Deep learning augmented numerical weather prediction digital twin experiments for global precipitation forecasting

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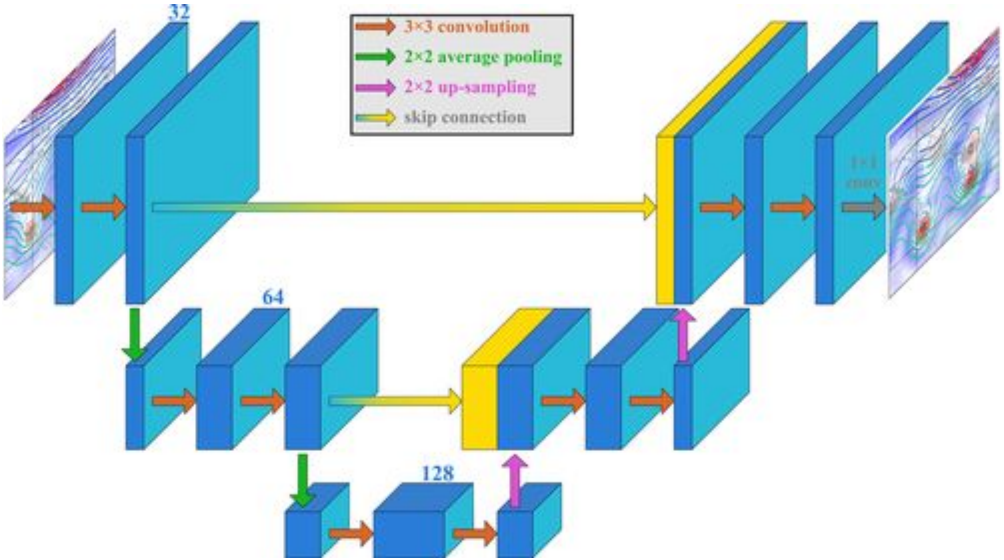
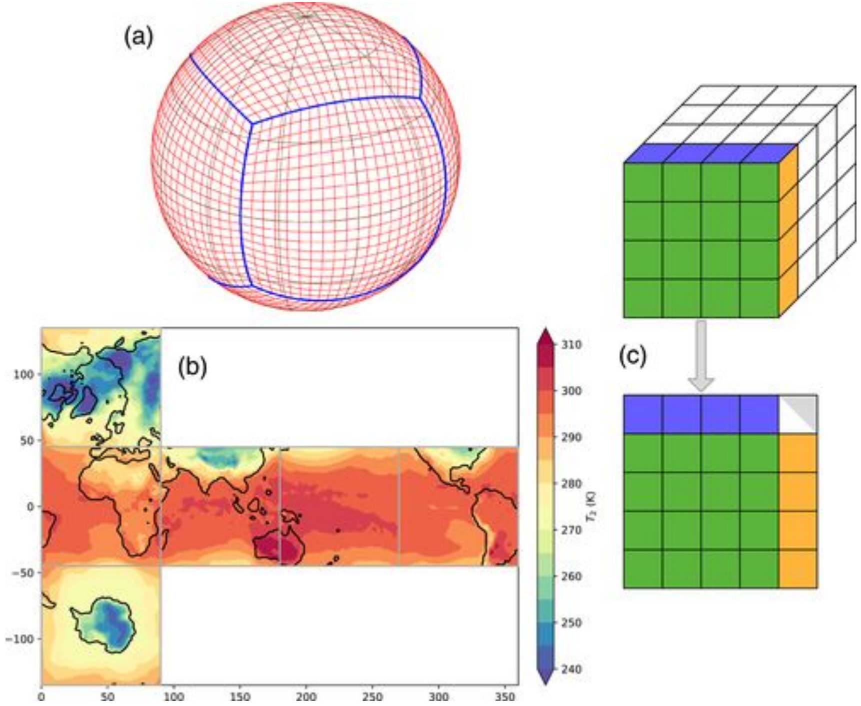
Deep Learning for Weather Prediction (DLWP)



Weyn, J.A., Durran, D.R. and Caruana, R., 2019. Can machines learn to predict weather? Using deep learning to predict gridded 500-hPa geopotential height from historical weather data. *Journal of Advances in Modeling Earth Systems*, *11*(8), pp.2680-2693.

