# Working with downscaled climate projections in R

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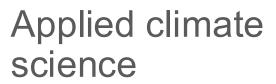


#### Who are we?

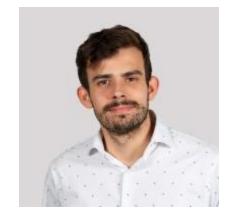


Science leader, coordinator

Ralph Trancoso







Hydrologist, climate extremes



Rohan Eccles

## Who are you?





## Open-source geospatial tools for conservation under climate change - A Koala case study

Session 1	Session 2	Session 3	Session 4	Session 5
Intro to geospatial data and tools	Downscaled climate projections	Koala SDMs	Spatial conservation planning	Making maps with QGIS
Jason Flower, Mitch Rudge, Catherine Kim, EcoCommons team	Ralph Trancoso, Sarah Chapman, Rohan Eccles	Charlotte Patterson, Scott Forrest	Brooke Williams, Caitie Kuemple	Emma Hain, Nyall Dawson, Jason Flower

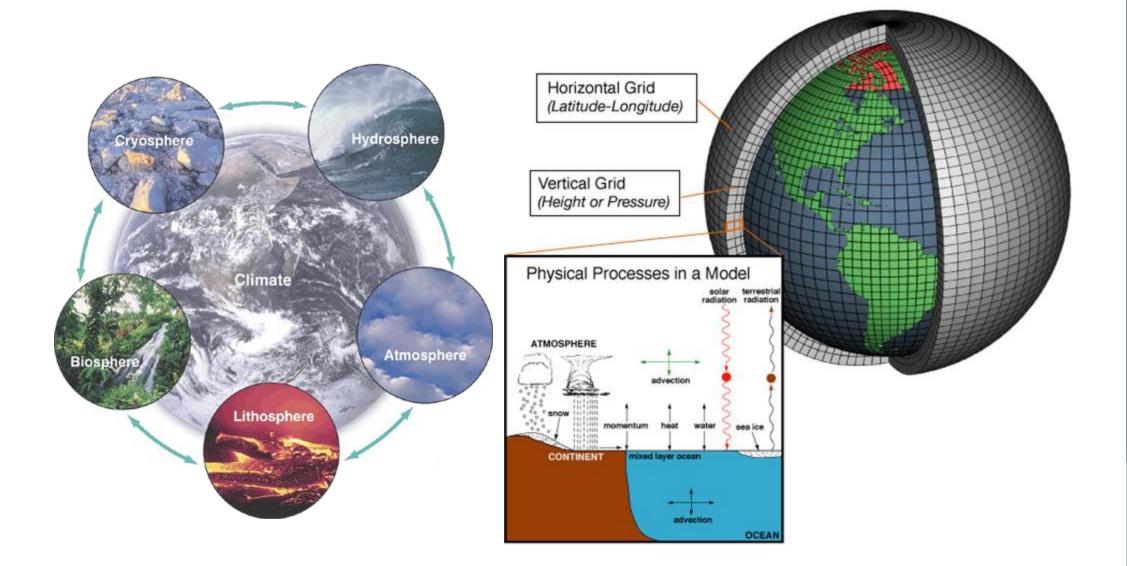




- Background on downscaled climate projections
- R scripts (~ 30 mins each)
  - Importing, plotting, subsetting climate projections
  - Calculating ensemble mean
  - Validating data and calculating bioclimatic indices
- Start installing packages while we talk!
  - terra, dplyr, sf, ggplot2, dismo, rasterVis, reshape



#### What is a climate model?





## What are downscaled climate projections?

 Global climate models (GCMs) have a spatial resolution of 100 – 200km

- CMIP (Coupled Model Intercomparison Project) major international modelling effort which feeds into IPCC reports
  - Currently on CMIP6

 Dynamical downscaling – running a higher resolution model with the inputs of a coarser resolution model (i.e., GCM) to improve the resolution of your data



