WORKSHOP ON DATA ASSIMILATION IN WEATHER AND CLIMATE MODELS
17 May 2024
International Centre for Theoretical Sciences, Tata Institute of Fundamental Research

Modelling Rainfall extremes and Floods over Karnataka

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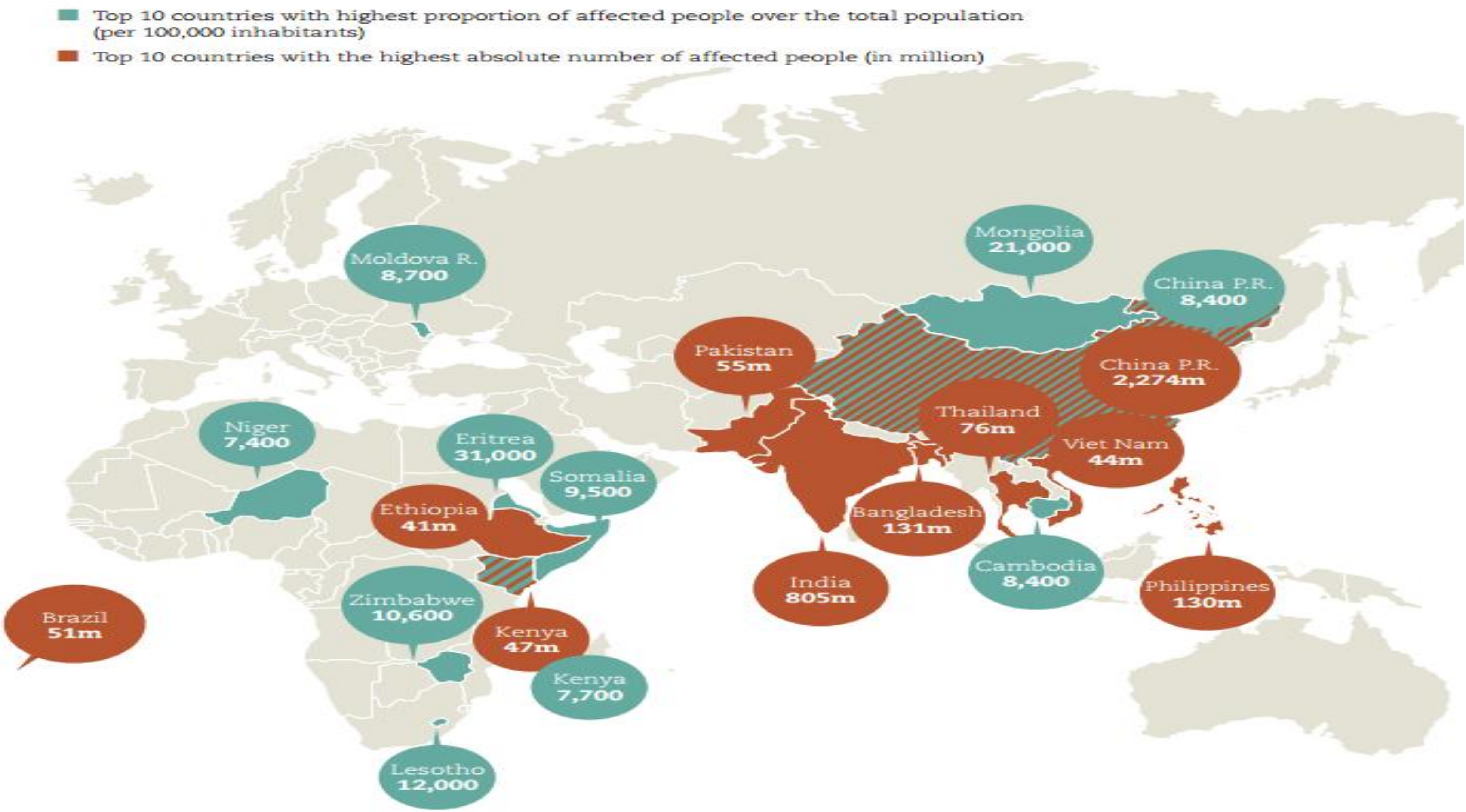
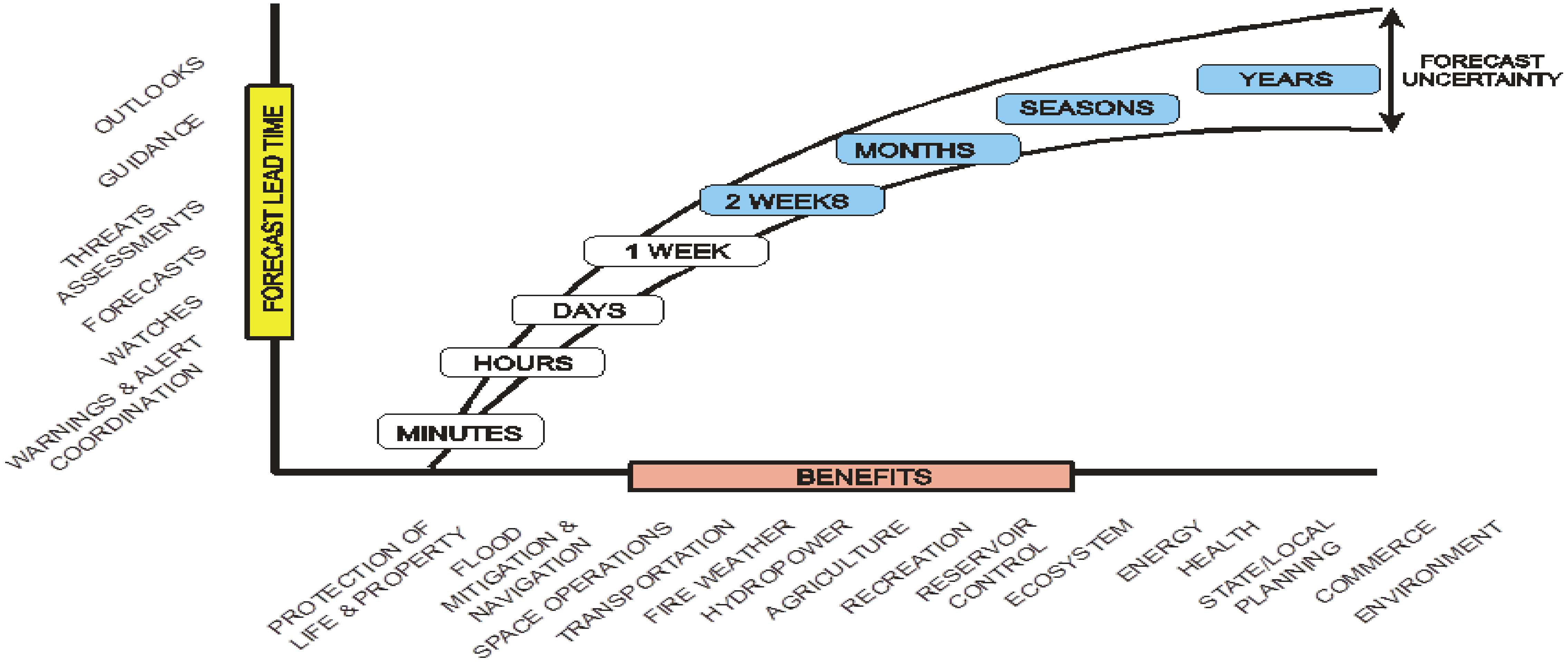
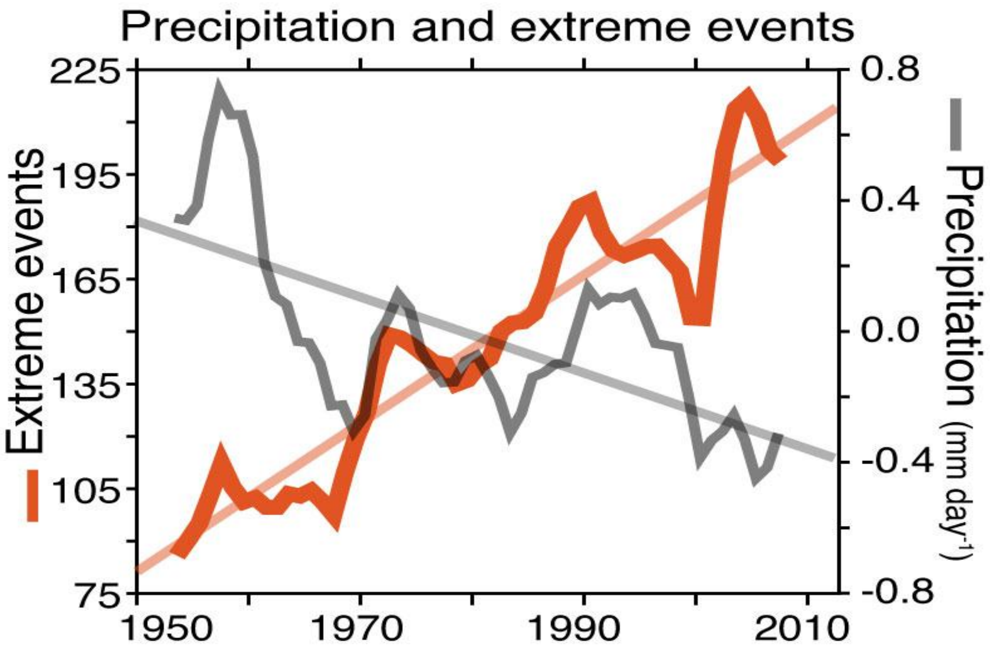
Why Forecasting Extreme weather is so important for our Country?

10 countries hardest hit by weather disasters



Forecast Leads- Applications

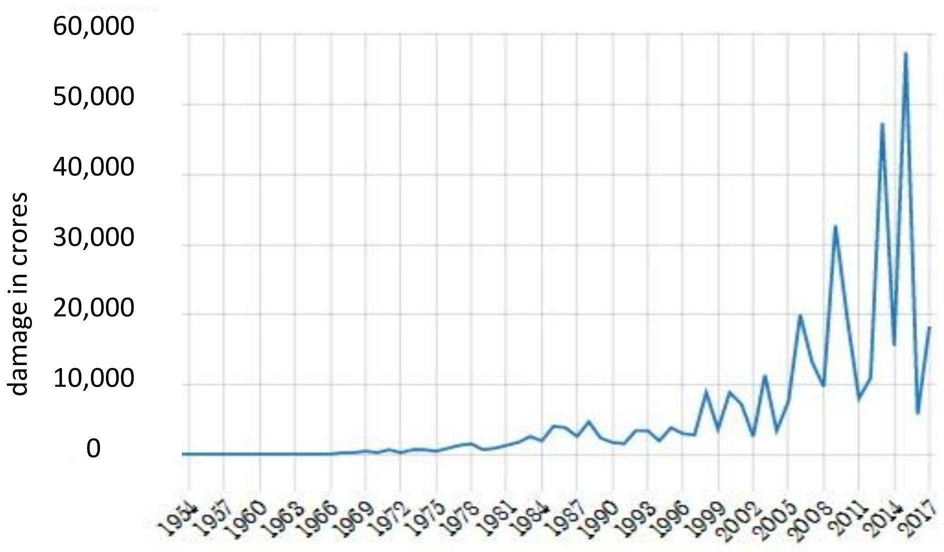




Roxy et al. 2017

- It has changed in frequency and intensity as a result of climate change (Yin et al. 2022)