DLWP Cubed Sphere



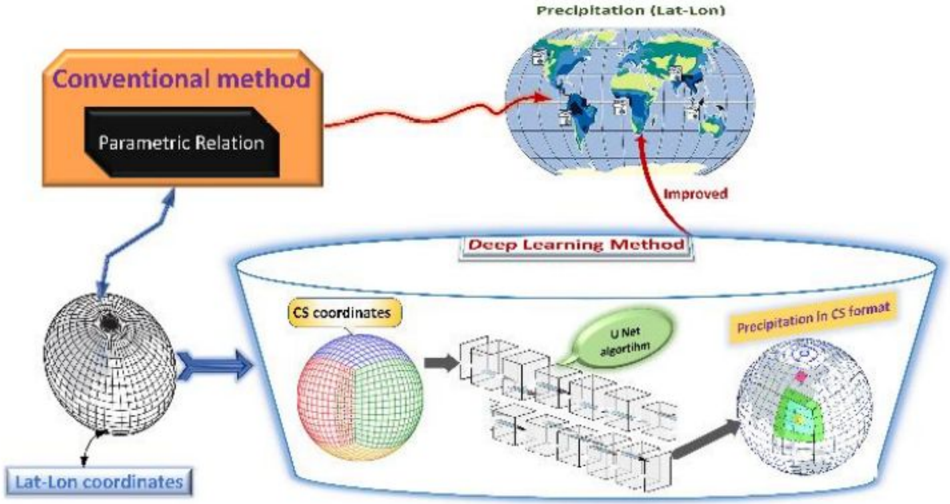
Weyn, J.A., Durran, D.R. and Caruana, R., 2020. Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. Journal of Advances in Modeling Earth Systems, 12(9), p.e2020MS002109.

Deep learning for global precipitation prediction

- DLWP and DLWP-CS use temperature at 850 hPa and geopotential at 500 hPa to show comparable and improved performance w.r.t operational models.
- DLWP and DLWP-CS use global domain for data-driven weather forecasting.
- Previous studies either use limited regions, do not consider spherical distortion, use fields simpler to simulate relative to precipitation, do not compare with operational forecasts or do not use CNNs limiting their capability to capture spatial patterns.
- Need for a system dedicated to global precipitation forecasts which can be considered a digital twin of the real system.

Modified DLWP-CS

Transforms DLWP-CS from a temporal mapping to a function simulating precipitation from different fields



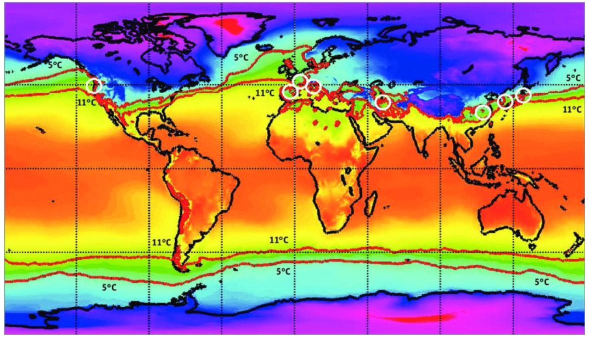
Proof of concept

WeatherBench

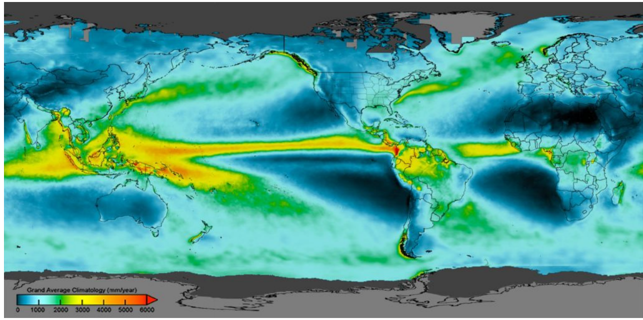
Weatherbench dataset corresponding to total cloud cover and two meter air temperature as precursors and precipitation as the label/target. Training: 1979-2009, Validation: 2010-2011, Testing: 2012-2015. Temporal resolution: hourly

