Embedding High Resolution Variability into Climate Models

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Introduction

Capturing and modelling cloud formation is one of the main sources of uncertainty in model-based climate projections. This uncertainty in cloud representations is the key driver of systematic errors in simulated precipitation patterns.

This works seeks to capture the variability caused by the cloud generating processes from high resolutions weather simulations and embed this into a coarse climate simulation at run-time to improve the representation of clouds and precipitation patterns.

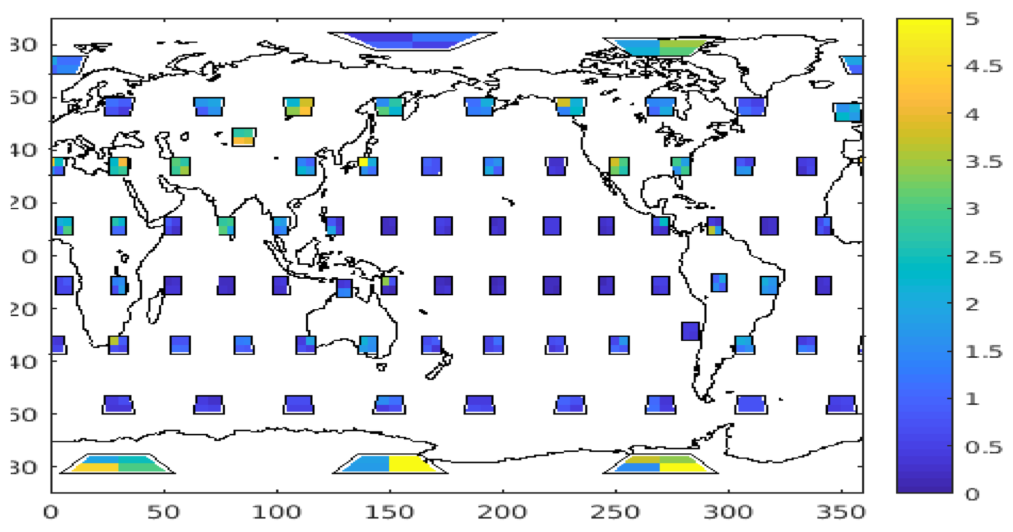
Our Approach

Similar projects capture the trend of parameterisation schemes using nerual networks, we capture the variability of a vertical column in the temperature and humidity fields from a high resolution hindcast using a Gaussian process (GP). Our explanatory variables are:

- Air temperature
- Air pressure
- Humidity
- Orographic mean
- Orographic var
- Land-sea ratio

Training Data

Training data from a nested limited-area hindcast simulation executed by the Met Office's Unified Model (UM) was coarse-grained to approximate the grid-box size of the climate model.



