Testing convolutional neural networks as a downscaling tool over southern South America in a climate change scenario: the case of daily extreme temperatures

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Objetive

Evaluate the potential of Convolutional Neural Networks (CNNs) as a statistical downscaling tool for the generation of climate projections of daily maximum and minimum temperatures (Tmax, Tmin) in different climatic regions of southern South America (SSA).

ESD methods

CNNs recently applied in Bano-Medina et al. 2022 over Europe:

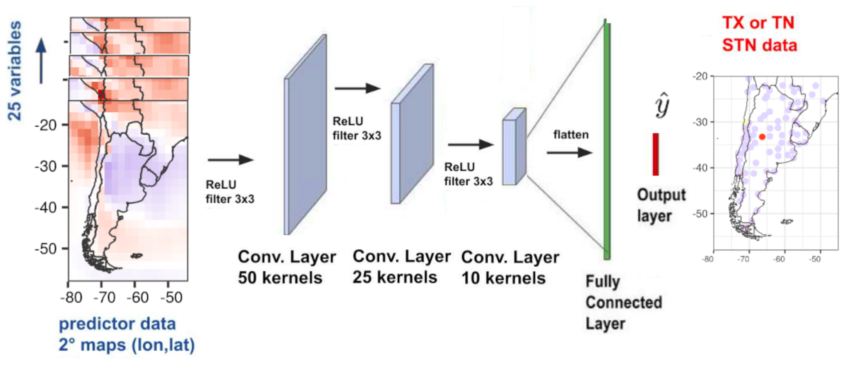

Fig.2 CNNs scheme.

- 3 convolutional layers of 50, 25 and 10 filter maps.
- Kernel size of 3 × 3.
- Linear (**CNN-L**) and non-linear activation (ReLU) functions (**CNN-R**).

GLMs were used as a benchmark method considering: 1 (**GLM1**), 4 (**GLM4**) and 16 (**GLM16**) nearest grid cells of the predictors' dataset to the target station point.

Experiments

1. Cross-validation: ESD models were calibrated and validated in the total observational period following the VALUE Experiment protocol (Maraun et al. 2015).
2. **Application to EC-Earth** under Perfect Prognosis (PP) conditions
3. **Pseudo-reality experiment:** CNNs were calibrated using GCM outputs as pseudo-observations for both predictors and predictands. CNN models were trained in the historical period and then applied to the RCP85 future scenario.

Application to EC-Earth: *historical scenario*

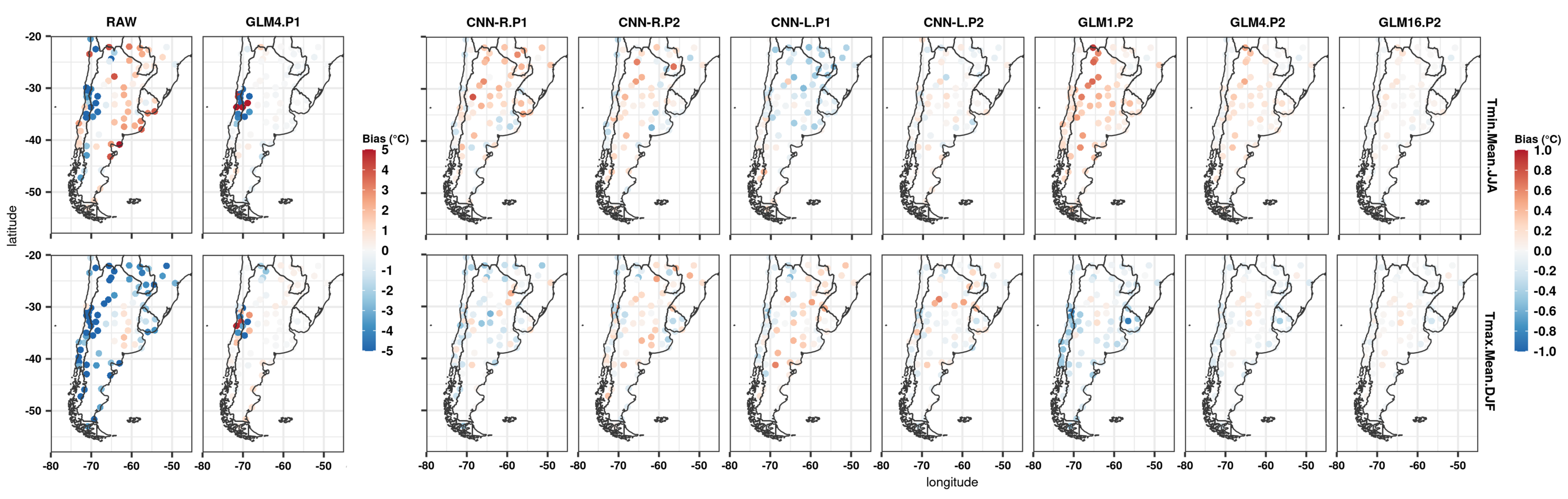

Fig.3 Bias of the historical period (1979–2005) between the observations (reference) and: EC-Earth raw data (RAW) and the different ESD models.