Total Cloud Cover

Surface air temperature

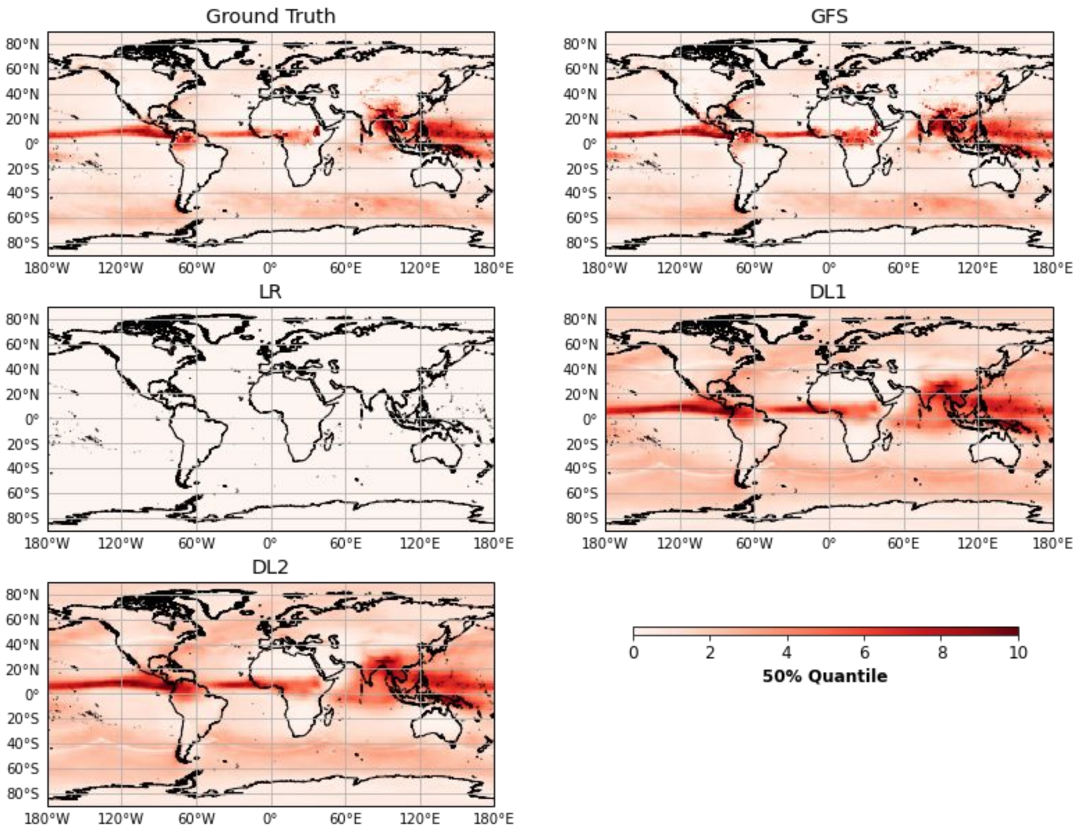


Precipitation



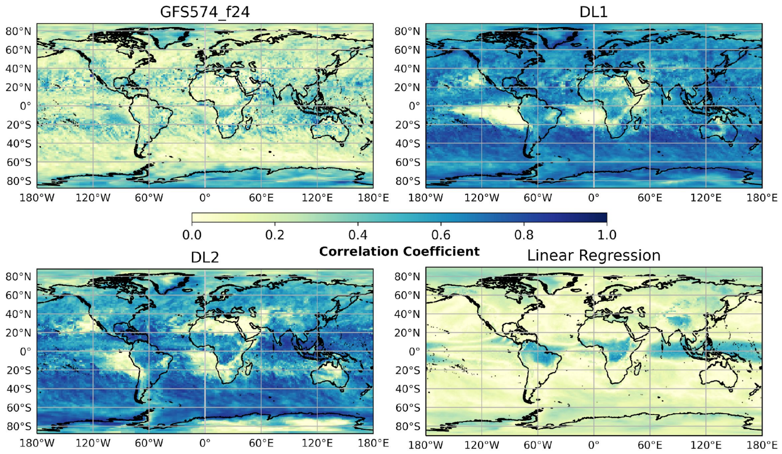
Rasp, S., Dueben, P.D., Scher, S., Weyn, J.A., Mouatadid, S. and Thuerey, N., 2020. WeatherBench: a benchmark data set for data-driven weather forecasting. Journal of Advances in Modeling Earth Systems, 12(11), p.e2020MS002203.

Median for proof of concept



Grid point correlations for 2012-2015

- DL1- Total cloud cover as input, DL2 - Surface air temperature as input
- Grid point correlations show that DL1 and DL2 outperform GFS and linear regression
- Comparability to GFS at 24 hour lead assuming that the input fields to precipitation parameterization do not significantly deviate from the observed states

