

Convolutional neural networks for local climate downscaling: precipitation extremes in the FPS in Southeastern South America

Maria L. Bettolli¹, Rocío Balmaceda-Huarte¹, Jorge Baño-Medina², Matías Olmo¹, José
M. Gutiérrez²

1University of Buenos Aires-CONICET, Buenos Aires, Argentina

2Instituto de Física de Cantabria (IFCA), CSIC-Universidad de Cantabria, Santander, Spain



FPS-SESA: Phase 2

- FPS-SESA: Extreme precipitation events in Southeastern South America: a proposal for a better understanding and modeling

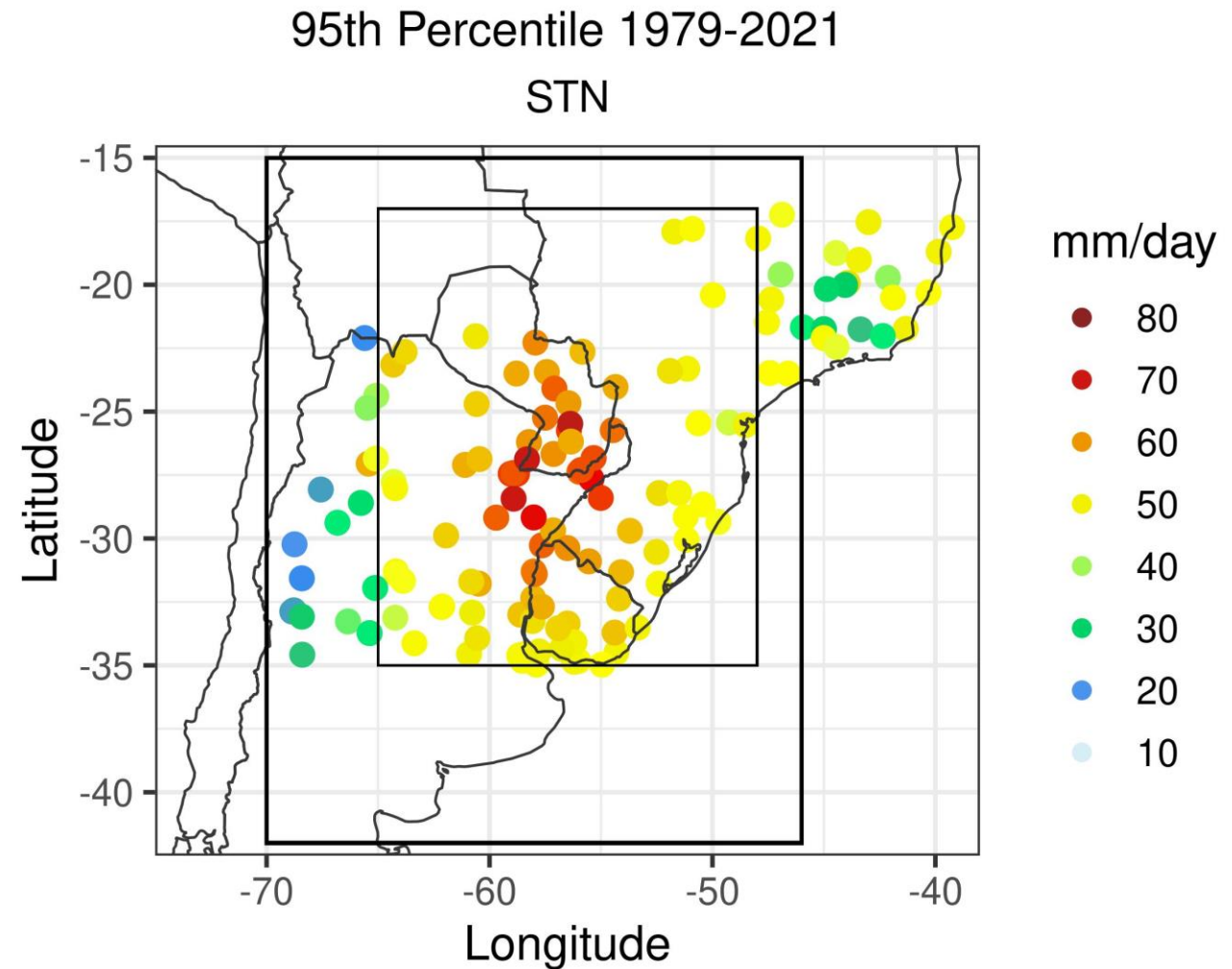
- **Phase I:** CPM & ESD simulations in the **2009-2010 warm season** (Oct-Mar) over SESA
- **Phase II:** 3 consecutive years of CPM simulations and **ESD based on deep learning** covering the period **June 2018 to May 2021** in an extended domain.

Objective

- Analyze the ability of convolutional neural networks (CNN) downscaling models in simulating daily precipitation in SESA with special focus on extremes.

Data & Methods

- **Perfect Prognosis Approach**
- **Predictand:** daily precipitation at Station point (STN) (inner square only)
- **Daily precipitation data from ERA5 and CPC (0.5°)** were also analyzed as reference.



