Stationarity of predictor-predictand relationships
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Introduction

When making a statistical hindcast model for a particular preditand, we make a list of potential preditors, from which the actually used preditors are selected. Usually, the selection criteria has been the ability of the chosen predictors to reconstruct the interannual variability of the predictor, measured e.g. by the linear (anomaly) correlation coefficient. But, as demonstrated in Schmith (2001) using a simple linear model, a high correlation coefficient (calculated on independent data by a cross-validation technique) does not guarantee that the lowest frequencies ('trends') are well captured by the model. In this case, some slow change is taking place in the system, which is not captured by the model. The poor abililty to capture the multidecadal variability of the climate, gives less confidence in the model being able to give realistic estimates of the predictor in future climate.

The model

We extend the work in Schmith (2001) to further examine the problem. As predictand data we use winter averages (Oct.-Mar) of precipitation series from the the ECA&D dataset (Klein Tank et al., 2002) over the period 1955-1995, see map of stations on figure 1. As predictors, we use several fields taken from the NCEP-NCAR reanalysis (Kistler et al., 2001) in 2.5x2.5 deg. resolution. Note, that the predictor and predictand fields are not detrended prior to analysis. The reason for this is that a good predictor set must explain also the trends in the predictand. Initially, each predictor field is truncated to the 10 most significant principal components and the time series, $\alpha_i^{(i)}, i = 1, \ldots N$, corresponding to the 10 most significant PC patterns of one of more fields are the potential predictors in the hindcast model. Mathematically this 'full' model is written as:

$$R_t = \overline{R} + \sum_{i=1}^{N} b_i \alpha_t^{(i)} + noise \,,$$

where R_t is the observed winter precipitation for a given station.

The potential predictors are screened using backward elimination, and a smaller number, M, of preditor PCs are kept. Once the coefficients in the model are determined, the hindcasted precipitation series can be calculated as:

$$\hat{R}_t = \overline{R} + \sum_{i=1}^{M} b_i \alpha_t^{(i)} \,.$$

The residual time series is calculated as

$$R_{res,t} = R_t - \hat{R}_t \,.$$

If the residual has a significant trend, this will be an indication of stationarity being not fulfilled for the model and predictors chosen.

Experiments and results

We used several combinations of predictors as given in the first column of the table below. The second column gives the range of correlation coefficients between observed and hindcasted station precipitation (.25 and .75 quantiles). The third column is the fraction of stations with a positive residual trend. Finally, the fourth column is the p-value of getting this or a larger fraction of positive residual trends, assuming that the 'true' residual trend equals zero for all stations. This p-value is calculated by carrying out 1000 permutations on the residual series for all stations simultaneously, destroying any systematic residual trends.

Potential predictors	**Hindcast corr coeff. .25/.75 fractile**	**Fraction of positive residual trends**	**p-value**
MSLP	.50/.73	.67	.02
MSLP, 850 hPa spec. humidity	.62/.82	.67	.02
MSLP, 850/500 hPa stat. stab.	.61/.79	.57	.22 *
500 hPa height	.46/.73	.52	.40 *

Table: Results from experiments with the linear hindcast model.

When using MSLP only as a predictor, as is done in much work on statistical downscaling, we get correlation coefficients centered within the range .50 to .73, a map showing the correlation coefficient for all stations is shown in figure 2. The distribution of residual trends is shown in figure 3. A fraction of .67 of them are positive and a p-value of .02 is obtained by the permutation test, which clearly indicates a non-stationarity relation. This illustrates that a high correlation coefficient does not ensure the absence of non-stationarity.

Due to global warming the humidity of troposphere has probably gradually increased during the last decades which would be expected to cause larger rainfall amounts. Therefore, in a second experiment, relative humidity at 850 hPa was added as an additional predictor. This yielded increased correlation coefficients centered within the range .62 to .82 but does not remove the non-stationarity, still a rather low p-value of 0.02 is achieved. A second hypothesis is that the warming of the lower troposphere has changed (diminished) the tropospheric stability. Simple quasigeostrophic theory (Holton, 1979) tells us that this will diminish the characteristic horizontal scale of the developing synoptic disturbances. That indeed adding the tropospheric stability has important implications is seen from the third experiment, where we get correlation coefficients centered within the range .61 to .79 and a p-value of .18 showing that the overall residual trend is not very significant and the non-stationarity therefore has been removed.

If our hypothesis of the diminishing typical scale of the synoptic disturbances is true, the tropospheric stability should be necessary as an additional predictor, also when height fields at e.g. 500 hPa is used as a circulation predictor. Therefore we applied our model using the 500 hPa height field and got a p-value of .40, implying that when using this circulation predictor the model has no non-stationarity. The overall performance of this model is descrbed by the correlation coefficients being centered with in the range .46 to .73, comparable to the MSLP only model.

