Statistical post-processing and generation of spatially correlated precipitation forecasts with convolutional neural networks

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1. Problem Description

NWP models provide valuable forecasts, but they often exhibit *systematic biases.*

Statistical post-processing is used to remove these biases and improve accuracy of NWP forecasts. It is done on *grid-cell to grid-cell* and *lead time by lead time* basis. However, this results in the loss of spatial correlation within the forecasts.

Ensemble forecasts are used to quantify forecast uncertainty.

Rank ordering methods are used to connect ensemble members and embed spatial correlation.

Rank ordering methods use templates based on archived forecast or observations. These templates have tied ranks because of zero values.

2. Motivation

State-of-the-art methods either rely on the rank ordering methods or use models tuned to specific range of values.

Also, Machine learning based ensemble forecasts usually lack skill and have poor uncertainty estimation.

The **goal** of the study is to use raw deterministic forecasts for generating ensemble forecasts with in-built spatial structures, without relying on rank ordering methods.

3. Methods

Input: Gridded NWP deterministic raw forecasts
Output: Gridded calibrated ensemble forecasts

- **Convolutional Neural Network (CNN)** [1] is used
  - for in-built spatial structures, and
  - processing the whole precipitation field simultaneously
- Monte-Carlo (**MC**) **dropouts** [2] are used for improved uncertainty estimation

4. Application to Precipitation Data

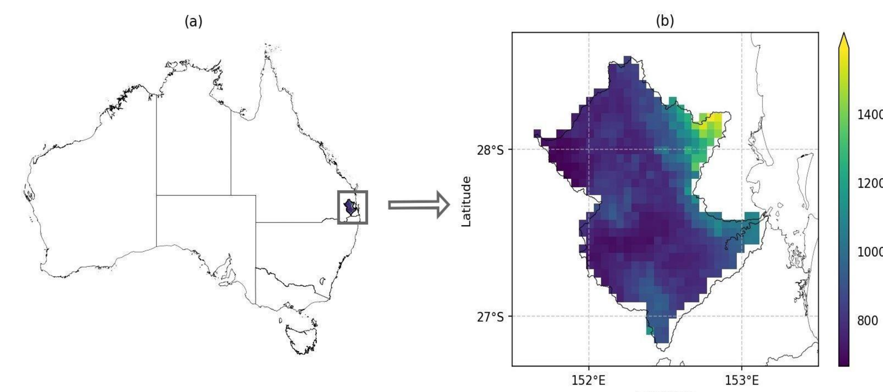

Fig. 1

- **Region:** Brisbane Drainage Basin, Australia (Fig. 1)
- **Data:** 3 years NWP (ACCESS-G3) raw forecasts & observation precipitation data
- **Lead Time:** 1 day
- **Period:** 2019-2021
- **Climatology:** 30 years long observations (AWAP dataset)

6. Conclusions

The method generates forecasts with in-built spatial structures, eliminating the need for reordering methods.

The generated ensembles are skilful, and have improved uncertainty estimation.

The method gives better results on both grid-cell and basin levels when compared to state-of-the-art methods [3].

Key references:
[1] Veldkamp et al., 2021: Statistical Postprocessing of Wind Speed Forecasts Using Convolutional Neural Networks. https://doi.org/10.1175/MWR-D-20-0219.1
[2] Gal et al, 2016: Dropout as a Bayesian Approximation. PMLR 48:1050-1059
[3] Zhao et al., 2022: Spatial mode-based calibration (SMoC) of forecast precipitation fields from numerical weather prediction models. https://doi.org/10.1016/j.jhydrol.2022.128432

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Abstract QR Code

5. Results

Fig. 3 and Fig. 4 for substantive precipitation events. Threshold for substantive events is **5.47** mm/day.

For the 3-year mean (Fig. 2), the calibrated forecast exhibits spatial correlations similar to those of observation.

