Short-range forecasts of global precipitation using deep learning-augmented numerical weather prediction

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Why are short-range weather forecasts important for precipitation

- Enable exact location of extreme weather events
- Planning for hydrological decision making such as dams, rivers can be improved
- Damage to the crops, life and property can be minimized
- Hurricanes, typhoons and cyclones wreck havoc - improved estimates from NWP models can lead to better planning

The problem or challenge

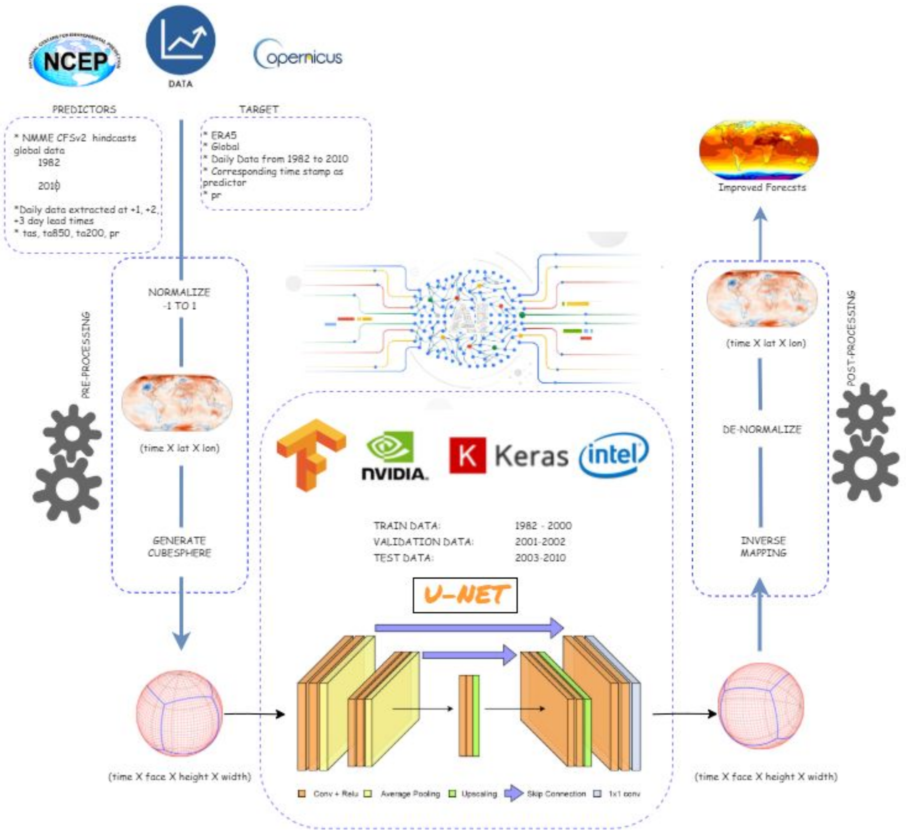
NWP models have high-biases in diagnostic fields like precipitation and soil moisture

