Validation of Statistical Downscaling Methods in terms of weather and climate: Surface temperature in Southern Ontario and Quebec.

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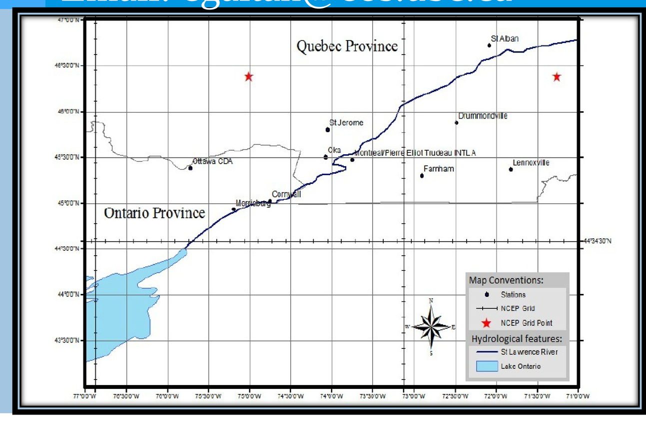
Overview

- Maximum and Minimum daily surface temperatures from 10 weather stations located in Southern Ontario and Quebec were obtained after statistically downscaling the NCEP/NCAR reanalysis (1961-2000).
- Stepwise Multiple Linear Regression and nonlinear Bayesian Neural Networks were used.
- Three different sets of predictors were tested.
- Comparisons were made not only in terms of daily variability "weather", but also in terms of 6 climate indices (STARDEX).
- The results show the nonlinear methods outperform the linear ones in terms of climate indices, and to a smaller extent in terms of daily variability.



Procedure

Predictors and Predictands

- 25 Predictors from each one of the closest four Reanalysis grid cells were available (Table 1).
- Observed Maximum (TMAX) and Minimum (TMIN) surface temperatures were obtained from the Environment Canada catalogue.

Predictor variables available for the CGCM 3.1 and the NCEP/NCAR Reanalysis

Mean sea level pressure	500hPa wind speed	850hPa wind speed
1000hPa wind speed	500hPa U component	850hPa U component
1000hPa U component	500hPa V component	850hPa V component
1000hPa V component	500hPa vorticity (Pa/s)	850hPa vorticity (Pa/s)
1000hPa vorticity (Pa/s)	500hPa geopotential	850hPa geopotential
1000hPa wind direction	500hPa wind direction	850hPa wind direction
1000hPa divergence (s^{-1})	500hPa divergence (s^{-1})	850hPa divergence (s^{-1})
1000hPa specific humidity	500hPa specific humidity	850hPa specific humidity
Temperature at 2m		

The STARDEX Climate Indices

The STARDEX indices were proposed by the European ENSEMBLES project.

From the observations and the SD series 6 temperature related climate indices were calculated (Table 2).

$$USI_{IOA} = (T10_{IOA} + T90_{IOA} + IATR_{IOA} + FD_{IOA} + GSL_{IOA} + HWDI_{IOA})/6 \quad (1)$$

A Unified STARDEX Index (USI) was created to represent the overall performance simulating the climate indices.

	Temperature Indices	Abbreviation
1	10th percentile of TMIN	T10
2	90th percentile of TMAX	T90
3	Intra-annual extreme temperature range (T90-T10)	IATR
4	Number of Frost days (TMIN < 0°C)	FD
5	Growing season length	GSL
6	Heat wave duration index (maximum period of consecutive days with TMAX exceeding T90)	HWDI

Validation

SD Methods and Models

Six different models (3 linear and 3 nonlinear) were used to SD daily values of TMAX and TMIN. (Table 3)

