

Challenges in using climate data for impact studies

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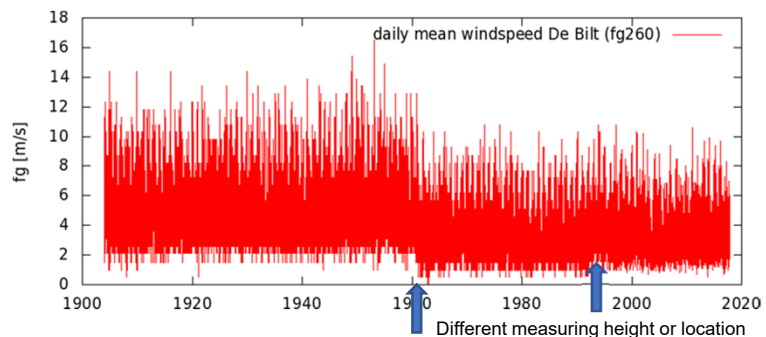


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1

Observational data

- **Inhomogeneities:** apparent changes in averages, statistics, etc. due to physical causes e.g. change of instruments, re-locations, etc.): homogenisation needed
- **Mixing data from different networks**
Sometimes different measuring networks for variable (different instruments: systematically higher/lower values)



2

Observational data

- Difficult to compare point data (from weather stations) to areal average data (from radar, satellites or models)
 - ✓ At a point much more/less rainfall than in area
 - ✓ Point may not be representative for an area, or a lot of spatial variation
- Translation of radar/satellite signals to climate variables introduces uncertainties
 - ✓ Translate surface temperature from satellites to air temperature
 - ✓ Very extreme rainfall not always measured well with radar

3

Extremes

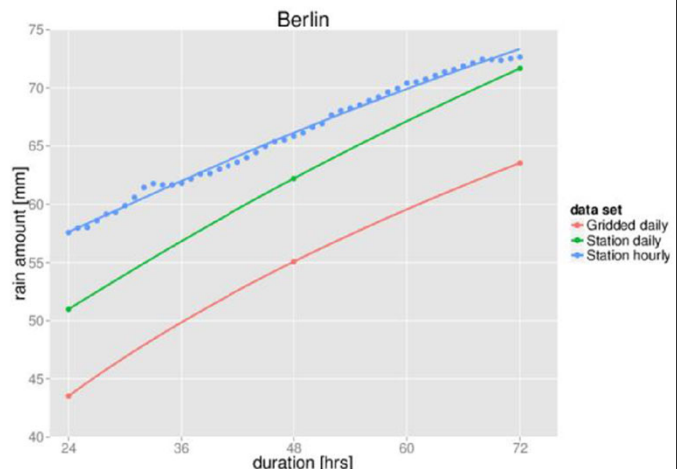
- **Calculation and interpretation of statistics**

Daily data is not the same as “24 hours”-data

Different sources for climate data may give different statistics

- **Calculation and interpretation of point and areal statistics**

Station vs gridded data

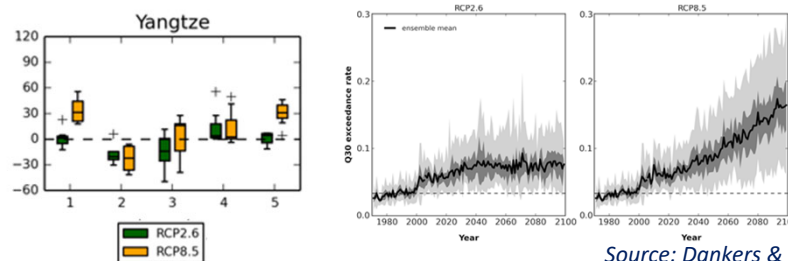


Intensity-Duration-Frequency curves for once in 10 year events for different rainfall durations
Source: RAIN project D2.5

4

Extremes

- Acknowledge the limitations of your data
 - Rule of thumb: 30-year timeseries can be used to robustly estimate a 10y return level, but not really more extreme
- Use established methods from extreme value statistics to estimate the uncertainty range around your estimate of an extreme
- Scale up to larger regions for more robust patterns