Damage Caused by Floods in India

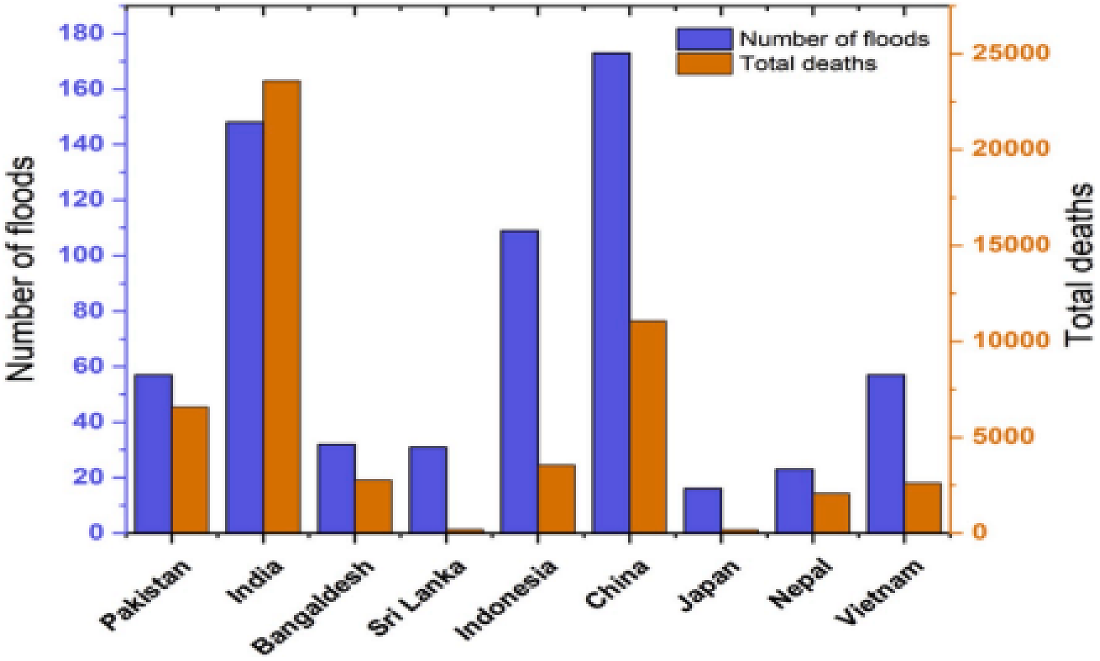


Mohanty et al. 2020

- In July 2021 alone, EREs caused property damage of around $12 billion USD in Europe and China (Liang 2022)

- Economic loss of over $3 billion USD per year in India (Swain et al. 2019)

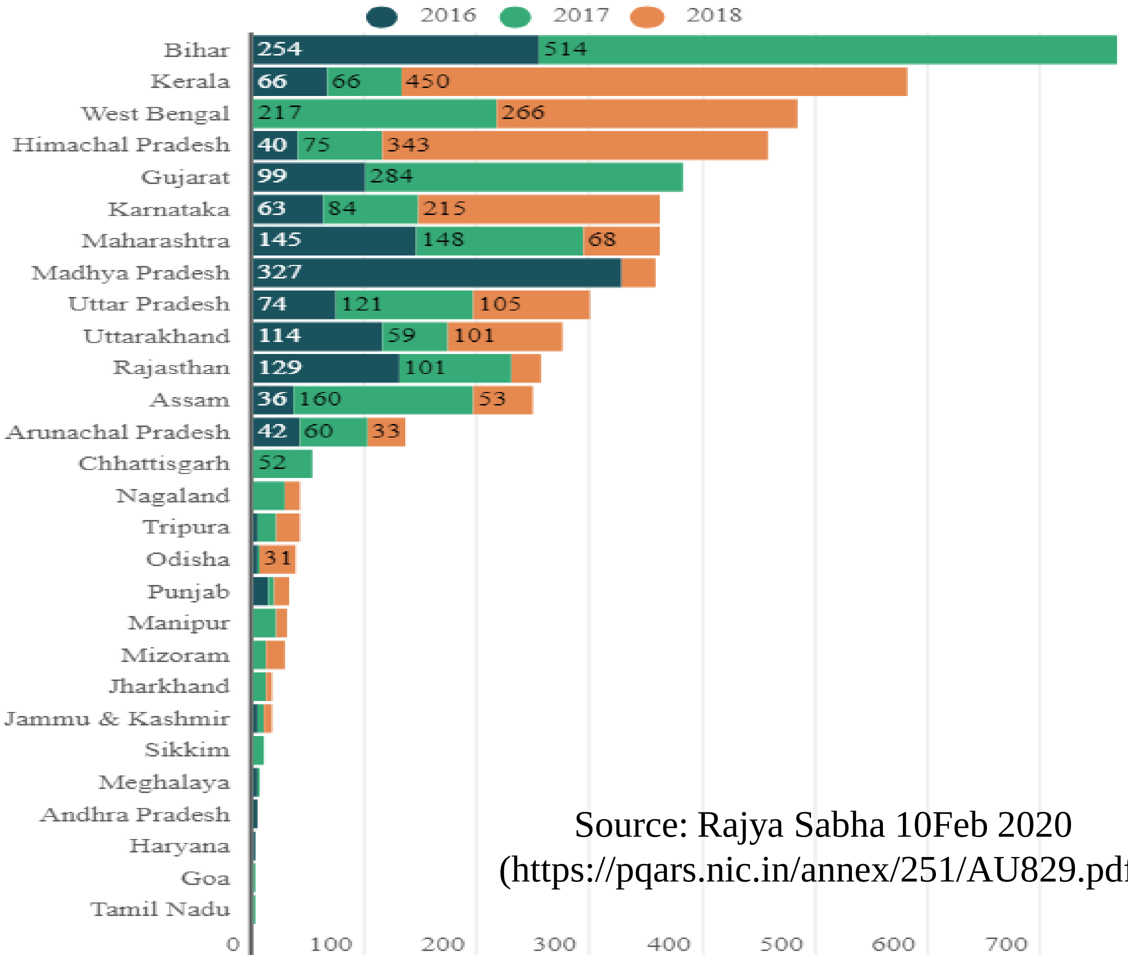
Why Prediction of EREs is Important



Asharaf et al. 2017

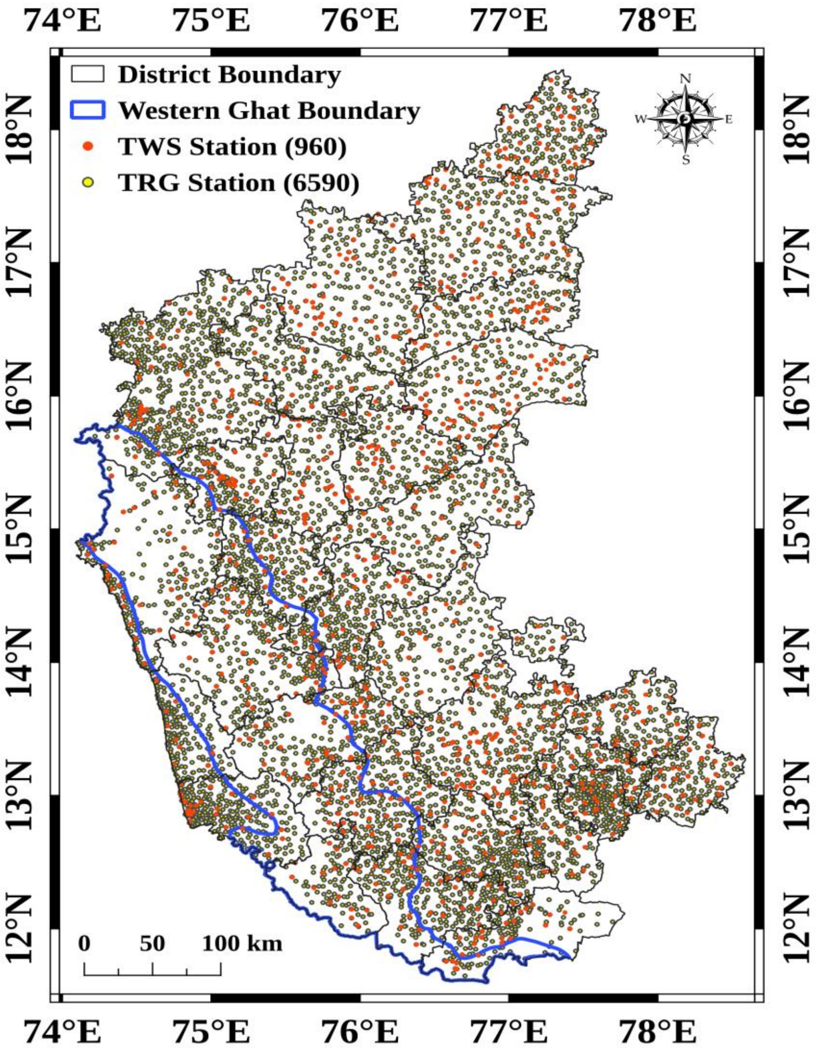
➢ It has highest share of mortality (46.1%) of all extreme weather events in India (Ray et al. 2021)

Lives Lost to Floods in India



Source: Rajya Sabha 10Feb 2020 (https://pqars.nic.in/annex/251/AU829.pdf)

Data Used for Validation



- **Telemetric Rain-Gauge Stations (TRG)** **~7000**

- **Telemetric Weather Stations (TWS)** **~950**

  (Temperature, Humidity, Wind Speed, Wind Direction)

Computer Weather Forecasts are like an experiment! Can we believe the computer weather forecast model?

Numerical models are not expected to be perfect: Forecast Models are susceptible to inherent errors

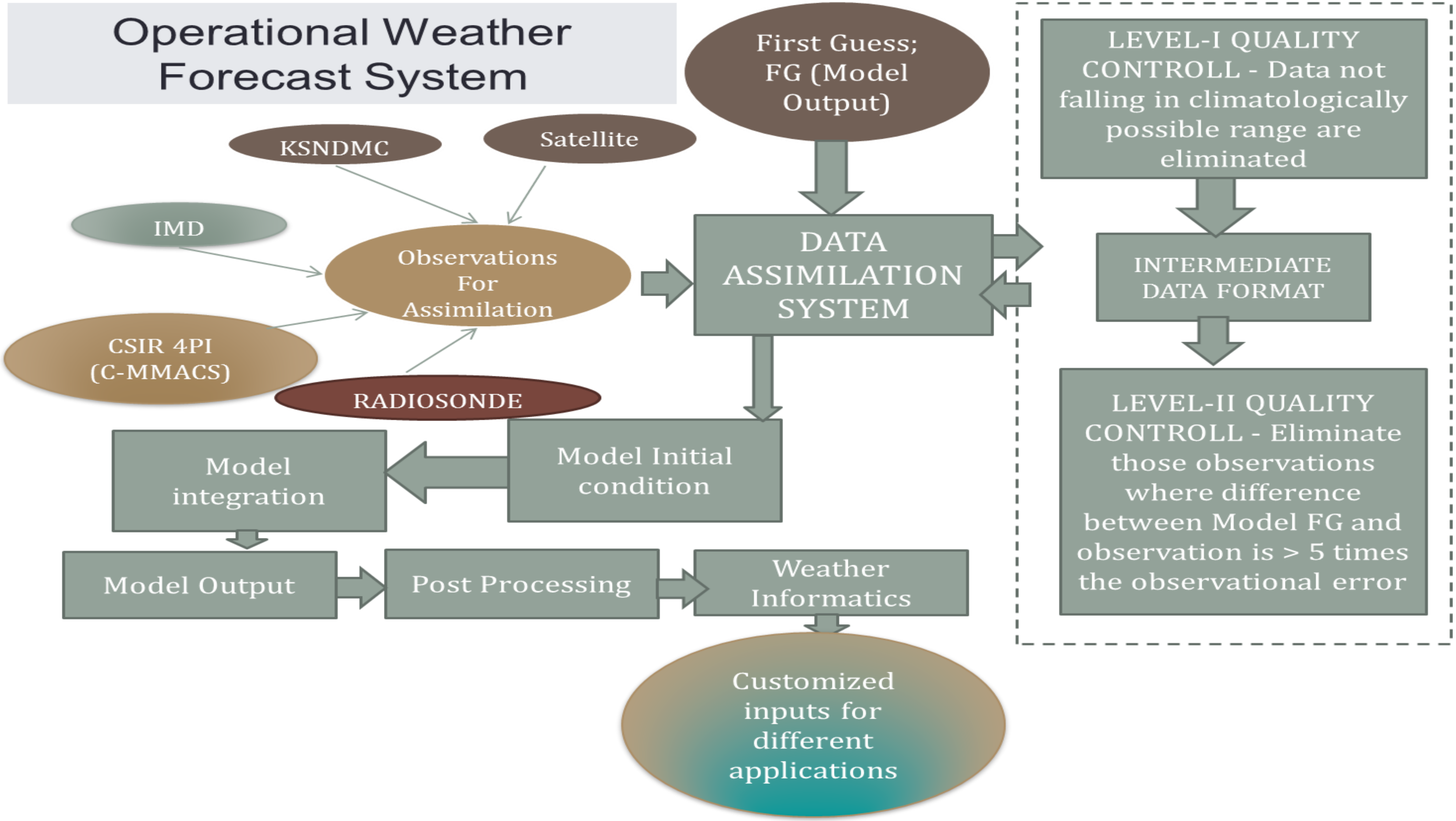
Forecast errors can be due to imperfections in