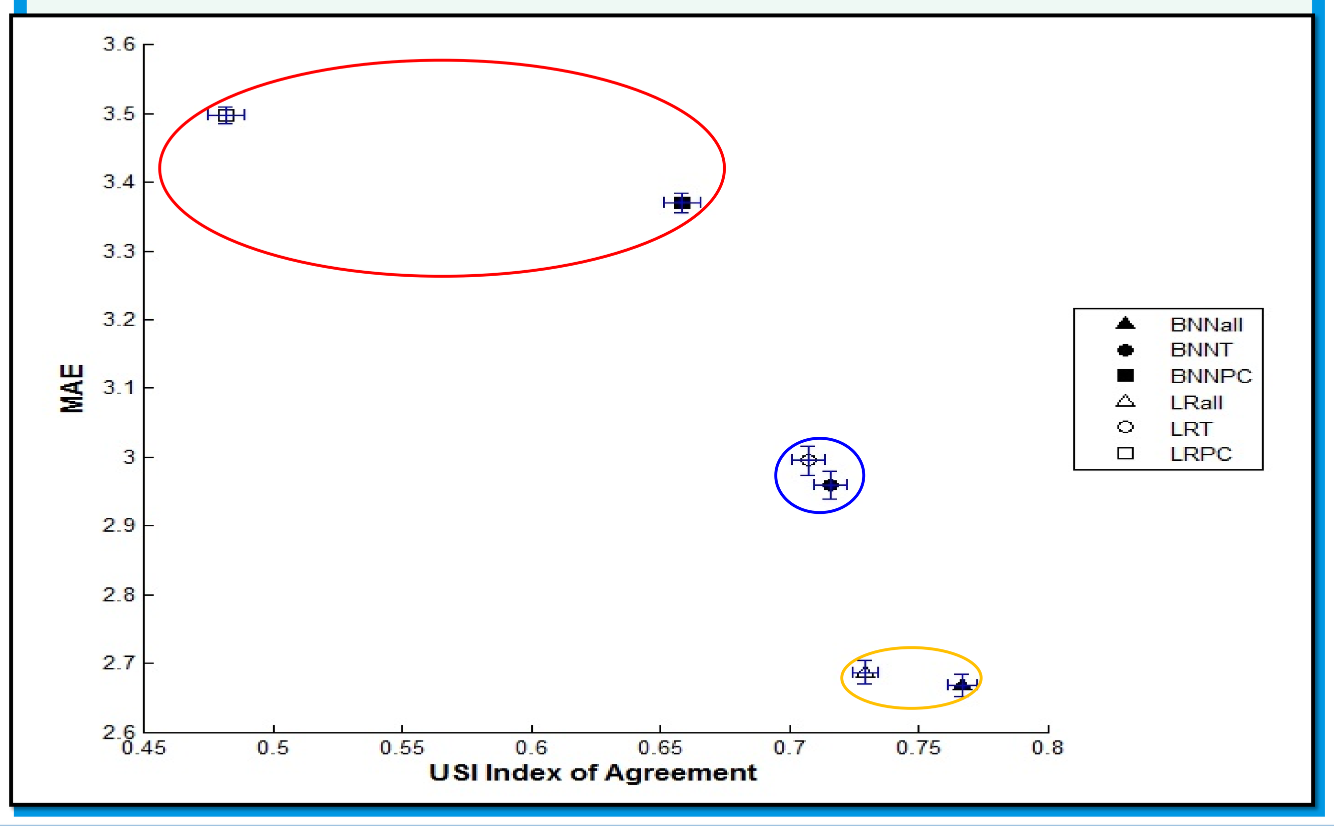
Model type	Regression method	Predictors used	Model ID
Linear	Stepwise MLR	SW selection from 100 NCEP/NCAR predictors	LRall
Linear	Stepwise MLR	21 leading PCs	LRPC
Linear	Stepwise MLR	SW selected from 4 NCEP/NCAR temperatures	LRT
Nonlinear	Bayesian Neural Networks	Same as in LRall	BNNall
Nonlinear	Bayesian Neural Networks	Same as in LRPC	BNNPC
Nonlinear	Bayesian Neural Networks	Same as in LRT	BNNT

The behaviour of the cross validated SD series simulating the STARDEX indices was compared with the observations' STARDEX indices using Willmott's Index of Agreement (IOA).

$$IOA = 1 - [\Sigma_i |f_i - g_i|^{\alpha}] \;/\; [\Sigma_i (|f_i - \bar{g}| + |g_i - \bar{g}|)^{\alpha}] \quad (2)$$

Figure 1 shows the multi-station average comparison results. The daily variability is shown in terms of TMEAN Mean Absolute Errors (MAE) in the ordinate, while the USI is represented in terms of IOA along the ordinate.

