An AI/ML approach to improve NWP products using remote sensing data

Amar Jyothi K
amarjyothi.k@gov.in

Group: DATA and AI/ML Team at NCMRWF

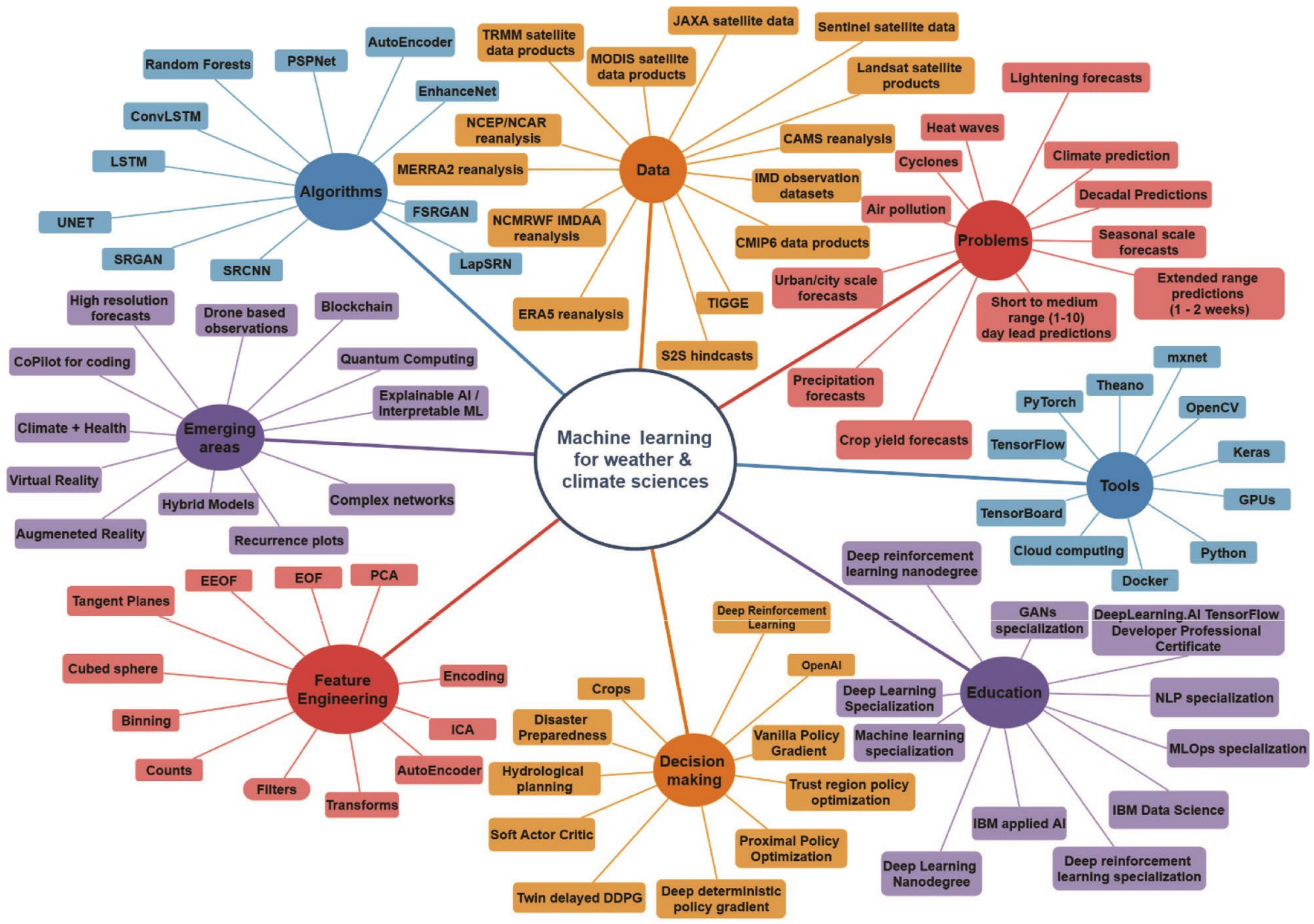
National Centra for Medium Range Weather Forecasting (NCMRWF)
Ministry of Earth Sciences, Govt. of India (MoES)

Global Seamless Modeling Workshop, Bristol, UK, 03-06 June, 2025

Overview

- Limitations of traditional Regional models (bias, resolution, lag in real-time)
- Potential of remote sensing data (e.g., satellite, radar, passive/active sensors)
- AI/ML as a corrective and augmentative tool

Machine Learning for weather and climate sciences



REVIEW ARTICLE

Artificial intelligence and machine learning in earth system sciences with special reference to climate science and meteorology in South Asia

Manmeet Singh[1,5,6,*], Bipin Kumar[1], Rajib Chattopadhyay[1], K. Amarjyothi[2], Anup K. Sutar[3], Sukanta Roy[3], Suryachandra A. Rao[1] and Ravi S. Nanjundiah[1,4,7]

Limitations in Regional models

- May struggle with representing complex terrain (the western Ghat, the Himalayas etc) and coastal boundaries accurately, affecting forecasts in those regions.

