

# Reducing model ensemble size - a sensitivity study

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## MOTIVATION

### Situation:

- Large matrices of GCM-RCM combinations are produced normally by projects, e.g. CORDEX.
- Often impact studies are only able to use a subset of those matrices.
- Climate models perform differently for different output variables, seasons, and regions.

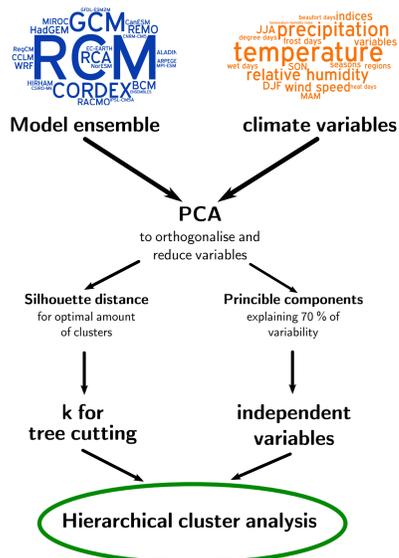
### Motivation:

- Selection of a climate model subset needs to be
  - flexibel regarding input variables, regions, and seasons.
  - fit the focus of the impact study.
- Evaluation of method using hierarchical clustering proposed by Mendlik and Gobiet (subm).

### Questions:

- How do the resulting clusters change with different combinations of variables, indices, regions and seasons?
- How sensitive is the clustering to different climate change signal (ccs) periods?
- How flexible is the clustering to different foci of impact studies?

## METHOD



For different climate variables and indices the ccs were calculated and averaged over the 4 seasons and 6 regions in northern Europe (see Fig. 3). To solve the strong interdependencies of the variables, they were transformed to an orthogonal space by using PCA. The new variables (PCs) are fed into the hierarchical clustering. For an objective suggestion of the optimum number of clusters, the average silhouette value is calculated.

Figure 1: Scheme of the procedure to cluster an ensemble of climate models.

## EXPERIMENTS DESIGN

|         | all | reducing PC rel var |     |     |     |     |     | tas | tas-pr | pr  | wss | wss-tas | hurs-pr |     |     |     |     |     |     |     |     |   |
|---------|-----|---------------------|-----|-----|-----|-----|-----|-----|--------|-----|-----|---------|---------|-----|-----|-----|-----|-----|-----|-----|-----|---|
|         | 1.1 | 1.2                 | 1.3 | 2.1 | 2.2 | 2.3 | 2.4 | 2.5 | 2.6    | 3.1 | 3.2 | 4.1     | 4.2     | 5.1 | 5.2 | 6.1 | 6.2 | 7.1 | 7.2 | 8.1 | 8.2 |   |
| tas     | ■   | ■                   | ■   | ■   | ■   | ■   | ■   | ■   | ■      | ■   | ■   | ■       | ■       | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■ |
| tas_x   | ■   | ■                   | ■   | ■   | ■   | ■   | ■   | ■   | ■      | ■   | ■   | ■       | ■       | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■ |
| tas_n   | ■   | ■                   | ■   | ■   | ■   | ■   | ■   | ■   | ■      | ■   | ■   | ■       | ■       | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■ |
| pr      | ■   | ■                   | ■   | ■   | ■   | ■   | ■   | ■   | ■      | ■   | ■   | ■       | ■       | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■ |
| hurs    | ■   | ■                   | ■   | ■   | ■   | ■   | ■   | ■   | ■      | ■   | ■   | ■       | ■       | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■ |
| wss     | ■   | ■                   | ■   | ■   | ■   | ■   | ■   | ■   | ■      | ■   | ■   | ■       | ■       | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■ |
| indices | ■   | ■                   | ■   | ■   | ■   | ■   | ■   | ■   | ■      | ■   | ■   | ■       | ■       | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■   | ■ |

Figure 2: Table showing a subset of different experiments, numbered in the header. Focus here lies on the combinations of variables and indices. The colors refer to variables and related indices (red: temperatures, blue: precipitation, purple: humidity, green: windspeed).



Figure 3: Rectangles show subregions used as variables for the PCA. Regions focus on study of Jönsson and Bärring (2011).