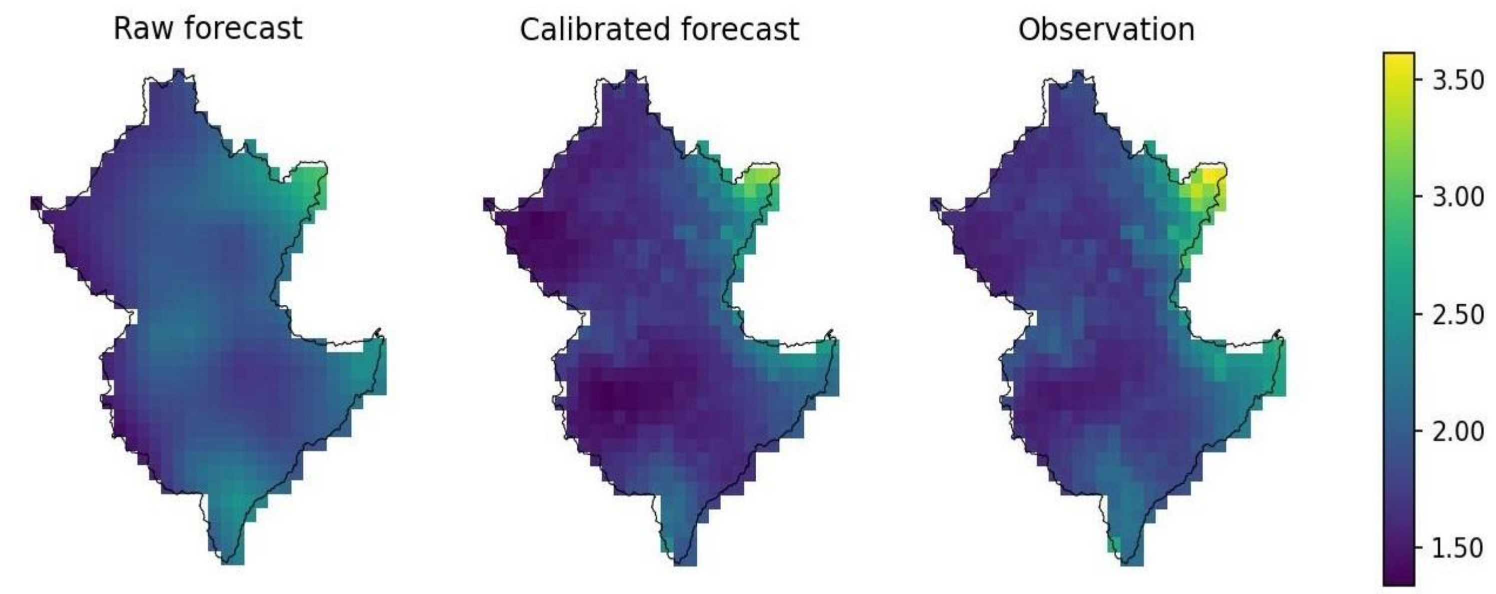

Fig. 2 3-year mean comparison of raw, calibrated and observation

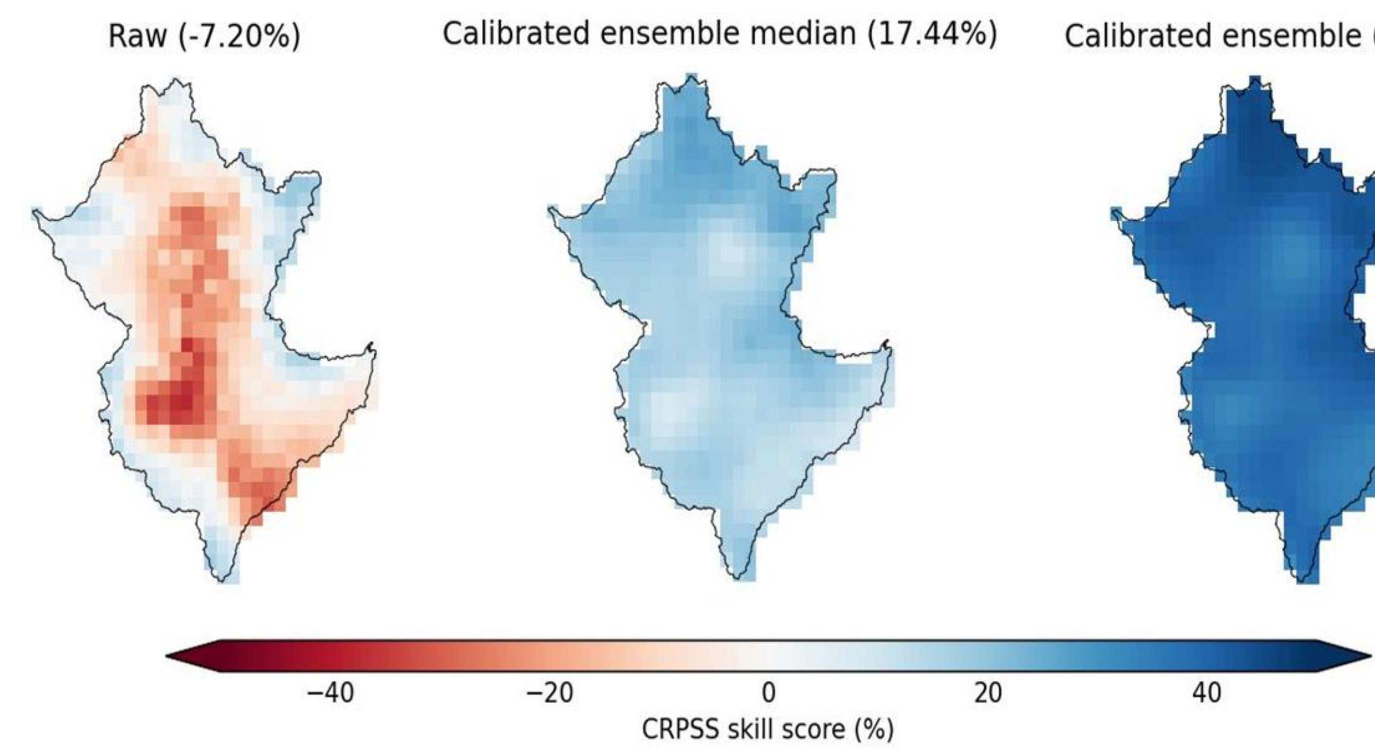

Fig. 3 CRPSS comparison of raw, calibrated ensemble median and calibrated ensemble with climatology

Climatology is compared to raw forecast, calibrated ensemble mean, and calibrated ensemble using the CRPS.