The hypothesis

Deep learning can enhance NWP forecasts

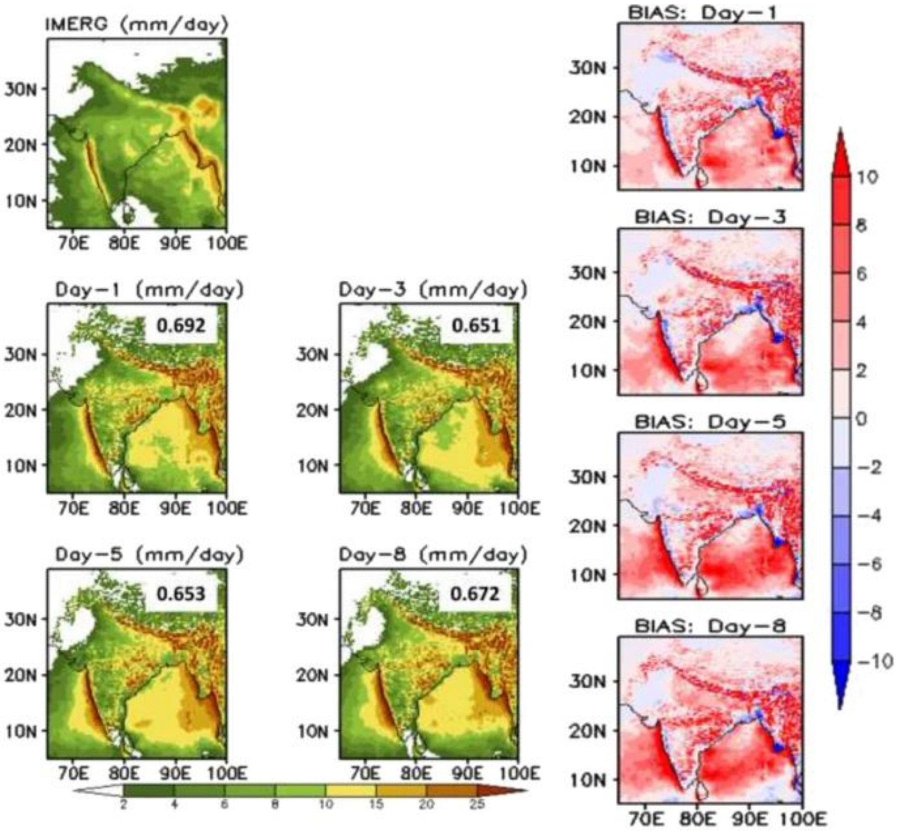
Datasets

- NMME hindcasts from CFSv2: Daily data upto +3 day lead time extracted
- Years: 1982-2010
- Precursors: tas and pr from CFSv2 at +1, +2 and +3 day lead times
- Target: ERA5 pr corresponding to +1, +2 and +3 lead times



Schematic for methodology using modified DLWP-CS

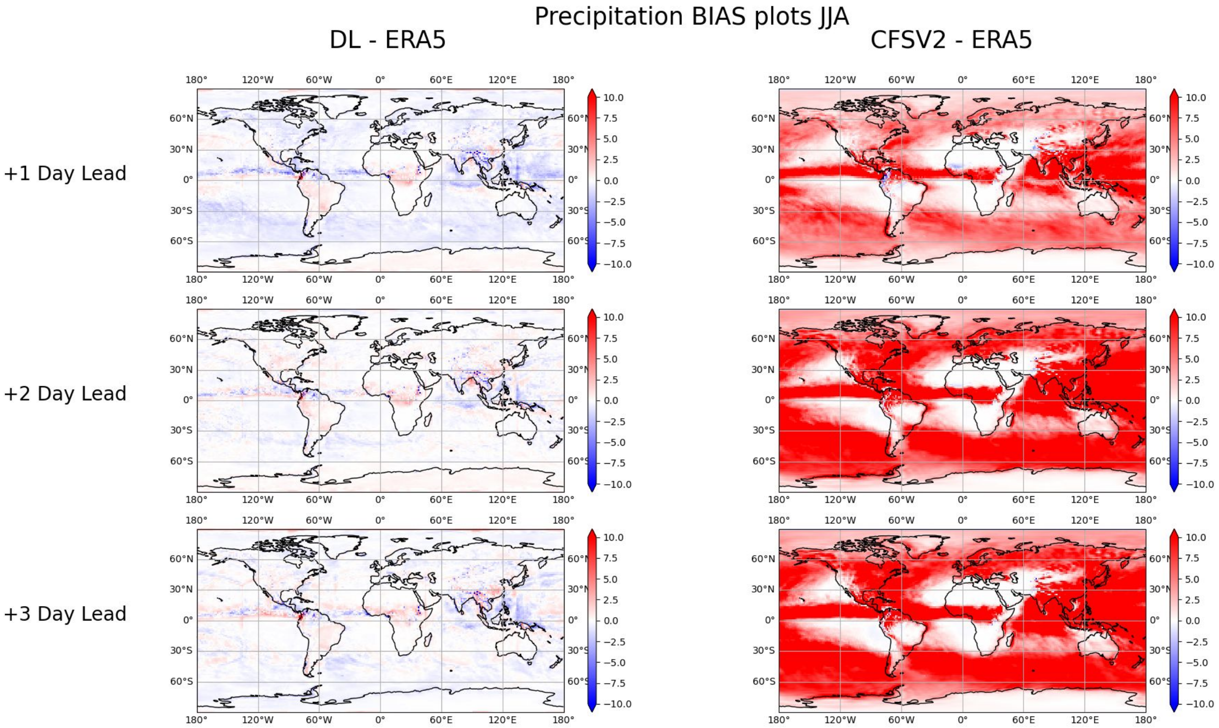
How are the precipitation biases in recent NWP studies ?