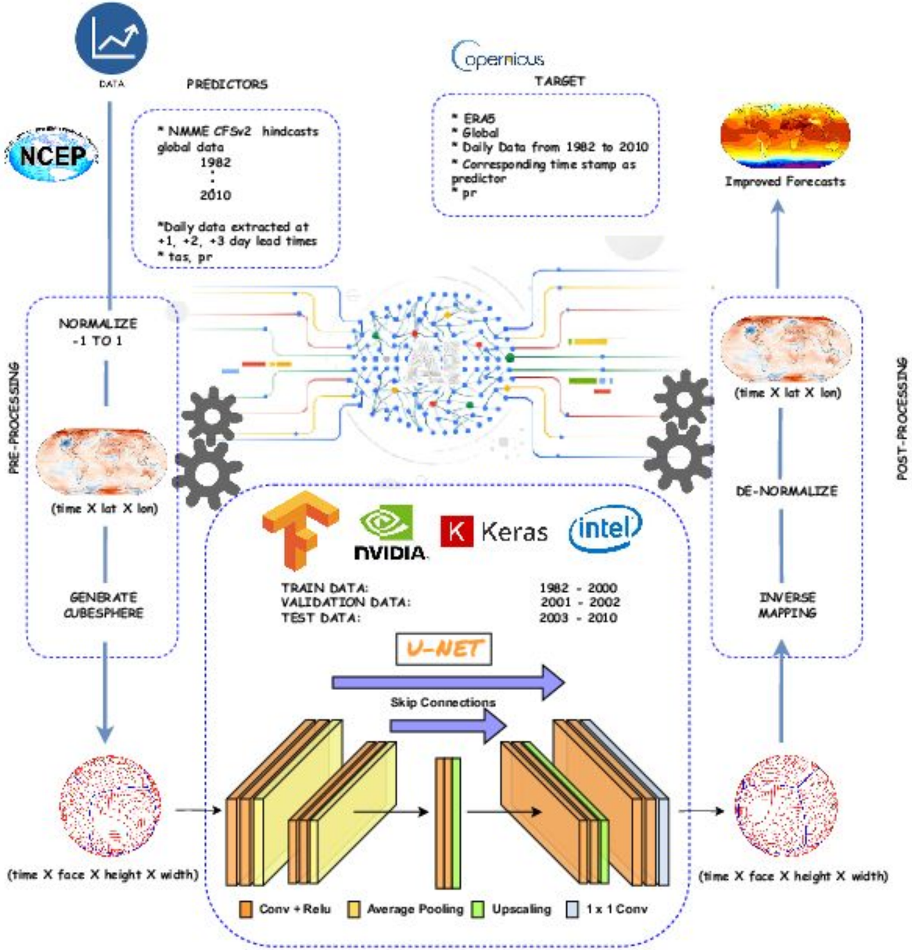


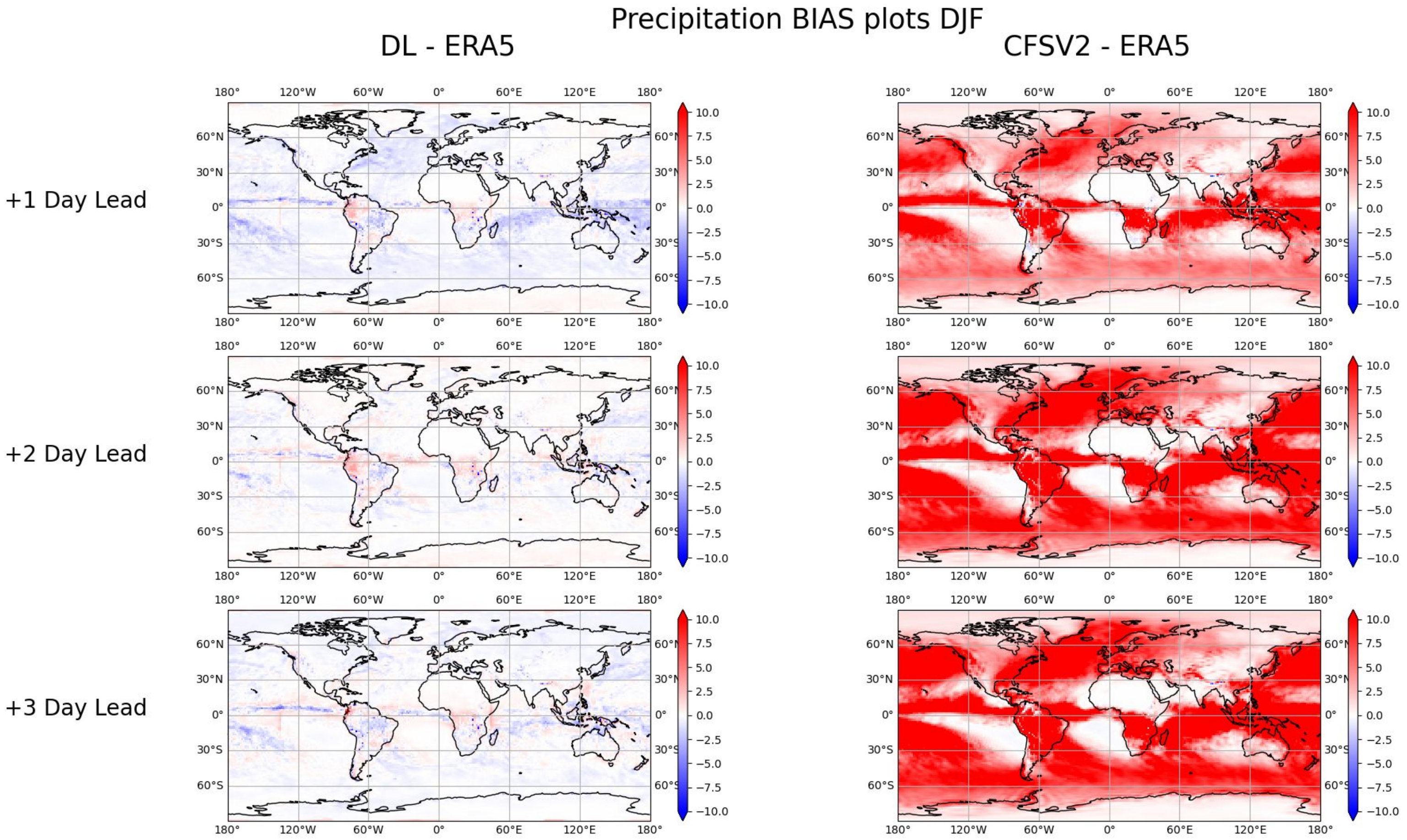
Comparison of different models