#### Why downscaling?

CLIMATE REGIONS

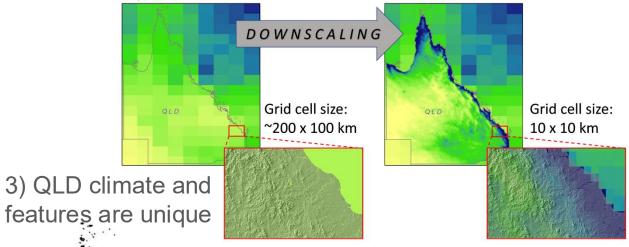
Equatorial

Tropical

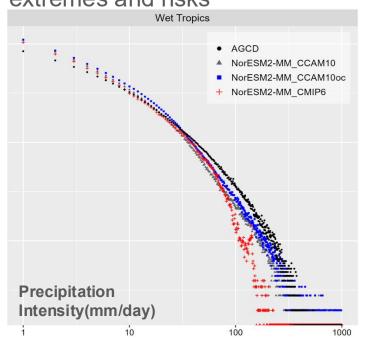
Sub-tropical

Temperate

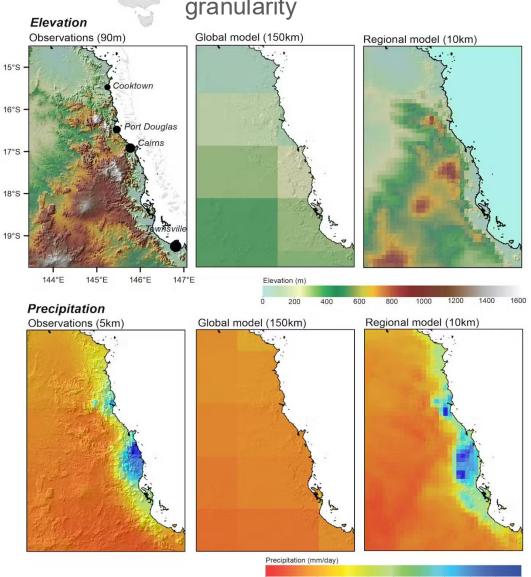
1) Global models do not represent well our climate



4) Global models underestimate extremes and risks



2) Global models misrepresent our landscapes and regional climate granularity

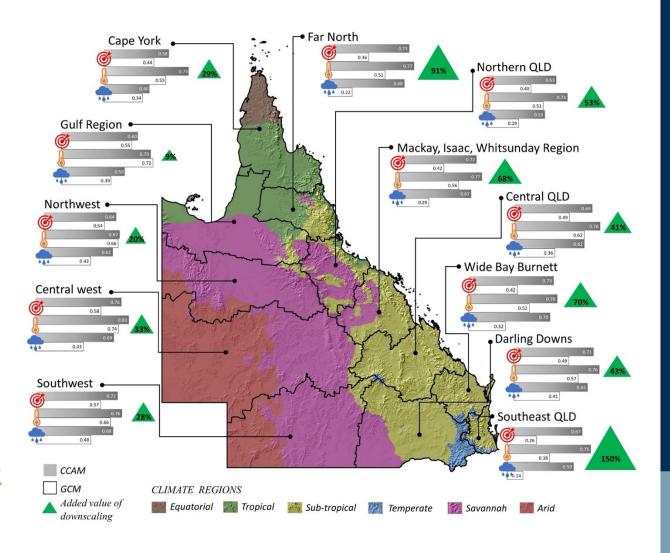


#### **Downscaling improvements to performance**

 Downscaling improved performance in all regions of Queensland

 Largest improvement along coasts, mountains, for extremes

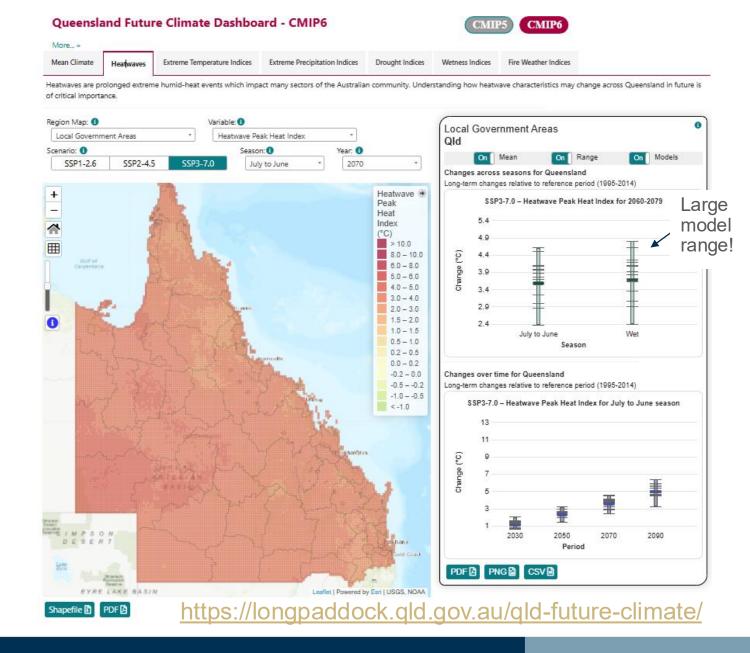
 Data available: <u>https://dx.doi.org/10.25</u> 914/8fve-1910