Data & Methods

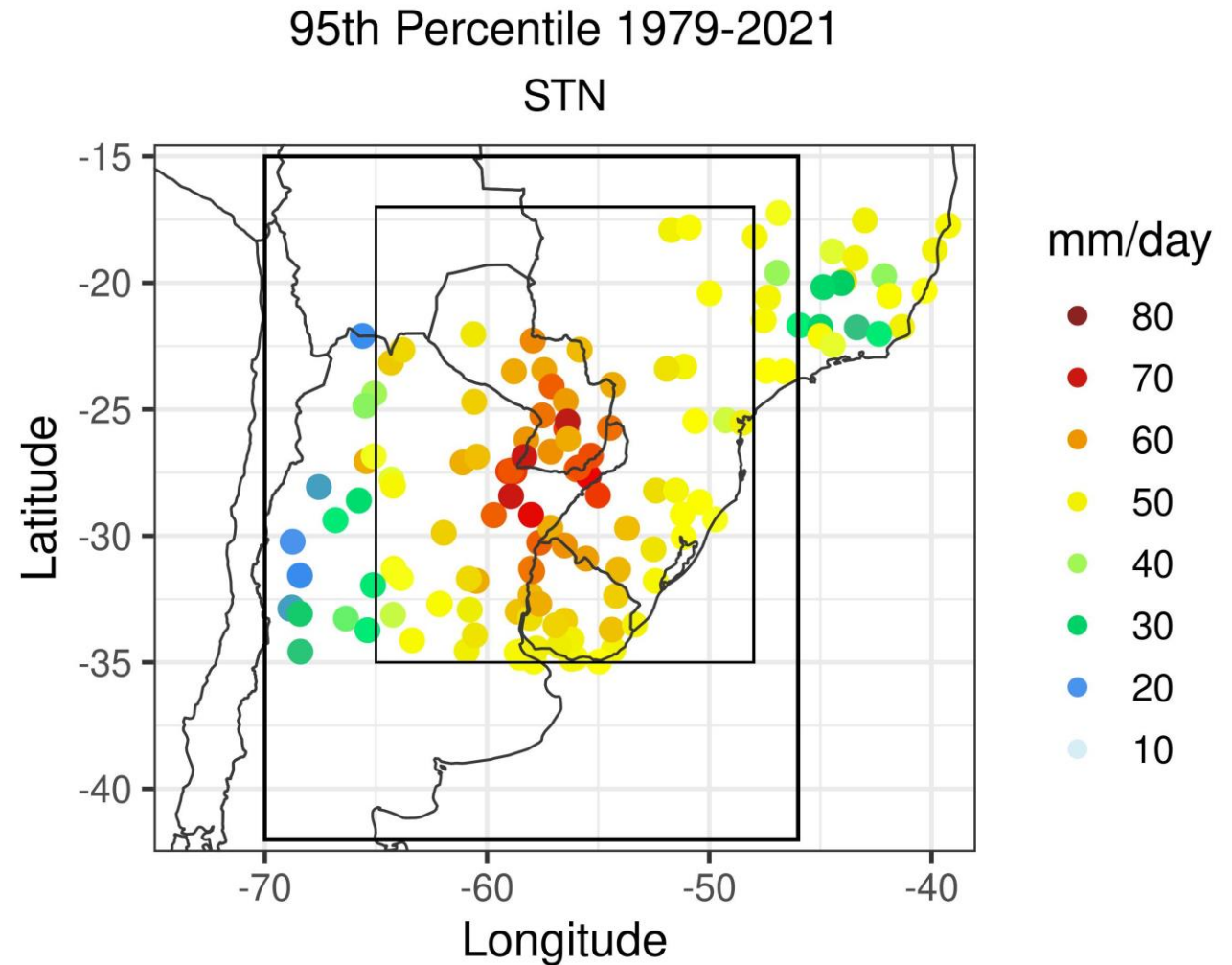
- **Predictors:** ERA5 reanalysis (1.5° resolution)

