UEA Primary Contribution to D12

Modelling UK indices of extreme rainfall using interannual variability of large scale circulation

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Introduction

A downscaling method has been developed that models seasonal indices of extreme rainfall at UK stations using large-scale circulation. The main philosophy behind the method is that, instead of modelling daily rainfall then calculating the indices of extremes, it may be possible to model the seasonal indices directly using seasonal predictors. This has the advantage of requiring less computer resources but means we do not have access to the downscaled daily rainfall series.

Data

Predictands

Daily rainfall was analysed for the years 1958 to 2000 from 28 stations in SE England and 15 stations in NW England. These stations are the same set as for the D9 analysis with the addition of stations from the STARDEX European data set.

Seven indices of extreme rainfall were calculated for the above stations:

pav	Mean daily rainfall
pq90	90th percentile of rainday amounts (mm/day)
px5d	Greatest 5-day total rainfall
pint	Simple Daily Intensity (rain per rainday)
pxcdd	Max no. consecutive dry days
pfl90	% of total rainfall from events > long-term P90
pnl90	No. of events > long-term 90th percentile of raindays

Predictors

Potential predictors were selected from the NCEP reanalyses using the results from the D10 analysis. The D10 study showed that the average correlations between the indices of extremes and the NCEP variables over the UK region were generally highest for MSLP and geopotential height, followed by relative humidity and temperature. Geopotential height, humidity and temperature were examined at 500, 700 and 850hPa. The NCEP variables were selected over the region 20W to 15E and 20N to 70N. Seasonal averages of the variables were calculated to be coincident in time with the predictands.

Method

Selecting predictors

An additional pre-screening of predictors was first carried out to further quantify the D10 results. To assess the skill of each of the NCEP predictors, a cross validation was done whereby each year was removed in turn and a CCA used to relate the predictor to the predictand. The predictand for the missing year was then hindcast. This was carried out for each year in the period 1958-2000 and the hindcast results compared with the actual observations. The Pearson correlation was used as the skill measure and show results to be variable depending on the extreme index being considered as well as the season.

Tables 1 and 2 show the correlation for each predictor-predictand combination for SE and NW England averaged across all stations in the region. The D10 results are confirmed with MSLP and geopotential height being the best general predictors, followed by humidity and temperature. For this analysis specific humidity was also included and is generally a better predictor than relative humidity.

Designing a model

MSLP

The first model to be designed used a CCA relating just MSLP and the predictand. This simple model was intended to be a benchmark against which any further improvements could be made.

For each season and extreme index, a CCA was carried out between the predictand and MSLP for the years 1958-1978 and 1994-2000. The indices were then hindcasted for 1979-1993 and the results compared with the observations.

The canonical patterns and series were calculated using a singular value decomposition of the cross-covariance matrix of the PCs of the two fields. This is numerically more stable than the more common method of working with the joint variance-covariance matrix (Press et al., 1986) and also incorporates the pre-filtering of the data by using just the significant PCs (Barnett and Preisendorfer, 1987). The number of PCs retained for the analysis was selected by a Monte Carlo process, whereby 1000 PC analyses were carried out using data randomly resampled in time from the original series (Preisendorfer et al., 1981). In each of the 1000 analyses the eigenvalues were calculated. Each of the eigenvalues of the real observations was then compared against the distribution of the 1000 randomly generated values to determine if they were greater than the rank 50 eigenvalue (equivalent to $p<0.05$). Therefore the number of eigenvectors retained was different for each predictor, predictand and season.

OTHER PREDICTORS

A second CCA model was designed that selected the best combination from up to four predictors. The four predictors were MSLP, relative humidity specific humidity and temperature at 700hPa. This level was chosen as it generally showed the best skill across all predictands. Over the training period the model then carried out a CCA between each predictand and all possible combinations of the four predictors (15 combinations), selecting the best combinations using a cross-validation approach. This model was then used to hindcast the period 1979-93 (which is excluded from the training period). The best model was selected using the Spearman rank correlation between the observed and modelled data.

Therefore the combination chosen varies between regions, predictands and seasons, but is the same for all stations in a region.