Source: Dankers & Kundzewicz, 2020

5

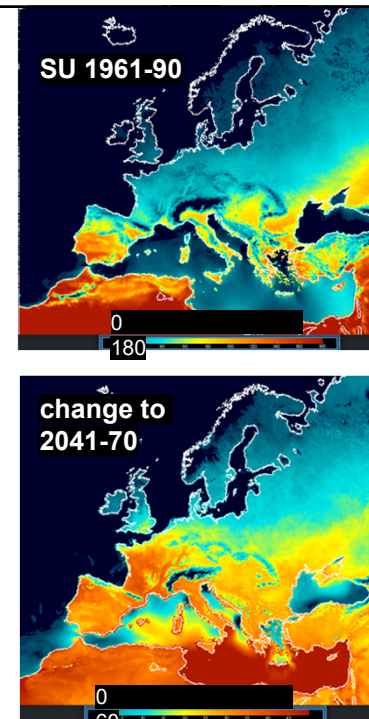
Climate indices

Arise from diversity of available options and lack of common terminology and standards:

- Multitude of alternative indices
- Inconsistent definitions and software
- Data sources (observations, models, indices)
- No standard data format and conventions
- Not always clear what is what

Example: heat wave index – probably 15+ different definitions

- Many indices are sensitive to model biases
 - esp. indices based on thresholds and/or extremes



6

Codes and abbreviations

Codes used for climate variables:

- Tavg, Tmean, T2m all refer to temperature
- P, RR used for rainfall

Codes used for data sources

- E-OBS: gridded version of the station data in Europe
- ERA5: most recent re-analysis from EWMCF

Codes used for weather stations

- Station 260 (Netherlands): Automatic weather station De Bilt
- Station 550 (Netherlands): precipitation station De Bilt

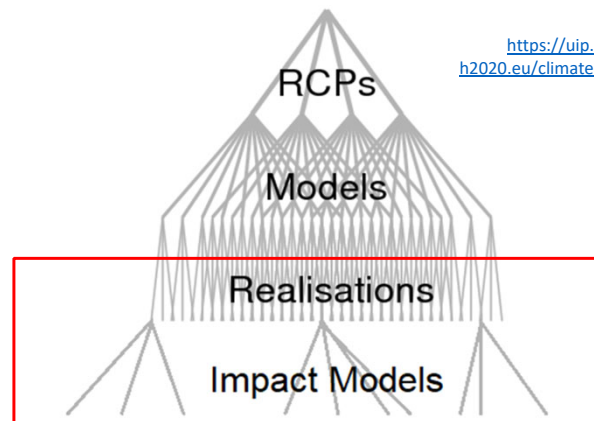
7

Uncertainties and ensembles

- Climate model output as input for impact models
- Hence existing uncertainties propagate further
- Also uncertainties in impact models (may be > than uncertainties from climate data)

Schematic cascade of uncertainty, from RCP scenarios, climate models and realizations to impact models.

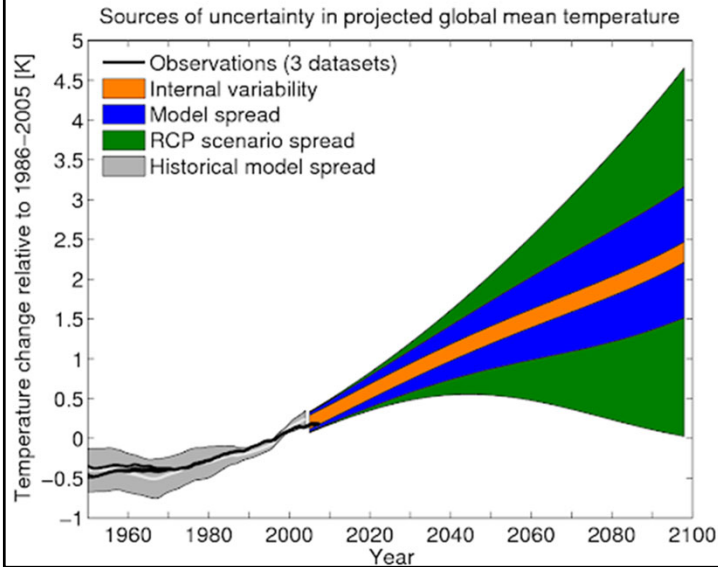
After Hawkins, www.climate-lab-book.ac.uk/2014/cascade-of-uncertainty/



More info:
<https://ui.primavera-h2020.eu/climate-factsheets>

8

Uncertainties and ensembles



- **Internal variability:** with ensemble of one model (different initial conditions)
- **Model uncertainty:** ensemble of models with same emission scenario (multi-model ensemble and perturbed physics ensemble)
- **Scenario uncertainty:** difference between averages for different emission scenarios

