4. Future climate change

4.2. Skill of methods for describing regional climate futures

Joanna Wibig
Rasmus Benestad, Erik Kjellström, Philip Lorenz, Douglas Maraun

--- Kopenhagen, 9-10. February 2012 ----

outline

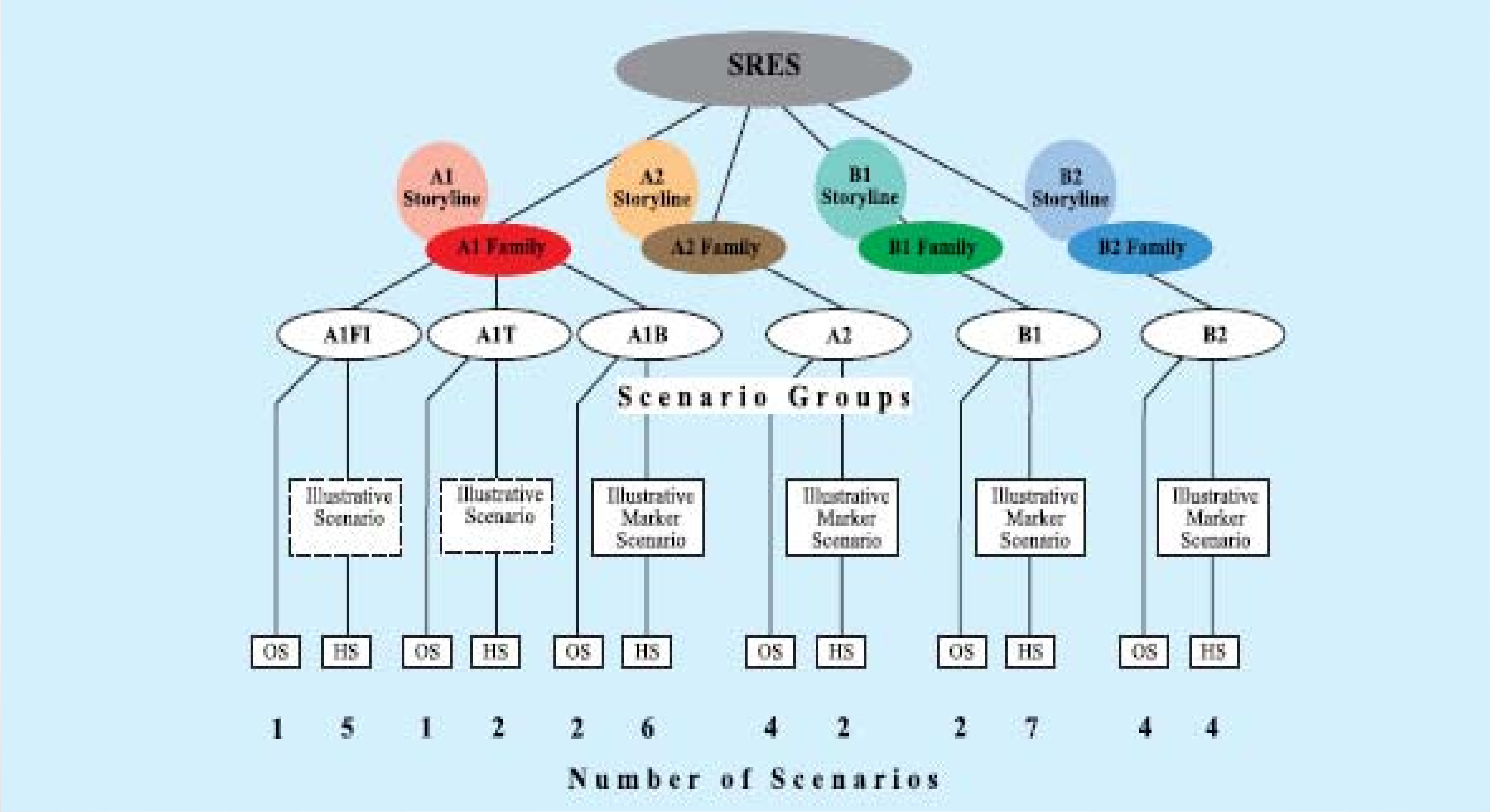
- Content review
- Some comments to reviewer comments
- Final (?) structure

Introduction:

GCM

- Physical core
- Parametrization of subgrid processes
- Forcings
- Initial conditions
- Internal variability

Future forcings:



Introduction:

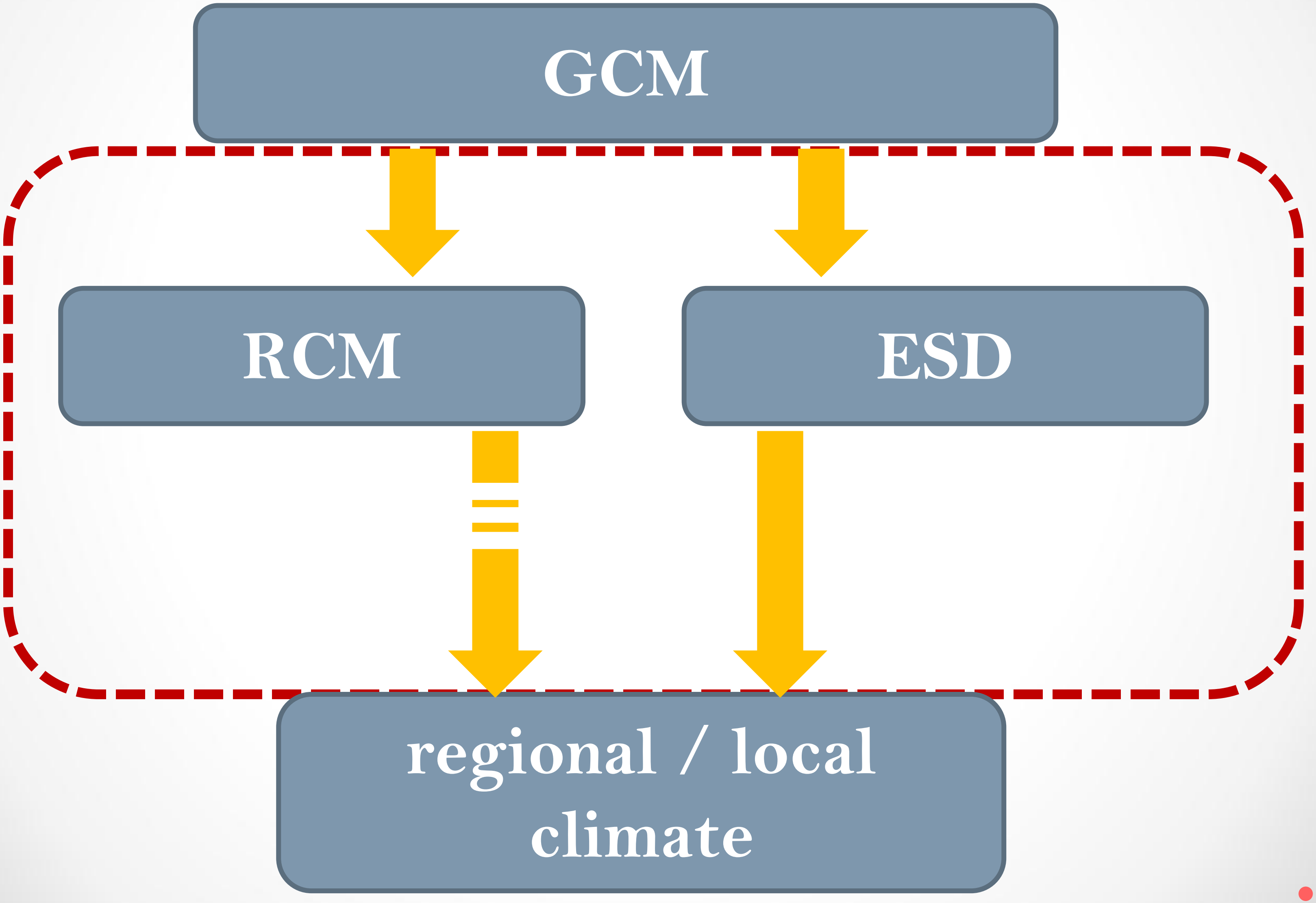
Why is GCM not enough?

Low spatial resolution

- **Subgrid processes**
- **Topography**
- **Coastline**
- **Land use**

Initial data

Introduction:



Validation techniques

Sources of errors and uncertainties of downscaled climate simulations:

- **Imperfect model formulation**
- **Uncertain future GHG emissions and concentrations**
- **Internally generated climate variability**

Errors of driving GCM

Errors inherent in the downscaling approach

Validation data

Observational data: addressing of such issues as

- Inhomogenities
- Outliers
- Biases
- Availability of long reference data sets

Gridded data sets : addressing of such issues as

- Density of the underlying network enough to represent weather extremes

Reanalysis: addressing of such issues as

- Deviation from reality
- Completeness and consistency

Validation indices

- **List:**

Expert Team on Climate Change Detection

The STARDEX project

The ENSEMBLES project

- **Characteristics of indices:**

Intensity (statistics?)