Results

MSLP

Figure 1 shows the Spearman correlation for the 1979-1993 hindcast results averaged across all stations in SE England. The highest correlations are for DJF while JJA shows the lowest. *pav, pxcdd* and *pnl90* are the best modelled indices and *pfl90* the worst. For two of the indices, *pint* and *pfl90*, correlations are negative in JJA.

Results are similar for NW England (Fig. 2) except that MAM and SON have higher correlations than DJF. Correlations are generally lower in the NW than the SE.

Other Predictors

IN SE England, adding other potential predictors improves the correlations in JJA but lowers them in MAM (Fig. 3). The additional humidity predictors were found to be reason for the improvement in JJA. For MAM the model generally selected humidity above MSLP but this produced lower correlations in the hindcast results than had MSLP been selected.

For NW England (Fig. 4) results are also improved in JJA so that there are no negative correlations for this model. However results are very low in MAM and the model performs not as well as using MSLP alone.

Comparison

To compare the two models a scatter plot was produced showing the hindcast Spearman correlation for the two approaches. Figure 3 shows the results for SE England. Points above the unity line are better modelled by the multi-predictor approach. In general all seasons are better modelled using the multi-predictor approach except for MAM.

For NW England (Fig. 6) the scatter plot shows that in MAM the correlations are higher when using MSLP than for the multi-predictor approach. For three of the indices correlations in SON are higher when using just MSLP but the additional predictors greatly improves the correlations in JJA.

References

Barnett TP, Preisendorfer R. 1987. Origins and Levels of Monthly and Seasonal Forecast Skill for United-States Surface Air Temperatures Determined by Canonical Correlation-Analysis. *Monthly Weather Review*. **115.** 1825-1850

Preisendorfer RW, Zwiers FW, Barnett TP. 1981. *Foundations of Principal Component Selection Rules*. *SIO Reference Series 81-4*. Scripps Institution of Oceanography, 192 pp.

Press WH, Flannery BP, Teukolsky SA, Vetterling WT. 1986. *Numerical Recipes : The Art of Scientific Computing*. Cambridge University Press, 818 pp.