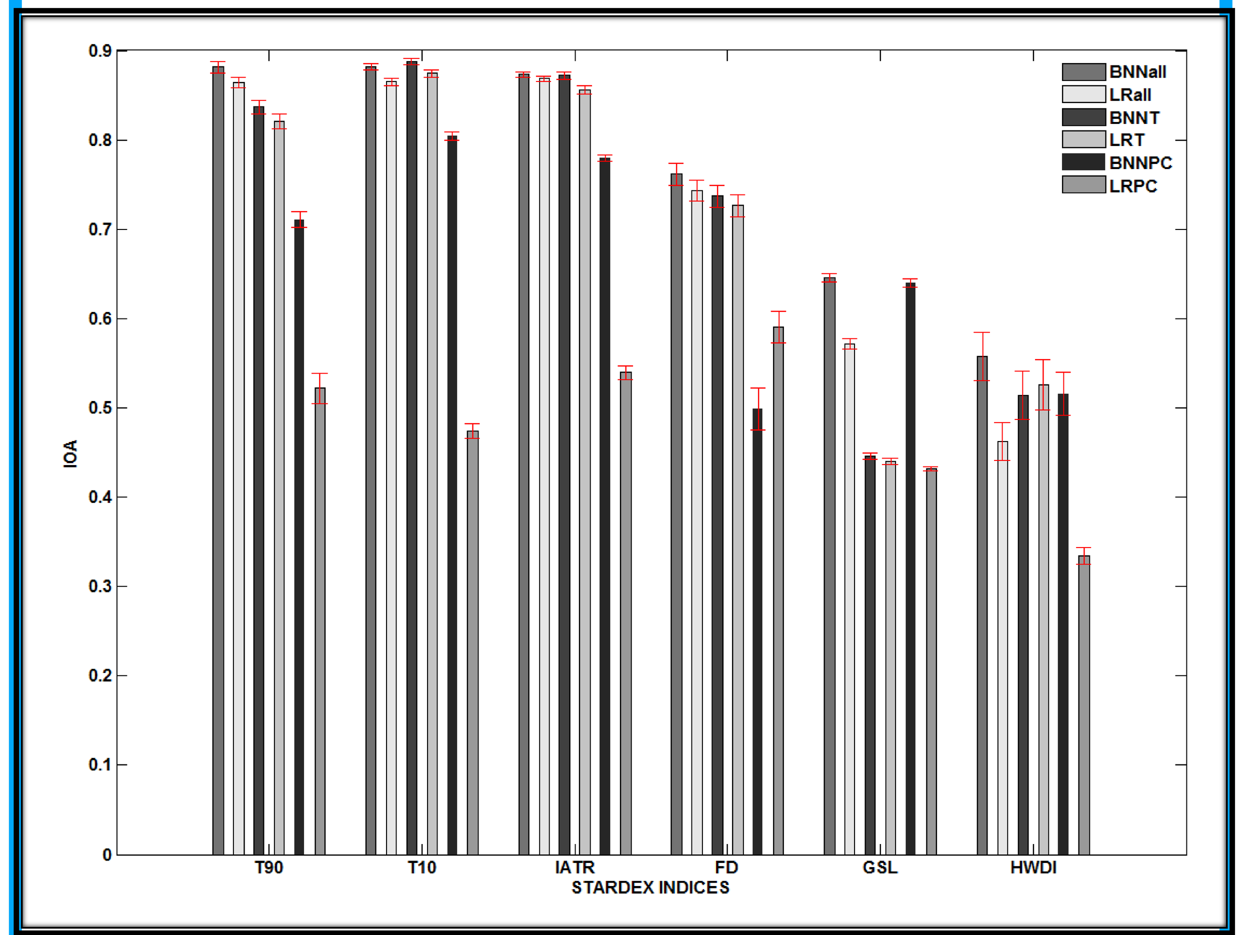
The figure shows 3 different clusters (red, blue, and orange) corresponding to the different predictors used. Each cluster has a linear and a nonlinear method.