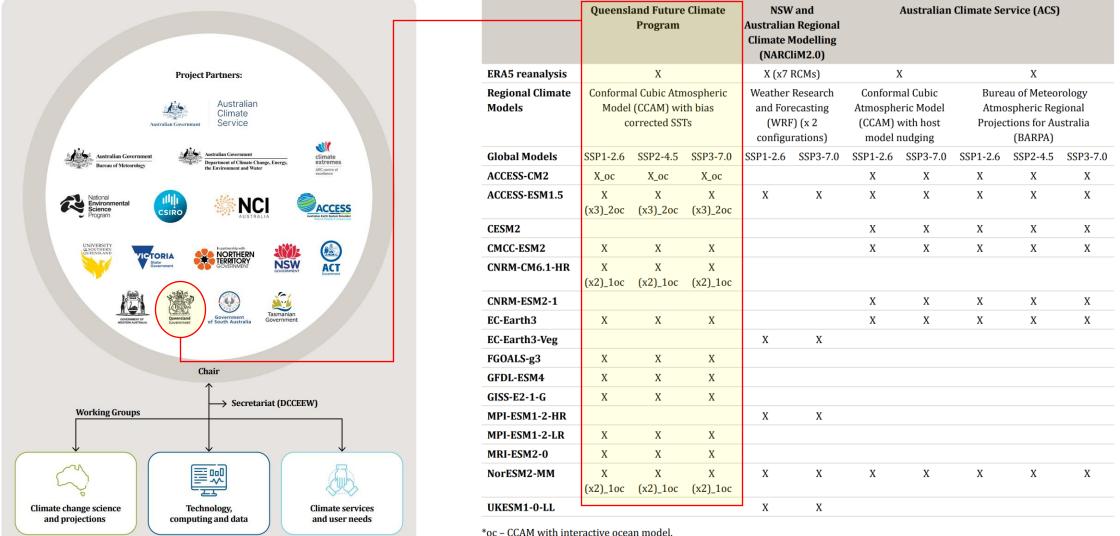
#### **CMIP6** Dashboard

- Three climate change scenarios (SSP126, 245, 370)
- 15 simulations per scenario
- Multiple regions
  - LGAs
  - NRMs
  - River basins
  - etc
- Multiple indices





## **National Partnership for Climate Projections**





## What are we doing today?

- Import climate data into R
  - Three models: ACCESS-ESM1-5, EC-Earth3, GFDL-ESM4
  - Climate scenarios: SSP370
    - If you have time the data folder includes SSP126 and SSP245
- Plot the data
- Calculate climate change impacts
- Validate the data against observations
- Calculate bioclimatic indices



#### What does a more realistic workflow look like?

- Find your data
- Evaluate against observations
  - Chapman, S., Syktus, J., Trancoso, R., Thatcher, M., Toombs, N., Wong, K. K.-H., & Takbash, A. (2023). Evaluation of Dynamically Downscaled CMIP6-CCAM Models Over Australia. *Earth's Future*, 11(11), e2023EF003548. <a href="https://doi.org/10.1029/2023EF003548">https://doi.org/10.1029/2023EF003548</a>
- Bias correct if required for your application
  - Tomorrow you will be using bioclimatic indices our team prepared. This dataset has been statistically downscaled (5 km) and bias corrected. Data will be available on EcoCommons.
- Evaluate some more
- Calculate your indices
- Calculate ensemble mean at the end



