Papers to discuss/present

Tiwari et al. (2018) "Comparison of statistical and dynamical downscaling methods for seasonal scale winter precipitation predictions over North India

- keywords: Dynamical downscaling, Statistical downscaling, Seasonal forecasting, India, RegCM, Post-processing
- Used:
  - GCM: NCMRWF (NOT suitable for our region!)
    - NCEP SST as boundary cond.
  - RCM: RegCM4
  - ensemble mean of 10 members (initial conditions from 1-10 november of each year and each initial date)
  - examined observed teleconnection patterns with:
    - Observed SST (Smith et al. 2008)
    - ERA-I reanalysis:
  - Evaluation data:
    - Observed daily rainfall data (India Meteorological Department)
    - Station data sets from Snow Avalanche Establishment)
- Analyzing capabilities of statistical (Canonical Correlation Analysis CCA) and dynamical (RegCM) downscaling
- both provided improved precipitation forecasts compared to global model (GM)
  - mainly due to better representation of orography, westerly moisture transport and vertical pressure velocity in RegCM
  - bias correction methods were used on downscaled RegCM, downscaled CCA and GM products: Quantile Mapping (QM) and Mean Bias-remove (MBR)
- In general: QM based bias corrected downscaled RegCM model => useful tool for wintertime seasonal scale precipitation prediction (over North India NI)
- Possible skill metrics
  - Mean squared error
  - Multiplicative bias
  - Kendall rank correlation coefficient
  - Willmott's index of agreement
  - Percent error of prediction

- Definition of Statistical downscaling and Dynamical downscaling
- similar motivation: “...attempted to downscale the GCM outputs so that these forecasts become useful to the user community at regional scale...”
- conclusions:
  - CCA (stat. Downscale) higher skill then RCM/GCM
  - QM based bias corrected downscaled RCM better quality then CCA based statistical downscaling and bias corrected CCA (maximum skill over NI)

Manzanas et al. 2017 “Dynamical and statistical downscaling of seasonal temperature forecasts in Europe: Added value for user applications”

- keywords: Dynamical downscaling, Statistical downscaling, Seasonal forecast, Europe
- Used:
  - GCM: EC-EARTH version 3.1
    - ECMWF SST as boundary cond.
  - RCMs
    - RACMO2
    - WRF
    - RegCM
  - ensemble mean of 15 members
  - SDMs
    - Perfect Prognosis (PP)
    - Model Output Statistics (MOS)
  - Evaluation Data: daily gridded observations from E-OBS
- “Dynamical and statistical downscaling methods...providing thus actionable products which properly represent the local features of interest”
- Similar motivation: Downscaling seasonal forecasts of summer temperature over Europe
- Intercomparison of statistical and dynamical downscaling
- Possible skill metrics:
  - ROCSS (accuracy for probabilistic forecasts of each of the three terciles (cold, normal, warm))
  - Attributes/Reliability diagramm (Weisheimer and Palmer 2014)
- conclusions:
  - suitability of dynamical downscaling highly dependent on region and model considered (showed a reducing effect on orographic bias)

  - dynamical downscaling followed by bias adjustment (see e.g. Tiwari et al. 2018) could be a solution
  - ability of statistical downscaling to systematically reduce errors in different moments from mean to P95 => more realistic then GCM, clear added value for user appl.
  - No added value in terms of model skill improvement/about the same overall performance as GCM

Nikulin et al. (2018) “Dynamical and statistical downscaling of a global seasonal hindcast in eastern Africa”

- keywords: Seasonal forecast, Statistical Downscaling, Dynamical downscaling, Eastern Africa
- Used:
  - GCM: EC-EARTH
    - ERA-I SST as boundary cond.
  - RCMs:
    - CCLM4
    - RCA4
    - RegCM4
    - different WRF versions
  - ensemble mean of 15 members
  - SDMs:
    - AN1
    - Generalised Linear Model
      - both calibrated in Perfect Prognosis conditions
  - Evaluation/training data:
    - a number of gridded precipitation products
      - gauge-based-only datasets
      - satellite-gauge combinations
    - WFDEI dataset
      - quasi-observational product
      - bias-corrected ERA-I reanalysis
- “...assessed utility of dynamical and statistical downscaling to provide seasonal forecast for impact modeling in eastern Africa”
- possible skill metrics:

    - Interannual correlation
    - Brier skill score (BSS)
    - ROCSS
    - Attributes or reliability diagram
- conclusions:
    - RCMs do not outperform GCM
    - tendency to improved reliability
        - benefit for end user
    - no added value in terms of higher predictive skill

Li et al. (2018): “Present climate evaluation and added value analysis of dynamically downscaled simulations of CORDEX-East Asia”

- Used:
    - GCMs:
        - EC-EARTH
        - CNRM-CM5
        - HadGEM2 (Met Office?)
        - MPI-ESM-LR
    - RCM: CCLM
    - Evaluation/Reference data:
        - observation datasets:
            - Global Precipitation Climatology Project - GPCP (precipitation)
            - Global Precipitation Climatology Center - GPCC (precipitation)
            - Tropical Rainfall Measuring Mission - TRMM (not useful to us)
            - Asian Precipitation-Highly Resolved Observational Data Integration Towards the Evaluation of Water Resources - APHRO (not useful to us)
            - Climatic Research Unit - CRU
        - reanalysis:
            - ERA-I
            - JRA55 (nicht sinnvoll)
            - Modern-Era Retrospective analysis for Research and Applications – MERRA2
- “...investigate the skills of the...CCLM...and their added value to the...GCMs...”

- “...better understanding of regional climate characteristics with a focus on the frequency and intensity of extreme events and related changes is of vital importance to climate risk assessments as well as adaptation implementation for regional communities.”
- CCLM with 4 different GCM inputs to create multi-model ensemble which (other studies showed) has better performance
- conclusions:
  - results in reproducing climatological features varies from region to region and is highly dependent on the variable, season, metric and forcing GCM considered
  - temperature biases are found in both directions, less intensive so for the summer
  - downscaling can add value to GCMs regarding precipitation (regional dicrepancies)