Tables

	MSLP	Z850	Z700	Z500	RH850	RH700	RH500	T850	T700	T500	SH850	SH700	SH500
DJF													
pav	0.83	0.84	0.85	0.86	0.71	0.68	0.56	0.76	0.82	0.83	0.73	0.79	0.66
pq90	0.35	0.38	0.40	0.41	0.27	0.33	0.25	0.45	0.47	0.41	0.42	0.41	0.28
pxcdd	0.51	0.52	0.52	0.49	0.39	0.33	0.29	0.32	0.31	0.36	0.36	0.36	0.37
px5d	0.44	0.45	0.46	0.46	0.22	0.37	0.34	0.47	0.50	0.44	0.41	0.44	0.23
pint	0.47	0.49	0.52	0.53	0.37	0.43	0.38	0.55	0.58	0.54	0.49	0.53	0.42
pfl90	0.21	0.22	0.25	0.23	0.09	0.20	0.14	0.31	0.31	0.23	0.23	0.20	0.13
pnl90	0.55	0.57	0.60	0.61	0.42	0.45	0.34	0.60	0.62	0.58	0.52	0.54	0.41
MAM													
pav	0.57	0.57	0.53	0.48	0.54	0.62	0.49	0.34	0.33	0.37	0.51	0.70	0.61
pq90	0.21	0.13	0.05	0.03	-0.06	0.14	-0.26	0.04	0.11	0.08	0.11	0.14	-0.03
pxcdd	0.55	0.57	0.58	0.57	0.58	0.64	0.63	0.30	0.37	0.40	0.43	0.57	0.49
px5d	0.13	0.08	0.00	-0.05	0.10	0.19	-0.06	-0.06	0.00	0.01	0.22	0.32	0.20
pint	0.15	0.06	-0.01	-0.02	-0.03	0.15	-0.21	-0.09	0.07	0.03	0.12	0.15	0.00
pfl90	0.16	0.09	0.01	-0.02	-0.01	0.16	-0.13	-0.01	0.05	-0.03	0.08	0.06	-0.04
pnl90	0.29	0.27	0.22	0.18	0.18	0.29	0.02	0.21	0.20	0.19	0.30	0.42	0.32
JJA													
pav	0.61	0.60	0.59	0.57	0.43	0.44	0.39	0.44	0.51	0.55	0.26	0.34	0.54
pq90	-0.13	-0.26	-0.27	-0.29	-0.17	-0.16	-0.05	-0.18	-0.17	-0.23	-0.01	-0.05	0.06
pxcdd	0.38	0.36	0.37	0.36	0.29	0.29	0.13	0.25	0.37	0.38	0.22	0.22	0.32
px5d	0.27	0.22	0.21	0.19	0.18	0.20	0.26	0.18	0.19	0.16	0.06	0.19	0.27
pint	-0.16	-0.32	-0.37	-0.39	-0.22	-0.13	-0.05	-0.33	-0.28	-0.29	0.01	-0.02	0.05
pfl90	-0.10	-0.17	-0.15	-0.13	-0.11	-0.09	-0.04	-0.09	-0.03	-0.09	-0.01	-0.06	0.00
pnl90	0.24	0.24	0.24	0.21	0.17	0.15	0.18	0.15	0.18	0.20	0.13	0.17	0.31
SON													
pav	0.73	0.73	0.74	0.75	0.69	0.66	0.57	0.57	0.67	0.75	0.59	0.65	0.61
pq90	0.16	0.12	0.11	0.13	0.09	0.07	0.07	0.15	0.21	0.22	0.15	0.18	0.17
pxcdd	0.65	0.65	0.65	0.65	0.64	0.66	0.56	0.49	0.57	0.59	0.53	0.56	0.44
px5d	0.33	0.33	0.33	0.34	0.36	0.28	0.26	0.26	0.36	0.37	0.30	0.38	0.33
pint	0.23	0.22	0.20	0.20	0.17	0.11	0.11	0.16	0.25	0.23	0.07	0.16	0.18
pfl90	0.12	0.09	0.08	0.10	0.10	0.11	0.11	0.13	0.17	0.16	0.03	0.07	0.10
pnl90	0.49	0.48	0.49	0.51	0.46	0.44	0.40	0.38	0.47	0.53	0.38	0.43	0.41