u & v 850

z 1000 & z 500

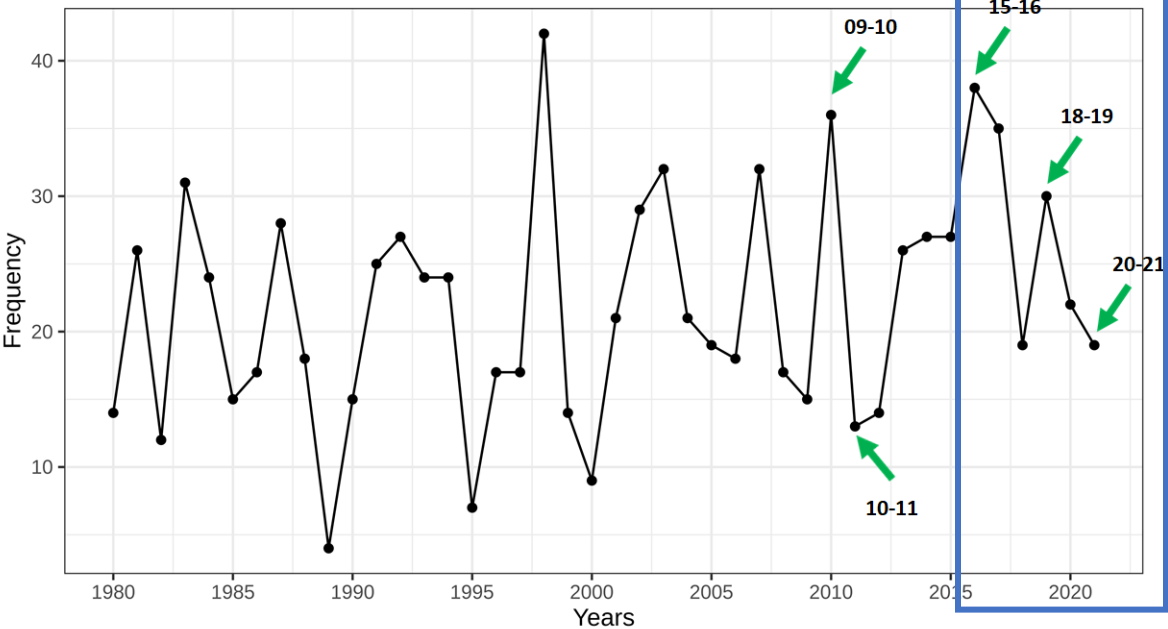
T 1000, 850, & 700

q 1000, 850, & 700



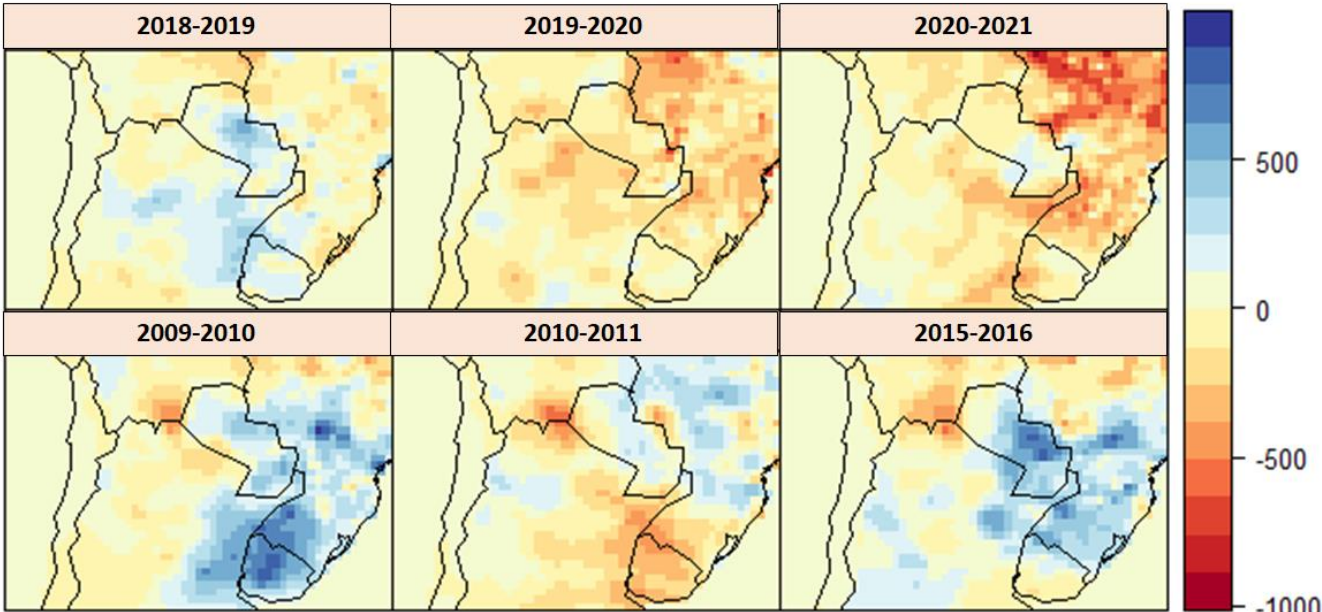
Data & Methods

CPC Extreme rainfall events (Warm Seasons 1979-2021)



Training and validation period (cross-validation): 1979-2014
Independent testing period: 2015-2021

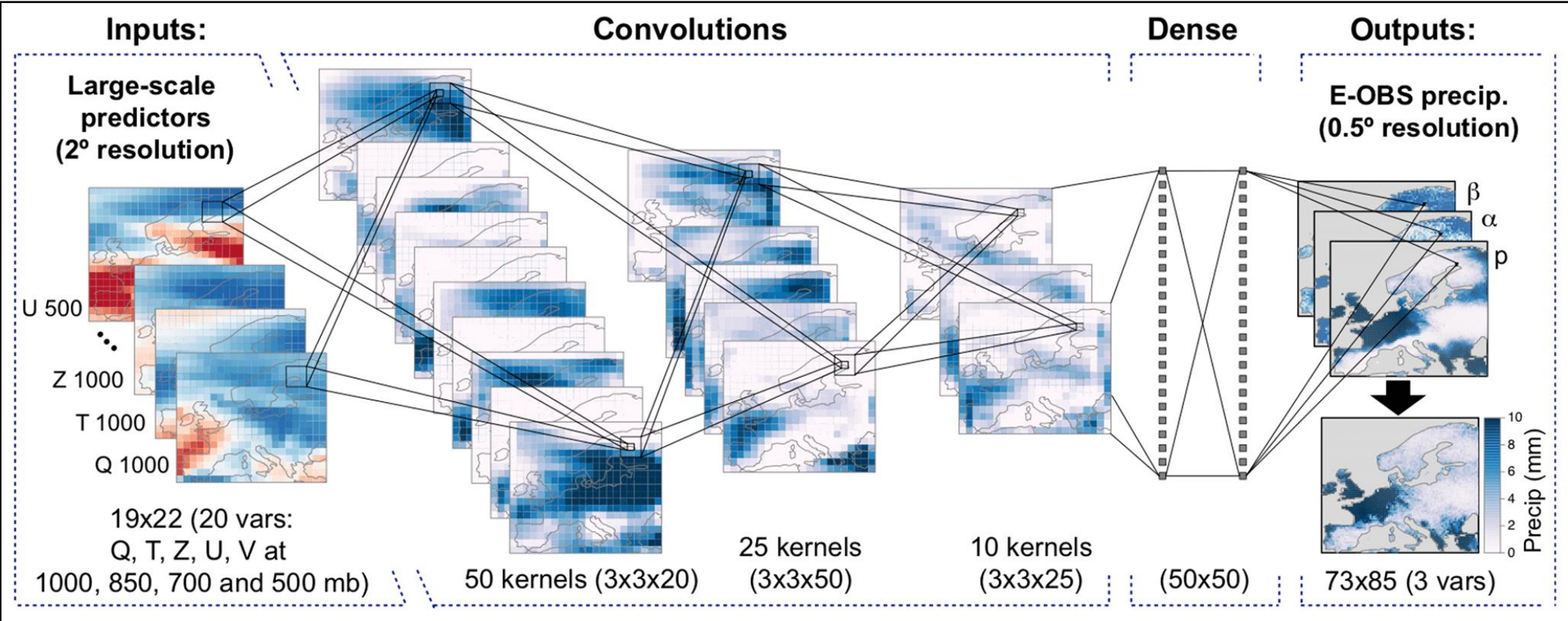
Seasonal Precipitation Anomalies CPC : Warm Season (OCT-MAR)



Data & Methods

CNN Models:

- We used the CNN architecture tested in Europe and Southern South America
- The CNN model architecture consisted of **three convolutional layers of 50, 25 and 10 filter maps**, each one with a **kernel size of 3x3**.