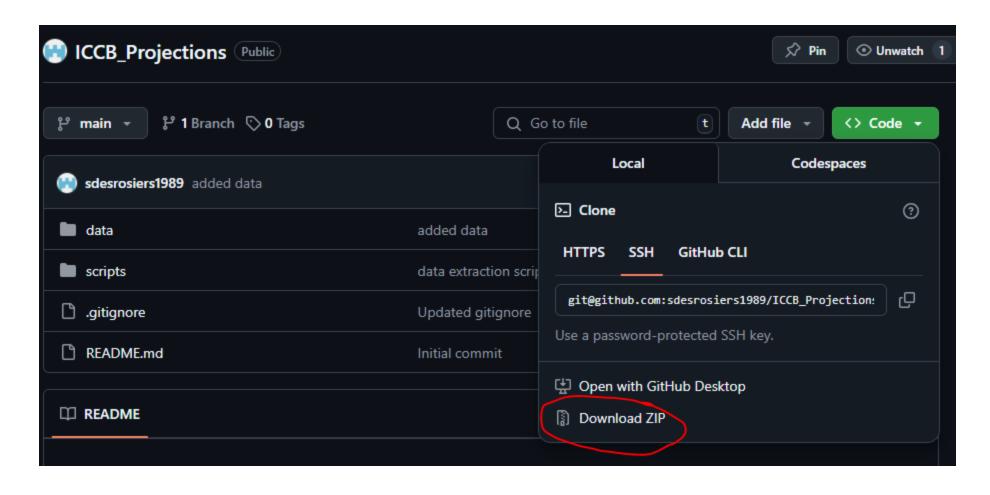
## **Questions?**



## **Getting started**



https://github.com/sdesrosiers1989/ICCB Projections

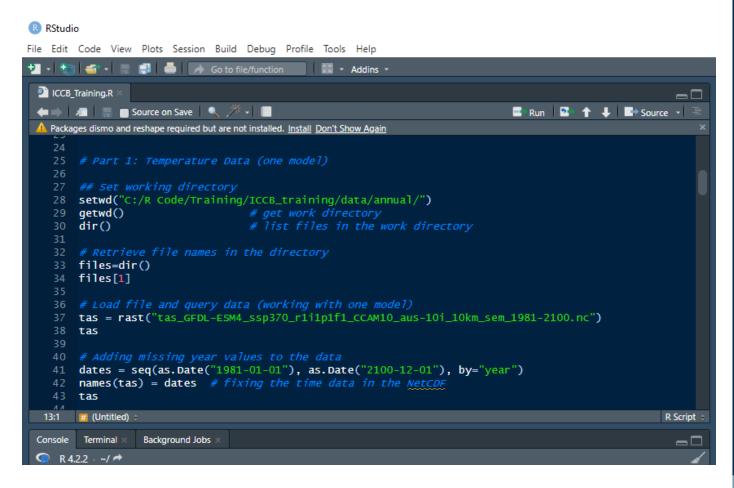




### Prepare your files

- Unzip the folder
- Move it to wherever you want it (make sure you can find it!)

- Open RStudio
- In RStudio, open the script 'ICCB\_Training.R'





## Set your working directory

- Install any packages you are missing (code at the beginning of the script)
- Import your packages
- Change wd to where you put the data
- dir() should now show you the data files

```
RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help

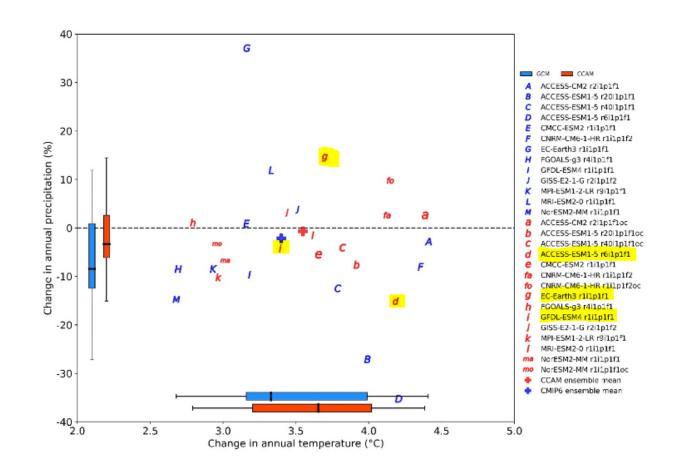
☐ Go to file/function

 ICCB Training.R
 🛑 📦 📗 🔚 🔳 Source on Save 🛚 🔍 🏸 🔻 📗
                                                                              Run Source V
 A Packages dismo and reshape required but are not installed. Install Don't Show Again
       setwd("C:/R Code/Training/ICCB_training/data/annual/")
       qetwd()
    30 dir()
                                   # list files in the work directory
    33 files=dir()
       files[1]
    36 # Load file and query data (working with one model)
        tas = rast("tas_GFDL-ESM4_ssp370_r1i1p1f1_CCAM10_aus-10i_10km_sem_1981-2100.nc")
        # Adding missing year values to the data
       dates = seq(as.Date("1981-01-01"), as.Date("2100-12-01"), by="year")
       names(tas) = dates # fixing the time data in the NetCDF
       tas
                                                                                                       R Script
                  Background Jobs
```