A positive CRPS skill score indicates that the forecasts are more skillful than reference climatology forecasts.

The significant improvement (≈40%) illustrates improved uncertainty estimation of ensemble forecast at grid-cell level.

Fig. 4 demonstrates:

- Calibrated ensemble median (●) aligns closely with observation (●), **outperforming** raw forecast (○).
- 50% and 90% ensemble intervals provide **insightful uncertainty estimates**.

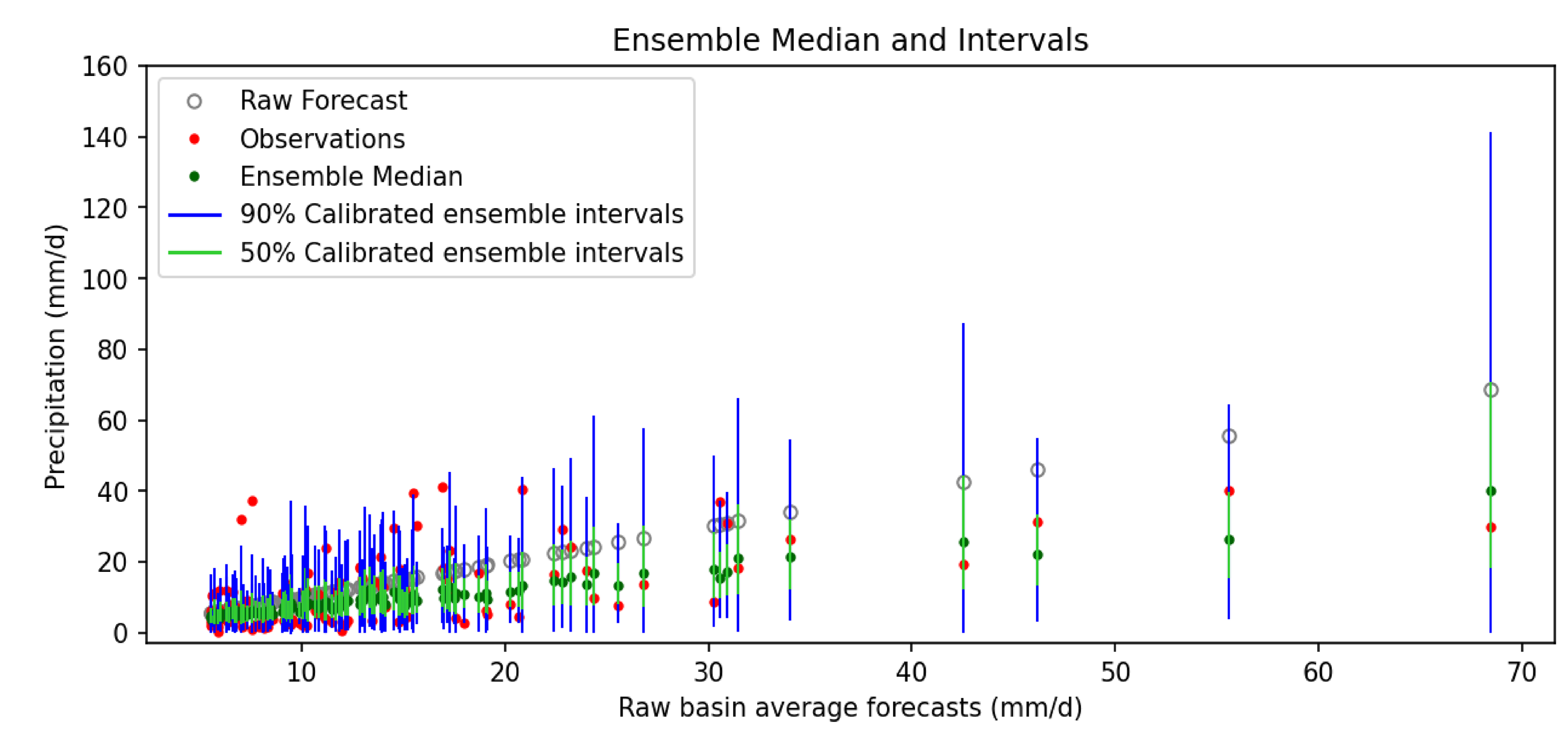

Fig. 4 Calibrated ensemble forecasts' intervals and medians with raw forecasts and observations