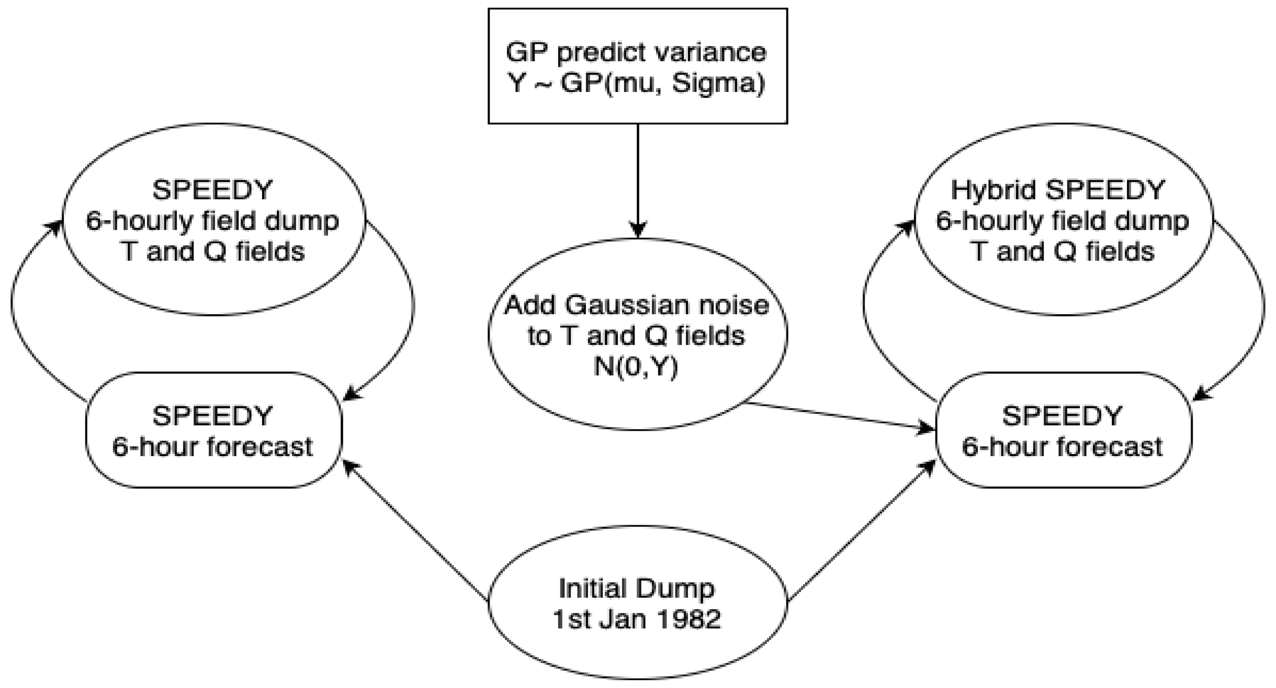
80 areas with 512 × 512 grid-points, each approximately 1.5km in horizontal length, coarse-grained to a 2 × 2 grid with grid-length scale 336km. Figure shows standard deviation of near surface temperature [K] at 00Z on 1 Jan 2020.

Climate Model - SPEEDY

SPEEDY (Simplified Parameterizations primitivE Equation DYnamics) is an atmospheric general circulation model (AGCM) written in modern Fortran. SPEEDY is fast, lightweight and can run on a laptop. Our setup uses a 96 × 48 grid with 8 vertical layers and outputs a forecast every 6 hours.

ML and Climate Model Coupling

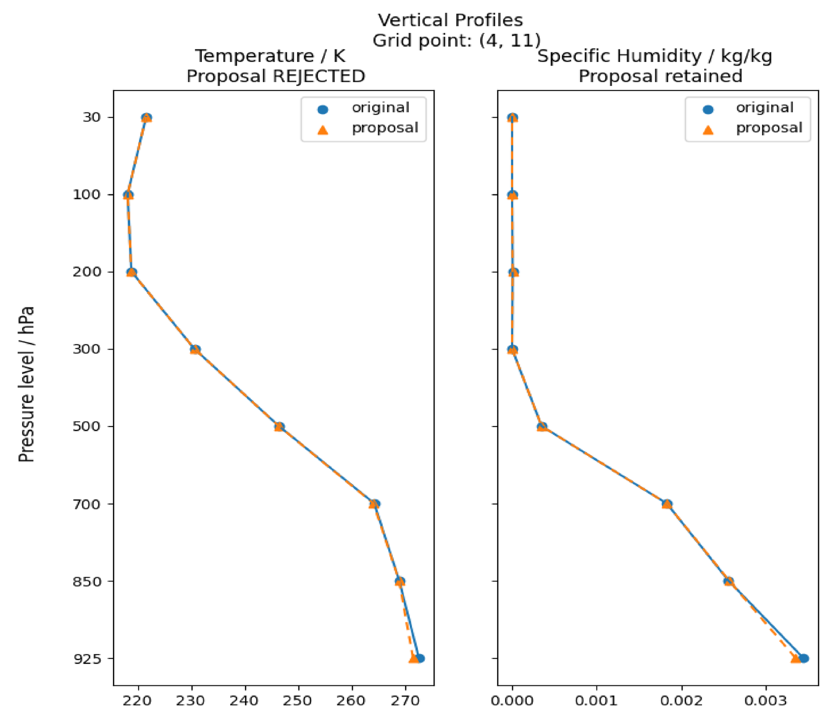
From the same initial input dump, the simulation workflow generates two datasets; a default SPEEDY and a hybrid SPEEDY dataset.