#### **Datasets - models**

- Annual temperature and precipitation for Queensland for 3 climate models for SSP370 1981 - 2100
  - ACCESS-ESM1-5 a dry model
  - EC-Earth3 a wet model
  - GFDL-ESM4 in the middle (this is the model we're starting with)
- Storyline approach can help address ensemble range





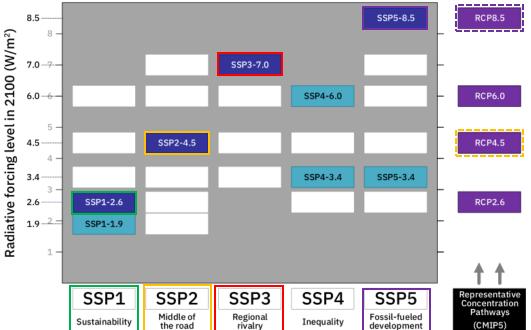
## Datasets – climate change scenarios

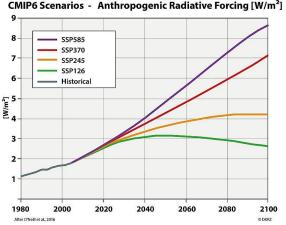
Previous

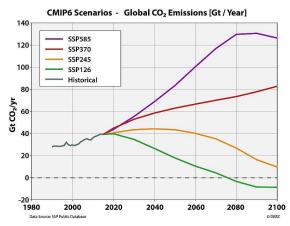
scenarios

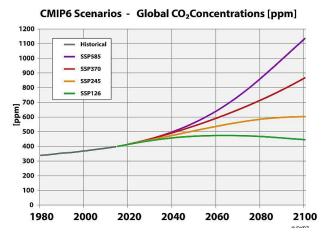
- SSP1-2.6: Sustainability
- SSP2-4.5: Middle of the road
- SSP3-7.0: Regional rivalry



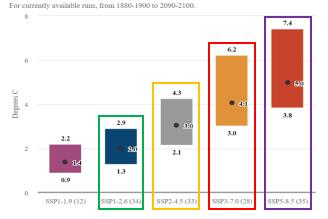






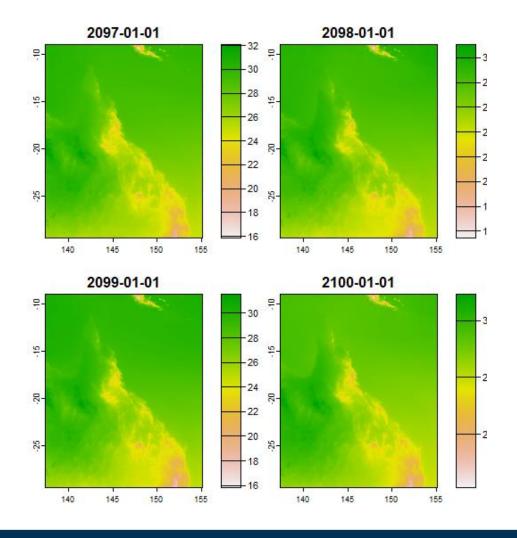








## Part 1: What does your data look like?



#### Your turn!

- Can you modify this plot? Add a title, modify the colours
- Can you plot the other models? How do they compare to this one?

- Hints:
  - plot(main = "title")
  - plot(col=brewer.pal(11, "YIOrRd"). See <a href="https://colorbrewer2.org/">https://colorbrewer2.org/</a> for ideas!
  - plot multi-panel figures using par(mfrow = c(nrows, ncols))
  - R is widely used there's lot of information on the internet!