- Errors in land-surface parameterization can degrade predictions, particularly for temperature and precipitation.

- Errors in initial conditions, especially from sparse observational data, propagate into forecast errors.

- Assimilation of local high-resolution observational data (like AWS, radar, or satellite) can be limited by availability, latency, or quality control.

Cont..

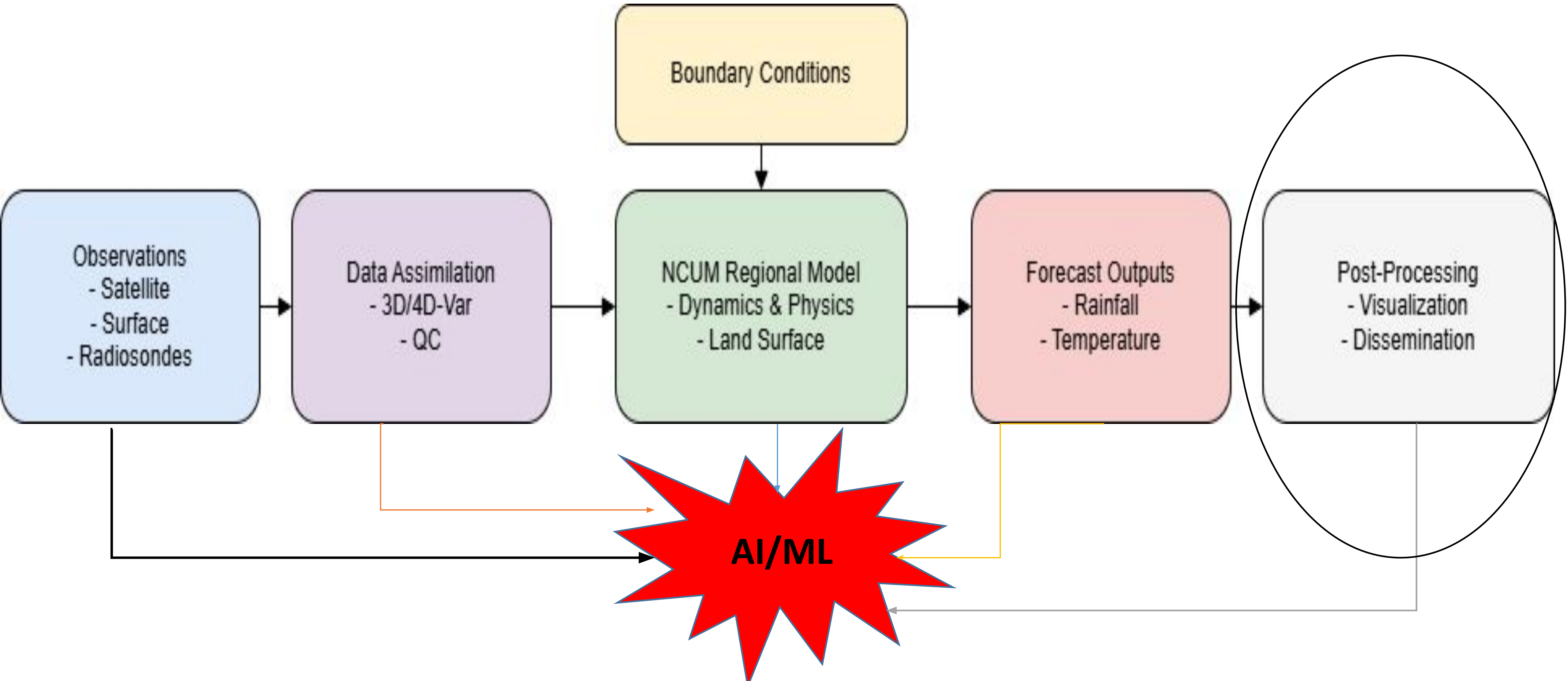
Cont…

- Often struggles with the timing, intensity, and location of convective precipitation.