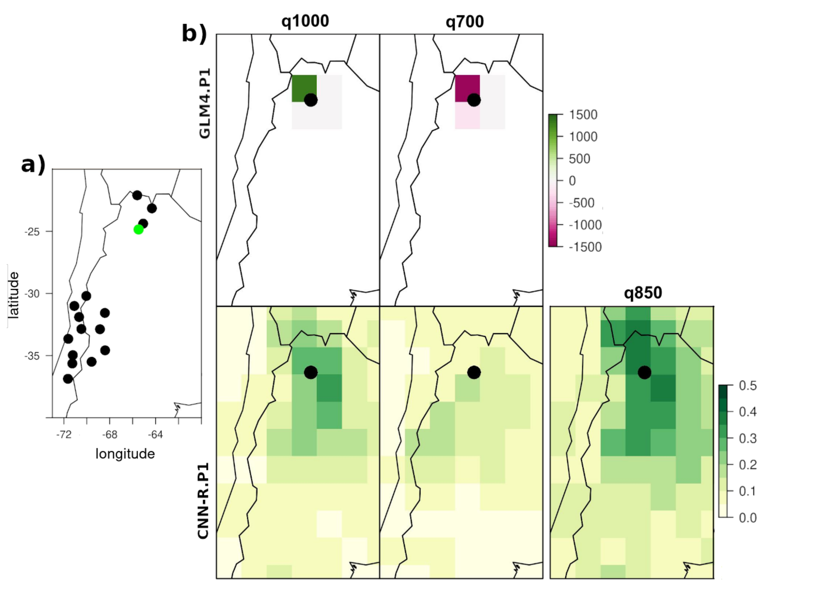

Fig.4 a) Meteorological stations where GLM models exhibited co-linearity issues (dots). b) For Salta station (green dot): GLM4.P1 coefficients for hus.700 and hus.1000; (row 2) Saliency maps of hus.700 and hus.1000 for CNN-R.P1.

A saliency map is a spatial representation of the contribution of predictor variables played in the output (downscaled Tmax/Tmin) quantified in terms of gradients (of the output with respect to the input).

- Generally, cold (warm) biases were observed in CNN-R.P1 model for maximum (minimum) temperatures during winter (summer) along the SSA. The lowest temperatures presented larger errors than for the warmest ones, mostly over central and northern SSA (AR and SESA).
- GLMs when applied to the EC-Earth predictors were not able to simulate the temperature values over the high altitude areas, reaching similar biases to the RAW data. This behaviour may be due to the presence of co-linearity in the regression model when considering the hus predictor variables in the stations near the Andes.
- *The CNN models with the same predictor set outperformed the GLM models and were capable of selecting the informative predictors (Fig.4)*

Finally a subset of P1 predictor variables only considering hus.850(P2) was used as input to the GLMs (GLM1.P2, GLM4.P2, GLM16.P2) which considerably reduce GLMs biases.

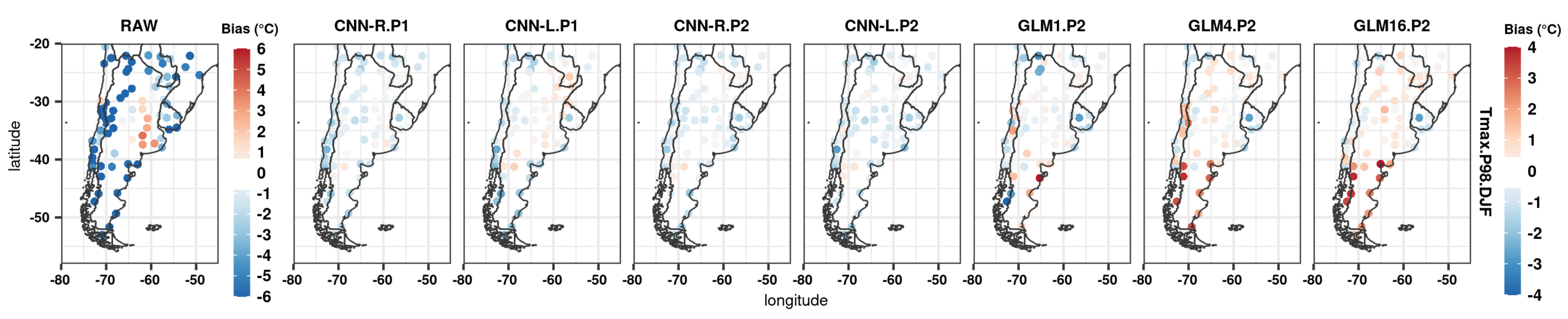

Fig.5 Same as Fig.3 for summer (DJF) 98th percentile.