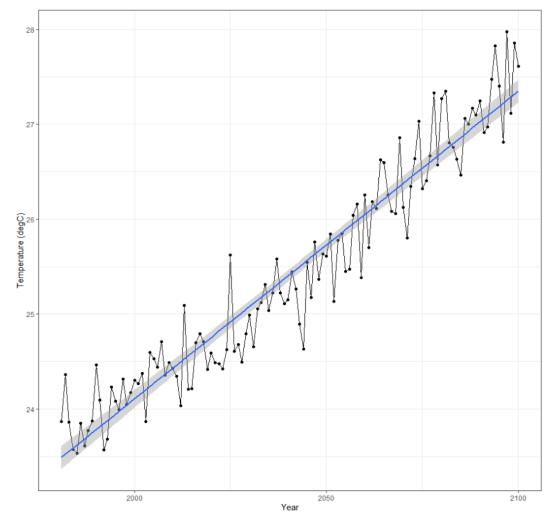
## What does your data look like?

Do these values make sense?

Want to customize your plot further?

https://ggplot2.tidyverse.org/articles/ggplot2.html

ggplot2 is a very popular package. You'll find many examples online!

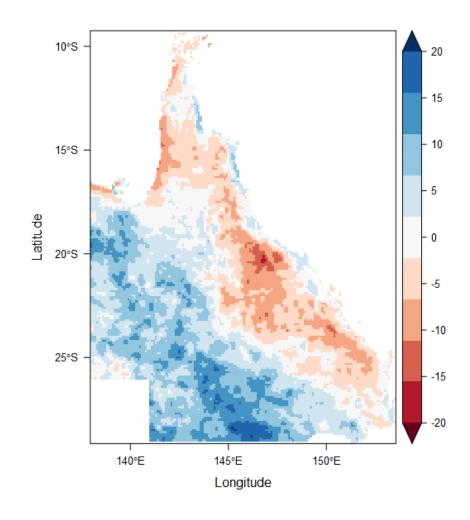




## Part 2: What does your data look like?

Do these values make sense?

How does the ensemble mean compare to the values for individual models?



#### Your turn!

- Can you modify this plot? Add a title and change the colours.
- Can you plot multiple models on one figure? Is that helpful?
- What do the other scenarios look like? SSP126 and SSP245 are in the data folder. Try plotting them!
- There's lots of information available online:
  - https://oscarperpinan.github.io/rastervis/#levelplot
  - https://colorbrewer2.org/



#### Part 3: Validation and Bioclimatic indicators

- Indices relevant to species which are derived from monthly rainfall and temperature
- **BIO1** = Annual Mean Temperature
- BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))
- BIO3 = Isothermality (BIO2/BIO7) (×100)
- BIO4 = Temperature Seasonality (standard deviation ×100)
- **BIO5** = Max Temperature of Warmest Month
- **BIO6** = Min Temperature of Coldest Month
- **BIO7** = Temperature Annual Range (BIO5-BIO6)
- **BIO8** = Mean Temperature of Wettest Quarter
- **BIO9** = Mean Temperature of Driest Quarter

- **BIO10** = Mean Temperature of Warmest Quarter
- **BIO11** = Mean Temperature of Coldest Quarter
- BIO12 = Annual Precipitation
- **BIO13** = Precipitation of Wettest Month
- **BIO14** = Precipitation of Driest Month
- BIO15 = Precipitation Seasonality (Coefficient of Variation)
- **BIO16** = Precipitation of Wettest Quarter
- BIO17 = Precipitation of Driest Quarter
- BIO18 = Precipitation of Warmest Quarter
- **BIO19** = Precipitation of Coldest Quarter