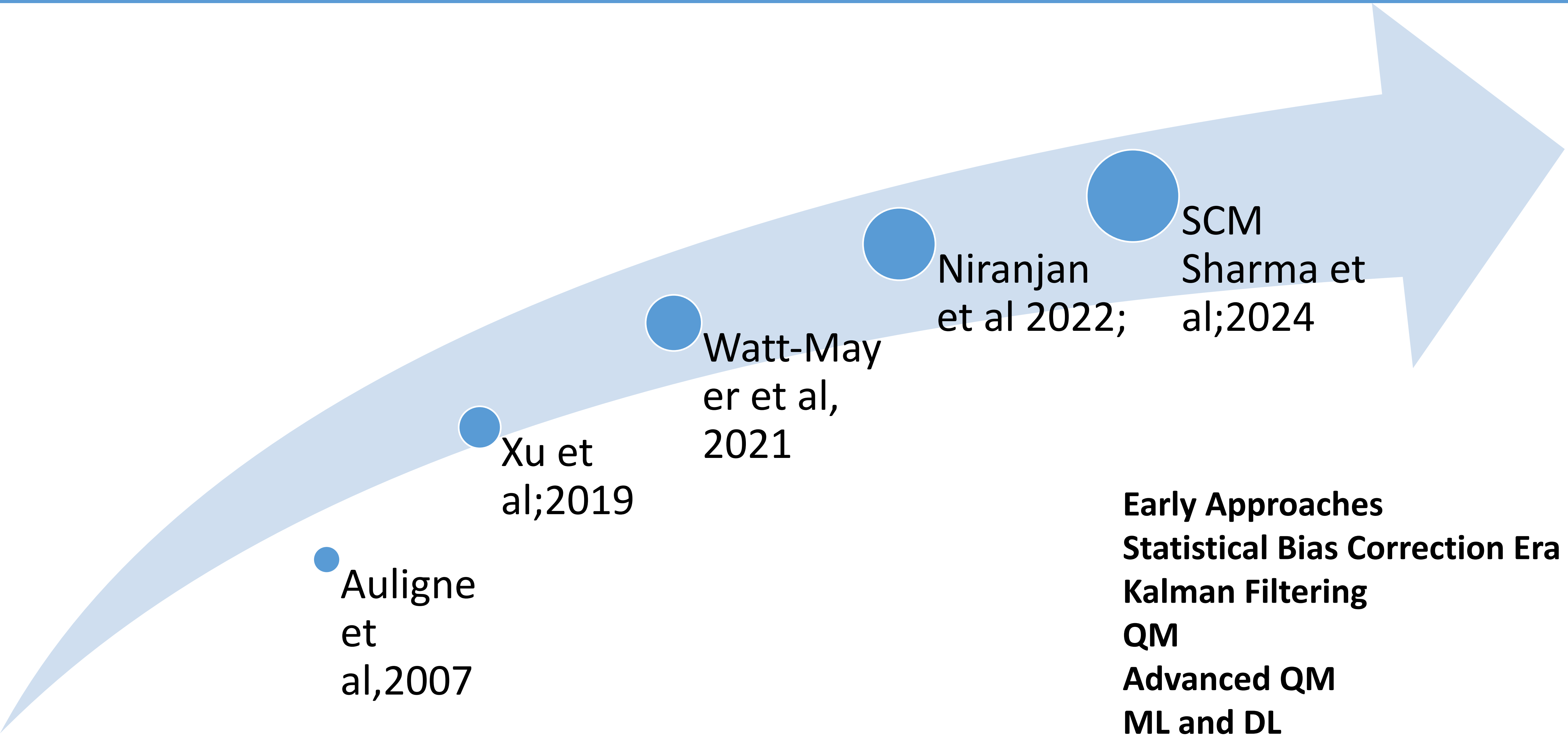
- It can overestimate or underestimate rainfall in specific regions and events.

Can we improve the precipitation estimates using the AI/ML approach?

