Identifying patterns of variability within the EuroCORDEX ensemble

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These slides expand on the presentation EGU22-7861 ‘Identifying patterns of variability within the EuroCORDEX ensemble’, presented at the annual meeting of the EGU in May 2022.

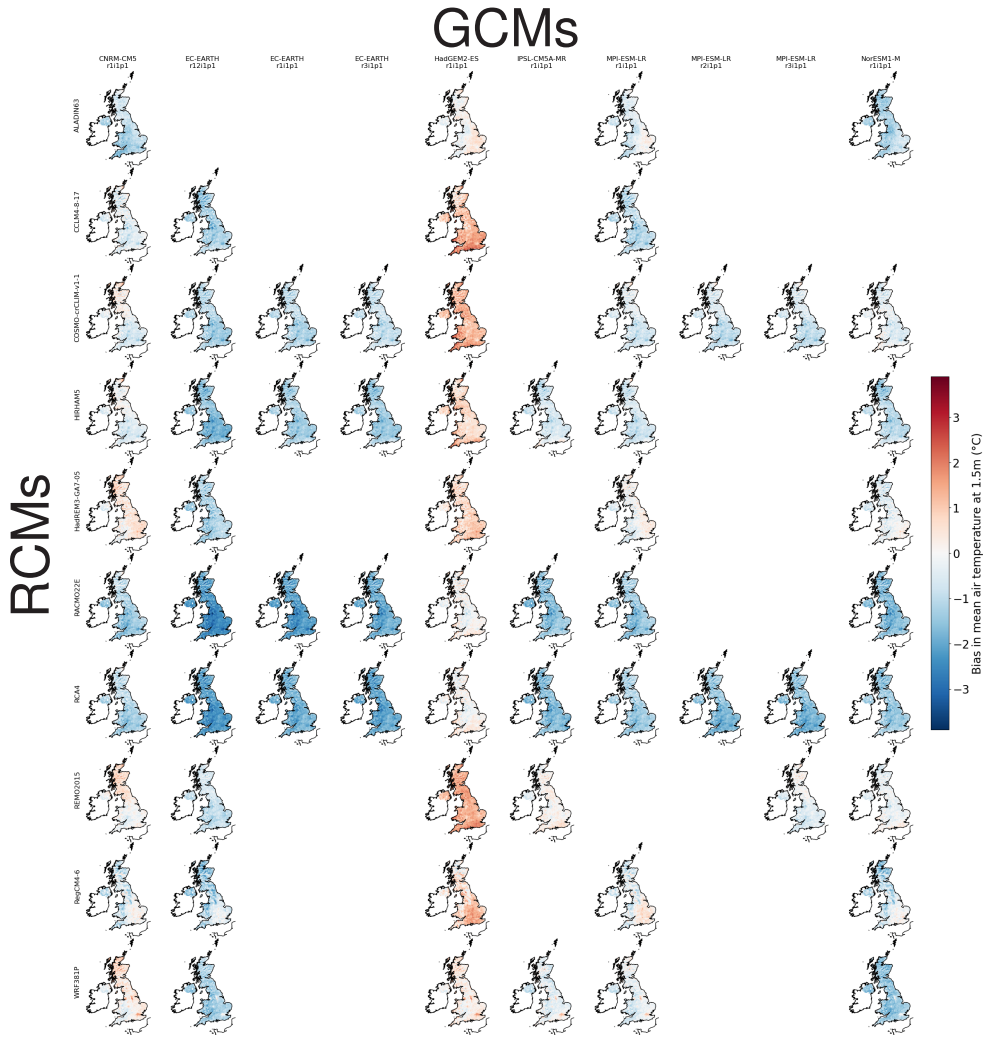
Further details of the methodology – along with Python scripts for implementation – are available at the UKCORDEX project website, https://www.ucl.ac.uk/statistics/research/ukcordex

Contents

Motivation

- The EuroCORDEX regional ensemble is a hierarchical multi-model ensemble
- Multi-model ensemble samples model uncertainty: we can learn about plausible scenarios
- 65 runs in total from 10 GCM variants and 10 RCMs - not all combinations have been produced
- How can we characterise the patterns of variation within the ensemble? For example, are runs more likely to be similar if they use the same GCM? Or the same RCM?