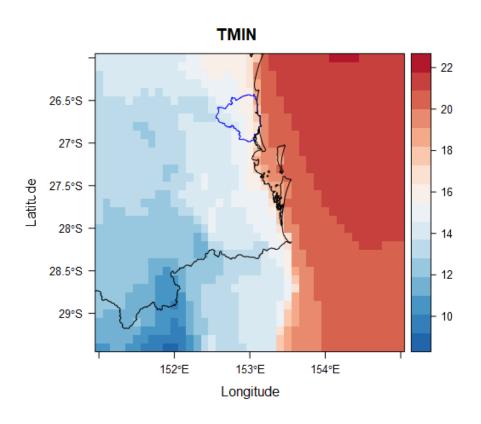
## Input data

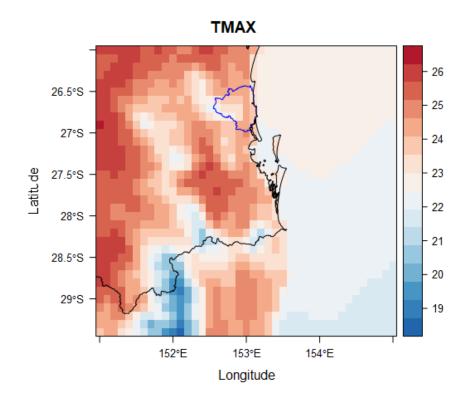
- GFDL-ESM4 model monthly tasmax, tasmin, precipitation
  - Due to the size of this dataset we've subset it to SEQ
  - Tomorrow you will use bioclimatic indicators based on a bias-corrected and statistically downscaled version of this dataset

- Statistical downscaling
  - Process of downscaling that relies on statistical relationships between the model and observations in the historical period
  - Assumes relationship remains the same in the future



## What does your data look like?



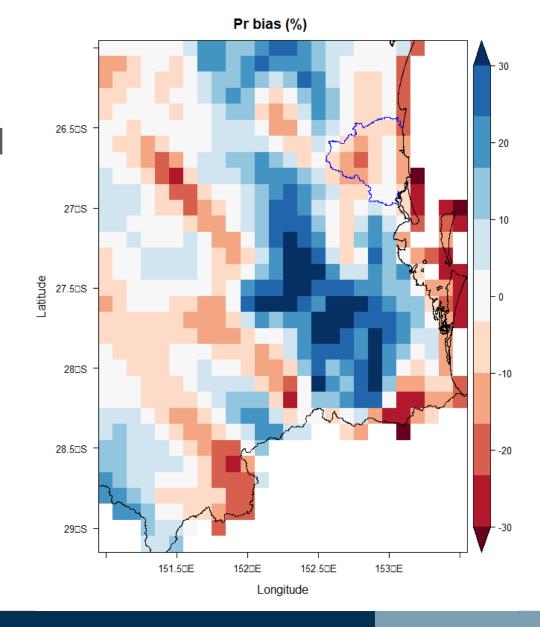


## Validating the data

- Ensure observations and modelled data are comparable
  - Spatial resolution
  - Temporal resolution
- Quantifying performance:

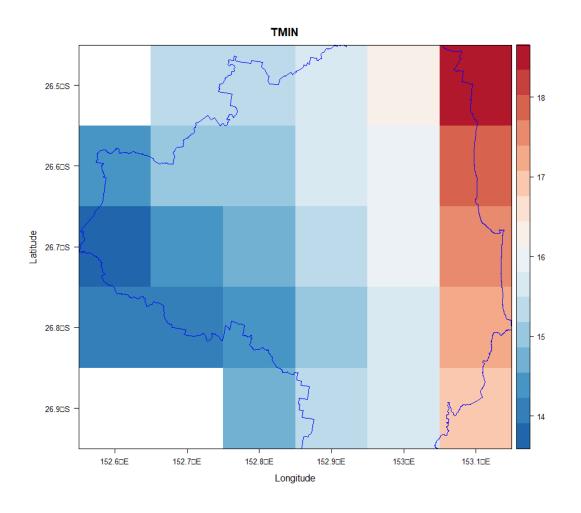
$$RMSE = \sqrt{\left\{\sum_{i=1}^{n} \frac{(\{model\}_i - \{obs\}_i)^2}{n}\right\}}$$

$$MAPE = \left\{ \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\{model\}_i - \{obs\}_i}{\{obs\}_i} \right| \times 100 \right\}$$





## **Spatial Averages**



Average of cut raster considers all cells

- terra::extract weights the mean by the area within the shapefile
- More precise results, especially for smaller shapefiles



## What does your data look like?

What are the final bioclimatic indicators?

How are they changing over time?

Do these changes make sense?

## Final tips

- There's a lot of data available. Think about the question you're asking and what you need before getting the data.
- Always check your units
- Plotting is a good way to check your data to make sure the numbers make sense
- Calculate ensemble average at the end!
- If you work with python and R the indexing is different!