Workflow simulates two 10-year hindcasts for 1982-1992.

Profile Perturbation

New temperature and humidity profile proposals are generated cell by cell by adding independently sampled Gaussian noise at each vertical level. The Gaussian noise variance is the prediction made by the trained GP given the 6-hourly SPEEDY output.



Perturbations are very small.

Physical Constraints

To avoid non-realistic profiles being generated the perturbed profile must satisfy two prescribed physical constraints; the total water content and the total moist static energy,

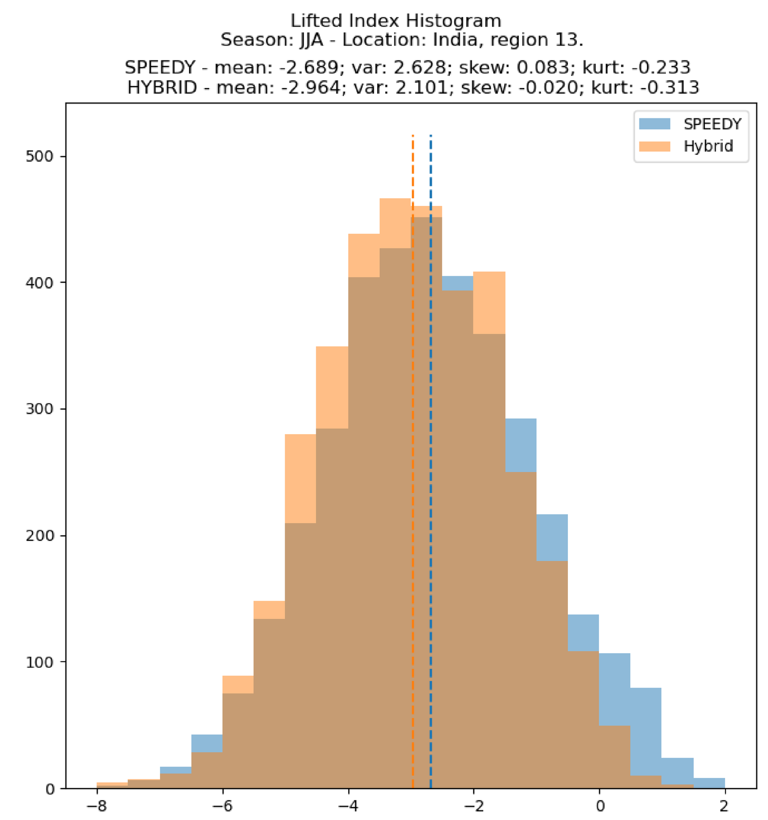
$$\text{Total Water Content} = \sum_{i=1}^{8} Q_i \rho_i, \tag{1}$$