Data and study region

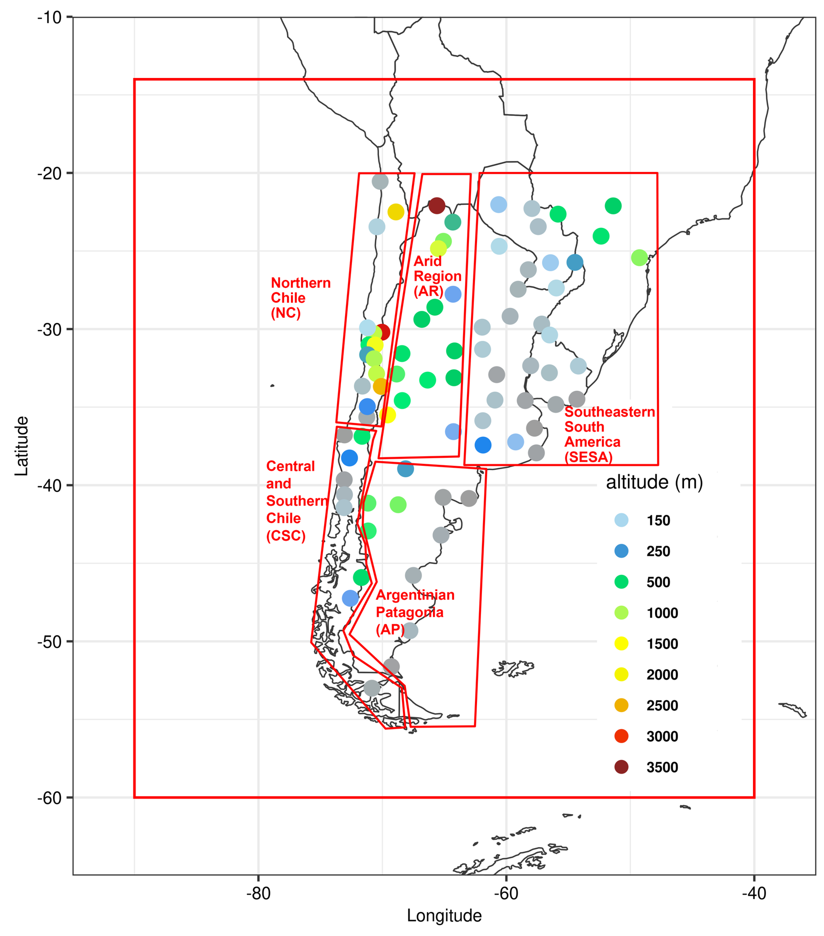

Fig.1 Meteorological stations used over SSA coloured by altitude and regionalised. The red box indicated the domain considered for the predictor sets

Predictands: observational data

Tmax and Tmin from 80 stations over SSA during the period 1979–2008.

Preditors: reanalysis and GCMs

P1: Daily fields of geopotential height (z), air temperature (ta), meridional and zonal wind (va and ua) and specific humidity at five different pressure levels 250,500,700,850 and 1000 hPa in the red box (Fig. 1).

- **ERA-Interim (ERA)** during 1979–2008.
- **EC-Earth** model simulations (r12i1p1, 1.12°) from CMIP5 in the historical and RCP8.5 future scenarios, considering 1979–2005 (historical) and 2071–2100 (far future) periods. Also Tmax and Tmin raw EC-Earth model outputs.