Discussion

What we can conclude from the experiments in the table (and supplementary experiments not described) is that circulation at 850 hPa or higher is by our model able to reproduce a fraction of the observed precipitation variability including trends. Additional predictors such as lower tropospheric humidity or tropospheric stability is not needed. Circulation described by MSLP leads to non-stationarity, which could, however, be removed by using lower tropospheric stability as an additional predictor.

To further test the stability of the above results, we applied the 'MSLP alone model' using to alternative predictor fields, namely the ERA-40 reanalysis an the NCAR historical, gridded MSLP field (Trenberth and Paolino, 1980) covering the period 1899-present. Using this last dataset also enabled us to test the stability of the result, by applying the model in a running 30 year window. The result of this is shown in figure 4, from which it is seen that a significantly large fraction of positive residual trends seems to be the rule rather than the exception throughout the 20th century. The hypothesis that non-stationarity is connected to the arising of enhanced radiative forcing due to greenhouse gases is not supported by this finding.

Concluding remarks

The above analysis has helped pin-pointing important aspects of choosing predictor variables for statistical downscaling, however has not so far been able to give a consistent piture of which predictors to choose. The results could be the result of multidecadal natural variability. In that case, this must regarded as an uncertainty of statistical downscaling, rather a deficiency of some predictors.

References

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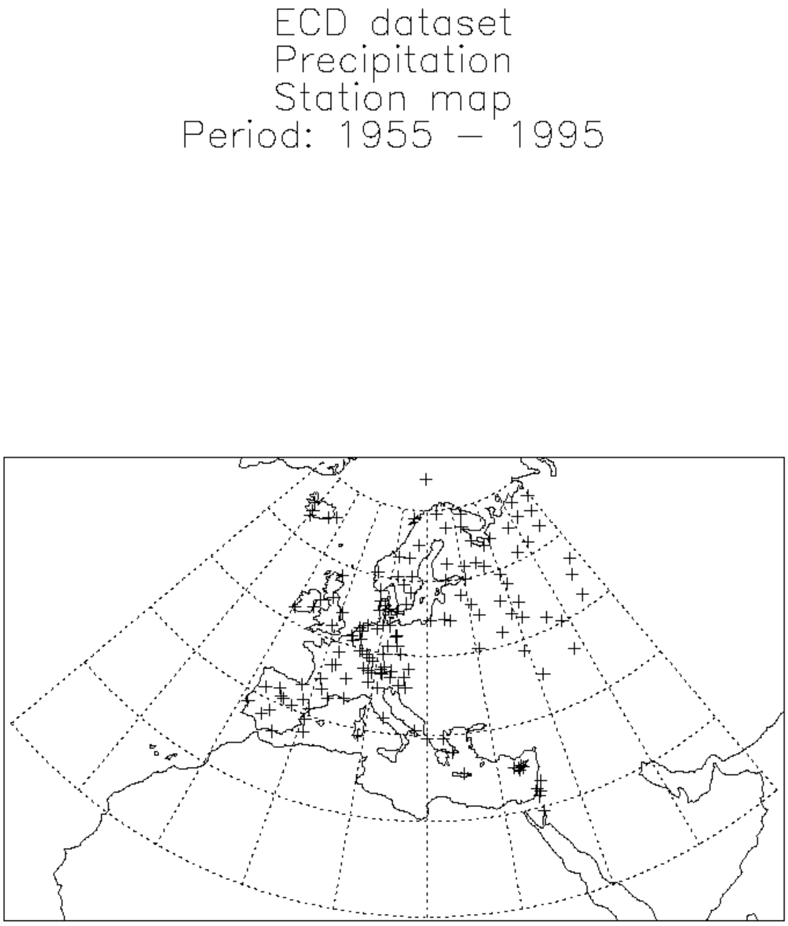

figure 1: Map showing locations of precipitation stations used.