Flow of NCUM regional



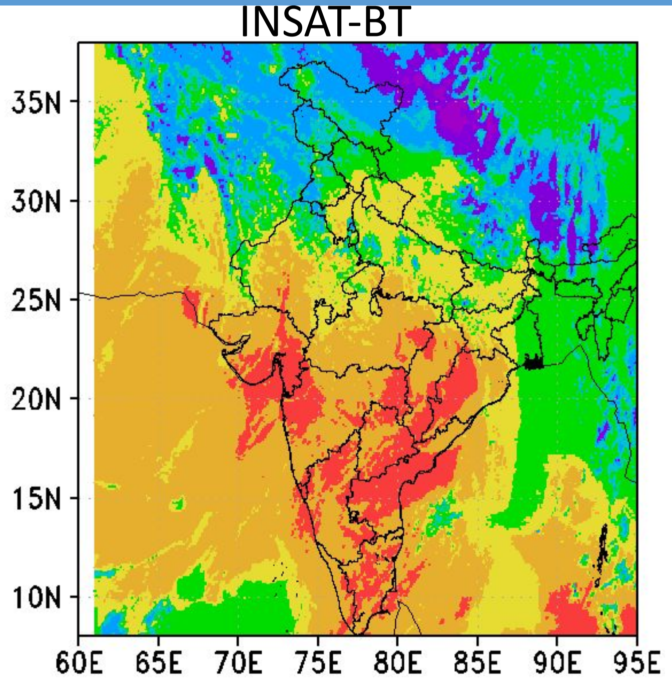
Literature

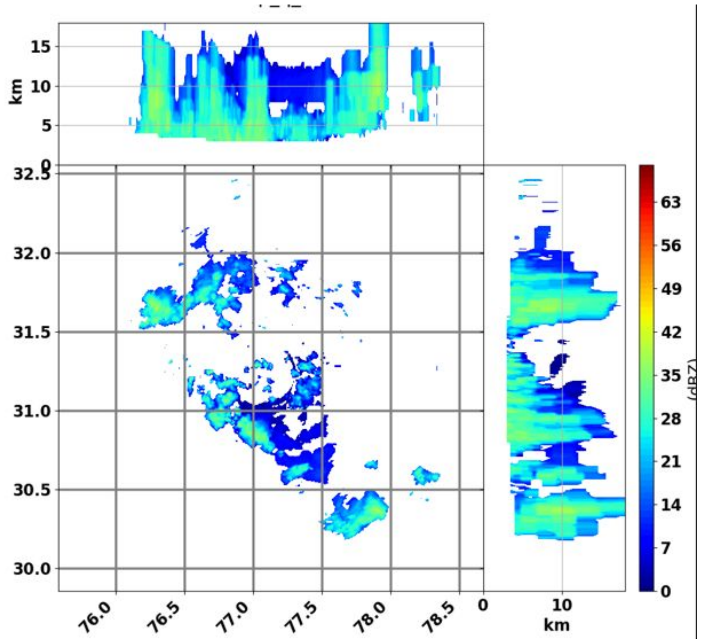


Early Approaches
Statistical Bias Correction Era
Kalman Filtering
QM
Advanced QM
ML and DL

Data Sources

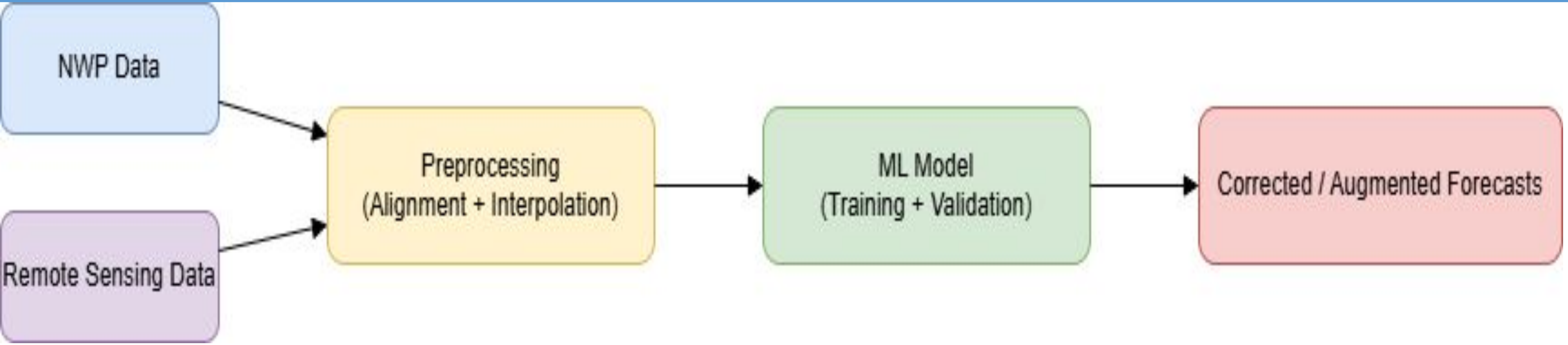
- **NWP Models**: NCUM Regional Model outputs
- **Remote Sensing**: INSAT-3D/3DR, GPM, DWR
- **Ground Truth**: Rain gauge, AWS/ARG stations





- Reflectivities from Ground based radar

System Architecture



- Combines NWP outputs and Remote Sensing data for richer, more diverse inputs.
- Handles spatial/temporal alignment and interpolation to unify data scales.
- Enables training, validation, and iterative improvements with flexible model choices.
- Produces corrected or enhanced outputs that outperform raw NWP predictions.
- Easily extendable to include additional sensors, features, or forecasting models.
- Architecture is designed to support retraining as more data becomes available.

Pre-Process……

PREPROCESS RADAR

- QC
- Classify Rain Type
- Identify the cores
- Check for missing data
- Compute Flags
- Compute Rainfall
- Upscale
- Hourly scale