Table 1: Pearson correlation for cross-validated modelling of the extremes indices using CCA with a single predictor. Results are averaged across all stations in SE England.

	MSLP	Z850	Z700	Z500	RH850	RH700	RH500	T850	T700	T500	SH850	SH700	SH500
DJF													
pav	0.71	0.72	0.72	0.72	0.64	0.61	0.56	0.60	0.67	0.69	0.62	0.68	0.54
pq90	0.14	0.15	0.16	0.19	0.12	0.14	0.16	0.18	0.17	0.22	0.10	0.16	0.09
pxcdd	0.40	0.40	0.39	0.46	0.43	0.42	0.42	0.28	0.30	0.36	0.35	0.30	0.25
px5d	0.11	0.12	0.12	0.12	0.01	0.14	0.15	0.15	0.14	0.18	-0.02	0.13	0.12
pint	0.29	0.30	0.31	0.33	0.27	0.30	0.31	0.30	0.30	0.36	0.18	0.31	0.23
pfl90	0.12	0.12	0.13	0.15	0.05	0.11	0.16	0.10	0.07	0.13	0.07	0.11	0.10
pnl90	0.45	0.46	0.47	0.47	0.40	0.37	0.39	0.41	0.42	0.44	0.41	0.46	0.31
MAM													
pav	0.67	0.67	0.63	0.58	0.47	0.55	0.47	0.39	0.41	0.45	0.49	0.60	0.55
pq90	0.24	0.26	0.22	0.21	-0.05	-0.12	-0.04	0.14	0.17	0.21	0.16	0.14	0.04
pxcdd	0.57	0.57	0.56	0.52	0.55	0.59	0.58	0.26	0.29	0.32	0.45	0.61	0.49
px5d	0.20	0.13	0.06	0.04	-0.01	0.01	-0.06	0.08	0.12	0.15	0.24	0.22	0.07
pint	0.30	0.30	0.24	0.22	-0.05	-0.04	0.01	0.16	0.21	0.25	0.22	0.21	0.08
pfl90	0.10	0.09	0.04	0.02	-0.11	-0.20	-0.15	0.00	0.05	0.09	0.02	-0.04	-0.08
pnl90	0.33	0.33	0.29	0.24	0.09	0.13	0.10	0.16	0.17	0.22	0.25	0.27	0.23
JJA													
pav	0.62	0.63	0.64	0.63	0.60	0.60	0.53	0.60	0.60	0.57	0.24	0.37	0.53
pq90	-0.05	-0.07	0.02	0.05	0.15	0.15	0.26	0.14	0.14	0.04	0.09	0.27	0.34
pxcdd	0.46	0.47	0.47	0.46	0.45	0.36	0.22	0.49	0.46	0.49	0.06	0.11	0.36
px5d	0.14	0.14	0.22	0.26	0.13	0.15	0.29	0.30	0.31	0.26	0.20	0.24	0.35
pint	-0.09	-0.04	0.06	0.09	0.12	0.14	0.24	0.14	0.14	0.02	0.06	0.22	0.30
pfl90	0.00	-0.05	0.02	0.05	0.12	0.15	0.24	0.19	0.14	0.02	0.11	0.25	0.31
pnl90	0.31	0.29	0.30	0.30	0.37	0.38	0.39	0.32	0.30	0.26	0.08	0.32	0.39
SON													
pav	0.71	0.70	0.69	0.67	0.69	0.61	0.58	0.58	0.59	0.63	0.57	0.54	0.53
pq90	-0.02	-0.01	0.01	0.04	0.12	0.10	-0.01	0.05	0.06	0.06	-0.02	0.02	0.01
pxcdd	0.43	0.38	0.35	0.33	0.59	0.58	0.46	0.39	0.30	0.32	0.44	0.50	0.23
px5d	0.11	0.10	0.09	0.08	0.20	0.05	0.05	0.11	0.08	0.09	0.07	0.05	0.10
pint	0.06	0.08	0.07	0.07	0.18	0.14	0.05	0.04	0.07	0.08	0.02	0.10	0.08
pfl90	-0.03	-0.03	0.01	0.04	0.05	0.00	-0.05	0.01	0.04	0.07	-0.08	-0.07	-0.09
pnl90	0.28	0.29	0.29	0.29	0.30	0.24	0.20	0.26	0.28	0.28	0.24	0.26	0.24

Table 2: Pearson correlation for cross-validated modelling of the extremes indices using CCA with a single predictor. Results are averaged across all stations in NW England.