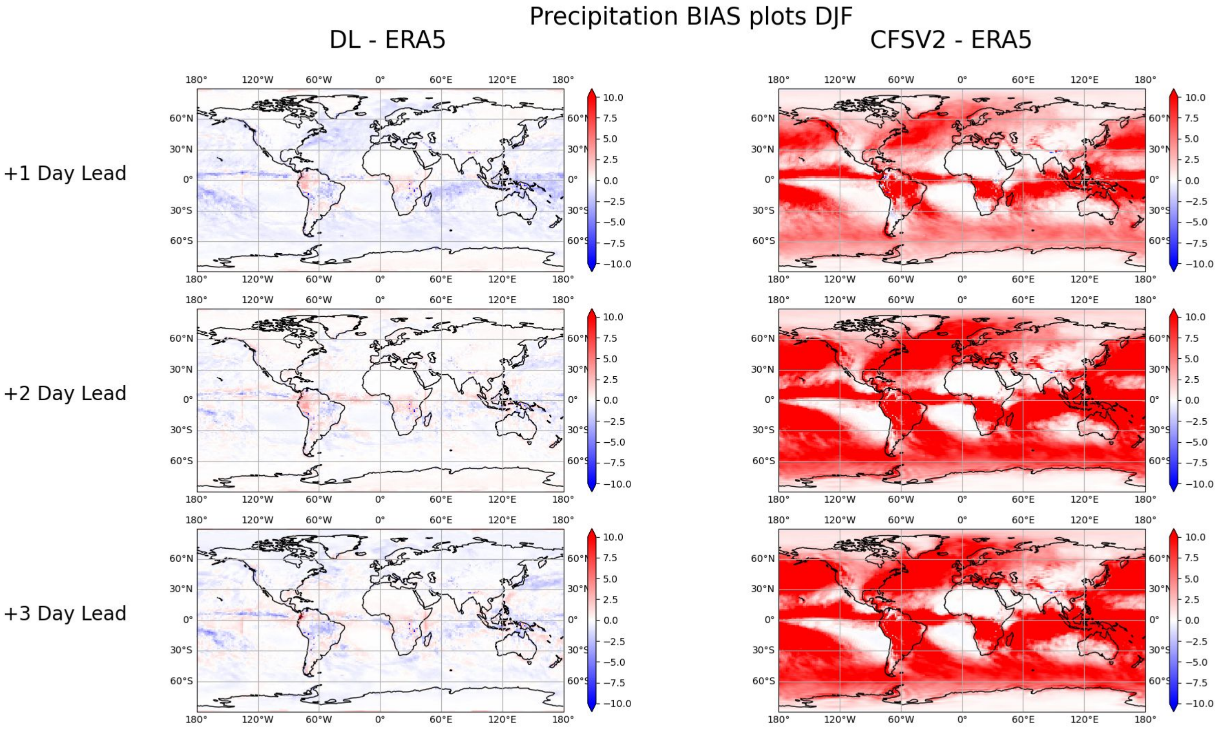
Mukhopadhyay, P., Prasad, V.S., Krishna, R.P.M., Deshpande, M., Ganai, M., Tirkey, S., Sarkar, S., Goswami, T., Johny, C.J., Roy, K. and Mahakur, M., 2019. Performance of a very high-resolution global forecast system model (GFS T1534) at 12.5 km over the Indian region during the 2016–2017 monsoon seasons. *Journal of Earth System Science*, *128*(6), pp.1-18.