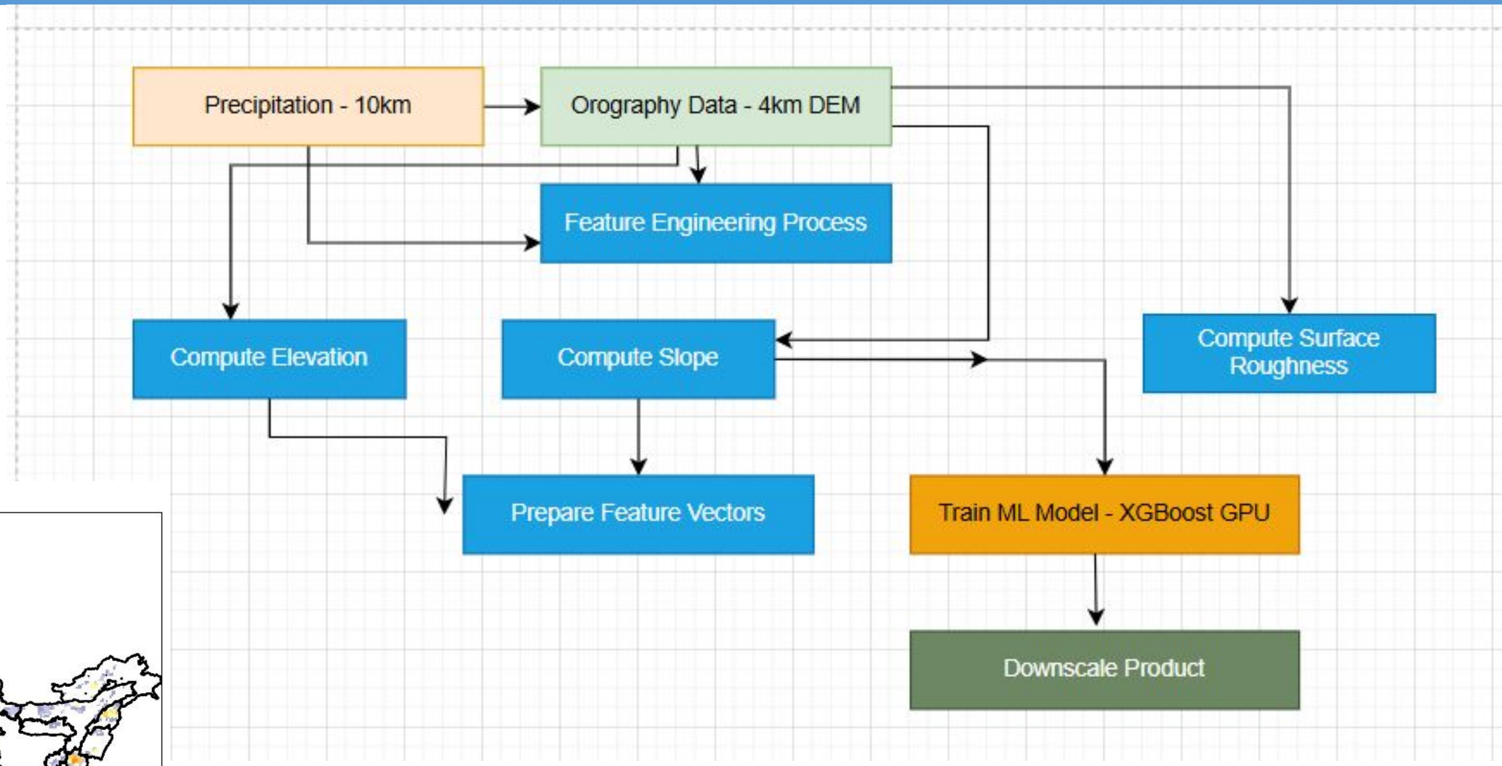
PRE-PROCESS SATELLITE

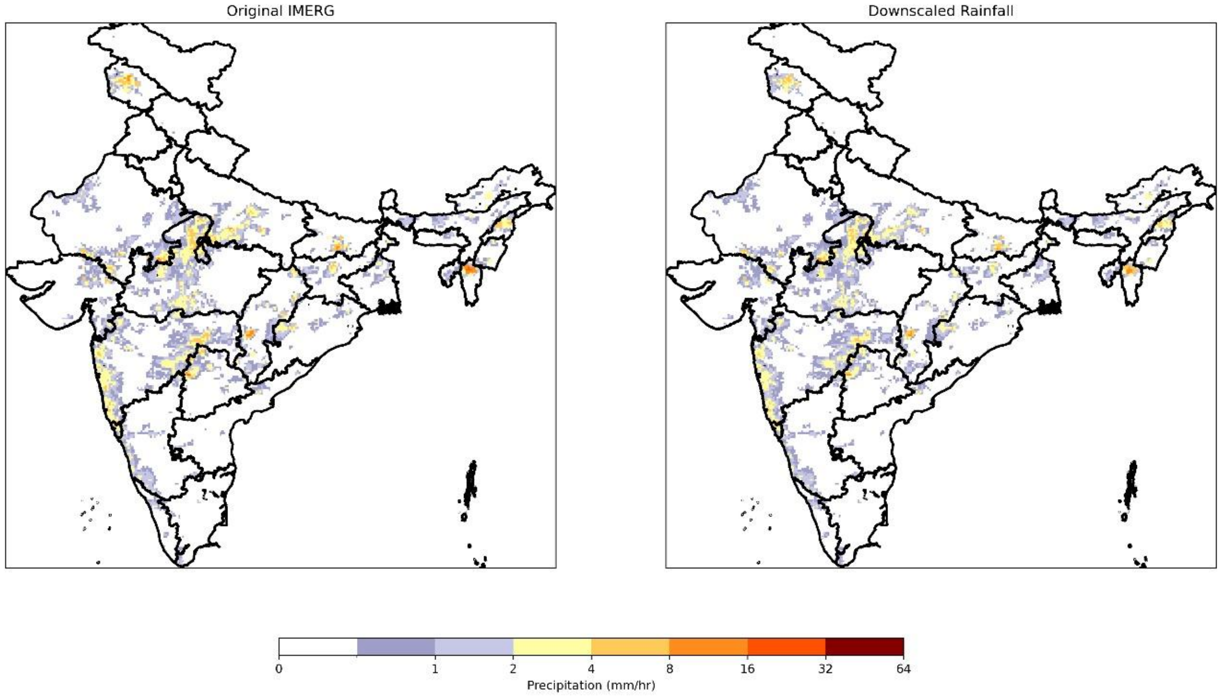
- Identify the region
- Downscale
- Uniform regions-INSAT/GPM
- Hourly scale