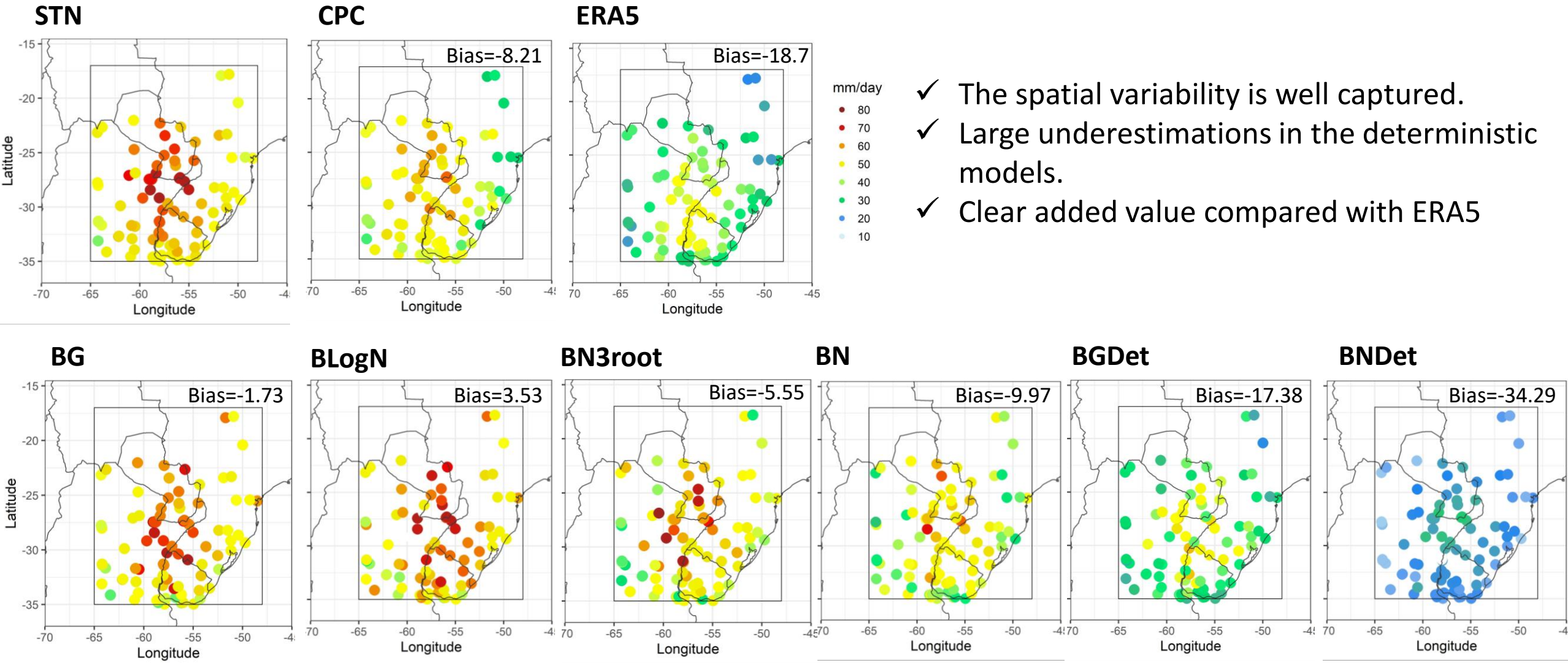


Data & Methods

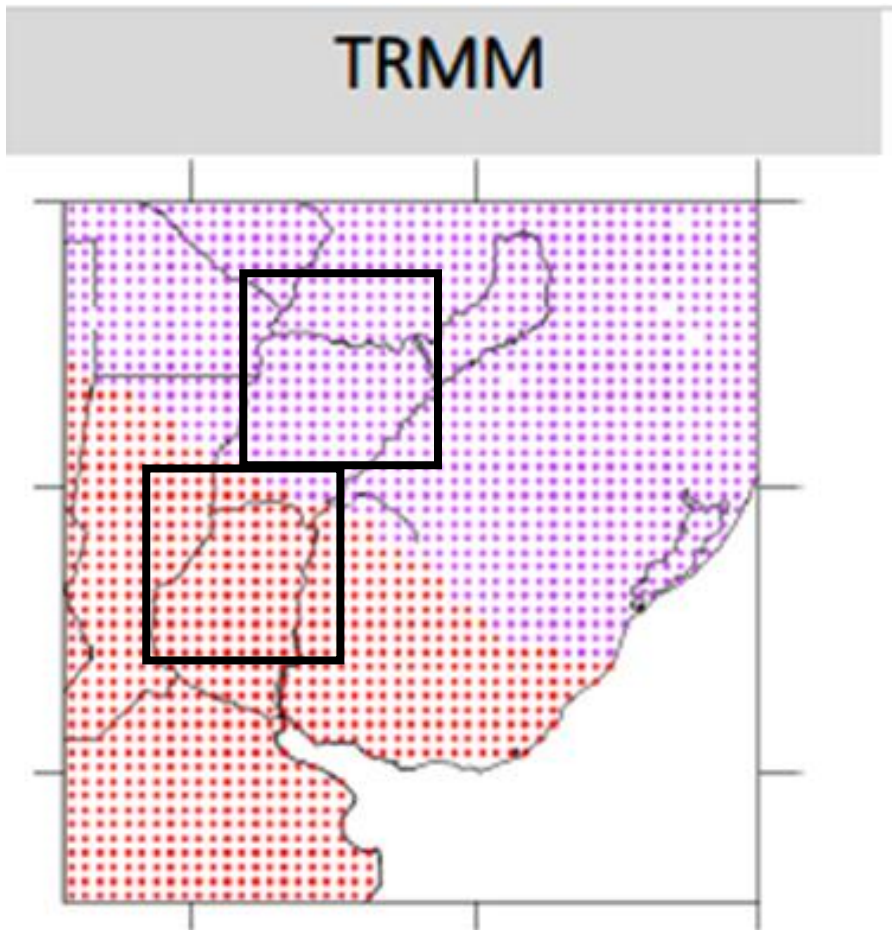
Loss Functions: Different loss functions were tested, and the corresponding parameters were estimated by the network, obtaining precipitation as a final product, either **stochastically** (generating a random value from the predicted distribution) or **deterministically** (the expected value).

