Learning the distribution of extreme precipitation from atmospheric general circulation model variables

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Motivation

Challenges of precipitation prediction for large scale NWP models:

- Need to parameterize subgrid-processes
- Underestimation of precipitation extremes

Here:

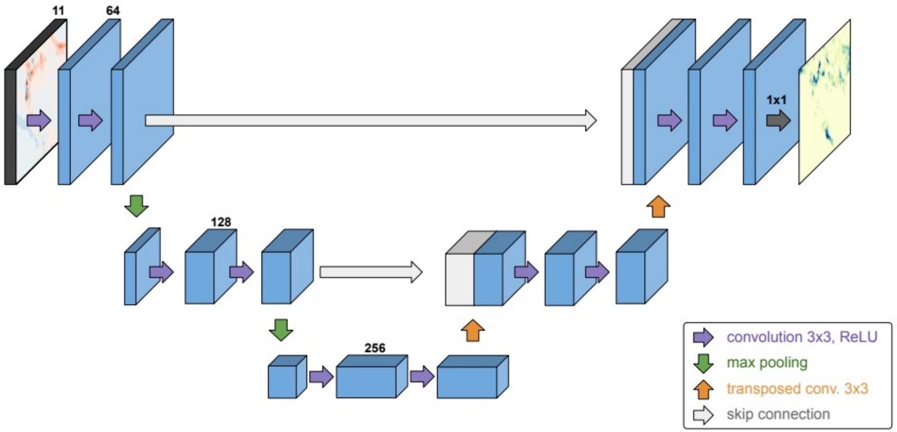
- Infer precipitation from explicitly resolved atmospheric variables using a deep artificial neural network (DNN)

$$P(t^n, x, y) \approx \mathsf{DNN}(X(t^n, x, y, z))$$

- P - Precipitation target: TRMM 3B42 V7 satellite based observations
- X - Atmospheric variables: here, vertical velocity from the IFS (ECMWF) 10-member ensemble mean

Architecture and loss function

UNet



O. Ronneberger et al. 2015

Weighted loss function

Averaged loss leads to:

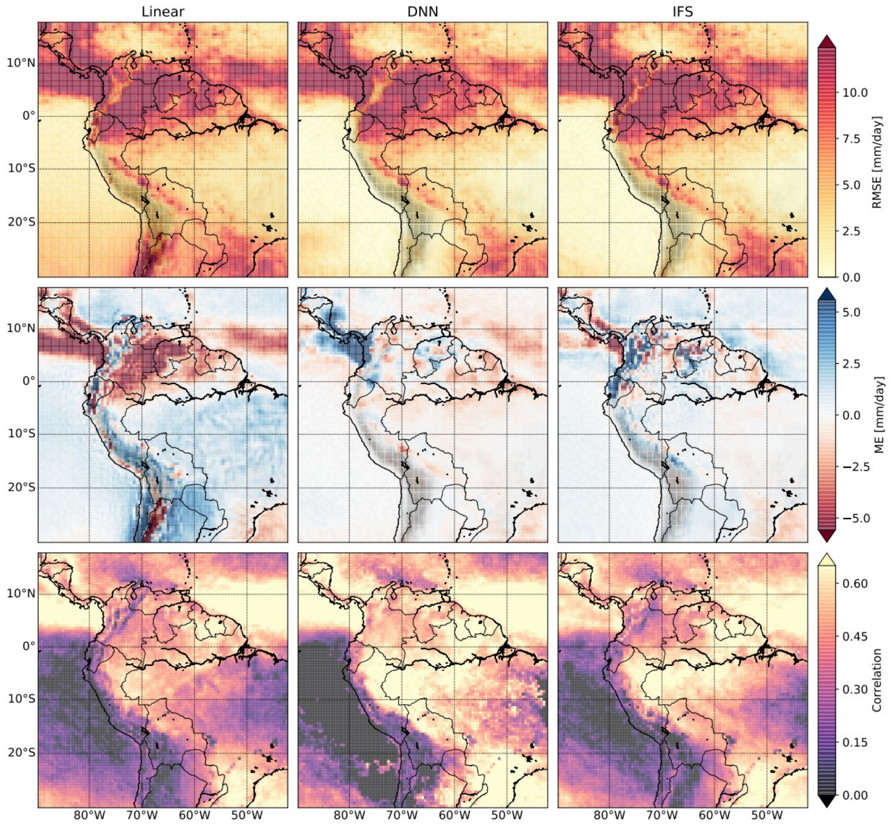
- Good approximation of the target mean.
- Underestimation of extremes in the tails.