NCUM Vars

- Hourly accumulated rainfall
- Orography
- Precipitation

DOWNSCALING

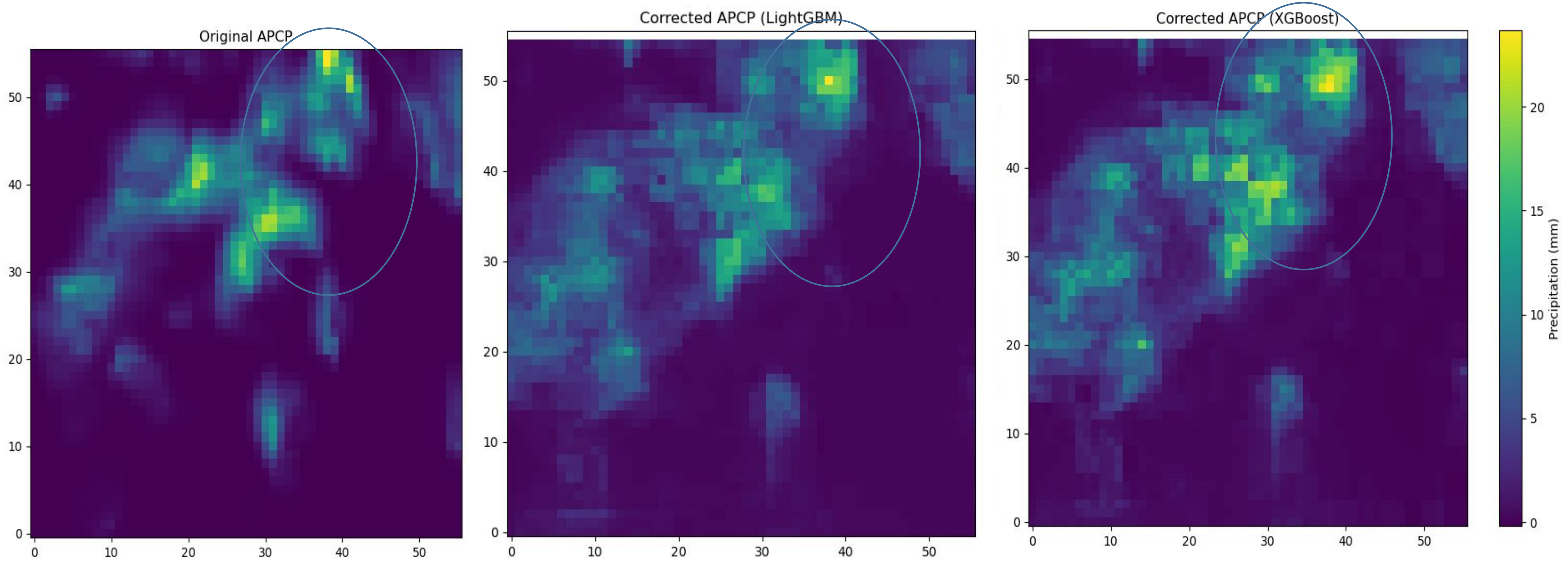




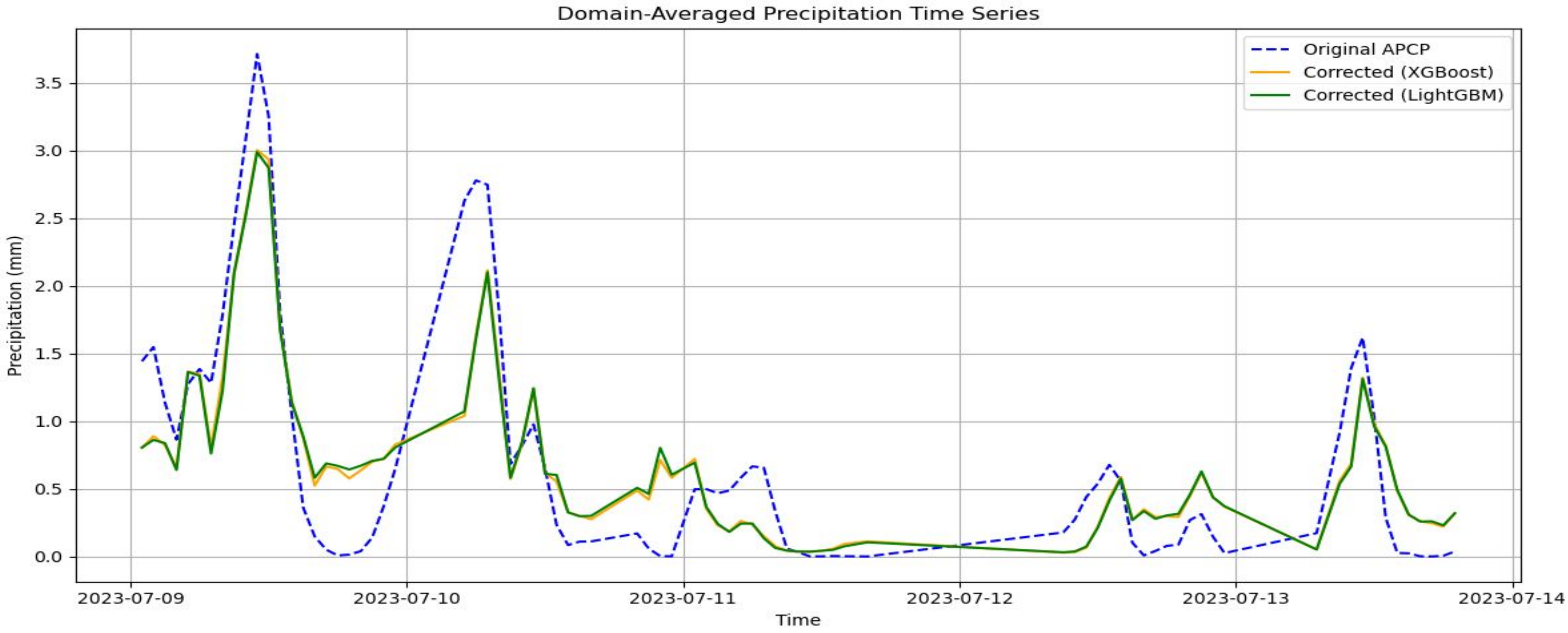
MODEL (XGBOOST/LightGBM)