- Bernoulli-Gamma (BG)
- Bernoulli-LogNormal (BLogN)
- Bernoulli-Normal3root (BN3root)
- Bernoulli-Normal (BN)
- Bernoulli-GammaDet
- Bernoulli-NormalDet

95th Percentile



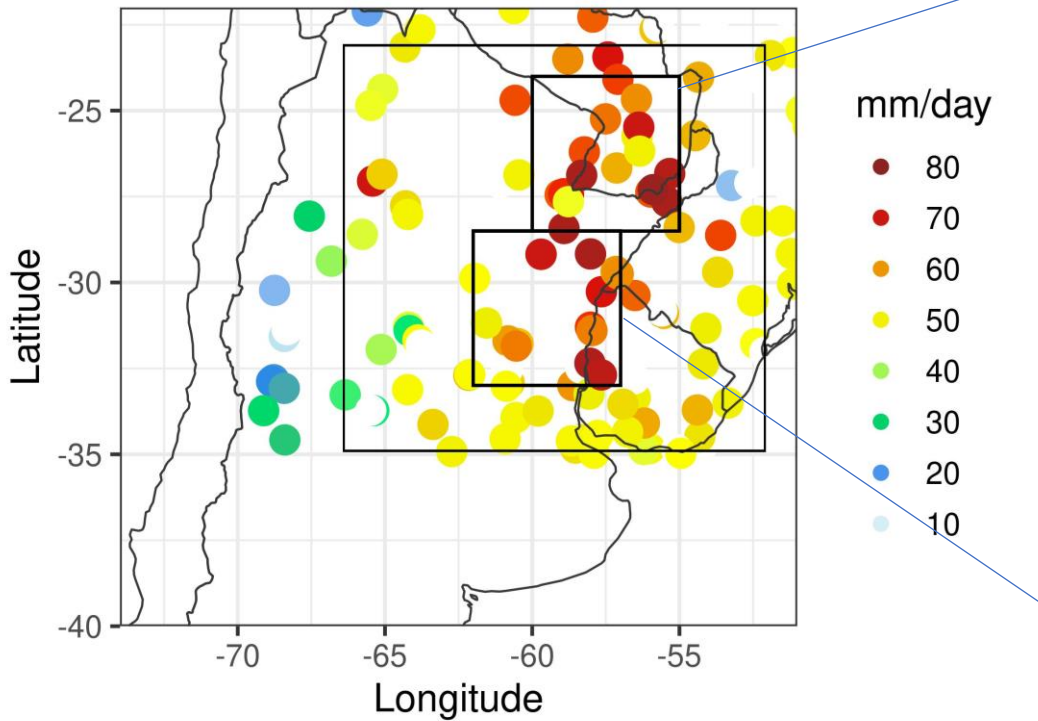
Location of extremes & Interannual Variability



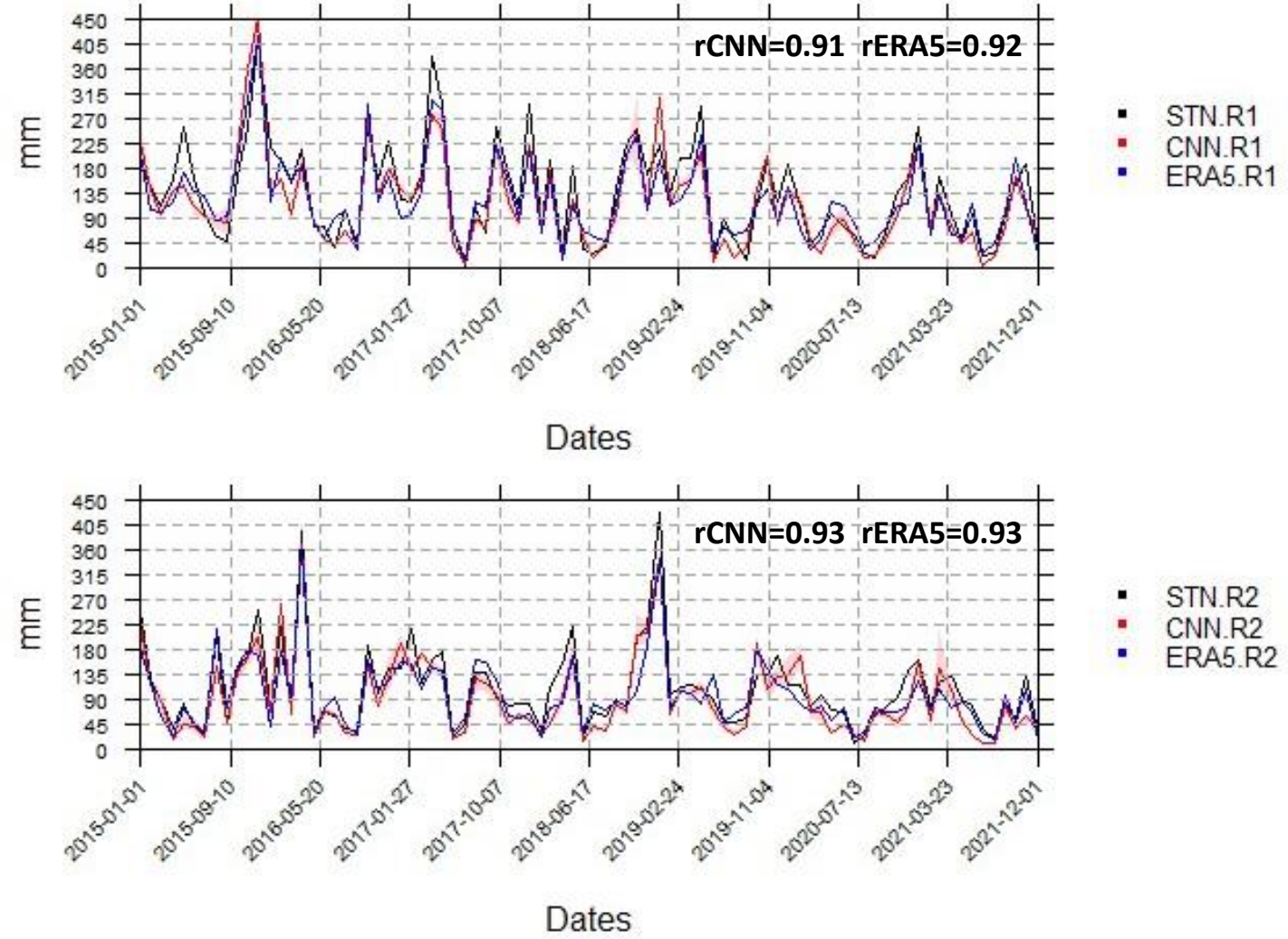
2000-2015 Climatology

- ✓ Regionalization of the joint occurrence of precipitation extremes.
- ✓ Extremes in SESA tend to occur in localized areas related with the dominant synoptic environment.