Figures

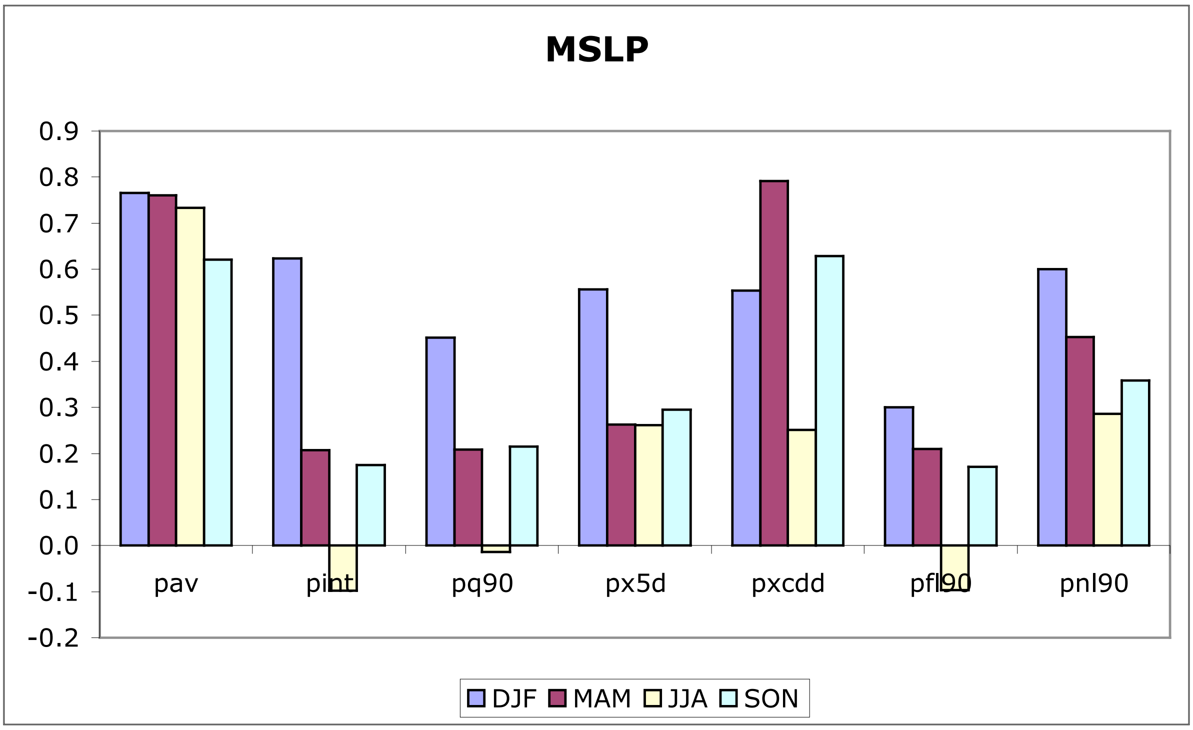

Figure 1: Spearman correlation for hindcast indices using MSLP averaged across all stations for SE England.

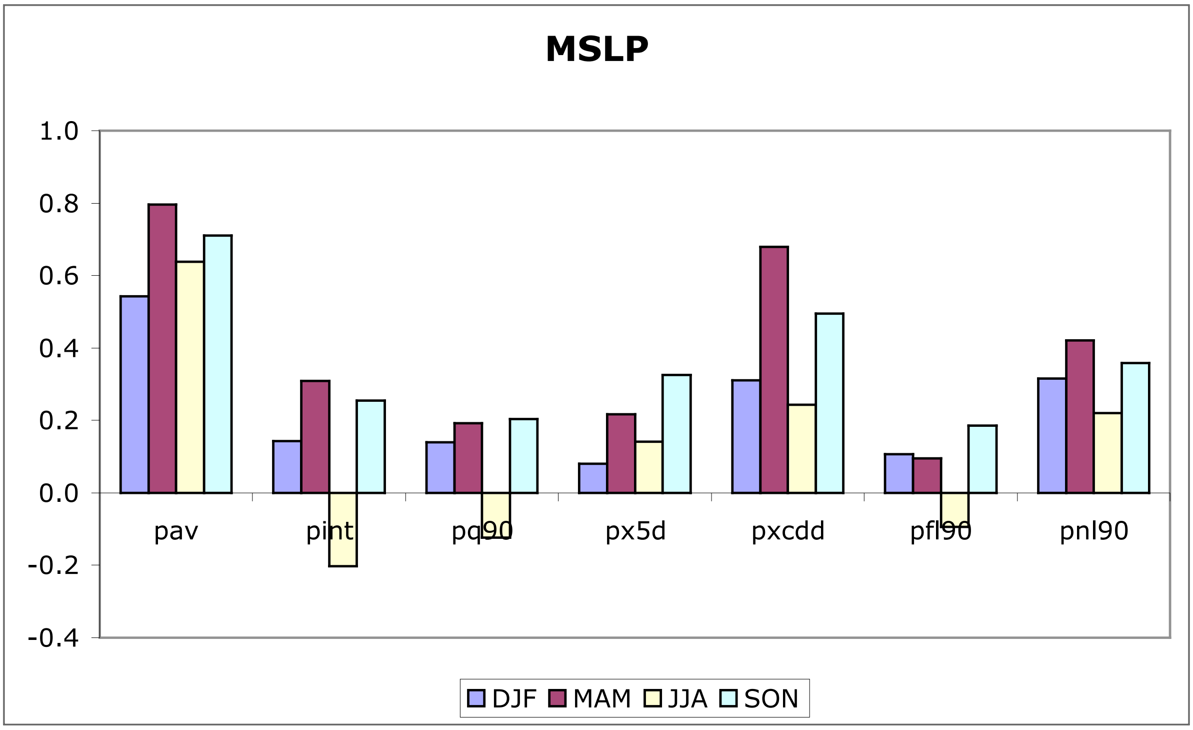

Figure 2: Spearman correlation for hindcast indices using MSLP averaged across all stations for NW England.