- ✓ Data (Initial and Boundary conditions)
- ✓ Physics
- ✓ Numeric
- ✓ Approximation in basic equations
- ✓ Model grid

Systematic errors : Inherent with the model, generally follows specific pattern
Relatively easier to eliminate
How to eliminate: Using methods like bias correction

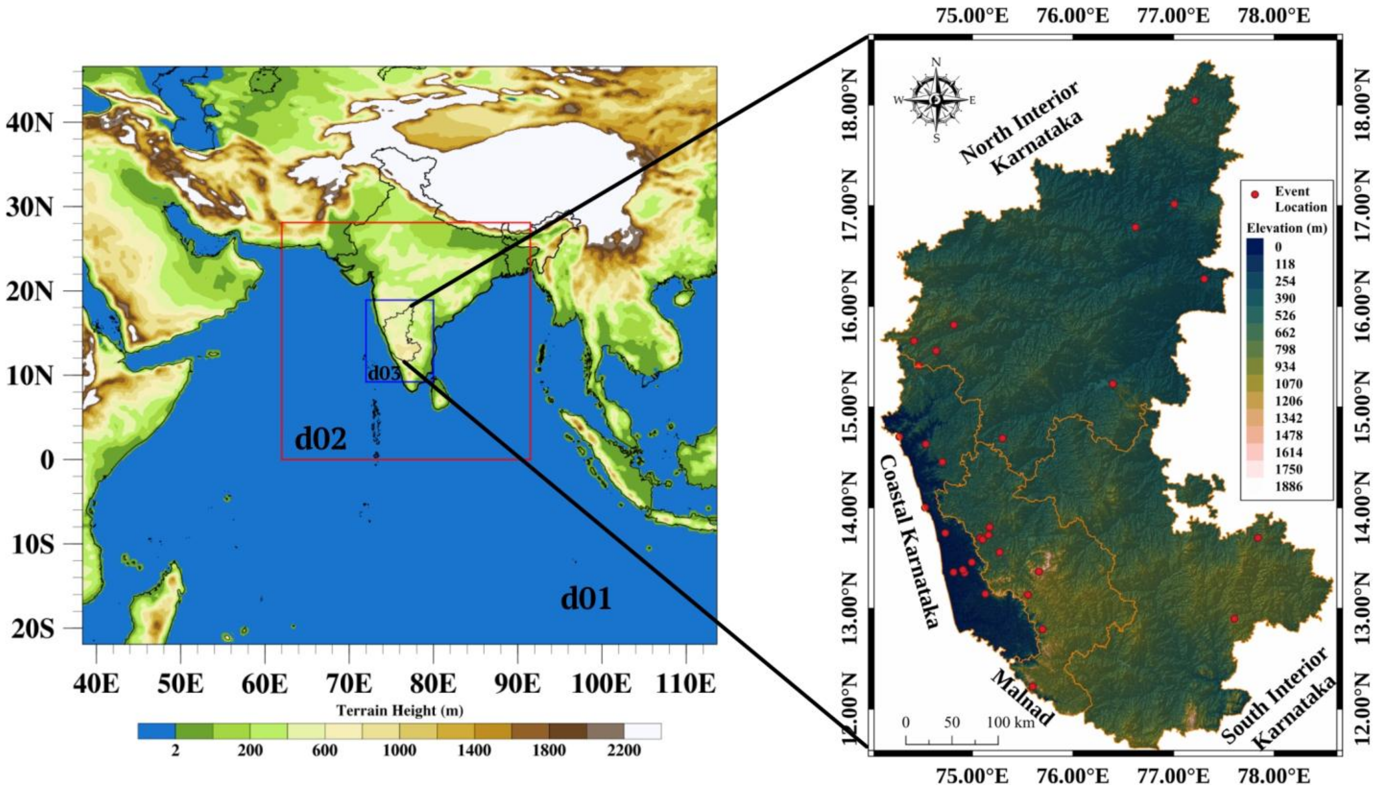
Non-Systematic errors: Random errors, not follows any specific pattern, Relatively difficult to eliminate, mostly due to errors in data (Initial and boundary condition)
How to eliminate: Using methods like **Data Assimilation**

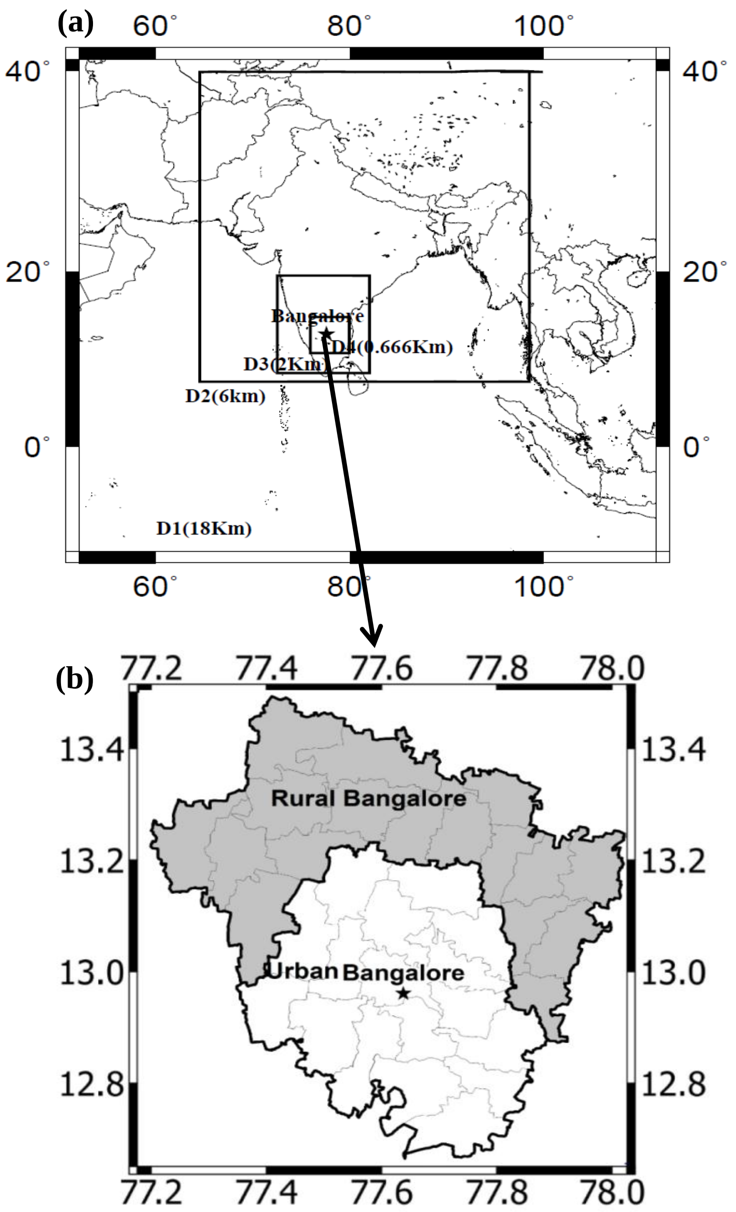
Operational Weather Forecast System



Rakesh and Goswami, JGR, 2015

Model Configuration: Karnataka (3 Km); Bengaluru (666 m)