Spatial structure

Temporal structure

Validation measures

Distribution-wise validation

- Spatial fields: pattern correlation, root mean square error relative to the reference pattern
- Time series: Kolmogorov-Smirnov, PP plots, QQ plots

Event-wise validation

Validation in climate change context

Problems

- Non-stationarity of the predictor-predictand realtionship
- Non-stationarity of biases
- Parametrizations of RCMs – will they be still valid in a future climate?

Solutions

- Calibration and validation periods
- Checking if the RCM performs well different present climate patterns

Dynamical downscaling

- Dynamical downscaling refers to the methodology to achieve climate simulations on high resolution for a specific region by application of RCMs
- Increased spatial resolution
- Similar set of dynamical equations and physical parametrizations as GCMs
- Lateral boundary condition
- Sponge zone
- SST and ice coverage
- Added value

Dynamical downscaling – versus Statistical

Based on physical laws (valid under changed climate conditions)

Applicable in any region of the world (not dependent on observations)

Large number of variables

Regular time and space grid

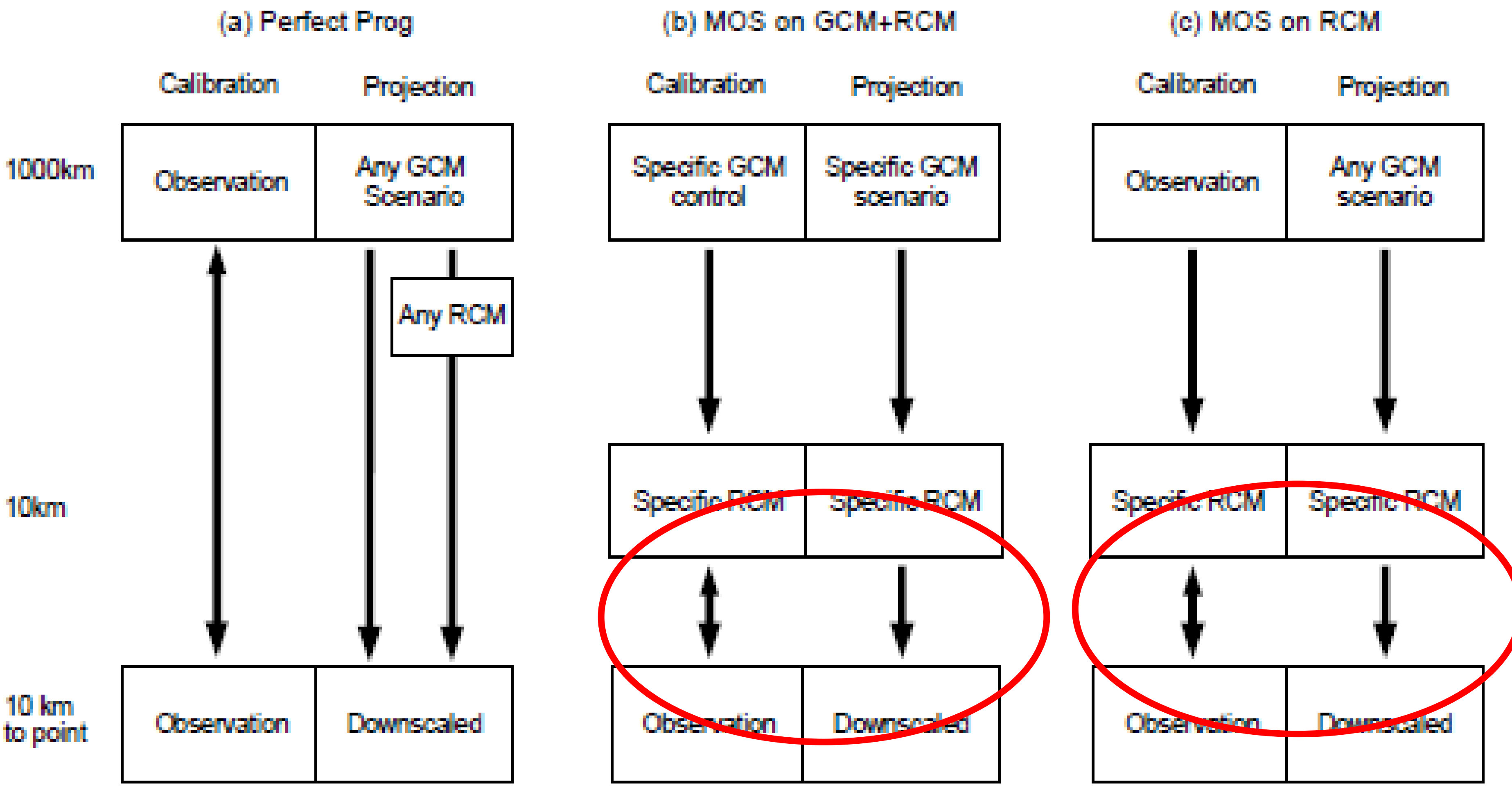
Physically consistent variables

Systematic biases (non-linear combination of GCM and RCM biases)