High biases over India Mukhopadhyay et al 2019

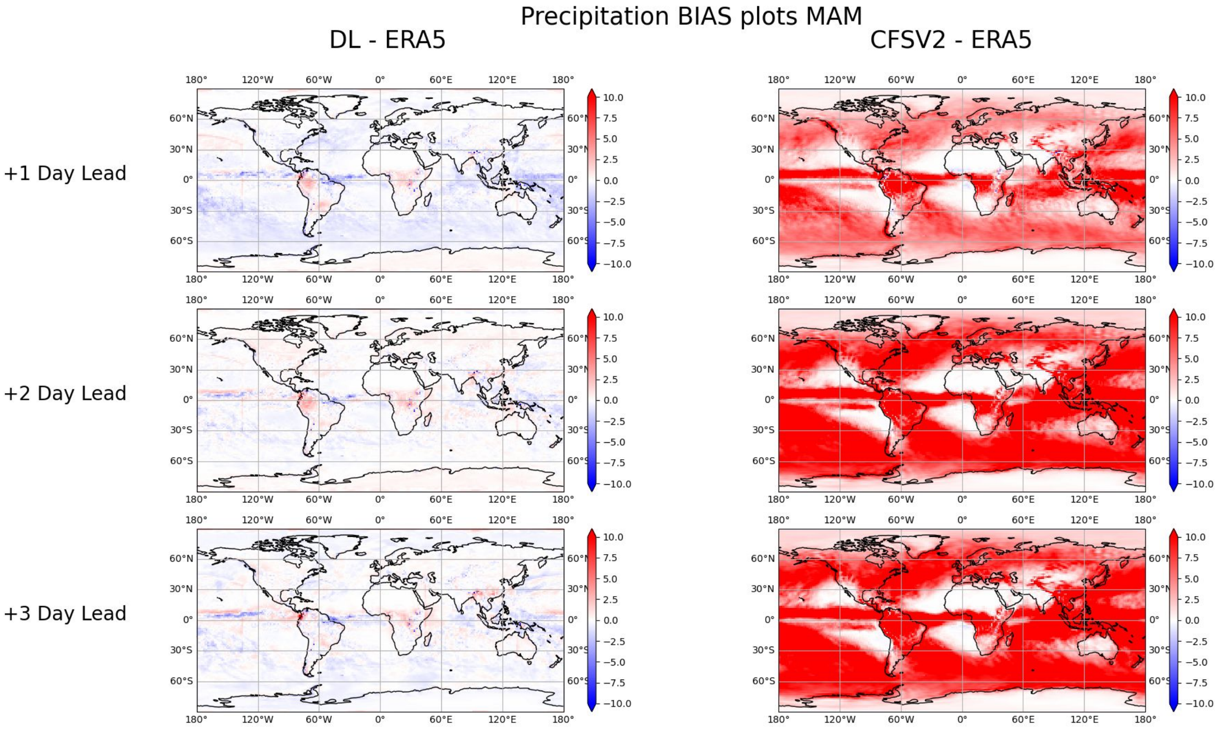
Do we get enhanced precipitation or reduced biases by deep learning ?