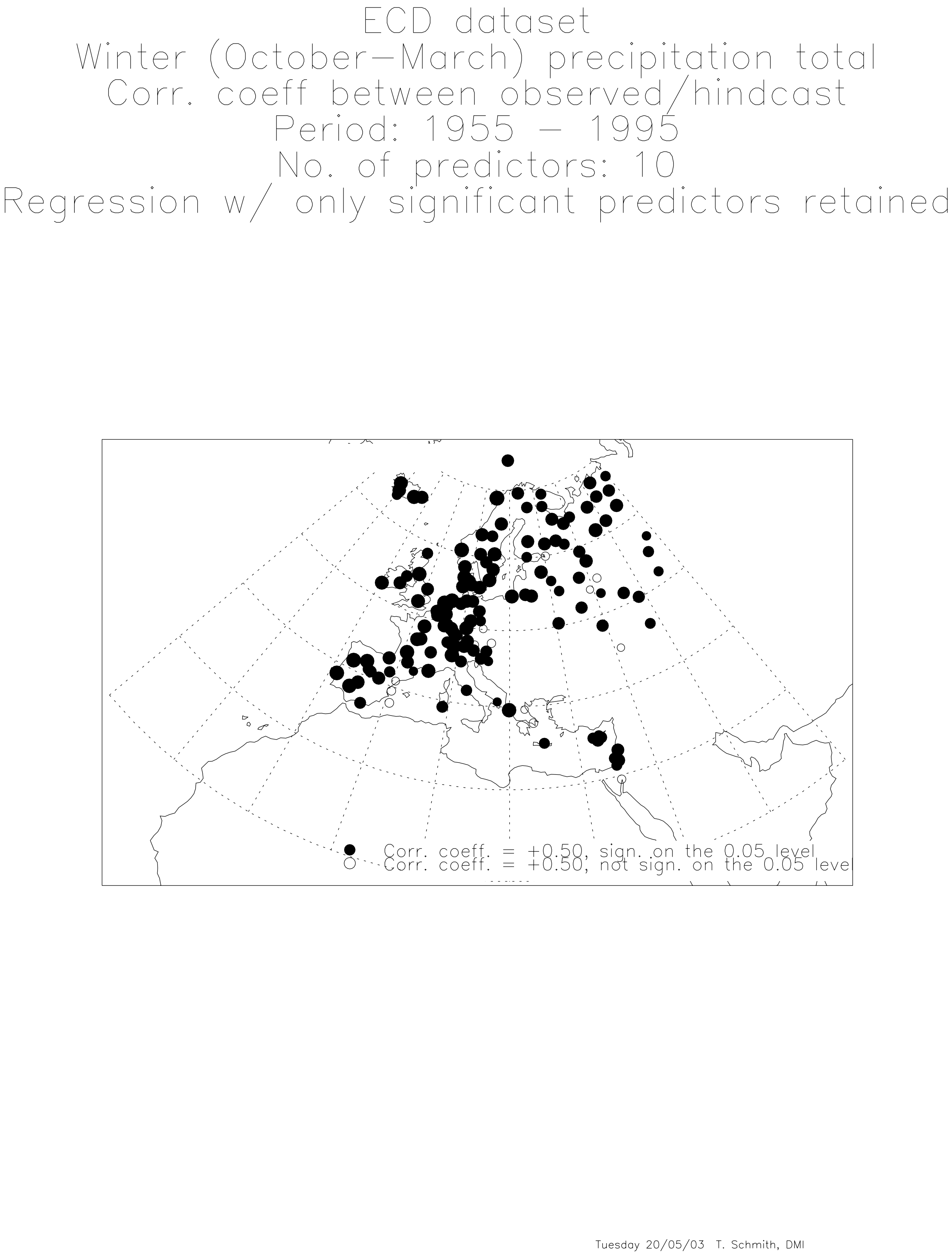

figure 2: Map showing the correlation coefficient between observed and hindcasted winter precipitation for the stations. The area of the circle is proportional to the correlation coefficient.