- Captures Nonlinear Relationships
- Heterogeneous Inputs
- Regularization (L1 & L2) → prevents overfitting.
- Sparse-aware → handles missing data automatically.
- Parallelizable → efficient on large datasets.
- Handles classification and regression tasks.

Spatial Comparisons



Time Series



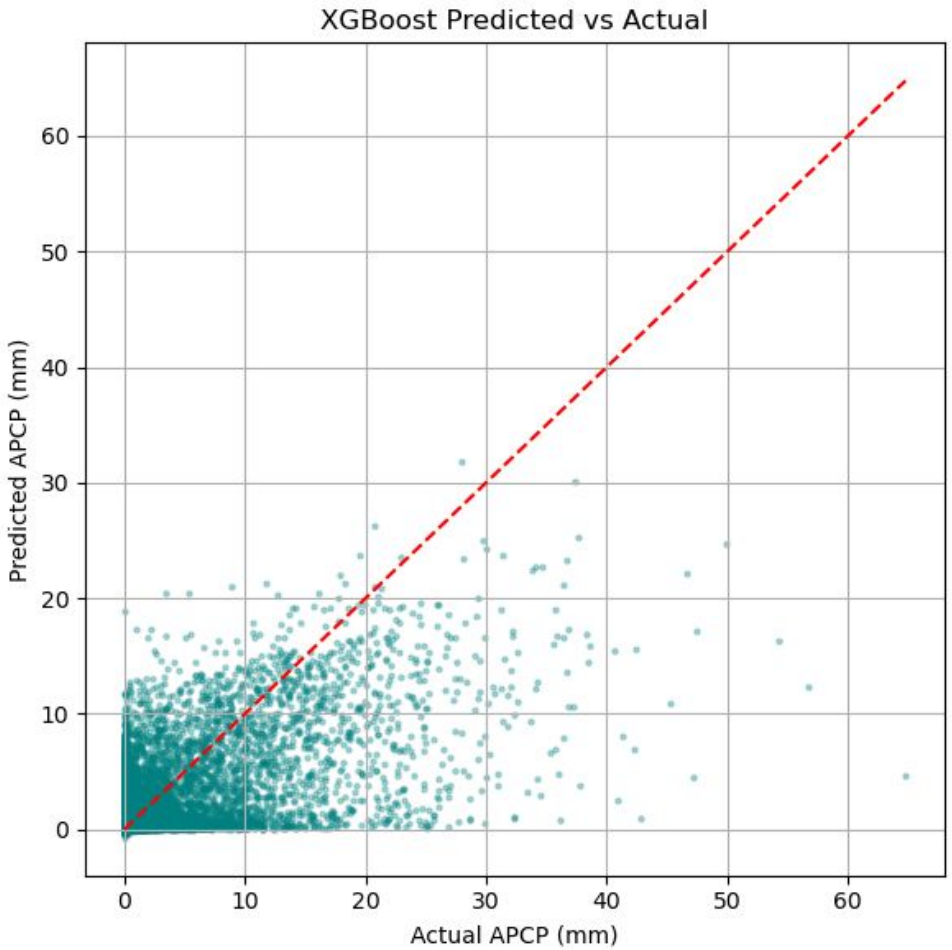
Domain-Averaged Precipitation Time Series
Original APCP
Corrected (XGBoost)
Corrected (LightGBM)
Precipitation (mm)
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
2023-07-09
2023-07-10
2023-07-11
2023-07-12
2023-07-13
2023-07-14
Time

Predicted vs Actual

- Indicates **underprediction** during heavier rainfall events.

