Downscaled extremes based on NCEP Reanalysis data (1958 – 2000)

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Introduction

A method of downscaling has been applied in the German side of the Rhine basin to downscale extreme precipitation and temperature indices from a range of predictor variables taken from the NCEP Reanalysis data set at a resolution of 2.5° × 2.5°. Instead of downscaling the daily series of precipitation of precipitation and temperature, the seasonal extreme indices are directly downscaled from the predictors. For this purpose, seasonal measures of extremes of the predictor variables were used.

Data

A range of potential predictor variables are selected from the NCEP Reanalysis data. These include geopotential height, air temperature, and relative humidity at 500, 700, and 850hPa levels. In addition, derived predictor variables such as vorticity and divergence at the same three pressure levels, the east west direction moisture flux at 700 hPa level, and objective circulation patterns obtained by classifying the sea level pressure using a Fuzzy rule approach (presented in D10) were used.

Downscaling of the extreme indices was done for stations selected from the FIC data set that are located in the desired study location. Based on the percentage of missing record (both for temperature and precipitation) and homogeneity test results (for temperature series), 10 stations were selected for calibration and validation of the downscaling. The same stations were selected for both temperature and precipitation. List of the selected stations is shown in table 1.

Table 1: List of precipitation/temperature stations selected from the FIC data set for downscaling.

Station_code	Latitude	Longitude	Elevation	Name	% comp(Tmin)	% comp(Tmax)	%comp(Tavg)	% comp(RF)	homo. Test(Tmin)	homo. Test(Tmax)	Homo test(RF)	max dTmin	max dTmax
2320000	4788	800	1486	FELDBERG/SCHW. (WST)	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	No	No	0	
107270	4901	838	114	Karlsruhe	%Tn-99	%Tx-99	%Tmd-99	%P-99	No	Yes	No		31
2695000	4952	855	96	MANNHEIM (WST)	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	Yes	No	49	0
2278000	4977	705	480	DEUSELBACH (AWST)	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	Yes	No	0	0
2222000	5087	717	92	KOELN-WAHN (FLUGWEWA	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	Yes	No	0	11
2609000	5058	870	186	GIESSEN (LIEBIGSH. W	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	Yes	No	0	34
2674000	4977	997	268	WUERZBURG (WST)	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	Yes	No	31	17
2105000	4922	712	320	SAARBRUECKEN-E(FLUGW	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	Yes	No	29	0
1594000	5118	848	839	KAHLER ASTEN (WST)	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	No	No	0	
4081000	4950	1105	314	NUERNBERG-KRA.(FLUGW	%Tn-99	%Tx-99	%Tmd-99	%P-99	Yes	Yes	No	55	23

Method

A multiple linear regression model was used for downscaling the seasonal extreme indices. They were downscaled from seasonal measures of the potential predictor variables. These measures include the seasonal mean values and measures of extreme such as the 10th

percentile and the 90th percentile seasonal values of the predictors. These measures apply only for predictors that have numerical values and a different measure should be used for the circulation patterns. The seasonal percentage of the circulation patterns associated with the wet days was used (D10). Table 2 shows the indices which are downscaled.

Table 2: Extreme indices for which downscaling is done

Designation	Index
	Precipitation related indices
Pav	Mean daily rainfall
Pq90	90^{th} percentile of rainday amounts
Px5d	Greatest 5 day total rainfall
Pint	Simple daily intensity
Pxcdd	Maximum number of consecutive dry days
Pf90	% of total rainfall from events > long-term 90^{th} percentile of raindays
Pn90	No. of events > long-term 90^{th} percentile of raindays
	Temperature related indices
Txav	Mean maximum temperature
Tnav	Mean minimum temperature
Txq90	90^{th} percentile maximum temperature
Tnq10	10^{th} percentile minimum temperature
Tnfd	Number of frost days
Txhw90	Heat wave duration index (percentile based)

Results

Table 3 and 4 show the predictor sets that are selected using the forward selection method for each of the precipitation and temperature indices respectively. The order of the predictors as they appear in the list indicates their rank in the selection procedure. It can be seen that generally, the best predictors for a given season for precipitation indices related to heavy precipitation conditions are the same. Similarly, the air temperature at 850 hPa pressure level appears to be the best predictor variable for temperature extreme indices.

Selection of the predictors and calibration of the downscaling model was performed for the period 1958-1978 and 1994-200 and finally validated for the period 1979-1993. Three skill measures were used to evaluate the downscaled indices: bias, debiased root mean square, and Spearman rank correlation between the observed and the downscaled indices.

The mean seasonal precipitation is the only precipitation index that is downscaled consistently well in all seasons. For the other extreme precipitation indices, the best performance was generally obtained for the winter season followed by spring. The worst performance was noticed for summer. The only exception is the maximum number of dry days, for which the best skill measures were obtained in summer. Table 5 shows summary of the mean correlation and mean square mean error values of the 10 stations for the precipitation indices in the validation period.

The temperature indices were generally found to be downscaled well in all seasons. The correlations were found to be very high for all seasons. However, the model performance for downscaling the heat wave duration index is not that satisfactory, with modest correlation and high ratio of standard deviation between the downscaled and the observed values. Table 6 shows summary of the mean correlation and mean square root error values of the stations for the validation period.