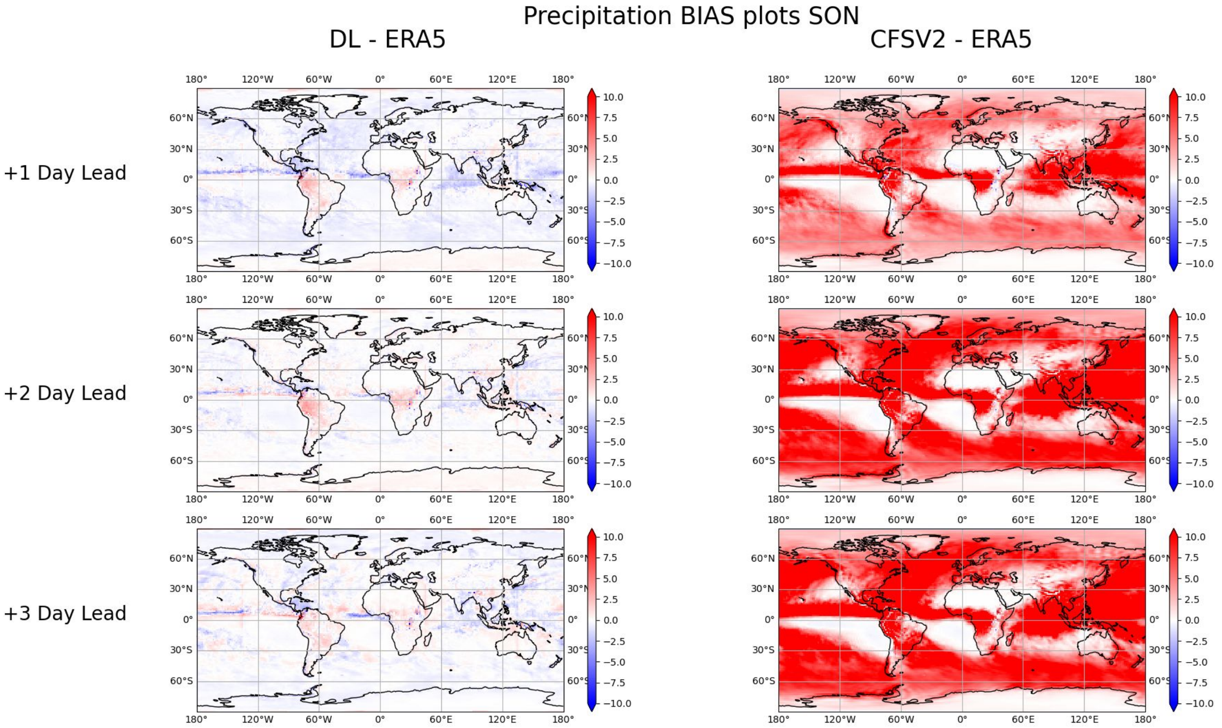
Results: Figure 1



Results: Figure 2



Results: Figure 3



Results: Figure 4

Season	Lead = 1 day (mm/day)		Lead = 2 day (mm/day)		Lead = 3 day (mm/day)	
	DL - ERA5	CFSv2 - ERA5	DL - ERA5	CFSv2 - ERA5	DL - ERA5	CFSv2 - ERA5
DJF	**-0.3**	3.827	**0.022**	7.66	**-0.158**	7.657
MAM	**-0.282**	3.834	**0.032**	7.811	**-0.11**	7.89
JJA	**-0.334**	3.97	**-0.02**	8.102	**-0.115**	8.239
SON	**-0.299**	3.954	**0**	7.95	**-0.148**	7.972

Table 1. Performance of the deep learning augmented numerical weather prediction system CFSv2 versus CFSv2 alone. The table shows global average bias/error in simulating precipitation by the hybrid deep learning and CFSv2 system versus CFSv2 alone. DJF (December to February), MAM (March to May), JJA (June to August) and SON (September to November) represent the different months of an year. The performance is shown for the entire test period from the year 2003 to 2010

Events	Lead = 1 day (mm/day)		Lead = 2 day (mm/day)		Lead = 3 day (mm/day)	
	DL - ERA5	CFSv2 - ERA5	DL - ERA5	CFSv2 - ERA5	DL - ERA5	CFSv2 - ERA5
Hurricane Katrina	**-0.345**	8.839	**0.453**	12.18	**-0.811**	10.227
Hurricane Ivan	**-0.22**	8.466	**-0.036**	13.48	**-1.485**	13.135
Cyclone Nargis	**-5.37**	21.151	**-1.245**	43.845	**2.338**	47.233
Europe Floods	**-0.2**	6.654	**-0.015**	8.134	**0.12**	6.94
China Floods	**-0.17**	11.233	**0.465**	18.903	**-0.48**	16.877
India flood	**0.003**	17.321	**0.139**	25.297	**-0.749**	20.259