Location of extremes & Interannual Variability



Monthly Precipitation

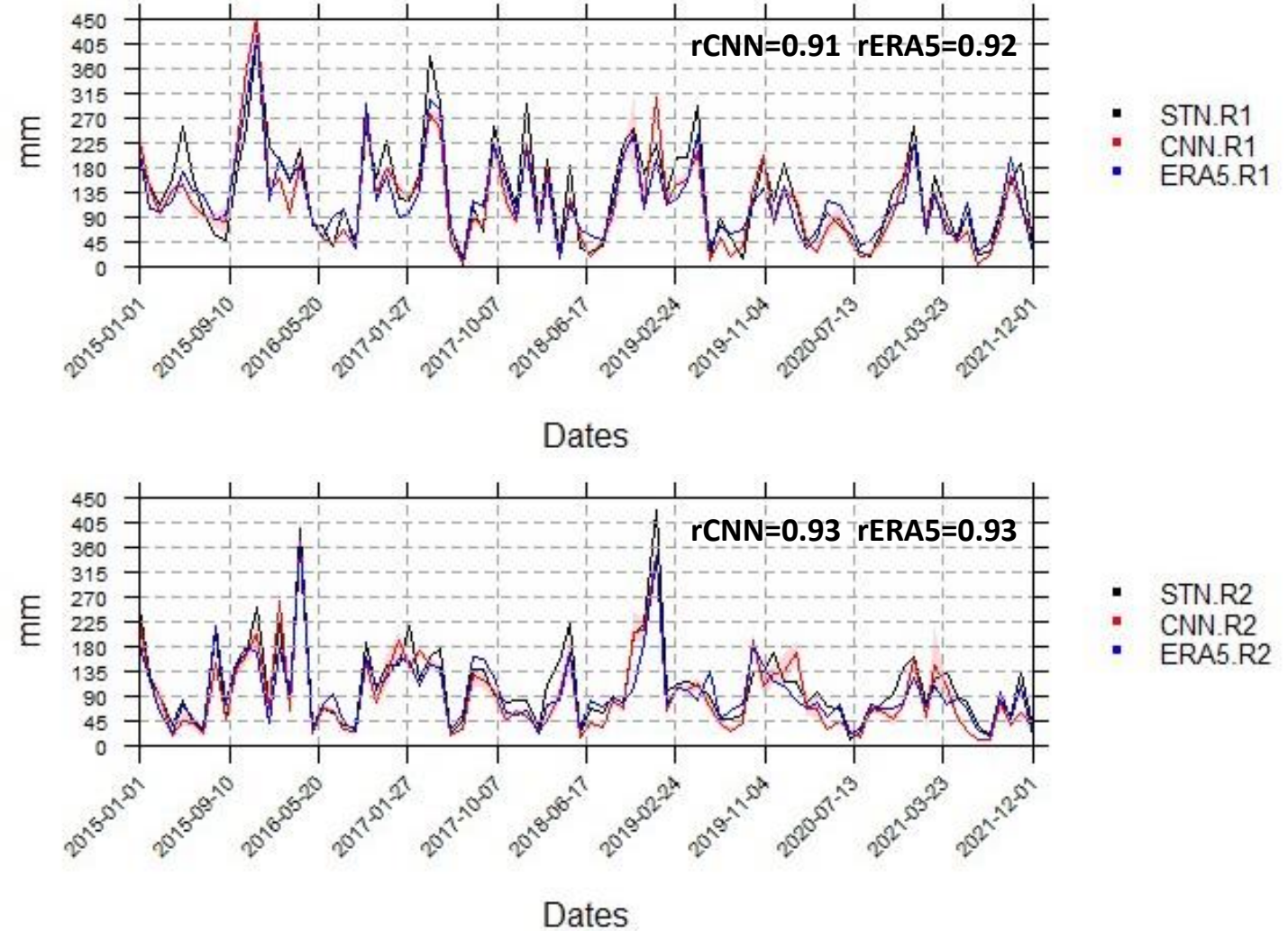
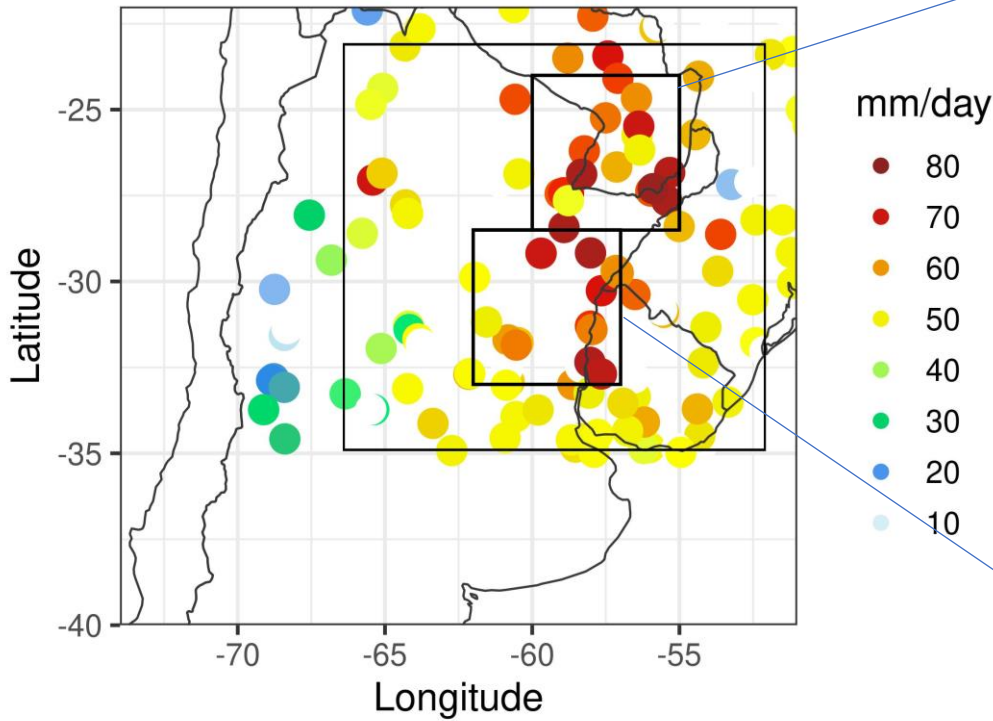