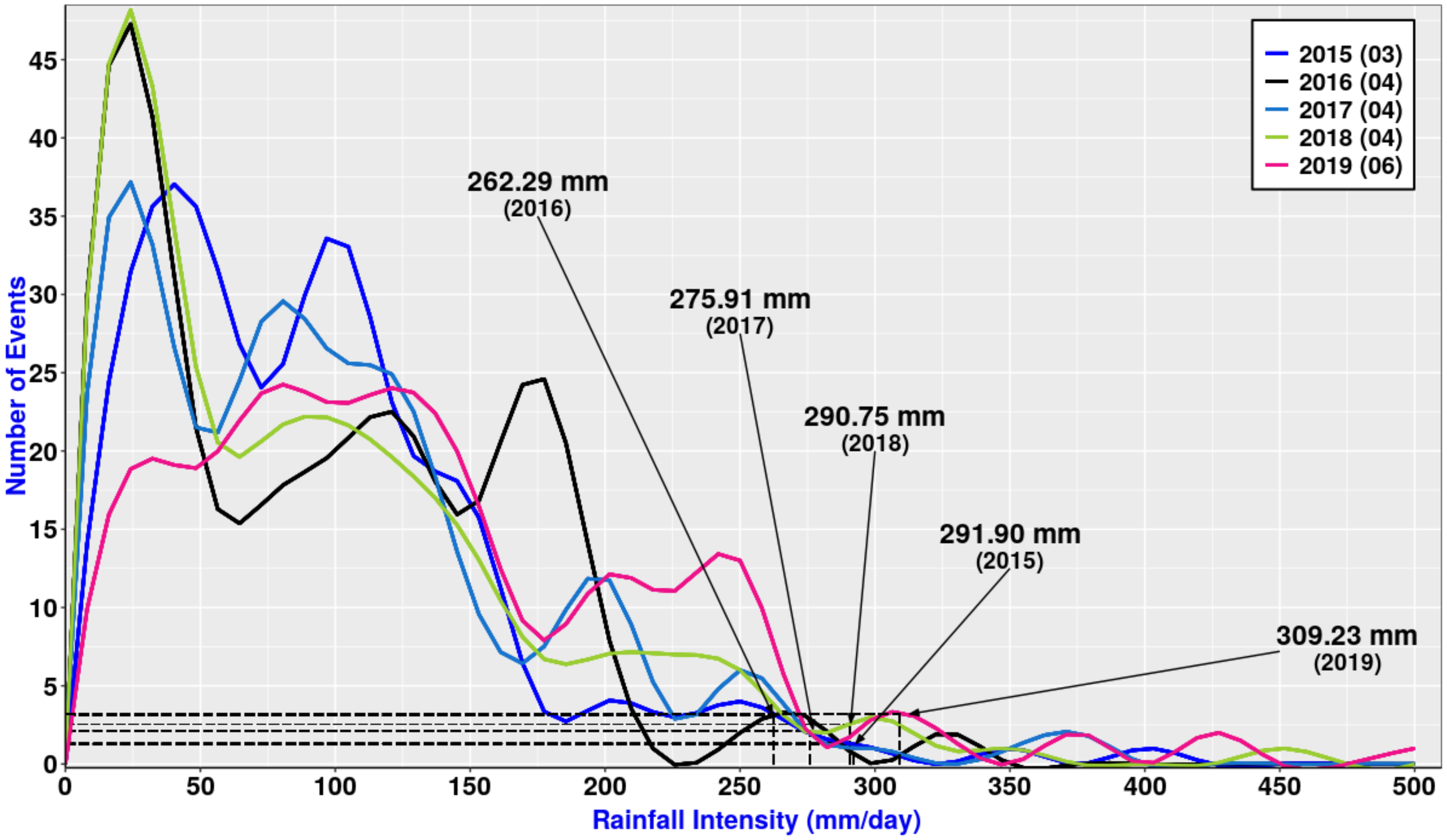


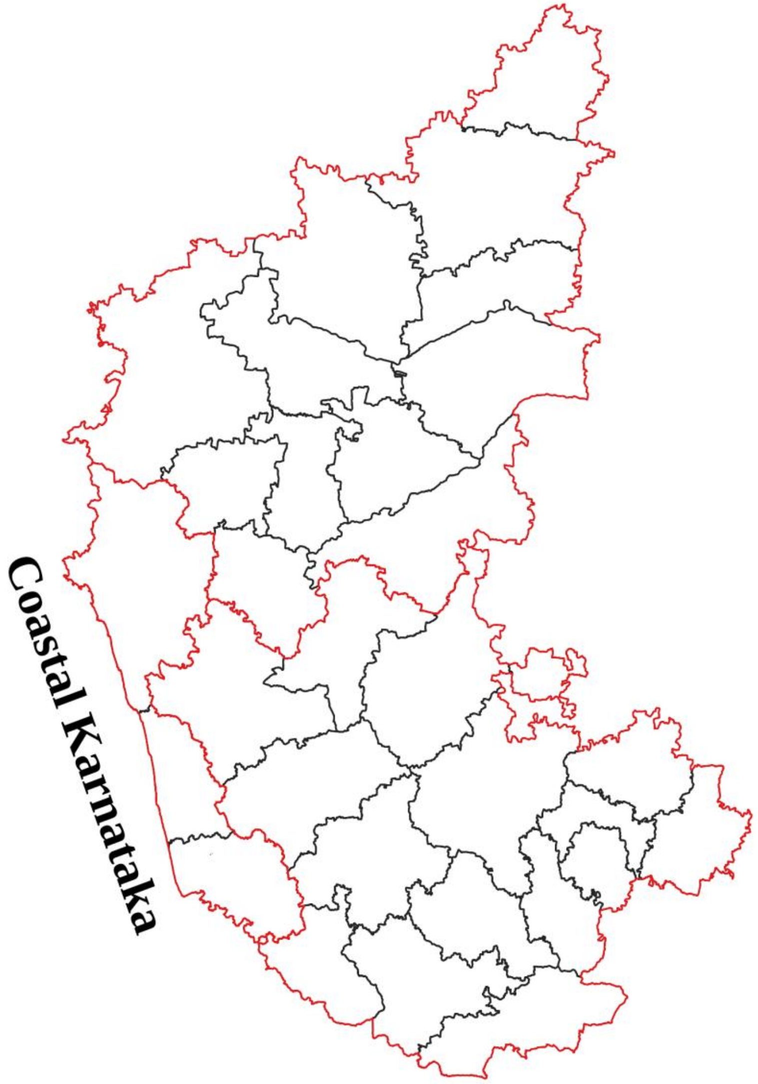


- Domain Resolution: 27, 9 & 3 km for d01, d02 & d03 respectively
- Grid Points: 300 × 300 (d01), 352 × 352 (d02) and 271 × 376 (d03)
- Initial & Boundary Condition Data: NCEP Global Forecast System (GFS) 0.25° × 0.25° three hourly forecast data

Identification of EREs from coastal Karnataka

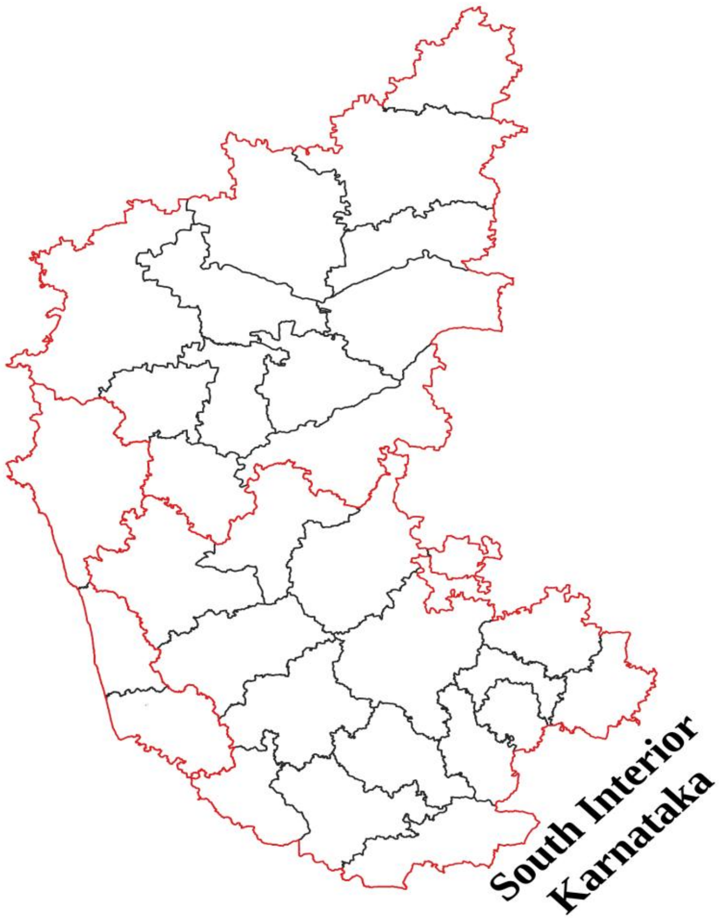
- Distribution of rainfall events from coastal Karnataka region and ERE threshold at 99.993 percentile

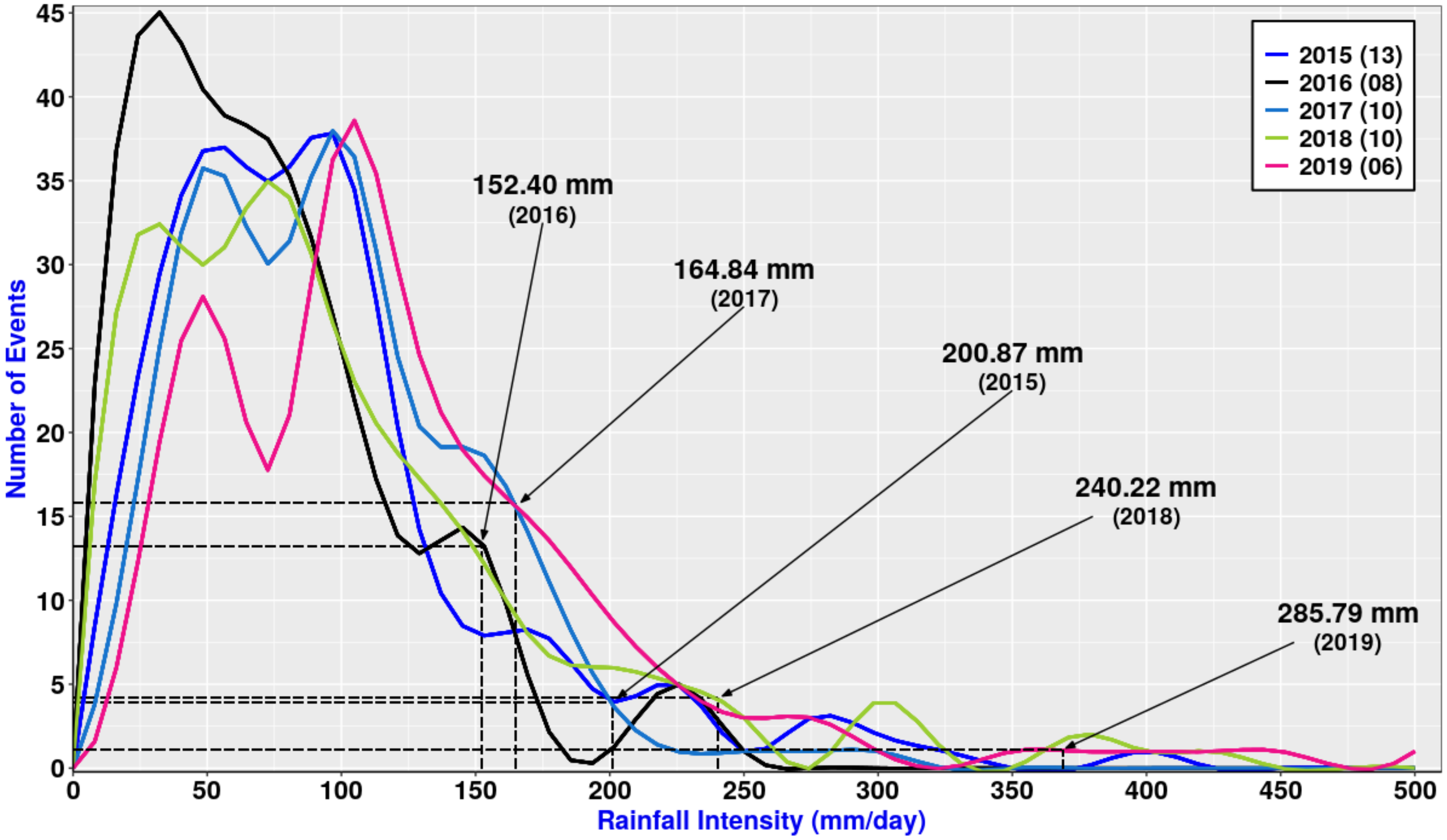




Identification of EREs from South Interior Karnataka (SIK)

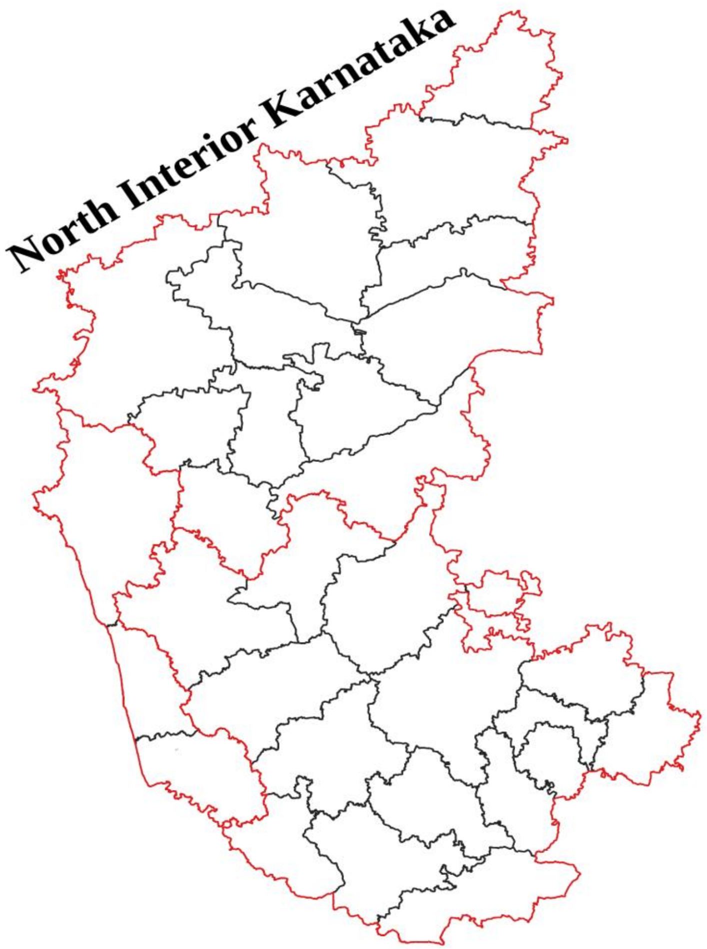
- Distribution of rainfall events from SIK region and ERE threshold at 99.993 percentile