For example, consider the biases in UK summer temperatures in each run:



Understanding sources of variation in the ensemble

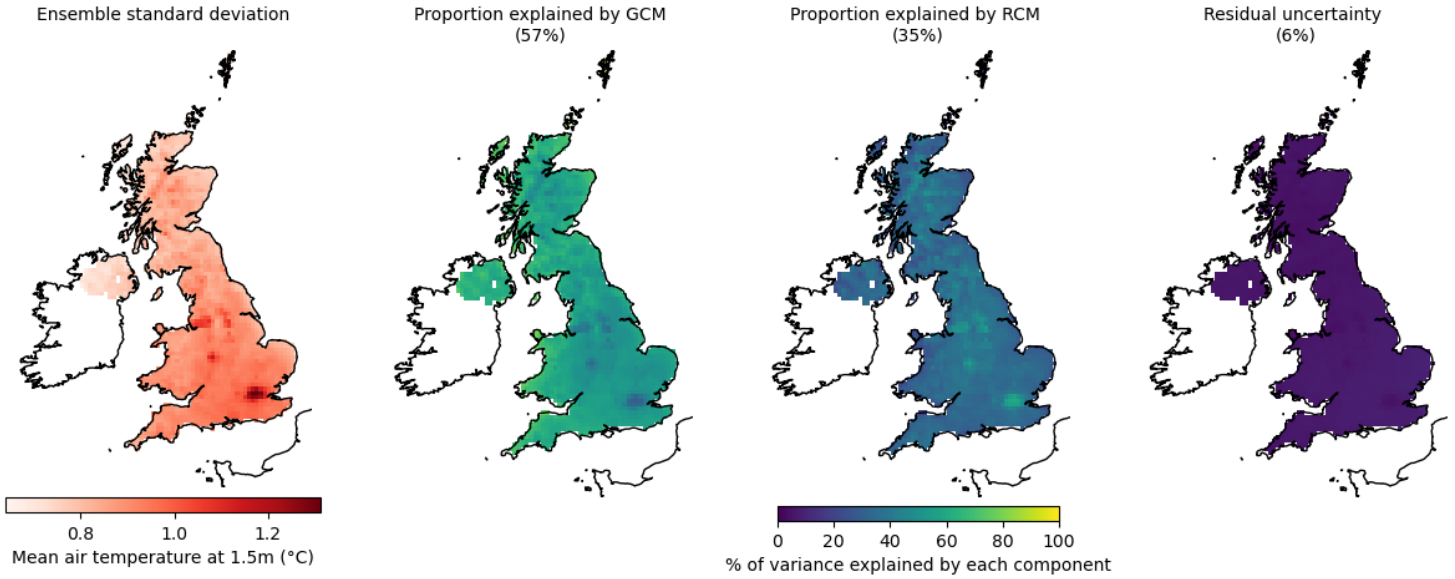
Analysis of variance (ANOVA)

ANOVA decomposes each map into a sum of effects from the ensemble as a whole, from the GCM and RCM, and some residual noise:

model output (CNRM-CM5_ALADIN63)	ensemble mean	GCM effect (CNRM-CM5)	RCM effect (ALADIN63)	residual

ANOVA

This decomposition also partitions the total variation into contributions from the GCMs and RCMs:



- We can see that variability within the ensemble is highest in urban areas
- In these areas, differences between the RCM effects account for 60-80% of the variability
- Elsewhere, differences between the GCM effects account for most of the variability

ANOVA

- This is an established approach: eg. Yip et al. (2011); Déqué et al. (2012); Christensen and Kjellström (2020)
- However: the standard formulation requires a balanced ensemble with no missing GCM-RCM combinations
  - GCM effects can be found by averaging over all runs using the same GCM (ie. over each column) and subtracting the ensemble mean
  - RCM effects can be found by averaging over all runs using the same RCM (ie. over each row) and subtracting the ensemble mean
- **We propose estimating the contribution of each GCM and each RCM using least-squares fitting**

Unbalanced ANOVA

The ANOVA decomposition for the run with GCM g and RCM r is

$$\mathbf{Y}_{rg} = \boldsymbol{\mu} + \boldsymbol{\alpha}_g + \boldsymbol{\beta}_r + \boldsymbol{\varepsilon}_{rg}$$

$$\underset{\text{output}}{\texttt{model}} = \underset{\text{mean}}{\texttt{ensemble}} + \underset{\text{effect}}{\texttt{GCM}} + \underset{\text{effect}}{\texttt{RCM}} + \texttt{residual}$$

where $\mathbf{Y}_{rg}$, $\boldsymbol{\mu}$, $\boldsymbol{\alpha}_g$, $\boldsymbol{\beta}_r$ and $\boldsymbol{\varepsilon}_{rg}$ are all vectors.