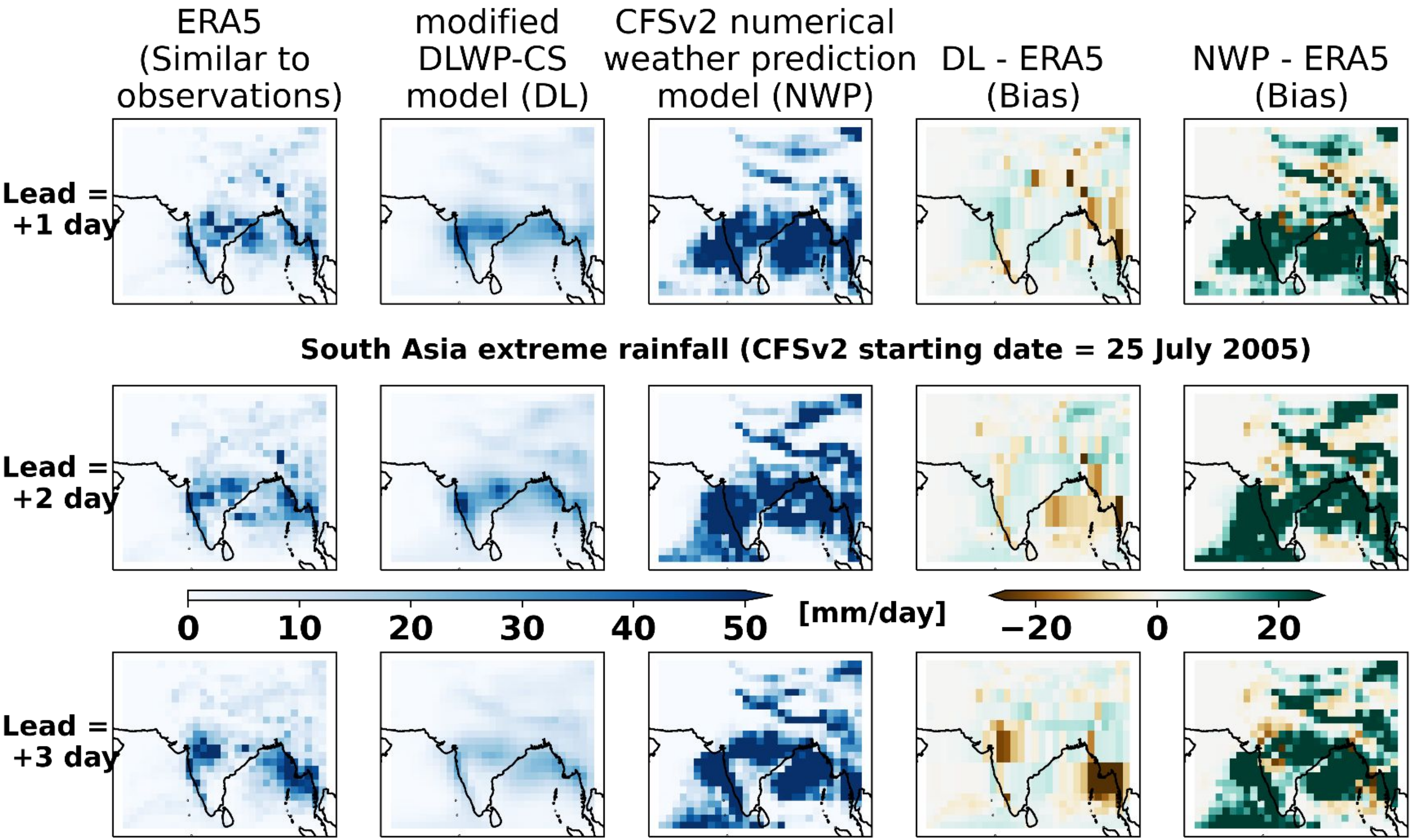
Table 4. Correlation coefficients (Mutual Information) averaged over different land-regions from GFS, DL1, DL2 and DL3 models and ERA5 precipitation for the test years 2012-2015