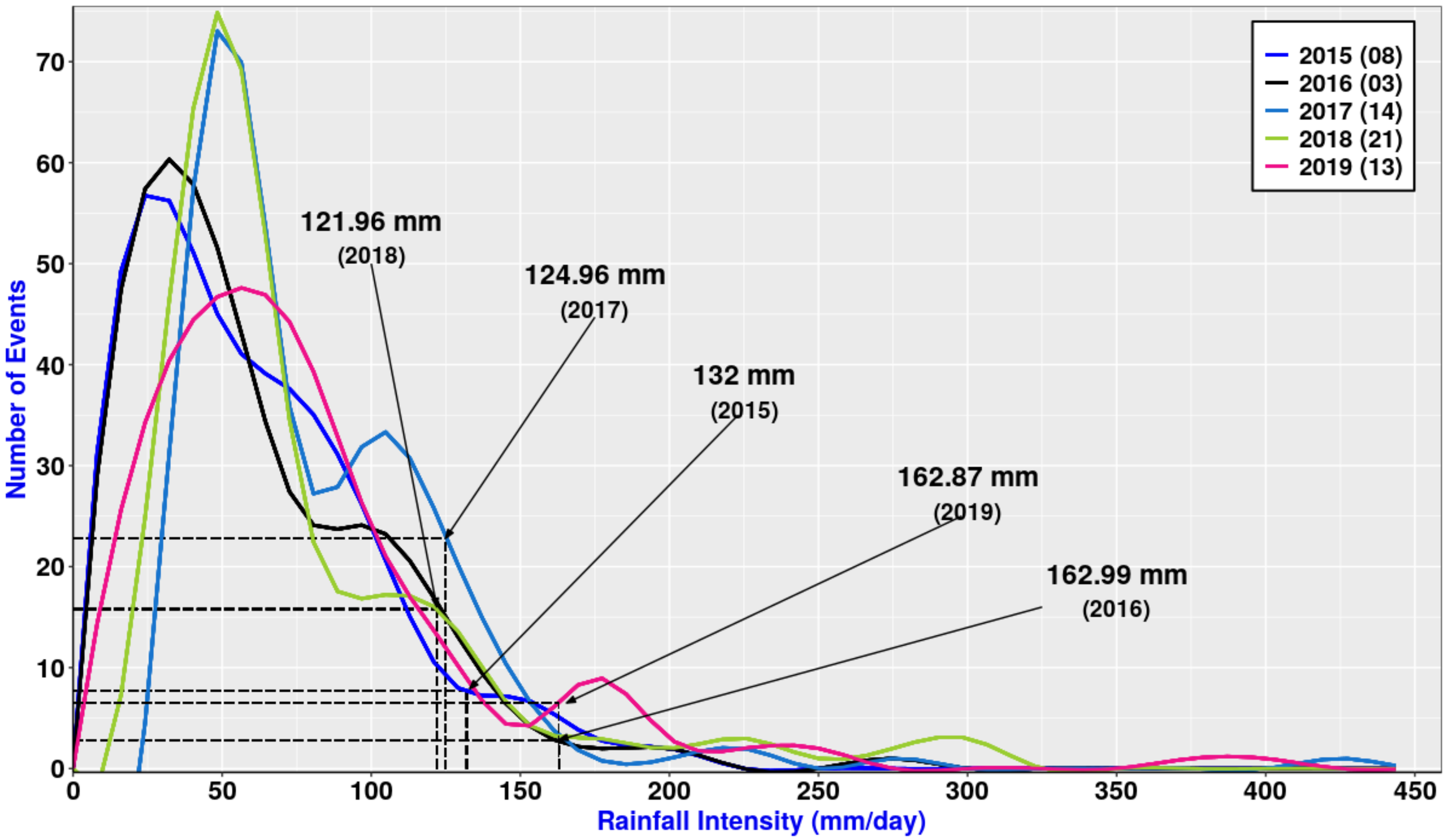




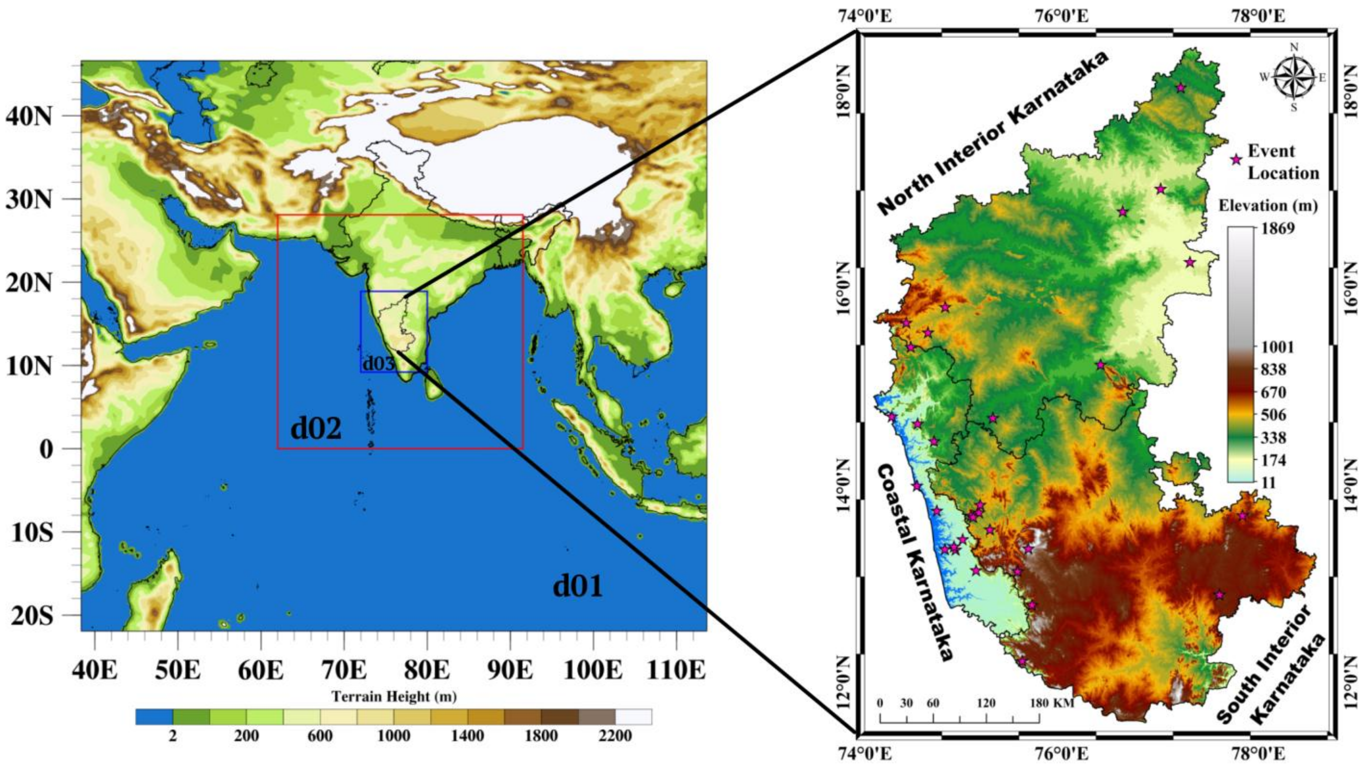
Identification of EREs from North Interior Karnataka (NIK)

- Distribution of rainfall events from NIK region and ERE threshold at 99.993 percentile





Domain Configuration & Locations of EREs



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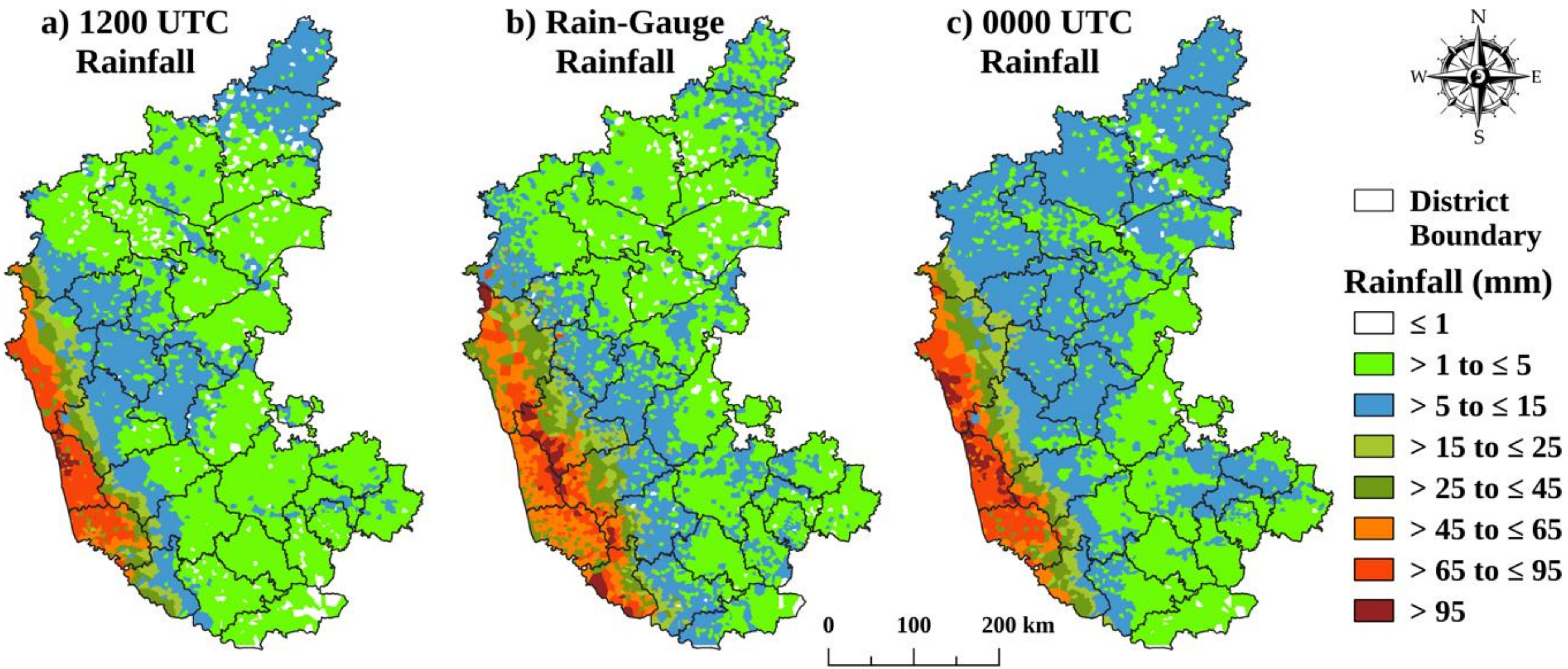
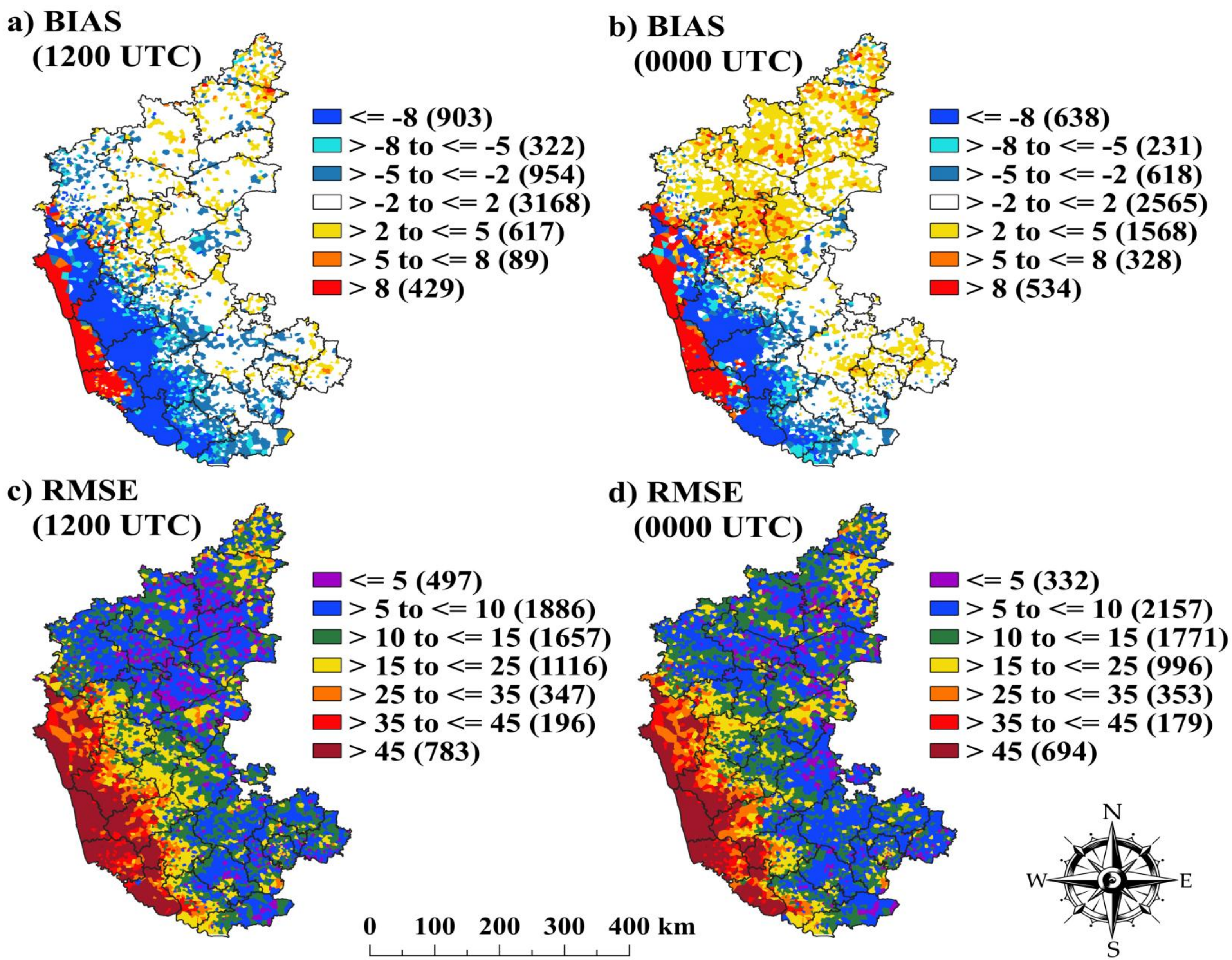
  NCEP Global Forecast System (GFS) 0.25° × 0.25° three hourly forecast data