Table 2. Performance of the deep learning augmented numerical weather prediction system CFSv2 versus CFSv2 alone. The table shows regional bias/error in simulating various extreme precipitation events by the hybrid deep learning and CFSv2 system versus CFSv2 alone. The events occured as (i) Hurricane Katrina in 2005, (ii) Hurricane Ivan in 2004, (iii) Cyclone Nargis in 2008, (iv) Europe floods in 2010, (v) China flood in 2005 and (vi) India flood in 2005

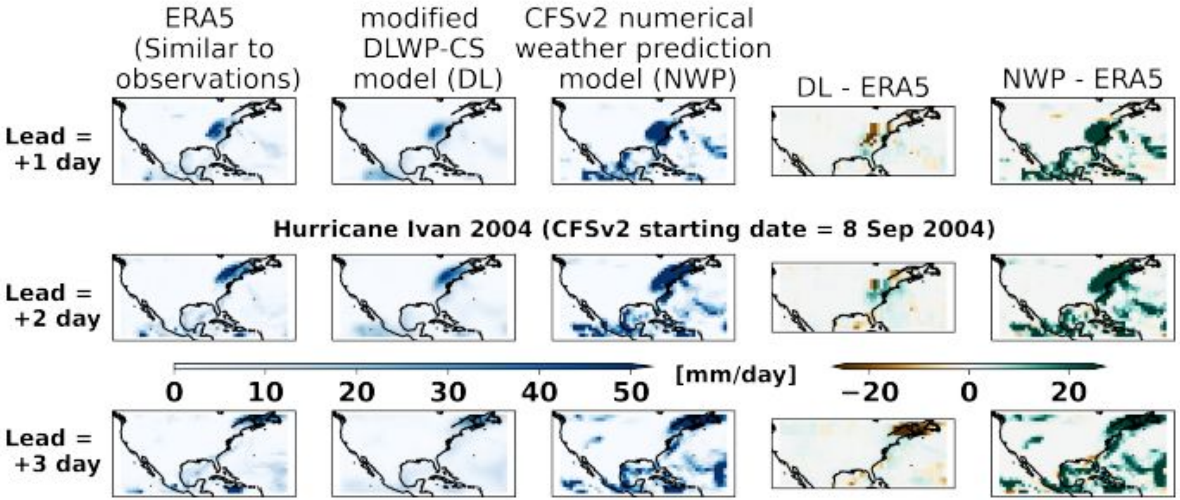
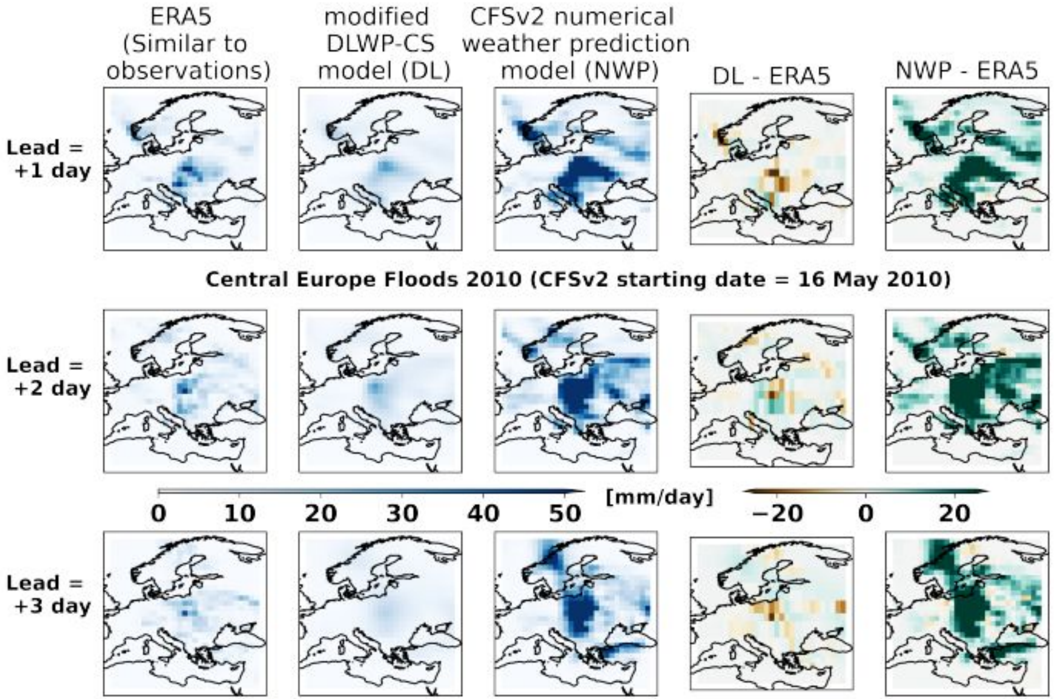