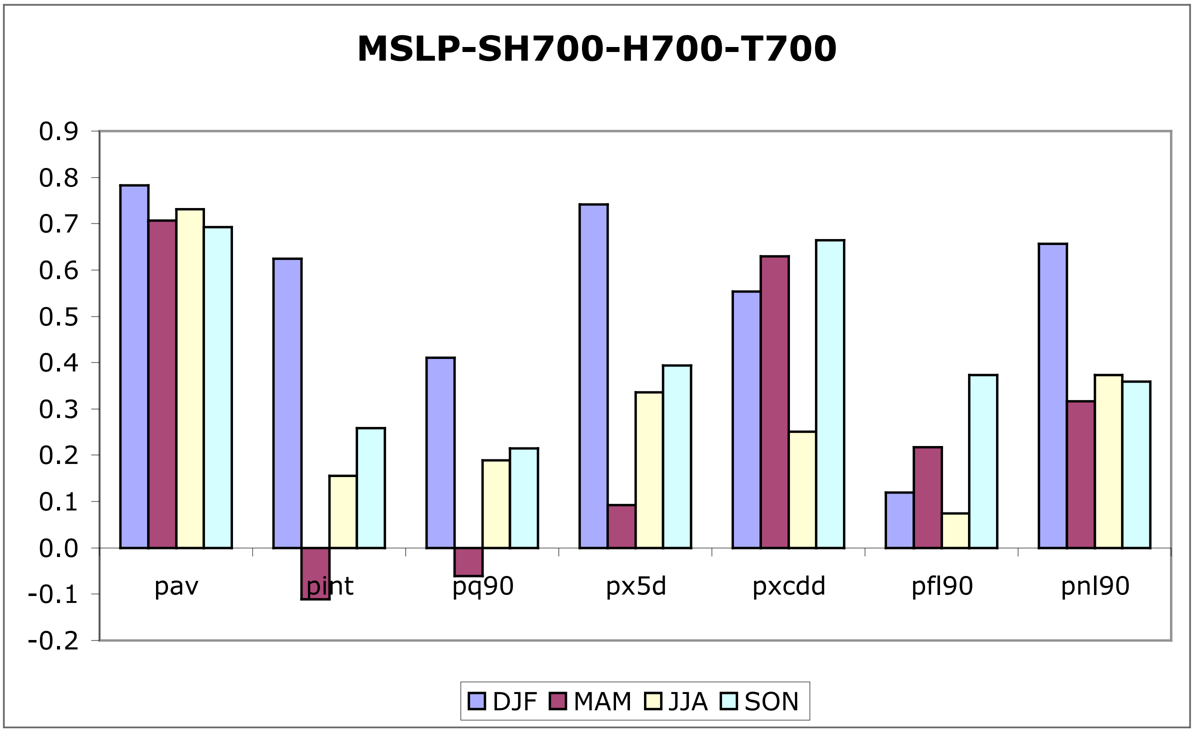

Figure 3: Spearman correlation for hindcast indices using the best combination of four predictors averaged across all stations for SE England.