Spatial Distribution of Average Observed & Predicted Rainfall



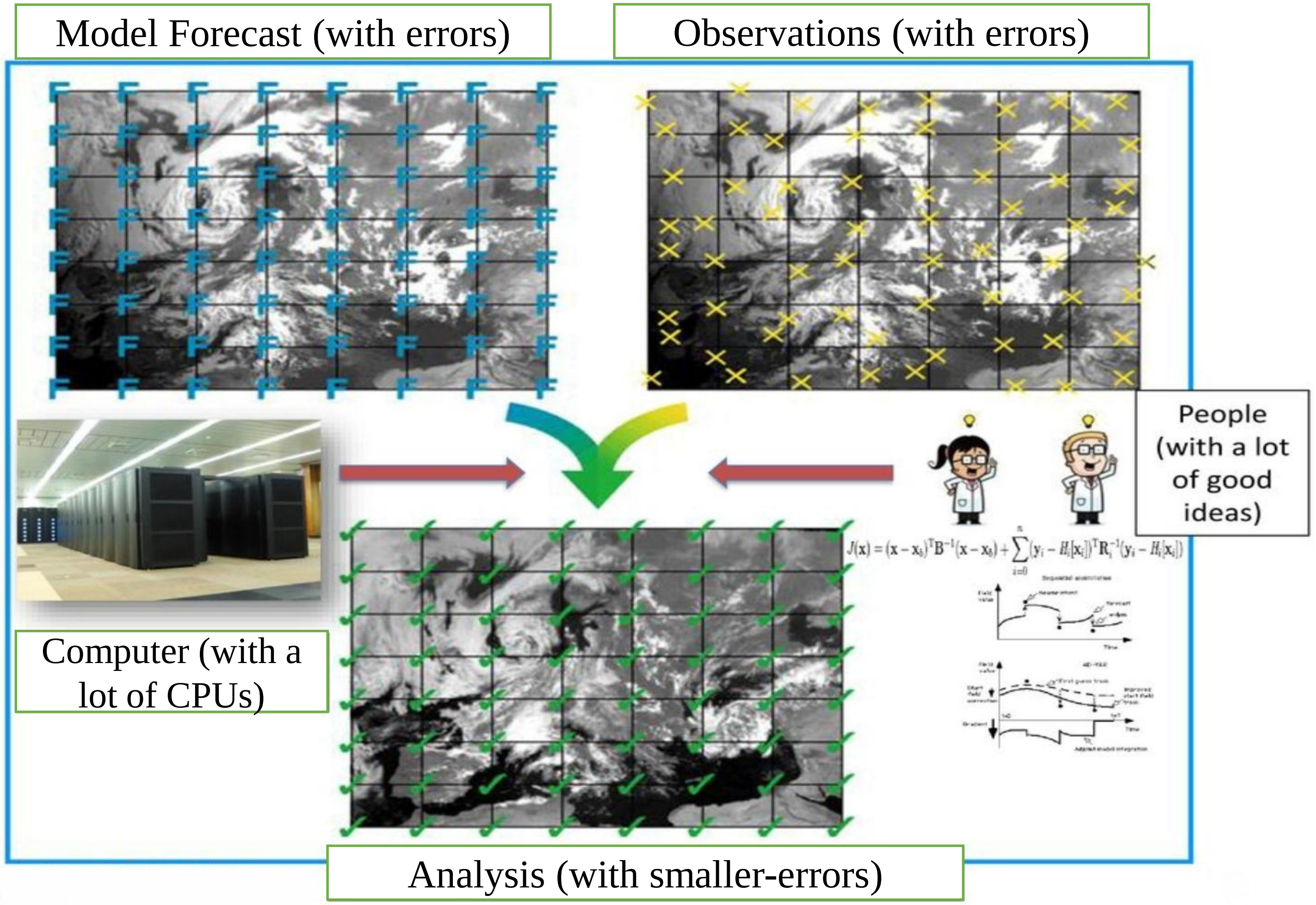
- Overprediction over the coastal region (windward side of western ghat (WG))
- Underprediction over leeward side of WG

Spatial Distribution of Errors in 24-h Accumulated Rainfall

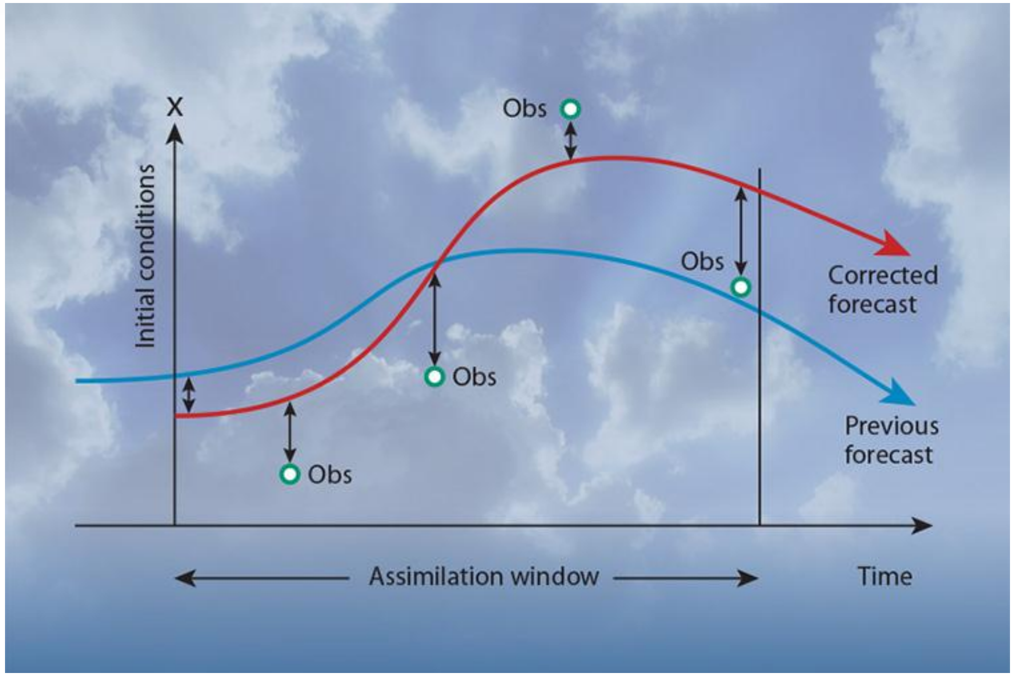


- Bias observed in regions influenced by orographic lifting and associated convection
- Model underpredicted the rainfall over western ghats (WG)
- Model overpredicted (bias > 8mm) the high intense rainfall over the windward side of the mountainous WG
- 1200 UTC simulations shown lower RMSE than 0000 UTC simulations

Data Assimilation (DA) to Improve the Analysis



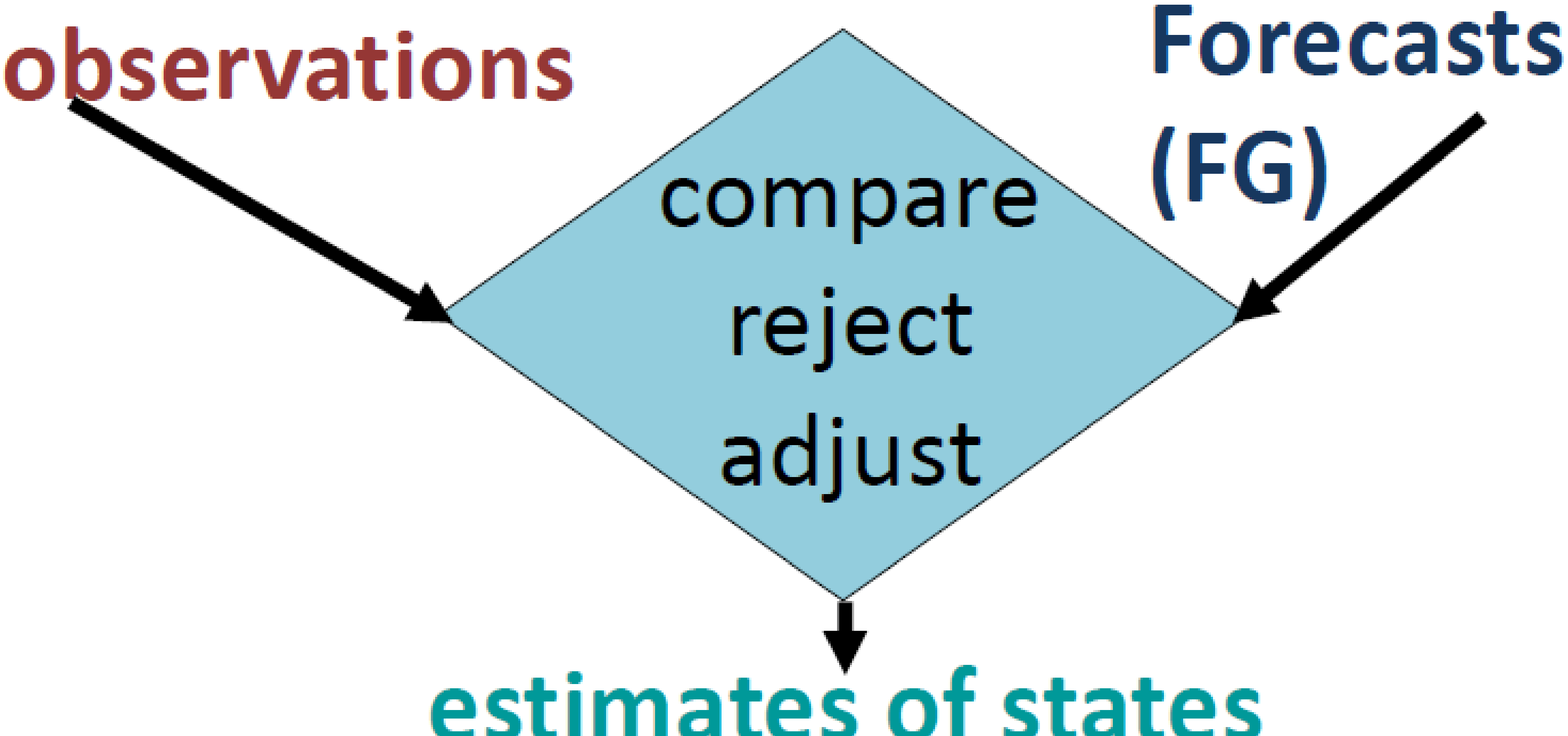
source: Massimo Bonavita (ECMWF)



