Stepwise analogue downscaling for hydrology (SANDHY): validation experiments over France

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Challenge

- Statistical downscaling relates large scale predictors from general circulation models (GCMs) to local predictands
- A necessary condition for downscaling in a climate change context is that the predictor-predictand relationship is still valid under past climate variability.

Objective

- Testing the performance of SANDHY on independent data under current climate conditions.
- Testing the dependence of the performance on the archive for searching analogue dates and on the predictor domains optimised for a given period.

SANDHY

- Principle: Similar large scale circulation leads to similar local precipitation (Fig. 1)
- Stepwise selection using four types of predictor variables: temperature, geopotential, vertical velocity and humidity (Fig. 2) (Ben Daoud et al., 2011)
- The precipitation on the 25 best analog dates gives an empirical distribution reflecting the uncertainty in the downscaling step
- Predictor domains for geopotential optimized individually for 608 target zone using a variant of the growing rectangular domain algorithm and retaining the five best domains found (Radanovics et al., 2013)
- ERA-40 Reanalysis data (Uppala et al., 2005) are used as large scale predictors and daily precipitation from the French near surface reanalysis Safran (Vidal et al., 2010) as predictand

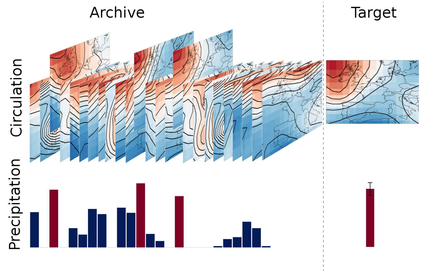

Figure 1: For a large scale target situation the N most similar situations are searched in the reanalysis archive. The local precipitation recorded on these analog dates gives an estimate for the target day.

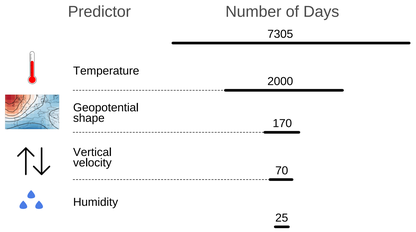

Figure 2: Analogue selection starts off with a 20-year archive (7305 days), from these a stepwise selection is performed: (1) temperature at 600hPa and 925hPa, (2) geopotential shape at 500hPa and 1000hPa, (3) vertical velocity at 850 hPa and (4) relative humidity at 850hPa*Total column water.

Experiments

1. **Reference simulation:** Simulation of the late period using the late period as an archive for searching the analogue dates, thus representing the best possible case. (Fig. 3)
2. **Out-of-sample validation:** Simulation of the early period using the late period as archive. The idea is to simulate a period whose local data is not "known" by the model as it would be the case in any application.
3. **Alternative archive:** The late period is simulated using the early period as archive.
4. **Imperfect predictor domains:** The early period is simulated using the early period as archive.

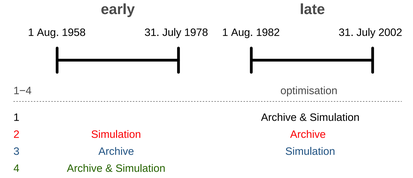

Figure 3: Time periods used in the different experiments. Predictor domains have been optimized over the late period for all experiments.

Results

1. **Reference simulation:** CRPSS and bias show a spatial distribution similar to the one of the mean precipitation with high skill and positive bias where mean precipitation is high, and lower skill and very small or slightly negative bias in dry regions. (Fig. 4 and 7 top left)
2. **Out-of-sample validation:** The average skill loss compared to the reference simulation is reasonable (Fig. 5) with some more skill loss in the northern part of the country and no loss in the southeastern part. (Fig. 6) The bias is somewhat stronger than for the reference simulation. (Fig. 7)
3. **Alternative archive:** Using the alternative archive leads to small and spatially uniform skill loss (Fig. 6), but changes the bias (Fig. 7) compared to the reference simulation.
4. **Imperfect predictor domains:** The skill loss is very similar to the out-of-sample validation, while the bias is rather similar to the reference simulation.

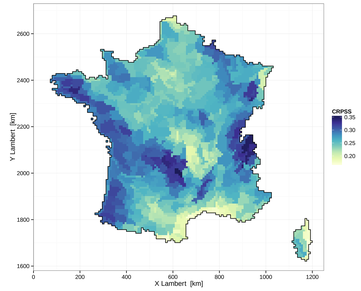

Figure 4: Spatial distribution of the continous ranked probability skill score (CRPSS) with climatological distribution as reference for the reference simulation.

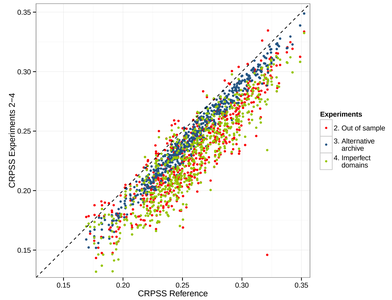

Figure 5: CRPSS for the reference simulation versus CRPSS for the other experiments for every zone in France.

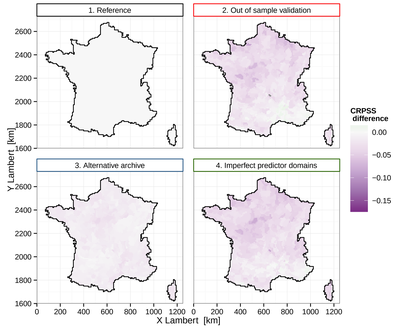

Figure 6: Spatial distributions of CRPSS differences between the four experiments and the reference simulation.

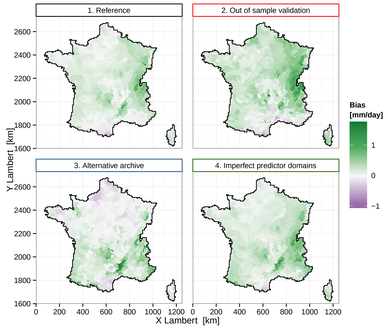

Figure 7: Spatial distribution of bias for the four experiments.

Conclusions

- SANDHY is quite robust in terms of downscaling skill at most locations (experiment 2)
- Changing the archive has only small impacts on the skill but changes the bias at some locations. (experiment 3)
- The skill loss observed in experiment 2 stems rather from the imperfect predictor domains than from the imperfect archive (experiment 4).
- The bias tends to be positive in regions with high mean precipitation and slightly negative in drier regions.
- We can not expect to have a constant bias if the archive period differs from the simulation period.
- Overall the results increase the confidence in applying SANDHY skillfully for downscaling in various contexts over France.

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