Results

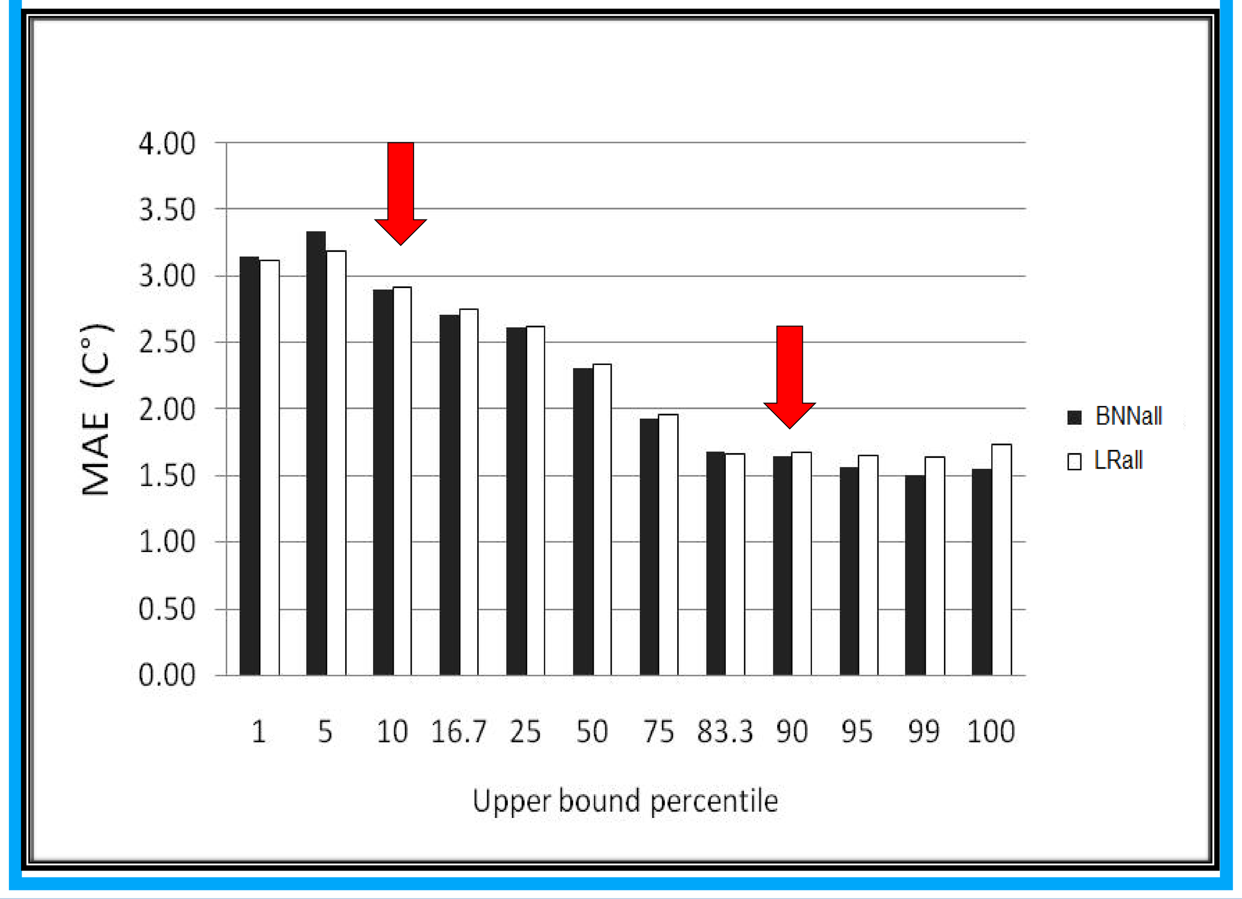
Overall, the nonlinear methods outperform the linear ones in terms of climate variability, and to a smaller extent in terms of "weather" simulation.

A closest look to the STARDEX climate indices simulation (Figure 2) shows the superiority of BNNall when simulating most of the indices. Error bars correspond to the standard errors.



To partially explain these differences between the linear and nonlinear models, different percentiles of BNNall and LRall were compared in terms of MAEs.

The results show (Figure 3) that the linear model errors were bigger for the first and last deciles. These deciles are the ones being predominantly used for calculating the STARDEX indices.



Conclusions

- **The results show the nonlinear methods outperform the linear ones in terms of climate indices, and to a smaller extent in terms of daily variability.**
- **The linear model errors were bigger for the first and last deciles, partially explaining their lack of skill simulating the climate indices.**
- **The predictor selection proved to be a key element in SD.**
- **The nonlinear Bayesian Neural Network model proved to be the best one. It has the highest IOA and the lowest MAE, when compared to the others.**