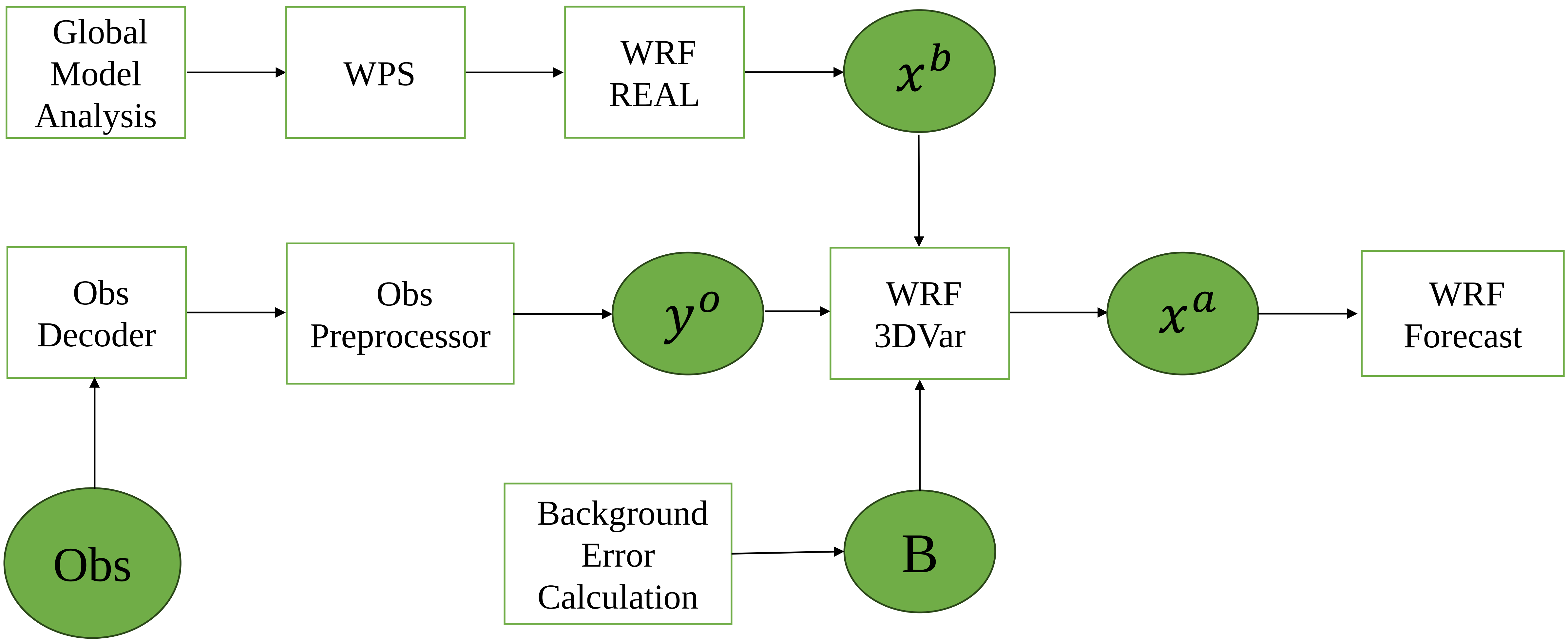
source: www.ecmwf.int

Data assimilation is the technique whereby observational data are combined with output from a numerical model to produce an optimal estimate of the evolving state of the system.

The Data Assimilation Process



WRF 3DVar Workflow



Cost Function for Three Dimensional Variational (3DVar) DA

$$J = J_b + J_o$$

$$J = \underbrace{\frac{1}{2}(x - x_b)^T B^{-1}(x - x_b)}_{\text{Background Term}} + \underbrace{\frac{1}{2}(y_o - H(x))^T R^{-1}(y_o - H(x))}_{\text{Observation Term}}$$

Where, J_b – Background term J_o – Observation term

x – Analysis field value x_b – First guess

y_o – Observed input H – Forward non-linear operator

B – Background Error Covariance Matrix

R – Observation Error Covariance Matrix

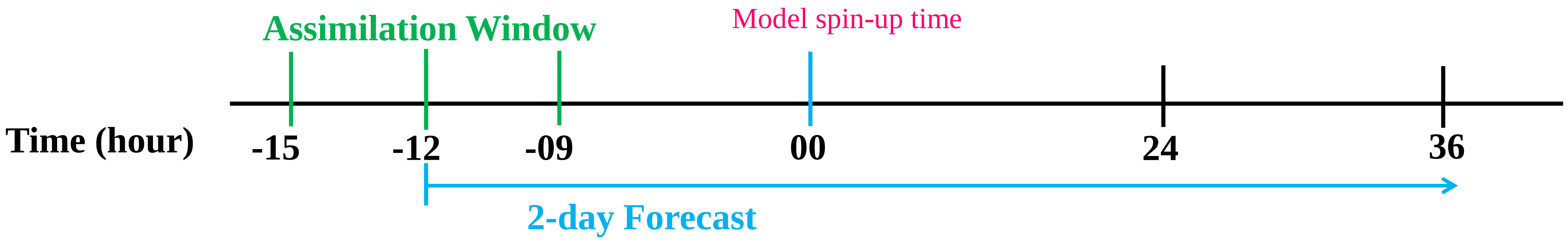
Optimal x_a is obtained by minimizing the cost function

$$\nabla_X J(X) = 0$$

Data Used in Assimilation

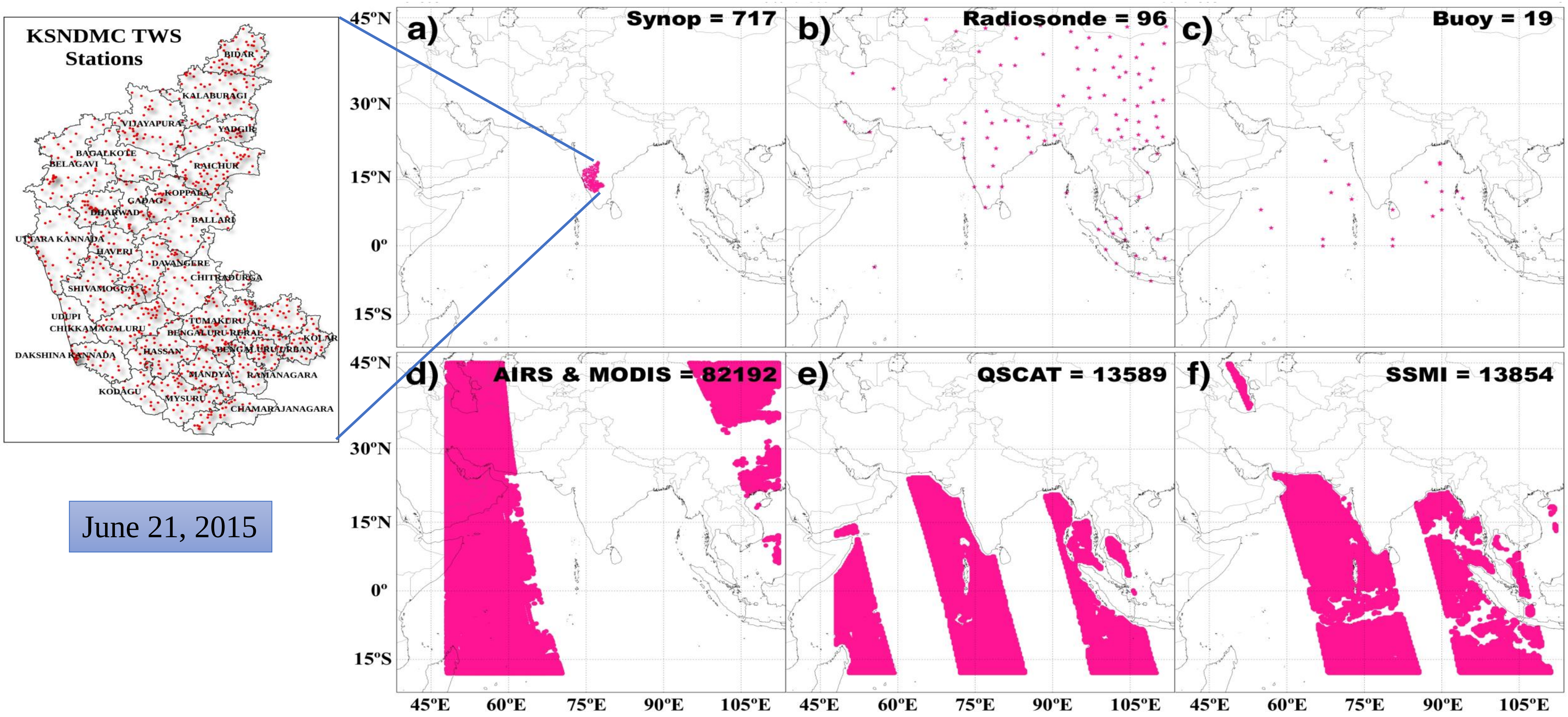
Source of the data	Variables assimilated in WRF
AIRS	Temperature, Relative Humidity, Dew Point Temperature
ASCAT	Wind Speed, Wind Direction
Buoy (RAMA & Moored)	Pressure, Temp, Relative Humidity, Wind Speed & Direction
KSNDMC	Temperature, Relative Humidity, Wind Speed
MODIS	Temperature, Dew Point Temperature
Radiosonde	Pressure, Height, Temperature, Dew Point Temperature, Relative Humidity, Wind Speed & Direction
SSMI	Wind Speed, Precipitable Water
WindSAT	Wind Speed, Wind Direction, & Precipitable Water

Experimental Setup



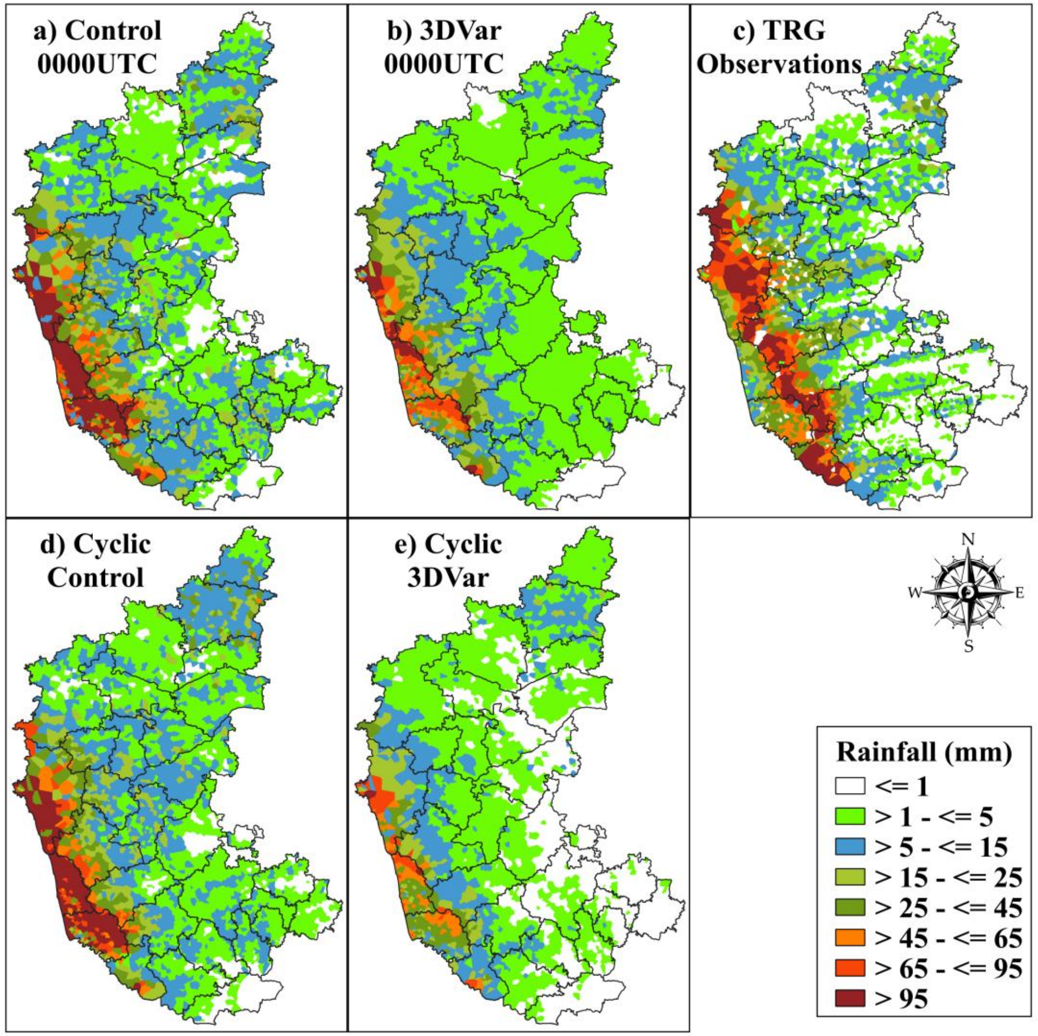
Experiment Name	Source of the data assimilated
Control (CNT)	None
Ocean Winds	ASCAT, Buoy, SSMI & WindSAT
Satellite Profile	AIRS & MODIS
Station Data	KSNDMC & Radiosonde
All Observations	ASCAT, AIRS, Buoy, KSNDMC, MODIS, Radiosonde, SSMI & WindSAT