Use of ensembles requires a lot of time

9

Common issues: model selection

Often too limited time/resources to use large ensemble

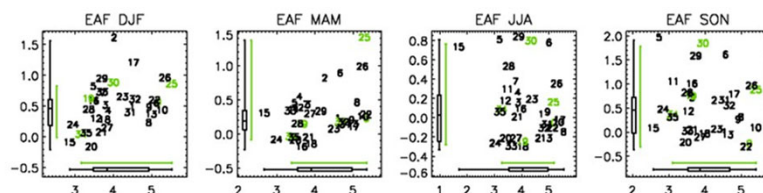
Criteria for selecting a subset of models or scenarios:

- Realism in simulating historical climate (model performance)
- Representative of spread in future projections
- Independence of models (“model family tree/lineage”)

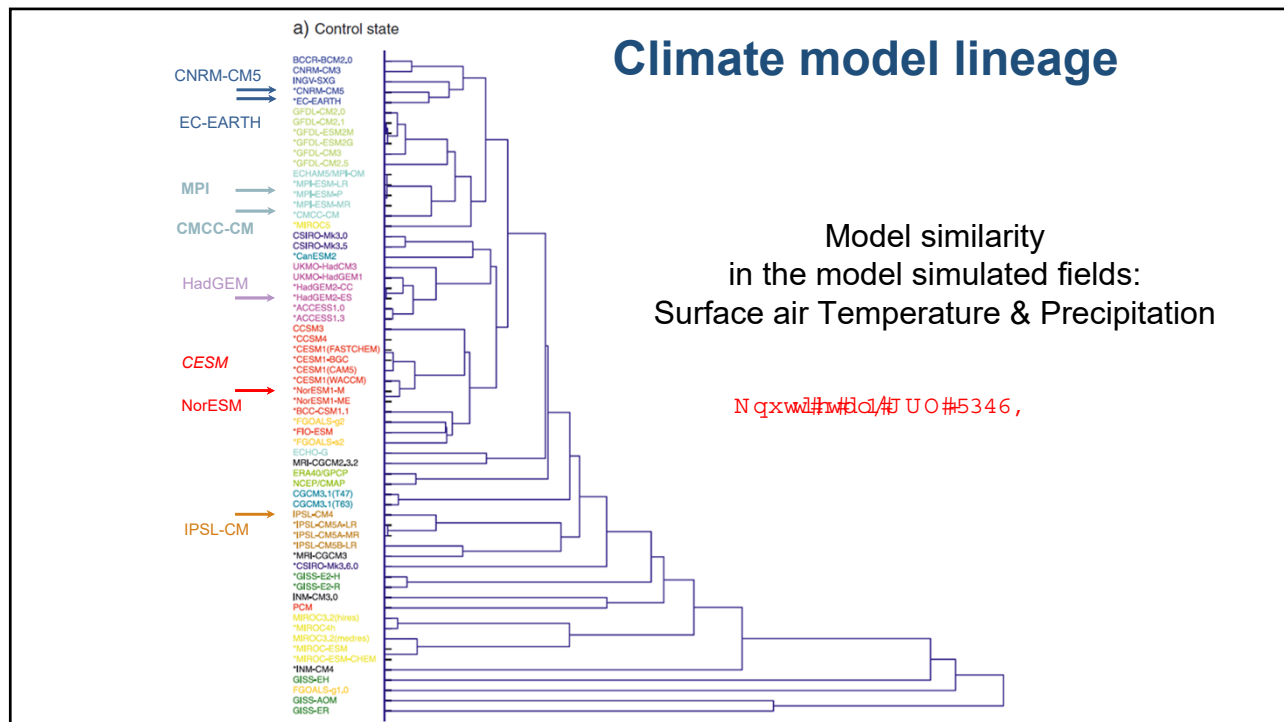
‘Optimal’ set of models will be different per region/variable.

Methods for selecting models have also been proposed in the literature.