Application to EC-Earth: *future projections* and pseudo-reality

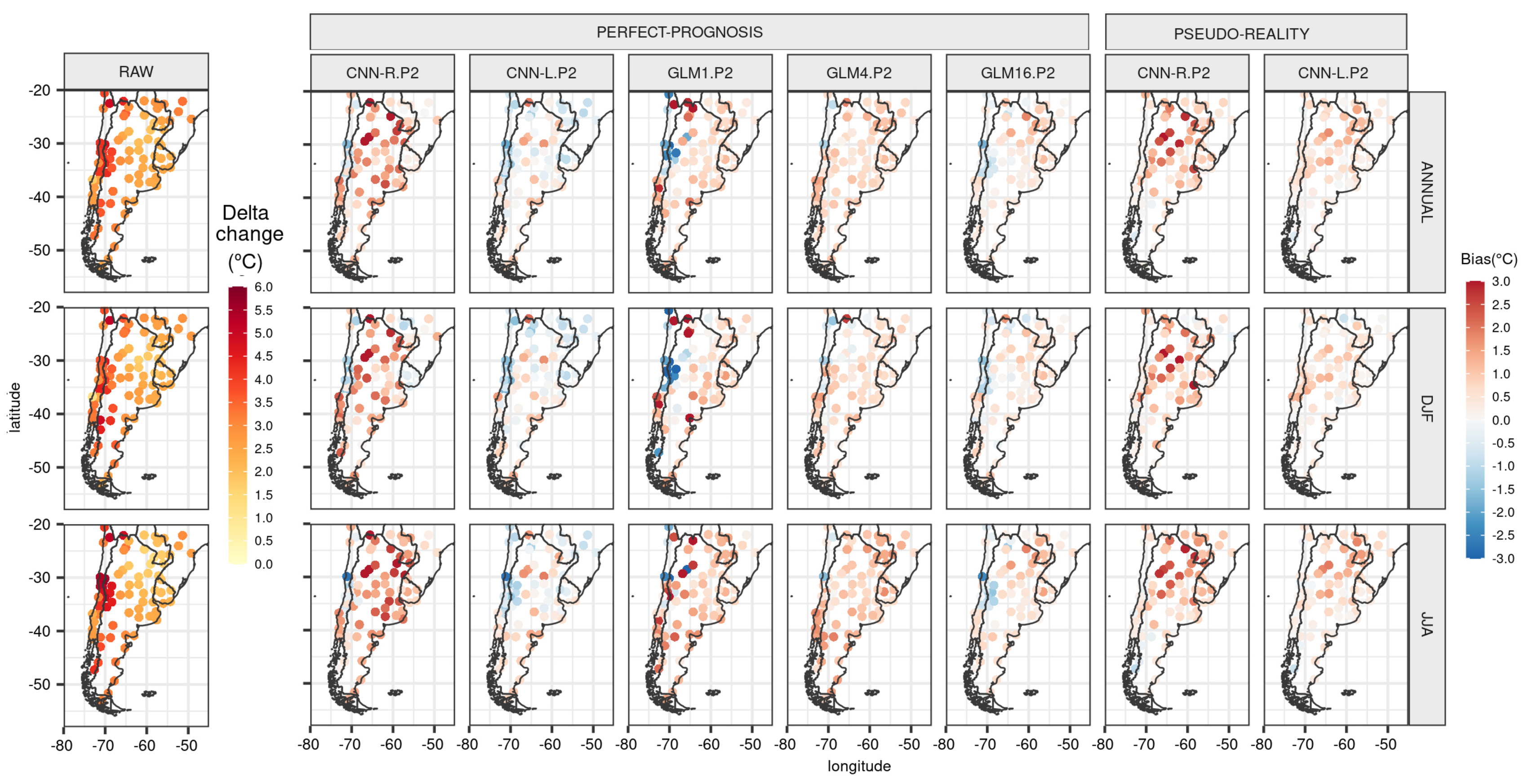

Fig.6 For Tmax: Delta change projected by RAW data for the late future (2071–2100) w.r.t the historical period (1979–2005), considering the RCP8.5 scenario; (c 2–6) differences between the delta changes of the ESD models and delta changes of RAW under the PP approach; (c 7–8) differences between the delta changes of CNN-R.P2 and CNN-L.P2 and delta changes of RAW in the pseudo-reality experiment.

- **PP conditions:** CNN showed good skills to produce plausible projections, however, differences with RAW and GLM in the intensity of the signal were identified when non-linearity was considered (CNN-R). When compared to RAW, CNN-R exhibited an exacerbated signal of warming, more noticeable in central SSA. CNN-L, instead, showed minor variations with respect to both the RAW and GLM signals.
- **Pseudo-reality:** CNN generally presented good skills to reproduce EC-Earth future Tmax and Tmin (pseudo-observations), although higher Tmax values were systematically predicted by the CNN-R models in central SSA. Whereas CNN-L presented a better performance in the future and stood close to the pseudo-observational values. This was a characteristic of Tmax not observed in Tmin, for which the sensitivity to the activation function did not seem to affect the model extrapolation skills (not shown here).

The evaluation of any ESD model must consider not only performance under perfect conditions, but also its applicability to GCMs.

Conclusions

Our results highlight the importance of including CNNs into the battery of downscaling techniques over SSA. This study moves forward in the statistical downscaling field over SSA, presenting a novel tool that has not been evaluated in the region up to now and providing some guidelines on their design for extreme temperature modelling.

Complete result and discussions:

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References

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