Dynamical downscaling

- **Baltic sea surface in RCM simulations**
- **Spectral nudging**
- **Hydrostatic versus non-hydrostatic approximation in RCMs**
- **One-way or two-way nesting mode**

Statistical downscaling



Maraun et al., 2010

Statistical downscaling

<u>Fundamental criterion</u>:

Local variable of interests depends on the large scale conditions

$$y = f(X, g) + \eta$$

- **X - predictor**
- **y - predictand**
- **g - geographical parameters**
- **η - small – scale noise**

Statistical downscaling

Perfect prognosis methods

- Linear methods: regression or generalised linear model, canonical correlation analysis, singular vector decomposition
- Non-linear methods: analogs, weather classification, cluster analysis, neural nets

Statistical downscaling

It adds and makes use of additional empirical information – build bridge between model and real world

Fast and cheap method

Limited to variables with long and good quality observations

Assumption of stationary relation predictor-predictand

Statistical downscaling

Choice of domain

Errors in observations

Identification of predictors

Large scale and convective precipitation

Ensembles

Spread between different models indicates on uncertainty related to:

- Structural differences between models
- Differences in parametrizations
- Differences in initial conditions

Models are not independent

Are ensemble projections better than those based on single climate projection ?

Ensembles

- To weight or not to weight?
- Other design dilemmas

MODEL OUTPUT STATISTICS (MOS)

PERTURBATION OF OBSERVED DATA (POD)
OR
DELTA CHANGE (DC)

BIAS CORECTION
OR
SCALING

Model Output Statistics

- Absolute or relative differences
- Annual, seasonal or monthly scale
- Distribution-based corrections
- Multivariate methods

AOB

- **Weather generators**
- **Randomization**
- **Impact studies**
- **Added value**

Internal reviewer comment:

The characterization of perfectProg is not ok. It was introduced by Klein (Klein, W.H. and H.R. Glahn, 1974: Forecasting local weather by means of model output statistics, Bulletin Amer. Met. Soc. 55, 1217-1227) in the 1950s in weather forecasting. Empirical downscaling was introduced in the 1990s perfectProg. MOS can be used only with downscaled "re-analysis" and local data, but would be applied to a RCM constrained by GCM simulation. Only if the RCM would be continued to be used with "re-analysis" (another time window?), it would represent MOS.

Both, PP and MOS originate from weather forecasting. Klein and Glahn , B.A.M.S., 1974 discuss the difference between the two methods: "The first, called perfect prog method, utilizes observed historical data to specify local weather elements from concurrent (or nearly concurrent) weighted combinations of meteorological parameters. To use the derived equations for making a forecast, we apply them to the output of numerical prognostic models which simulate the observed circulation [...] The second statistical technique has been named Model Output Statistics […] Instead of a long period of observed data, the predictor sample in MOS usually consists of a relatively short period of prognostic data produced by numerical models. Thus the MOS method involves archiving the output from numerical models and matching it with observations of local weather […] In this way, the bias and inaccuracy of the numerical model, as well as the local climatology, can automatically be built into the forecast system."

According to this definition, **the essential difference** between PP and MOS is therefore, that **PP is calibrated on observed predictors and predictands, and then transferred into the model world,** whereas **MOS is calibrated on observed predictands, but modelled predictors.** Rummukainen (Methods of statistical downscaling of GCM simulations, Rep. Meteorol. Climatol., 80, Swed. Meteorol. and Hydrol. Inst., Norrköping, 1997) discusses both PP and MOS in a climate change context. **According to the abovementioned definition, also the widely used bias correction of climate model simulations is a form of MOS** (see, e.g., Widmann et al., J. Climate 16(5): 799-816). The obvious difference, of course, is that **in case of weather forecasting (and to a certain extent also re-analysis driven RCM simulations), simulation and observation are synchronous, whereas in the case of climatological control simulations the modelled and observed weather sequences are independent.**

Maraun et al. (Rev. Geophys., 48, RG3003, 2010) therefore distinguish between

event-wise MOS (in case of synchronous time series where a regression like in weather forecasting can be applied) and

distribution-wise MOS, where only long term distributions can be compared and corrected.

Final structure ;)

Skill of methods for describing regional climate futures

- **Introduction**
- **Validation measures**
- **Dynamical downscaling**
- **Empirical-statistical downscaling**
  - **PP methods**
  - **MOS**
  - **Weather generators**
- **Ensembles**
- **Discussion (randomization, spectral nudging, added value)**
- **Impact studies**
- **Summary**