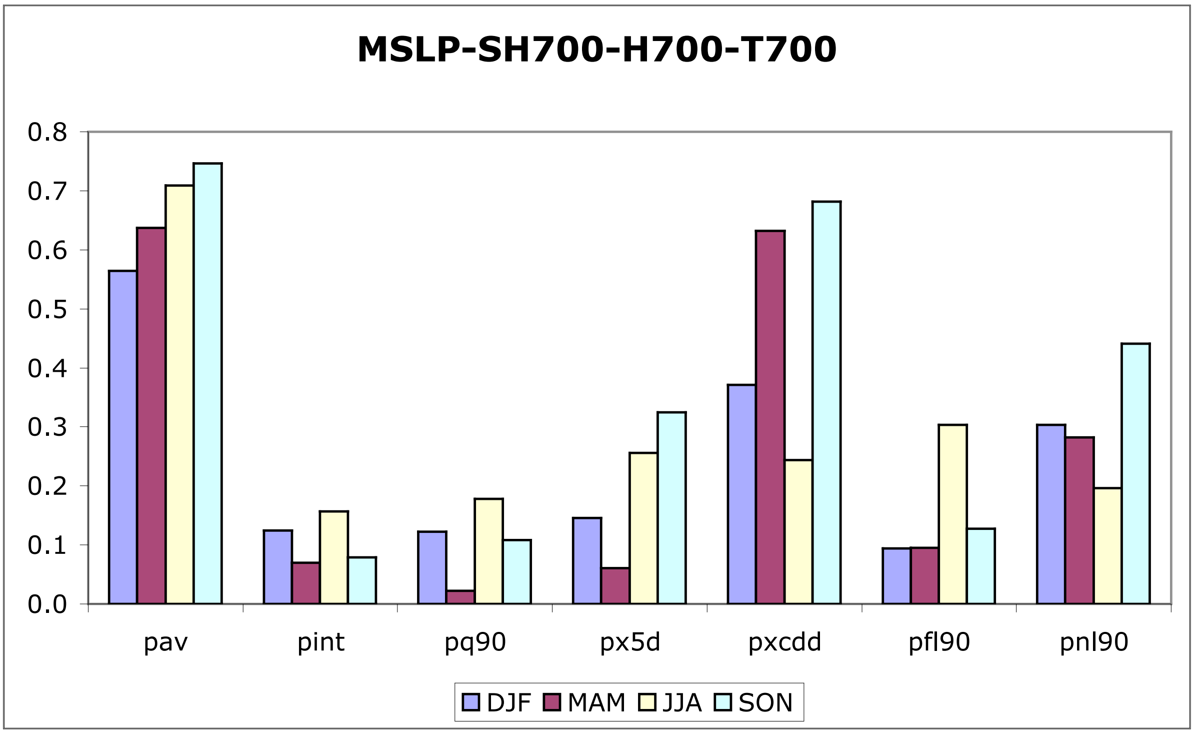

Figure 4: Spearman correlation for hindcast indices using the best combination of four predictors averaged across all stations for NW England.