We can estimate $\boldsymbol{\mu}$ and the effects $\boldsymbol{\alpha}_g$ and $\boldsymbol{\beta}_r$ for each GCM and RCM by treating this as if it were a regression problem, and finding the estimators that minimise the residual sums of squares. This requires the use of Singular Value Decomposition (SVD), which is not described here, but is straightforward to implement.

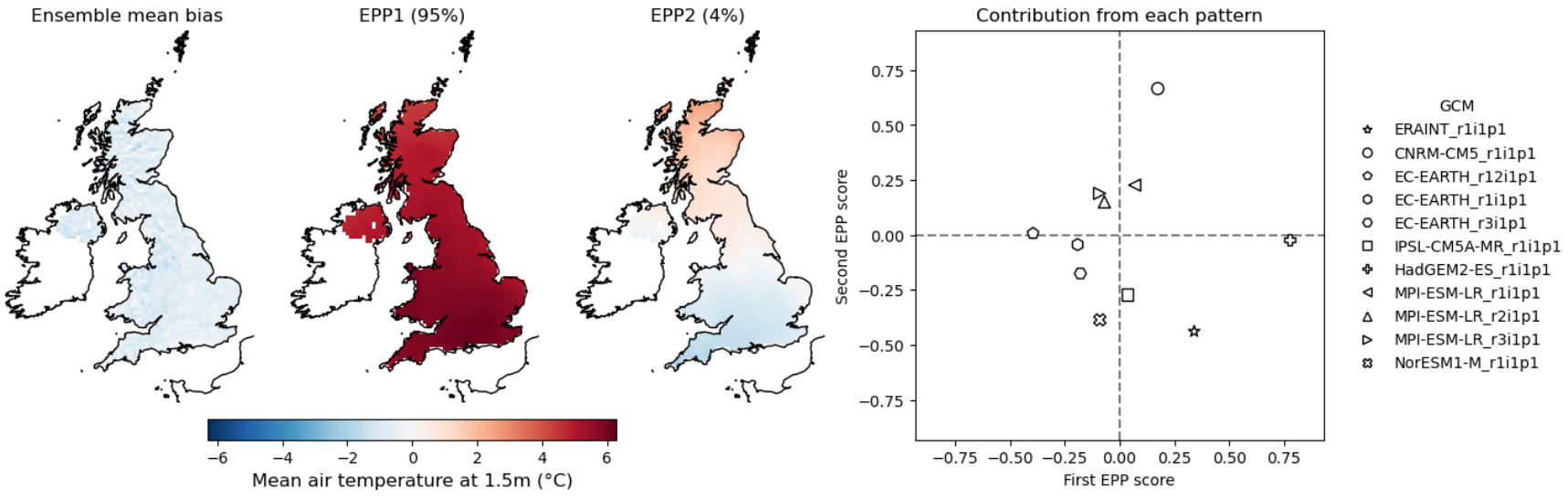
Identifying patterns of variation in the ensemble

Ensemble Principal Patterns (EPPs)

- In the EuroCORDEX ensemble, we still have 10 fitted GCM effects and 10 fitted RCM effects: this doesn't tell us much about the ways in which the models differ, or the ways in which they are similar.
- We again use SVD, this time over the fitted GCM / RCM effects, to break down the contribution from each GCM (RCM) into linear combinations of a small number of spatial patterns.
- Lower-numbered patterns explain more of the variation between the different models: so we may be able to capture most of the variability within the ensemble using linear combinations of a very small number of these **ensemble principal patterns**