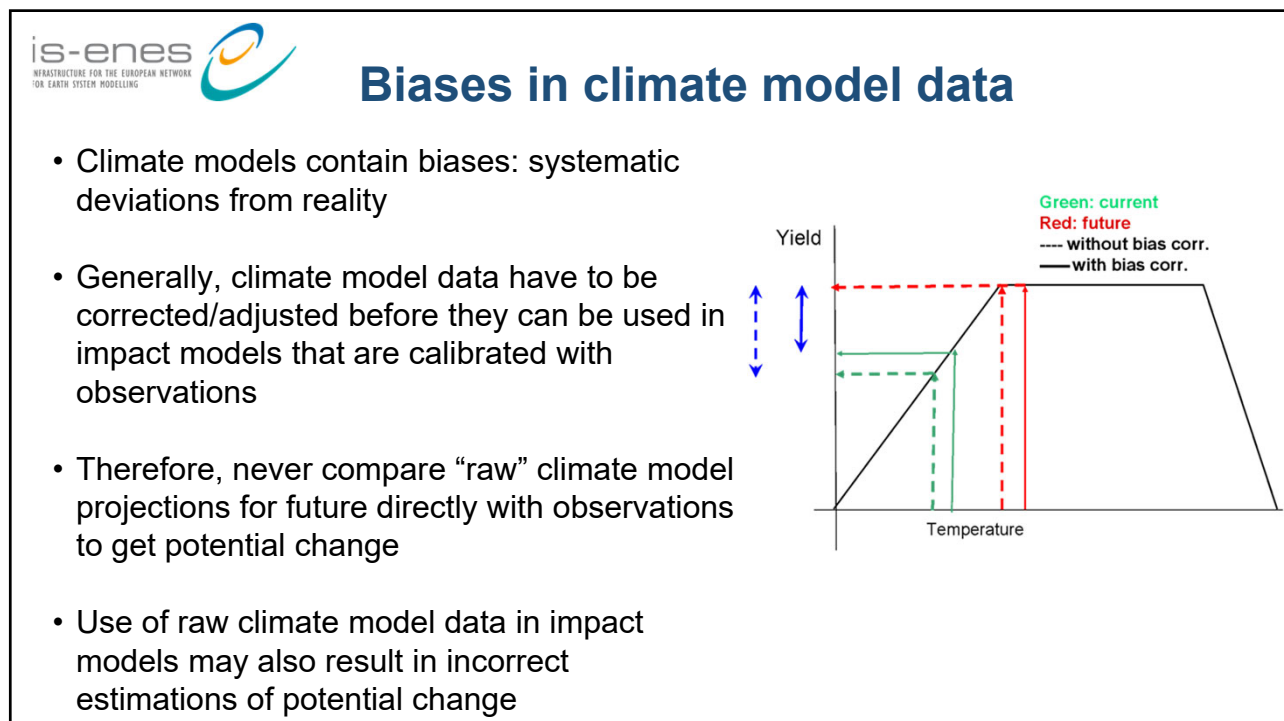
Some C3S (in particular SIS) datasets have done the work for you.



10



11

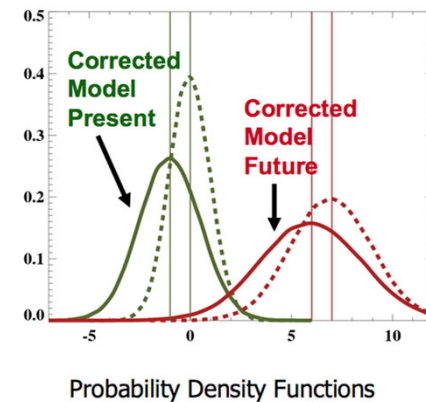


12

Some practical advice

Recommended steps:

- Start with one projection and one scenario (historical + future period)
- Check how projection compares with observations for historical period, even if results are bias-adjusted
 - statistical sense,
 - NOT time-series agreement !!!
- ✓ If not bias-adjusted, bc may be necessary, although not a silver bullet
 - many methods (some fairly similar)
 - do not use bias adjustment as a black box “just press the button and then we’re done” thing
- Determine change by comparing bias-adjusted historical and future period
- Select projections from various models and/or scenarios and repeat steps



13

Some practical advice

Some checks!

- Do all data/projections have same units for same variables (it should be, but better to check!)
- Do all projections cover the same periods, past and future (some finish in 2099, or 2049!)
- Do all projections (in case of daily data) have same calendar (some use 360- or 365- day calendar, sometimes software take care of this, better to check!)
- Try to cover different scenarios with a same number of projections (not 10 for RCP8.5 and 2 for RCP4.5)

14

Some practical advice

- In general, various scenarios are presented for the future to show the uncertainties, and to make it easier for users to deal with uncertainties for the future: do not average climate scenarios or use one scenario only
- the “middle” scenario is not the most probable one (although often implicitly assumed)
- When using climate model output, use periods of multiple years, not single years; this also applies to historical climate simulations!

When in doubt, consult an expert!!