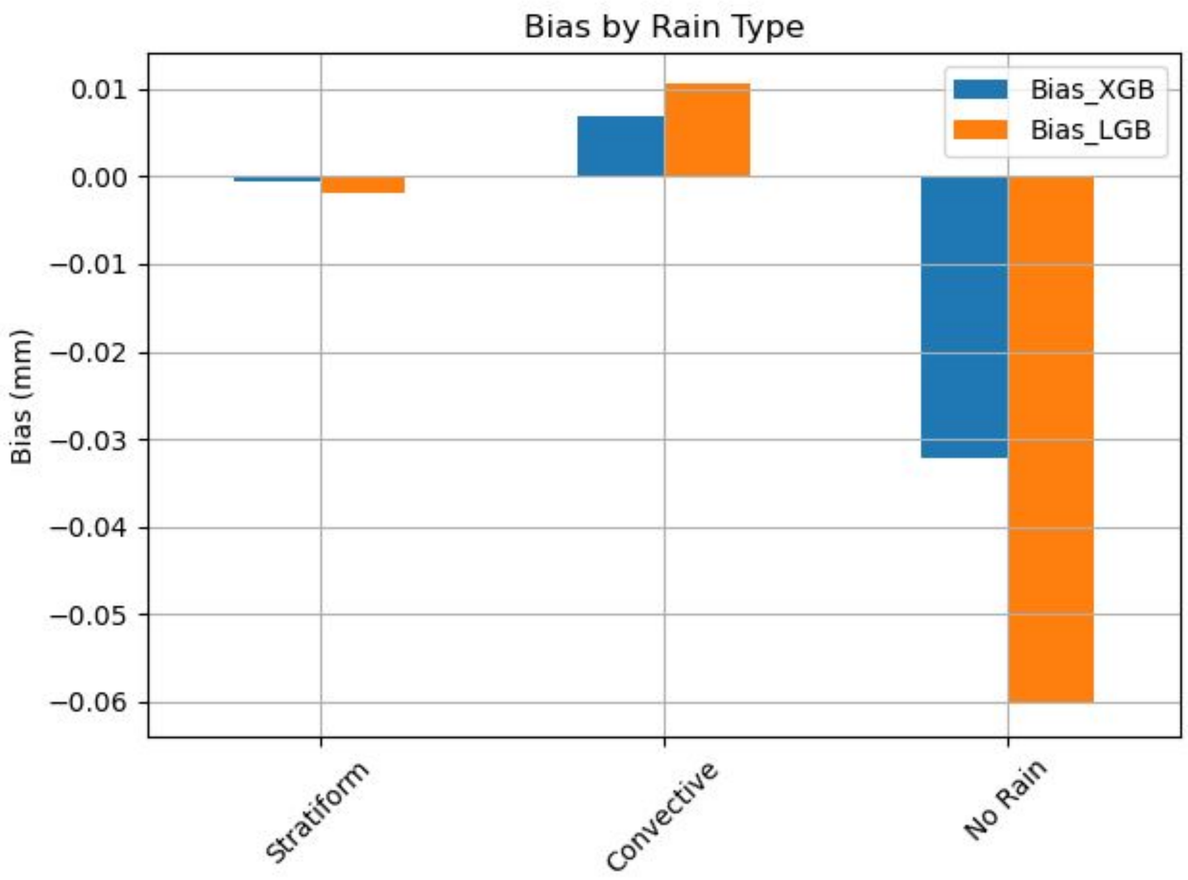
- Good agreement in light to moderate precipitation.

XGBoost captures general trends in rainfall but **struggles with extremes** — a common trait in regression models trained on skewed datasets.



XGBoost Model Performance: Predicted vs Actual Precipitation (APCP)

Bias



Stratiform Rain:

- Both models show very small bias (close to zero), meaning they predict stratiform rain fairly accurately.

Convective Rain:

- Both models slightly overpredict precipitation (positive bias), with LightGBM showing a slightly higher bias than XGBoost.

No Rain:

- Both models have a significant negative bias, indicating they tend to overpredict rainfall when it actually doesn’t rain.
- LightGBM has a slightly larger negative bias than XGBoost in this category.

Evaluation Metrics

Metric	Raw NCUM	NCUM-ML
RMSE	0.82	**0.54**
MAE	0.65	**0.42**
Correlation	0.72	**0.89**6
Bias (mm)	+0.15	**+0.04**

Extreme rainfall evaluation

XGBoost Metrics

RMSE: 2.204

MAE : 0.709

R^2 : 0.452

LightGBM Metrics

RMSE: 2.194

MAE : 0.704

R^2 : 0.457

Challenges in Integration

- Temporal/spatial mismatches
- Noise and missing data in RS
- Differences in physics-based and data-driven paradigms

Timing Challenge

Time	Available Data	Status
T_0	NWP forecasts	Ready
$T_0+\Delta t$	Observations	Arriving

- Correct short-term forecasts in post-processing, especially for the first few hours
- Learning systematic forecast biases using years of NWP + obs data

Summary & Conclusion

- AI/ML enhances NWP by learning from observations
- Remote sensing provides crucial spatiotemporal granularity
- Hybrid frameworks show promise for operational improvements
- Bias correction consistently adds rainfall during monsoon, if model under represents convection or moisture transport processes then these would be more.

QUESTIONS?