$$\text{Total Moist Static Energy} = \sum_{i=1}^{8} Q_i L_v + C_p T_i, \tag{2}$$

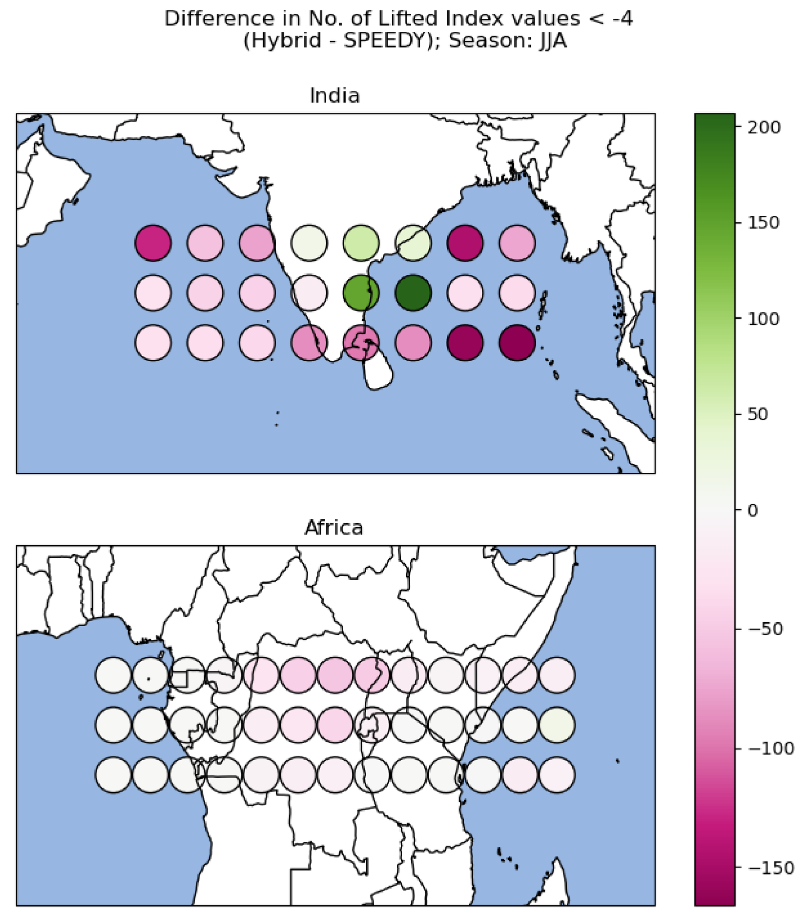
where ρ is a defined density are each level, $L_v = 2260$ and $C_p = 1.005$. Calculated values with the perturbed profiles which differ from the mean values beyond a prescribed tolerance are discarded and the mean profile is retained. These checks are completed on each grid cell independently.

Results

Lifted index (LI) is a measure of atmospheric stability. Negative values indicate rain and storms - an unstable atmosphere.

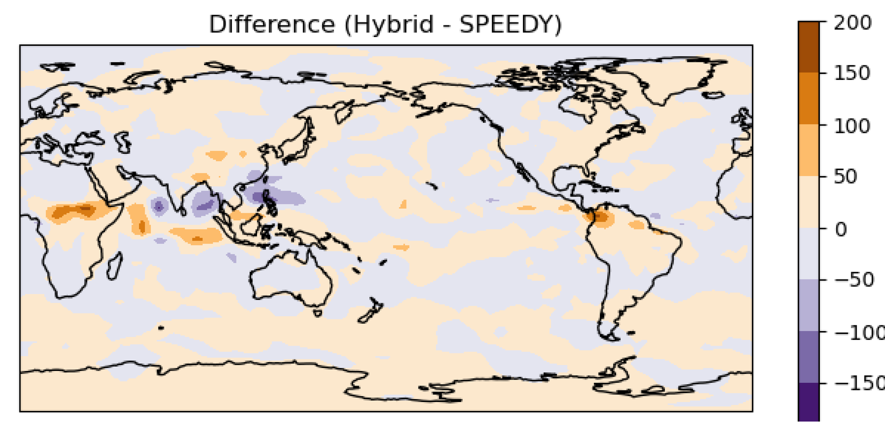


Histogram of LI values on East Indian coast.



Difference in number of LI values below -4.

The hybrid simulated atmosphere is less stable along Indian coast during monsoon season indicating potential for monsoons. Less rainfall in the Indian ocean corrects bias historically present in climate models.



10-year average precipitation in June, July & August. $[g/m^2/s]$

Conclusion

This method samples new possible atmospheric states without changing the Earth's climate. Modelling improvements have been observed around the Indian ocean, especially during monsoon season.

References

Molteni, F. (2003). *Atmospheric simulations using a GCM with simplified physical parametrizations. I: model climatology and variability in multi-decadal experiments.* Clim. Dyn. 20, 175–191.

Arcomano, T, et al. (2023). *A Hybrid Atmospheric Model Incorporating Machine Learning Can Capture Dynamical Processes Not Captured by Its Physics-Based Component*. Geophysical Research Letters, 50.