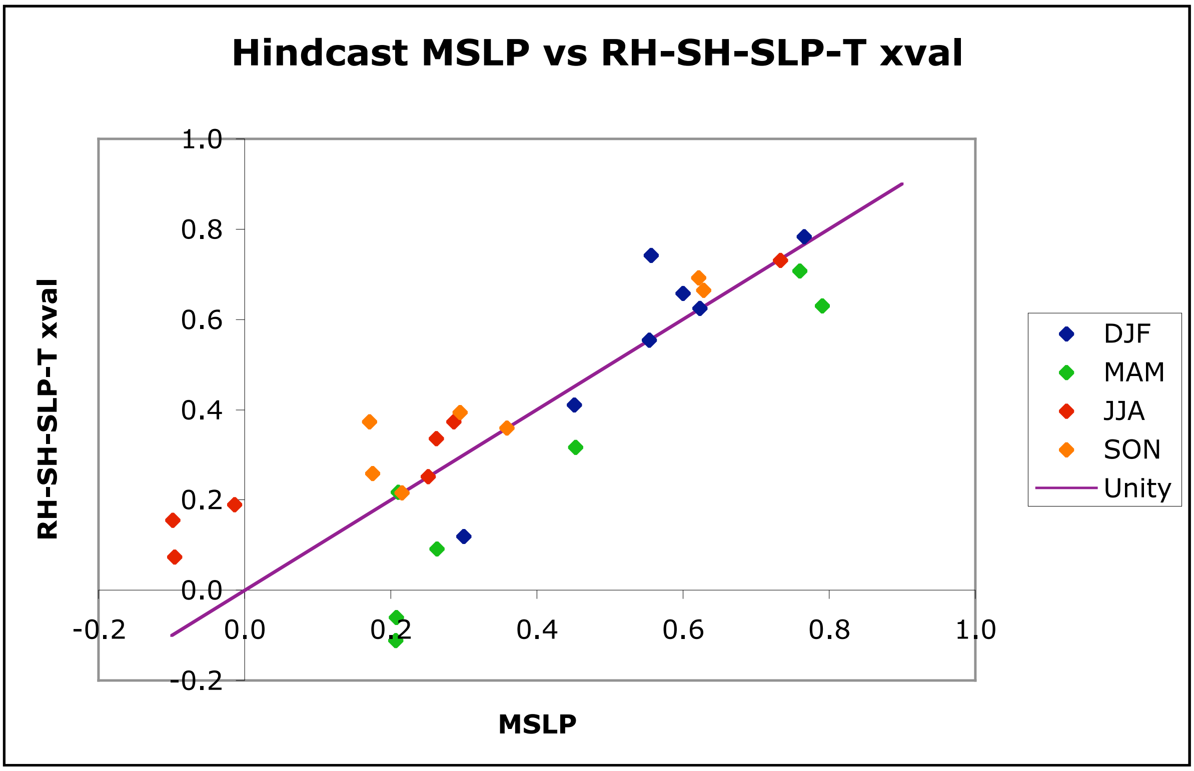

Figure 5: Comparison between MSLP and 4-predictor model for SE England. Points are the Spearman correlation for both models for each index and season.

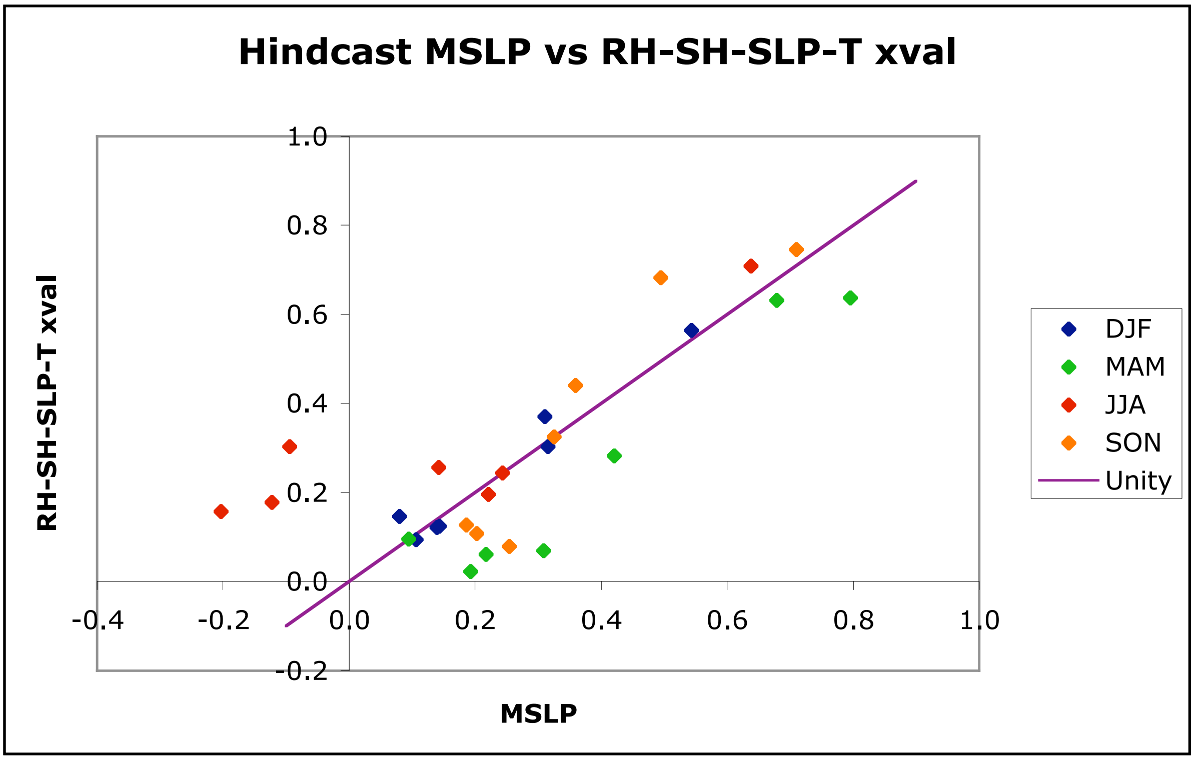

Figure 6: Comparison between MSLP and 4-predictor model for NW England. Points are the Spearman correlation for both models for each index and season.