CNN Ensemble of Stochastic Models Only (except BN)

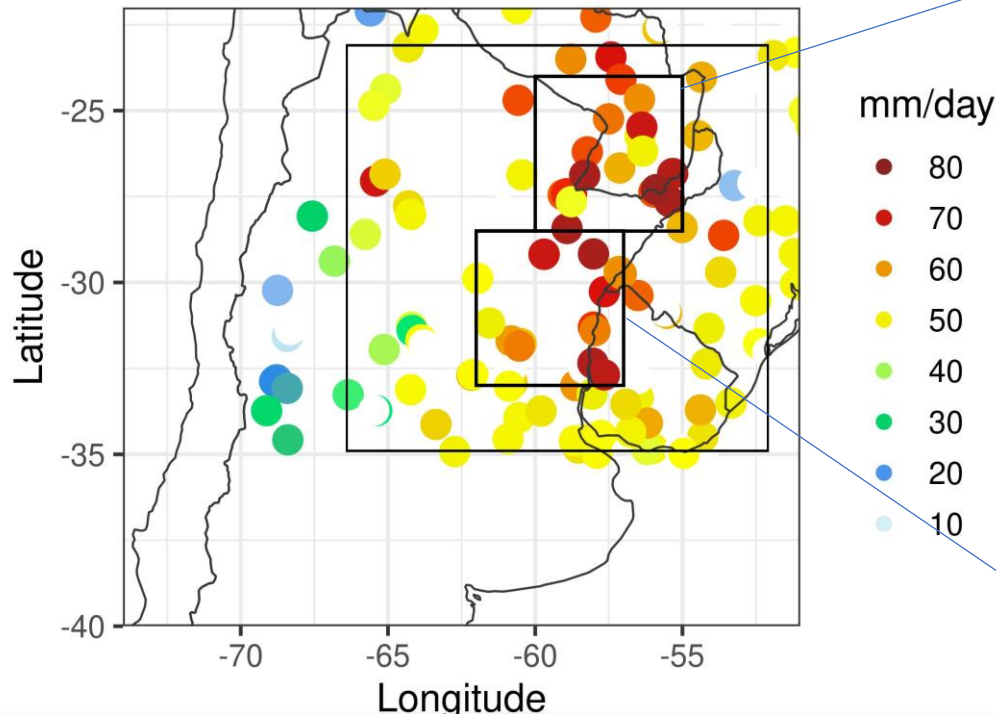
- ✓ The distinctive behavior of the two subregions is very well captured.
- ✓ The interannual variability is also captured.
- ✓ Good performance in dryer years