REGION	GFS (BASELINE)	DL1 (TCC)	DL2 (TAS)	DL3 (TISR)	LR
CANADA (50-70N, 130-90W)	0.19 (0.68)	**0.63** (0.90)	0.49 (0.90)	0.02 (0.89)	0.19 (1.15)
NORTH ASIA (50-70N, 25-140E)	0.24 (0.89)	**0.64** (1.05)	0.54 (1.05)	0.03 (1.04)	0.19 (1.38)
EUROPE (44-54N, 40-100E)	0.28 (0.98)	**0.64** (1.09)	0.55 (1.09)	0.01 (1.08)	0.05 (1.63)
UNITED STATES (32-50N, 110-80W)	0.21 (0.62)	**0.62** (0.76)	0.50 (0.76)	0.02 (0.75)	0.08 (1.12)
CENTRAL ASIA (35-50N, 40-100E)	0.23 (0.49)	**0.53** (0.67)	0.38 (0.67)	0.07 (0.67)	0.14 (1.06)
AMAZON (5N-10S, 50-70W)	0.16 (0.61)	0.49 (0.66)	**0.58** (0.66)	-0.09 (0.65)	0.09 (0.81)
EQUATORIAL AFRICA (10N-10S, 14-35E)	0.21 (1.26)	0.47 (1.30)	**0.59** (1.30)	0.19 (1.30)	0.44 (1.82)
INDIA (18-35N, 70-90E)	0.32 (0.94)	0.62 (1.02)	**0.59** (1.02)	0.07 (1.01)	0.16 (1.00)

Ongoing development of product


DATA
PREDICTORS
* NMME CFSv2 hindcasts global data 1982 : 2010
*Daily data extracted at +1, +2, +3 day lead times
* tas, pr
NCEP
copernicus
TARGET
* ERA5
* Global
* Daily Data from 1982 to 2010
* Corresponding time stamp as predictor
* pr
Improved Forecasts
PRE-PROCESSING
NORMALIZE -1 TO 1
(time X lat X lon)
GENERATE CUBESPHERE
(time X face X height X width)
Keras
intel
NVIDIA
TRAIN DATA: 1982 - 2000
VALIDATION DATA: 2001 - 2002
TEST DATA: 2003 - 2010
U-NET
Skip Connections
Conv + Relu
Average Pooling
Upscaling
1 x 1 Conv
POST-PROCESSING
(time X lat X lon)
DE-NORMALIZE
INVERSE MAPPING
(time X face X height X width)


Precipitation BIAS plots DJF
DL - ERA5
CFSV2 - ERA5
+1 Day Lead
+2 Day Lead
+3 Day Lead
180°
120°W
60°W
0°
60°E
120°E
60°N
30°N
30°S
60°S
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0


ERA5 (Similar to observations)
modified DLWP-CS model (DL)
CFSv2 numerical weather prediction model (NWP)
DL - ERA5 (Bias)
NWP - ERA5 (Bias)
Lead = +1 day
South Asia extreme rainfall (CFSv2 starting date = 25 July 2005)
Lead = +2 day
0
10
20
30
40
50
[mm/day]
−20
0
20
Lead = +3 day

Conclusions

- Framework for fast and reliable global weather forecasts developed
- System performs reasonable in a theoretical setup with ERA5 inputs and outputs
- Some issues with representation of extreme precipitation
- Can be easily transferable to a real time product for deep learning enhanced NWP outputs
- Preliminary results using multivariate inputs from NWP model show substantial improvements in numerical weather prediction model outputs.

Thank you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Det goda universitetet. Festskrift till Anders Hallberg
FÖLJ ERA CAPRICER
Studenten, Staden och Sanningen