Table 3: Predictor variables for extreme precipitation indices

Index	Winter	Spring	Summer	Autumn	Annual
Pav	mflx-avg(700) CP-wet	CP-wet rhum-avg(850)	rhum-avg(700) CP-wet hgt-avg(850) dvg-avg(850)	mflxavg(700) CP-wet hgt-avg(500)	CP-wet mflx-avg(700) rhum-avg(700)
Pq90	mflx-P90(700) vort-P90(700) air-P10(500)	CP-wet air-P10(850) dvg-P90(500) air-P10(500)	rhum-P90(700) vort-P90(500)	dvg-P10(700,850) mflx-P90(700) CP-wet air-P90(500,700,850) vort-P90(700)	CP-wet hgt-P10(850) rhum-P90(500)
Px5d	mflx-P90(700) hgt-P90(500,850) dvg-P90(850) air-P10(700)	CP-wet air-P10(700) rhum-P90(700)	rRhum-P90(700) vVort-P90(500) CP-wet	dvg-P10(500,700) air-P90(500,700) rhum-P90(700) hgt-P90(500)	mflx-P90(700) rhum-P90(500,850) vort-P90(500) dvg-P90(850)
Pint	mflxp90(700)	CP-wet rhum-P90(700) air-P10(850)	rhum-P90(700) dvg-P90(500,700) hgt-P90(850)	dvg-P10(500,700,850) rhum-P90(700) hgt-P90(500,700) air-P90(500)	CP-wet mflx-P90(700) rhum-P90(500) hgt-P10(850) vort-P90(500)
Pxcdd	hgt-P90(700,500) dvg-P90(500) air-P90(700)	CP-wet dvg-P10(700) vort-P90(850) rhum-P90(500,700)	rhum-P10(850) vort-P90(500) mflx-P10(700)	rhum-P10(850) CP-wet air-P10(500,700)	mflx-P10(700)
Pf90	mflx-P90(700)	CP-wet mflx-P90(700) vort-P10(500) dvg-P10(500)	rhum-P90(700) vort-P90(500) CP-wet	dvg-P10(850,700) CP-wet air-P90(500,700,850) hgt-P90(500)	vort-P90(500,700) mflx-P90(700) rhum-P90(700,850) hgt-P10(850)
Pn90	mflx-P90(700) hgt-P90(500)	CP-wet vort-P10(500) rhum-P90(700)	rhum-P90(700) vort-P90(500) CP-wet	mflx-P90(700) air-P90(500,700,850) rhum-P90(700)	CP-wet mflx-P90(700) rhum-P90(700)

Table 4: Predictor variables for extreme temperature indices

Index	**Winter**	**Spring**	**Summer**	**Autumn**	**Annual**
Txav	air-avg(850) mflx-avg(700)	air-avg(850) rhum-avg(700)	air-avg(850)	air-avg(850)	air-avg(850)
Tnav	airavg(850) CP-wet vort-avg(850) rhum-avg(850)	air-avg(850)	air-avg(850) rhum-P90(700)	air-avg(850) rhum-avg(850) vort-avg(850,700)	air-avg(850) CP-wet
Txq90	air-P90(850) mflx-p90(700)	air-P90(850)	air-P90(850)	air-P90(850)	air-P90(850)
Tnq10	air-P10(850,700)	air-P10(850,700)	air-P10(850,700)	air-P10(850)	air-P10(850) CP-wet dvg-P90(700) mflx-P90(700)
Tnfd	air-P10(850) mflx-P10(700) vort-P90(850)	air-P10(850) vort-P90(500) rhum-P90(500)		air-P10(850) rhum-P10(850) air-P10(700)	air-P10(850) CP-wet vort-P90(850)
Txhw90	air-P90(850) CP-wet vort-P90(850) rhum-P90(850)	rhum-P90(500) air-P90(500,700,850) mflx-P90(700) dvg-P90(500)	air-P90(850,700) vort-P90(500) dvg-P90(850)	air-P90(850) vort-P90(500,700,850) dvg-P90(850)	rhum-P90(500,700,850) air-P90(500,850) CP-wet

Table 5: Summary of mean correlation and root mean square values for precipitation indices

Index	Correlation				RMSE			
	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn
Pav	0,717	0,6533	0,4965	0,4994	0,4562	0,508	0,6504	0,5166
Pint	0,4001	0,3208	0,079	0,2779	1,0064	1,0759	1,3745	1,258
Pq90	0,3746	0,033	0,2029	0,2632	2,6377	3,7121	3,4968	4,0202
Px5d	0,4415	0,401	0,3373	0,3046	15,1434	15,7781	17,7507	19,4892
Pxcdd	0,4178	0,4532	0,5409	0,4043	4,4486	3,7597	3,9828	5,7837
Pf90	0,3135	0,0972	0,0932	0,1294	0,1177	0,1491	0,1392	0,1455
Pn90	0,4168	0,462	0,2695	0,2499	1,839	1,7505	1,6385	1,6504

Table 6: Summary of mean correlation and root mean square values for temperature indices

Index	Correlation				RMSE			
	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn
Txav	0,8985	0,9363	0,8977	0,7629	0,7159	0,3791	0,5168	0,5339
Txq90	0,7575	0,9019	0,8444	0,85	0,9462	0,8479	0,7325	1,1012
Tnav	0,8743	0,9247	0,8793	0,7958	0,8132	0,3661	0,3339	0,3927
Tnq10	0,8751	0,662	0,7026	0,8433	1,5354	1,1543	0,5063	1,2061
Tnfd	0,7248	0,6951		0,8336	7,5983	4,5527		3,9995
Txhw90	0,624	0,4714	0,6125	0,2525	2,1686	2,0238	1,3476	1,9877