Interannual Variability

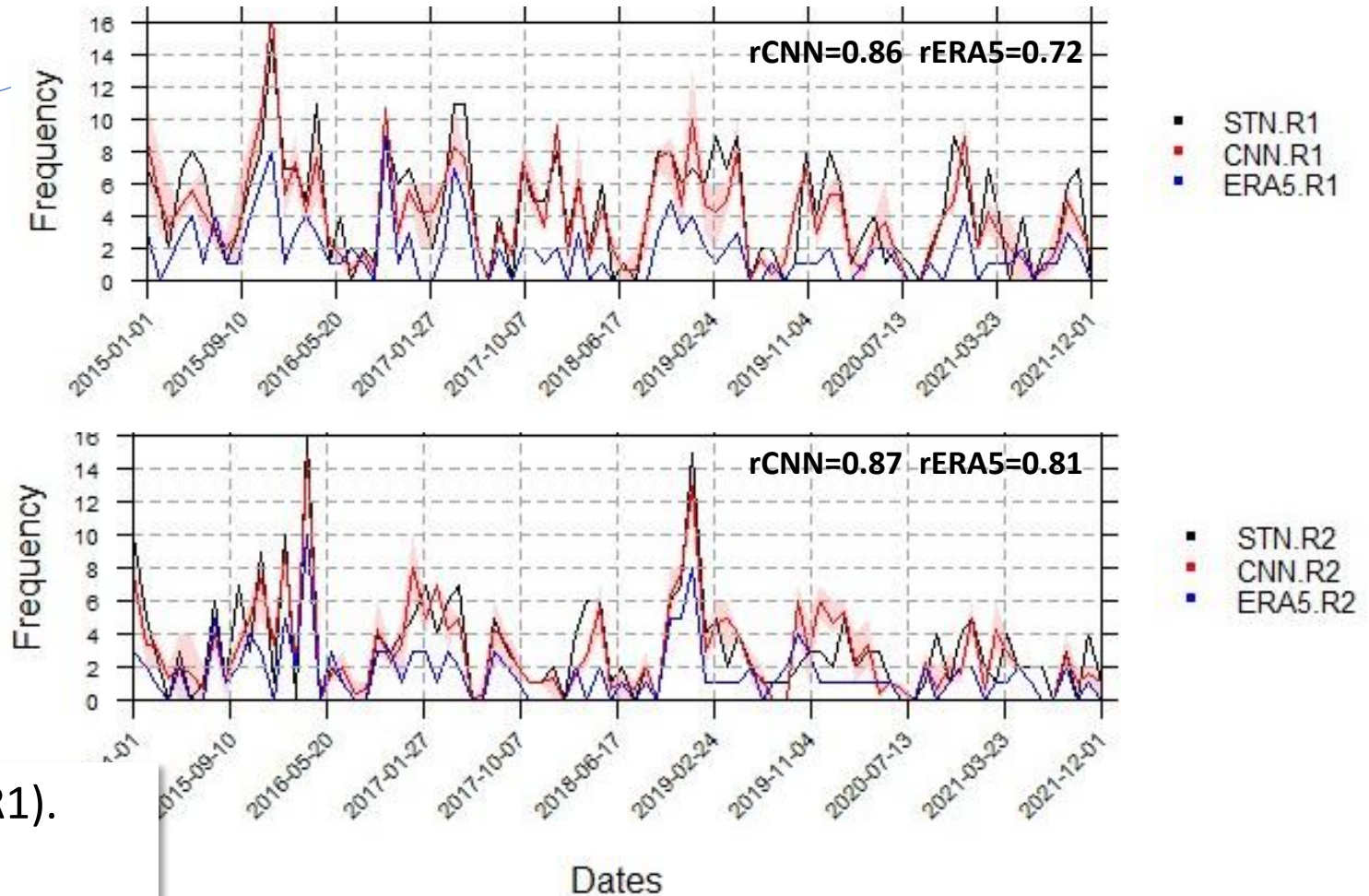
Monthly Precipitation



Location of extremes & Interannual Variability



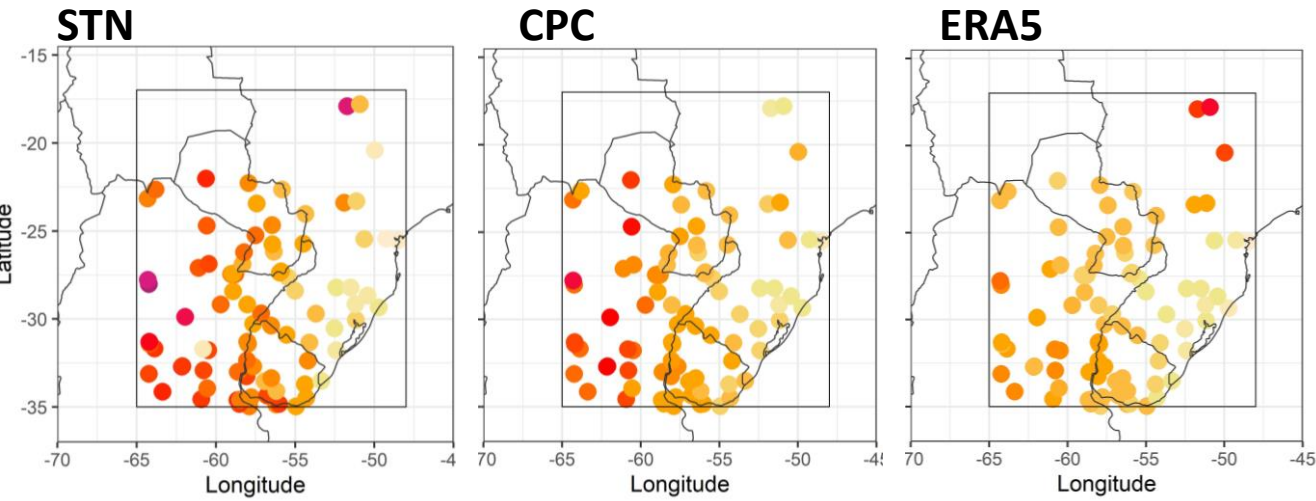
Monthly Frequency of Extreme Events



- ✓ Larger uncertainty in the northern region (R1).
- ✓ Clear added value compared with ERA5

Threshold: 50 mm over more than 10% of stations

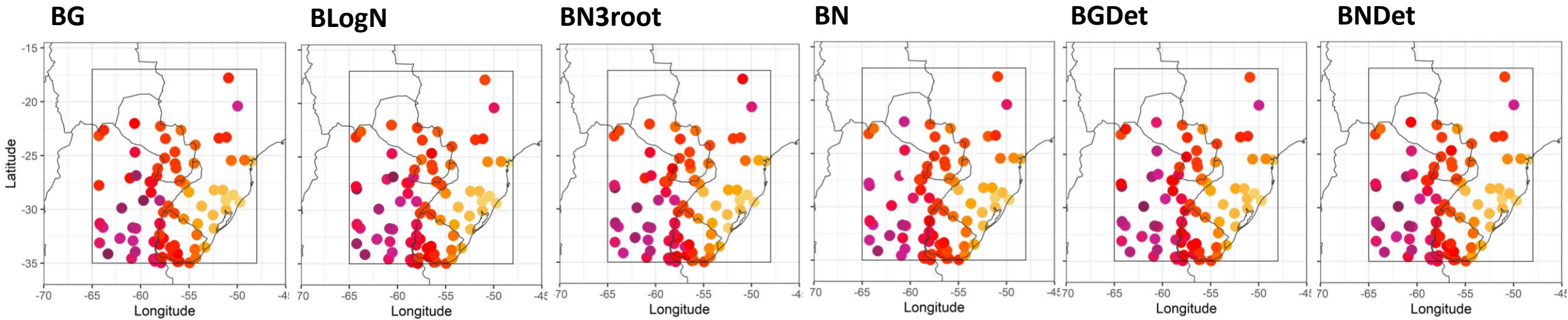
DrySpell90



days



- ✓ The spatial pattern of dry sequences is well captured.
- ✓ Large overestimations are observed in all models.



Conclusions

- **The lack of observational data** is a major constraint for model development and evaluation.
- **CNN** showed promising results **adding value and regional detail** of the distinctive characteristics of daily precipitation extremes over SESA subregions.
- **No single model performed** best over all aspects evaluated, evidencing the need of **coordinated experiments to better sample the uncertainties**.
- **The Bernoulli-Gamma distribution** seems to have potential for capturing the different aspects of precipitation over SESA.