## SUMMARY

### Preliminary results:

- The method is very flexibel and fits to all impact studies by simply including the impact relevant variables.
- Climate indices affect the clustering only marginally (only 1-var-indices tested)
- The result is sensitive to period of ccs. Towards 2100 it is advisable to use a bigger reduced ensemble to maintain the information of the ensemble spread.
- The strong ccs of temperature dominantes the results.

### Outlook:

- Including multi-variate indices to cover the inter-variable relations.
- Include more climate models (as soon as available).
- Test different/more regions in southern Europe.

## FIRST RESULTS

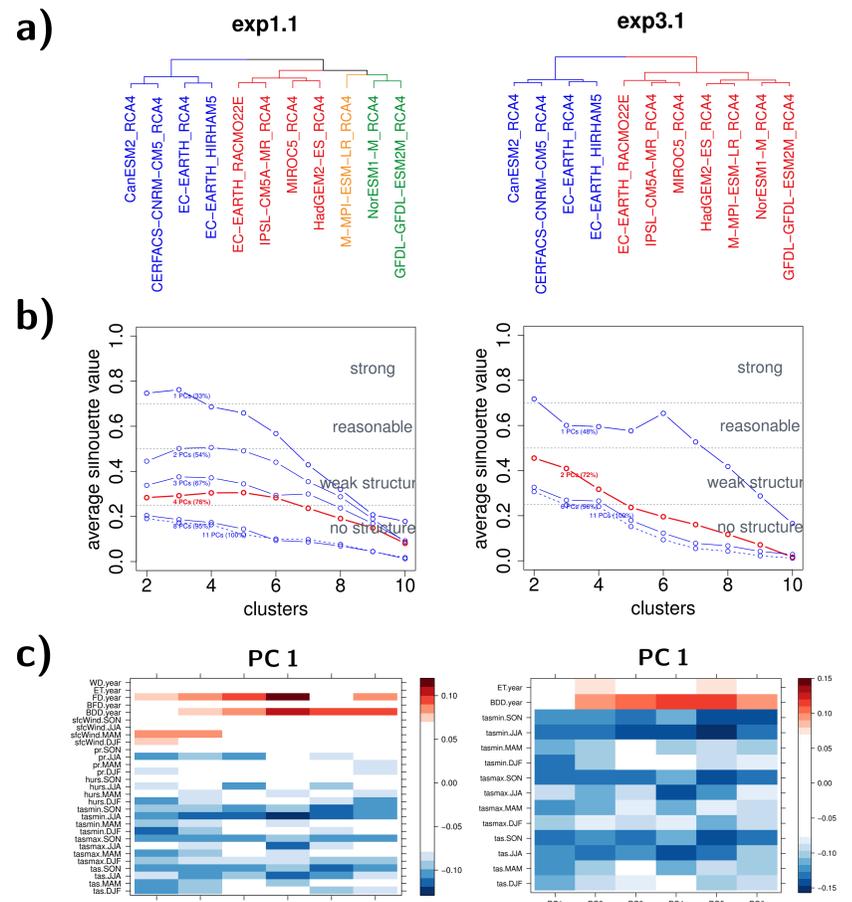


Figure 4: Exemplary results for exp. 1.1. and 3.1 showing a) hierarchical clusters of 11 RCMs, where the colors represent the clusters, b) silhouette plots, showing in red the number of PCs used for clustering, and c) loadings of first PC for each variable. Experiments were done for ccs 1971-2000 vs. 2051-2080.

- The results for the different ccs periods show the increasing spread in the ensembles till the end of the century (not shown). → More models are needed to preserve the information of the ensemble.
- In experiments including temperatures, they are represented by the first PC (in particular for JJA and SON) (Fig 4c)).
- Experiments including the ccs of temperature indices show an alteration in clustering whereas the other indices do not effect the result.
- A robust structure in clustering is found, i.e. some models are never in the same cluster (e.g. CanESM2\_RCA4 and NorESM1\_M\_RCA4) while others are sensitive to certain variables (EC-EARTH driven RACMO22E and HIRHAM5) (not shown here).

## REFERENCES

Jönsson, A. M. and Bärring, L. (2011). Future climate impact on spruce bark beetle life cycle in relation to uncertainties in regional climate model data ensembles. *Tellus A*, 63(1):158–173.  
 Mendlik, T. and Gobiet, A. (subm.). Selecting climate simulations for impact studies. *Clim. Change*.