Ensemble Principal Patterns

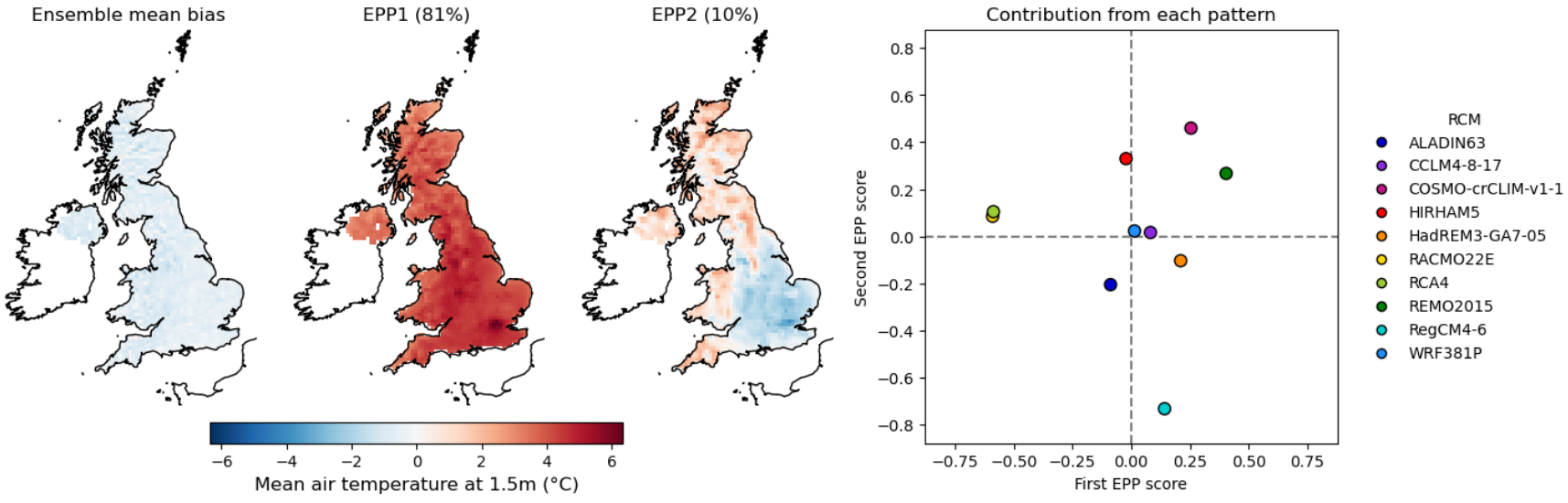
Example: GCM EPPs



- 95% of the difference between the GCM effects is due to a fairly uniform offset across the UK - combining this with the ANOVA decomposition, this accounts for $95\% \times 57\% = 54\%$ of the total variation within the ensemble
- Most of the remaining differences between the GCMs are ascribed to the strength of the north-south gradient in EPP2

Ensemble Principal Patterns

Example: RCM EPPs



- 81% of the difference between the RCM effects can be ascribed to EPP1, a fairly uniform offset over the UK, with larger differences in urban areas: this suggests that the RCMs differ a lot in their treatment of urban heat islands
- EPP2 represents a contrast between high and low elevations: one model has a large negative score, which may indicate a difference in lapse rate to the others

Ensemble Principal Patterns

- The EPPs are designed to describe the variation within the ensemble as efficiently as possible
- EPPs of GCM effects tend to be fairly smooth, reflecting the coarser resolution of the models
- EPPs of RCM effects often pick out fairly small-scale features such as orography, rain shadows, or urban heat island effects
- Within a single-model ensemble, EPPs can be computed directly on the model output to identify the dominant patterns of spatial variability

Further applications of EPPs

Selecting representative runs

Suppose that we wish to carry out further analysis on this ensemble, but can only include a small number of the available runs. How can we choose runs that are as representative as possible of the entire ensemble, in terms of the climate variable of interest?

- Use ANOVA to identify the main sources of variation, then
  - If the GCMs contribute most of the variation, choose runs driven by GCMs with very different scores in the first two EPPs
  - If the RCMs contribute most of the variation, choose runs from RCMs with very different scores in the first two EPPs
  - If both contribute the same amount, try to choose runs with very different scores in the first EPP for both GCMs and RCMs

Further applications of EPPs

Identifying runs that exhibit unusual behaviour

If a particular model (or, in the case of a single-model ensemble such as a large model ensemble or perturbed physics ensemble, a particular ensemble member) has an unusually high or low score for one EPP, this suggests that this particular model is behaving quite differently to the others in some way.

The processes driving this different behaviour may require further investigation.

Visit the project website for more information:

https://www.ucl.ac.uk/statistics/research/ukcordex

- Links to technical report describing the method in detail
- Python scripts to compute the ANOVA and EPPs, with examples
- Plots of ANOVA and ensemble principle patterns in the EuroCORDEX and UKCP18 ensembles will shortly be available to browse online

References

Christensen, O. B. and Kjellström, E. (2020). Partitioning uncertainty components of mean climate and climate change in a large ensemble of European regional climate model projections. *Climate Dynamics*, pages 1–16.

Déqué, M., Somot, S., Sanchez-Gomez, E., Goodess, C., Jacob, D., Lenderink, G., and Christensen, O. (2012). The spread amongst ENSEMBLES regional scenarios: regional climate models, driving general circulation models and interannual variability. *Climate Dynamics*, 38(5):951–964.

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