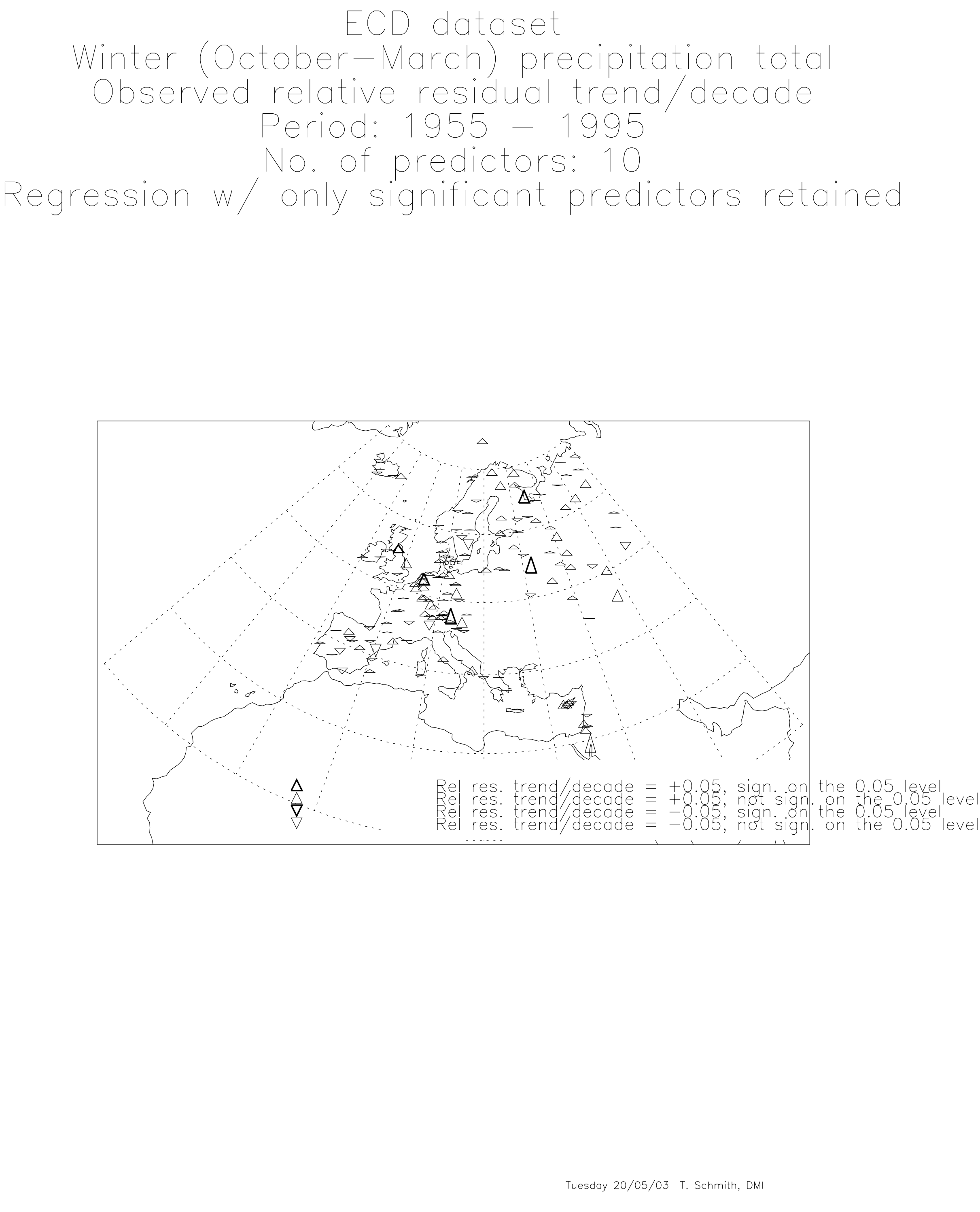

figure 3: Map showing the residual trend in winter precipitation for the stations. The height of the triangle is proportional to the residual trend.

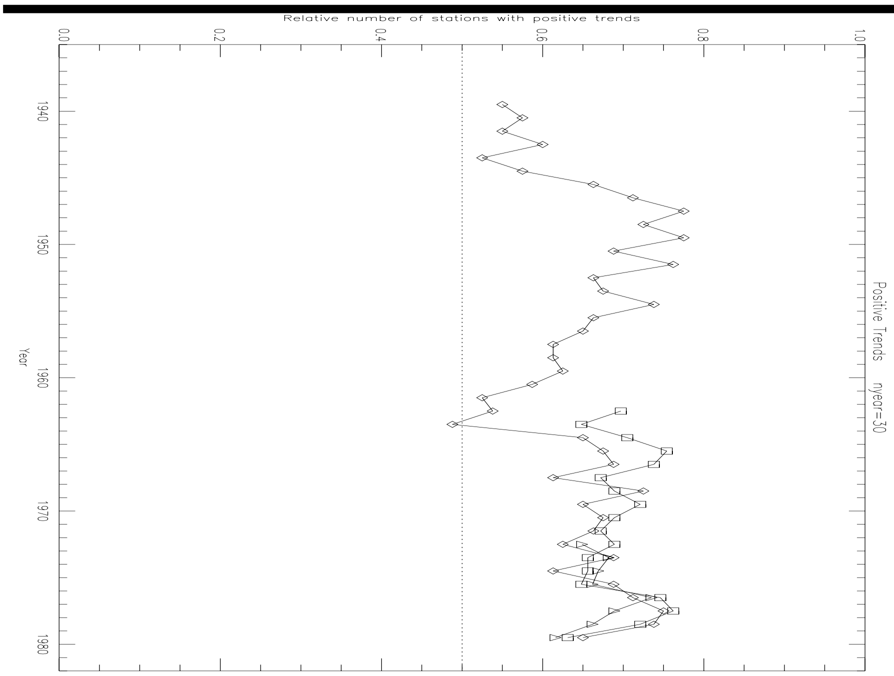

figure 4: MSLP used as a predictor in running 30 year windows using different MSLP datasets. Triangels: ERA-40, squares: NCEP/NCAR reanalysis, diamonds: Trenberth historical, gridded MSLP dataset.