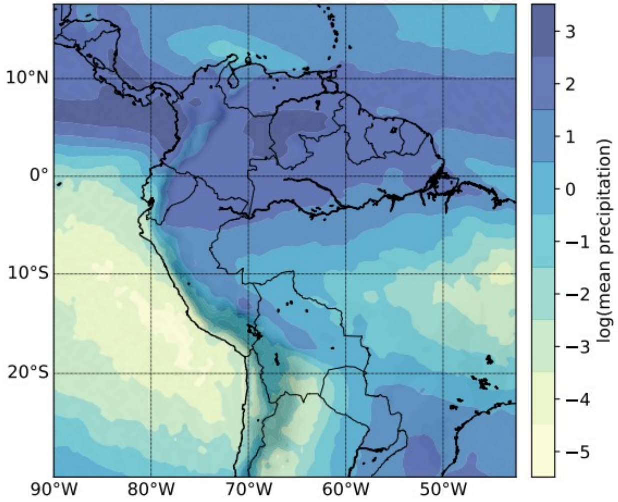
Here:

- MSE loss is weighted proportional to the inverse of target frequencies.

$$L(y, \hat{y}) = \frac{\lambda}{N} \sum_{i=1}^{N} w_i (y_i - \hat{y}_i)^2 + \frac{1-\lambda}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|$$

Results

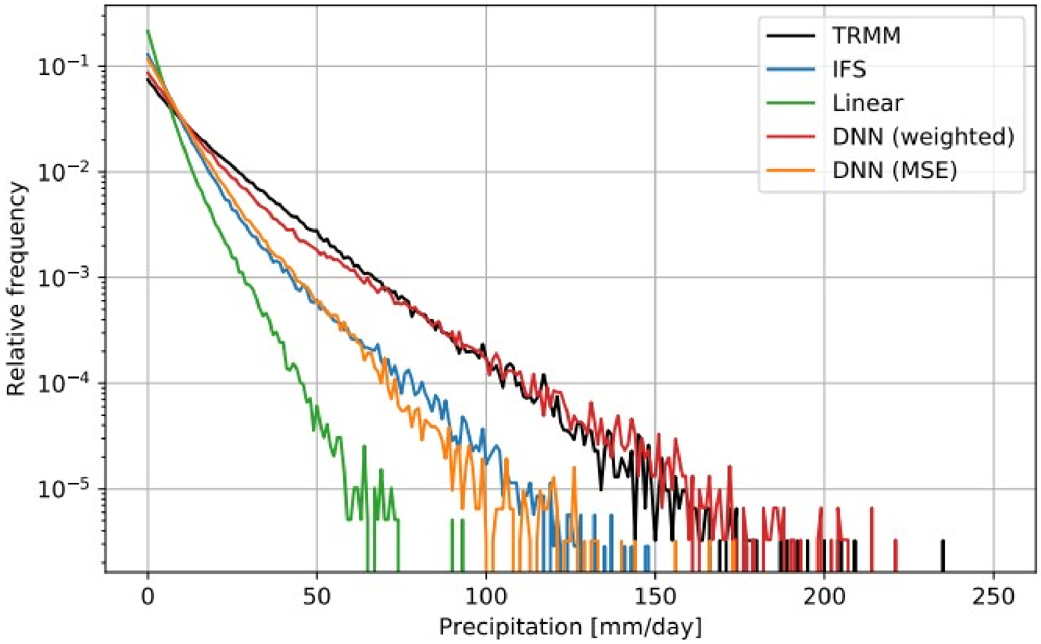




Model	RMSE	ME	Correlation
Linear	6.380	1.744	0.378
DNN	**5.016**	**0.687**	**0.438**
IFS	5.367	0.814	0.411

Test set: JJA season, 2015-2018. Resolution: daily, 0.5° grid (96 x 96).

Precipitation frequencies



Future work

- Scaling the method to:
  - Global data
  - 3-hourly temporal resolution
- Test it on longer forecast lead times of several days
- Integration into a physical model