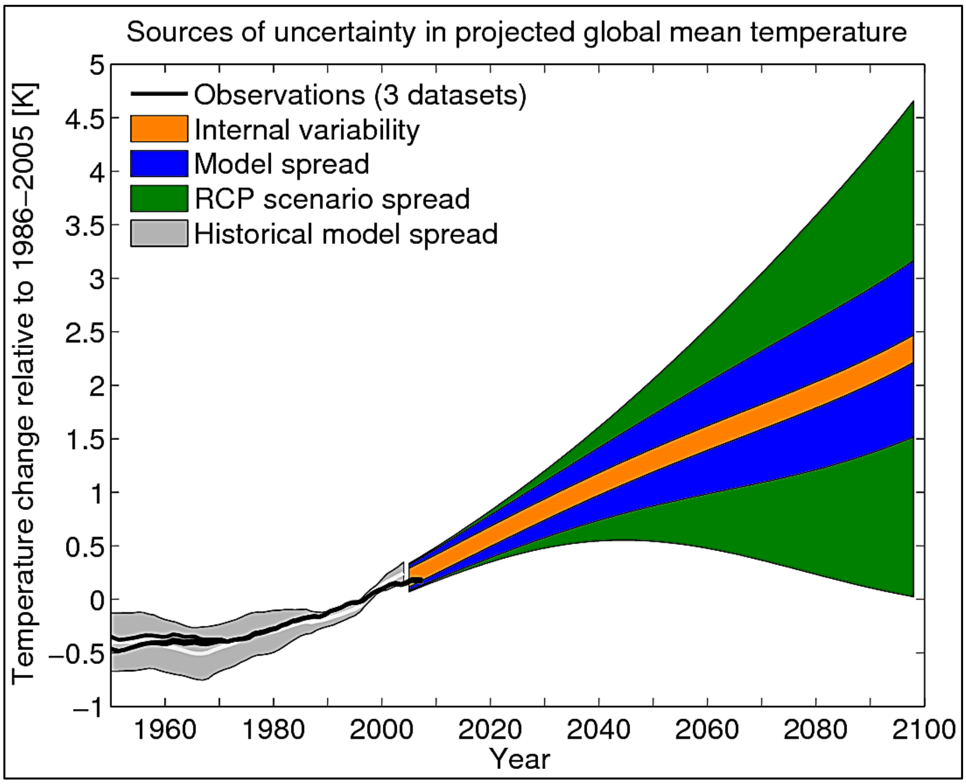

Figure 3 – Sources of uncertainty in projected mean temperatures (https://www.climate-lab-book.ac.uk/)

4.1 Downscaling methodologies

Global Climate Models are designed to give reasonably accurate climate information at a global scale. These models do not include all the physical processes within the climate system, and they are typically run with a with a coarse spatial resolution (typically hundreds of kilometres) due to limitations in computational resources (Trzaska and Schnarr 2014). As a result, fine-grained local features such as strong temperature or precipitation gradients near coasts may not be represented fully in these outputs (Barsugli et al. 2013) and some physical processes such as clouds may not be fully resolved. To increasing the credibility of the outputs at the local scale, downscaling methodologies are applied, either dynamical or statistical in nature.

To apply dynamical downscaling, a model is created which is similar to a GCM except that it includes additional data and climate processes, the spatial topographical and/or temporal resolution is higher, and the model is restricted to only the portion of the globe that is of interest (Trzaska and Schnarr 2014). The larger-scale outputs of the GCM are applied to the RCM at the boundaries of the area of interest to generate climate information at higher resolutions. This allows the model results to recover important regional-scale features (Trzaska and Schnarr 2014). For many areas of the globe, regionally-downscaled climate projections have already been computed, such as through the CORDEX initiative (WCRP Coordinated Regional Climate Downscaling Experiment 2020). However, RCMs are currently limited to approximately 10km spatial resolution (Christensen et al. 2019) . Nevertheless, RCMS may be biased due to the limitations in the GCMs and other boundary conditions, artifacts at the boundaries of the model area, insufficient coupling between the GCM and RCM, and the remaining limitations within the physics and resolution of the RCM itself (Barsugli et al. 2013). RCMs also require expert knowledge and computational resources, making it more costly and time-consuming that statistical methodologies (Trzaska and Schnarr 2014).

Statistical downscaling takes historical or current information about local climate variables. By comparing these outputs to large-scale atmospheric variables during the same time period, a relationship between large-scale and local variables is established. This relationship can then be applied to future projections for large-scale variables to infer the resulting local variables (Trzaska and Schnarr 2014). This approach can yield higher resolution output than dynamical downscaling, but assumes that the relationship between large-scale and local variables will not change as the climate changes (Trzaska and Schnarr 2014). This 'stationarity assumption' may break down, particularly as warming increases (Dixon et al. 2016). There are a numerous methods that can be used for statistical downscaling:

- Linear: A linear relationships is calculated between the large-scale predictor variable(s) and local predicand variable. This method is simple to apply but requires both predictor and predicands to be normally distributed. This makes it inappropriate for some variables such as daily rainfall (Trzaska and Schnarr 2014).
- Weather classification: Historical large-scale weather patterns are classified into particular c "states" are such as synoptic weather patterns. A future atmospheric state from a GCM will be matched to the closes historical state. The range of local variable values associated with that state can then be used to approximate the projected local variables.
- Weather generators: Weather generators are used to generate realistic sequences of weather variables with a higher temporal resolution (e.g. daily values, or hourly values). There are a five common models that used to accomplish this, WGEN , CLIMGEN , CLIGEN , WeaGETS and LARSWG (Chen and Brissette 2014).

Dynamically downscaled results can also be further-downscaled using statistical methods (Smid and Costa 2018).

4.2 Data sources

- Simulations of climate models are available, sometimes already at a regional scale, e.g.:
  - CM2 (https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/cm2-global-coupled-climate-models-cm2x)
  - UKCP (https://www.metoffice.gov.uk/research/approach/collaboration/ukcp/index)
  - EC-EARTH (http://www.ec-earth.org/)
  - EURO-CORDEX (https://www.euro-cordex.net/)
  - CMIP3, CMIP5, CMIP6

References

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