Figure 3. Absolute values corresponding to ERA5, deep learning augmented CFSv2 (DL) and CFSv2 are shown in the first three columns. Last two columns show the bias as difference between deep learning augmented CFSv2 and CFSv2 alone. The rows correspond to the different lead times, viz, 1, 2 and 3 days. The figure shows example for Hurricane Ivan in 2004.



ERA5 (Similar to observations)
modified DLWP-CS model (DL)
CFSv2 numerical weather prediction model (NWP)
DL - ERA5
NWP - ERA5
Lead = +1 day
Central Europe Floods 2010 (CFSv2 starting date = 16 May 2010)
Lead = +2 day
0
10
20
30
40
50
[mm/day]
−20
0
20
Lead = +3 day

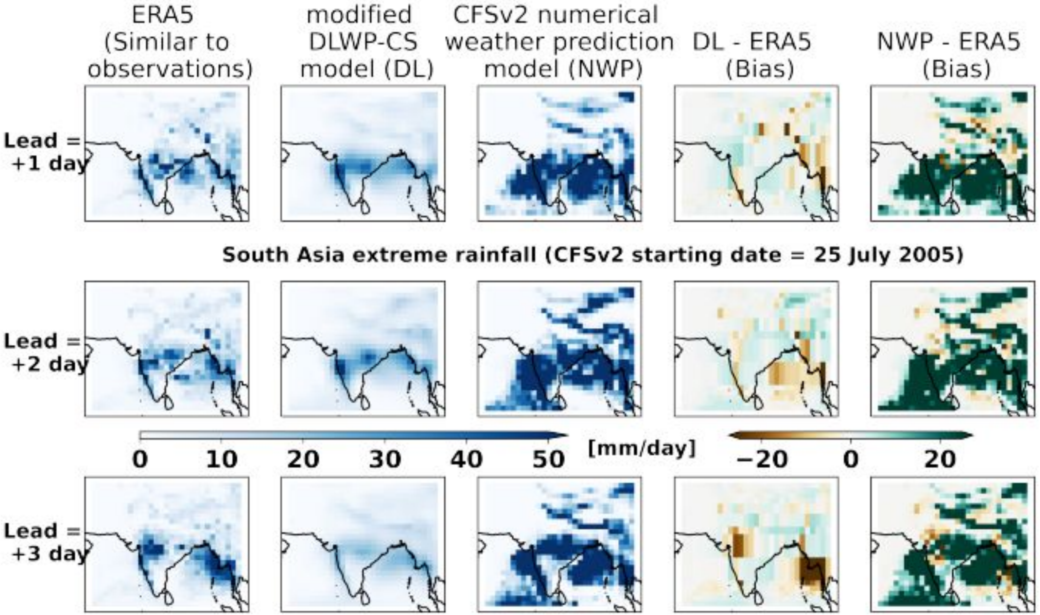


Figure 6. Same as figure 3 but for South Asia extreme precipitation in 2005

Conclusions and future work

- Short-range forecasts of global precipitation crucial for extreme weather events.
- Modified DLWP-CS used in this study to map the outputs of a numerical weather prediction model (CFSv2) to observed/reanalysis precipitation (ERA5).
- The model learns to map the physics-based dynamical model to observed precipitation resulting in substantial improvements in the precipitation forecasts.
- Mean bias at 1,2 and 3-day lead time forecasts improves by ~10x and the same is verified by case studies from test data corresponding to extreme rainfall events.
- We are working towards increasing the number of predictors for the model to further improve the short-range forecasts of global precipitation.

Thank you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