Locations of Observations Used in Assimilation



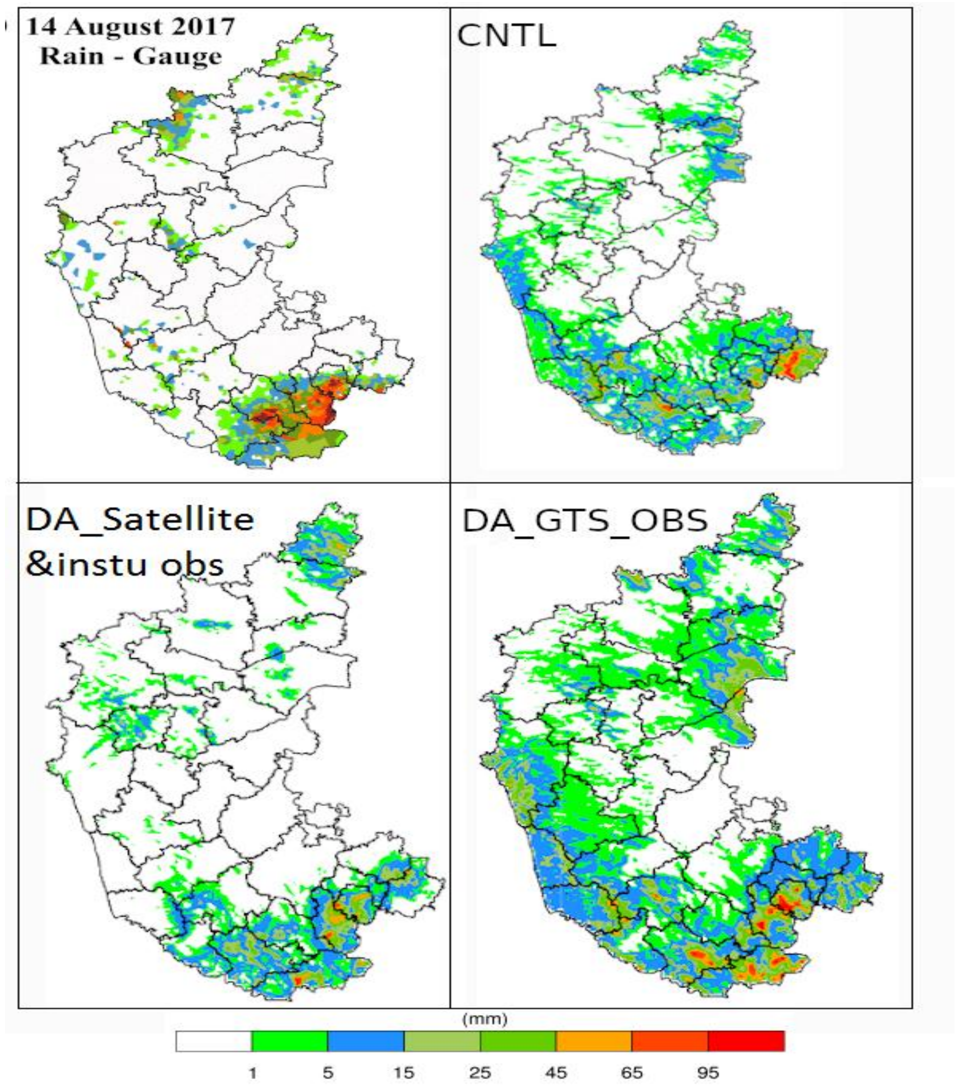
June 21, 2015

3D-Var DA in Cyclic mode



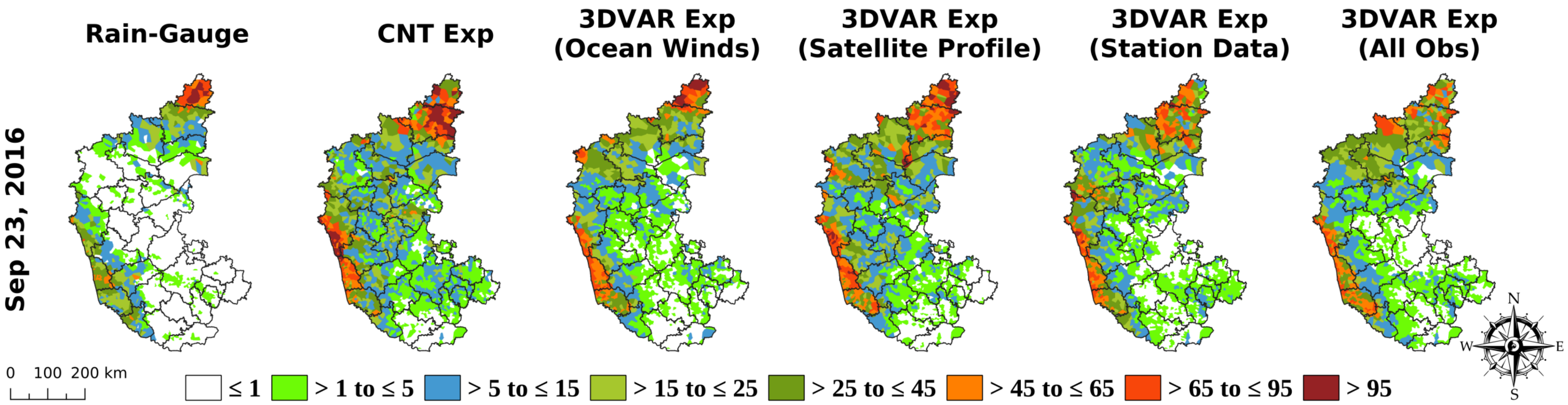
- Extreme rainfall event (June 21, 2015) simulated using 3D-Var in WRF
- 24 hour accumulated rainfall from June 21, 2015 0000 UTC – June 22, 2015 0000 UTC
- Cyclic forecasts are updated with 06 hour forecast cycles
- Cyclic forecasts initiated at 0600 UTC on June 20, 2015
- Cyclic forecasts has reduced over-prediction

Comparison different assimilation Datasets



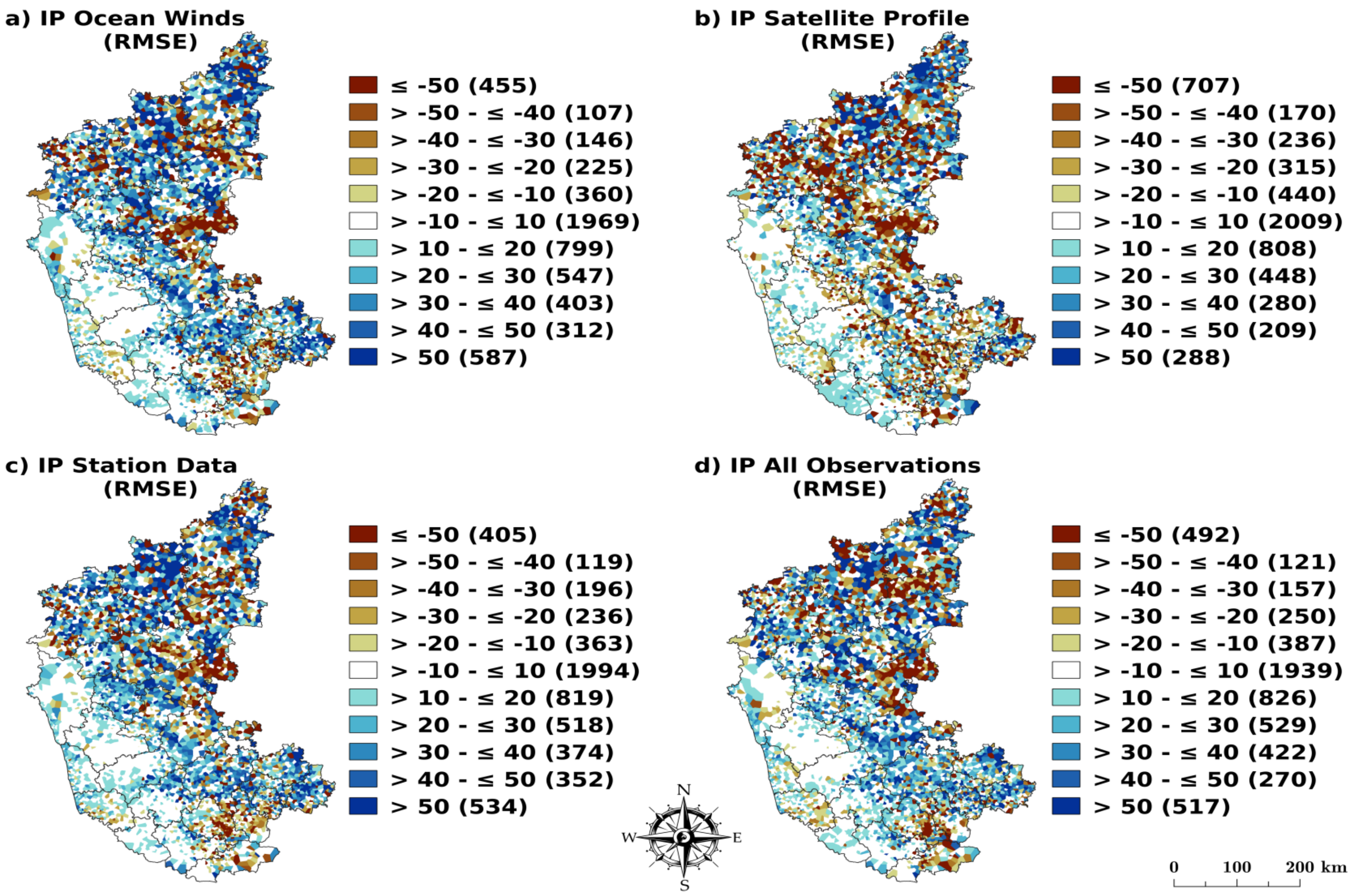
- Historical rainfall case over Bangalore: August 14, 2017
- Simulation performed using 3D-Var at 0000 UTC
- 24 hour accumulated rainfall is compared with ~6000 in-situ observations from TRG network of KSNDMC
- CNTL represents rainfall from experiment without assimilation
- DA_Satellite & in-situ obs represents rainfall from experiment with 3D-Var data assimilation using satellite profiles & in-situ data from buoy & station data from network of ~650 TWS stations
- DA_GTS_OBS represent rainfall from experiment with 3D-Var DA using NCEP prepbufr data

Spatial distribution of 24-h accumulated rainfall



- In assimilation experiment using Ocean Winds, the spatial distribution of rainfall is simulated better.
- After assimilation, overprediction in comparison to the control experiment is reduced in the state's south-east regions.

Improvement Parameter (IP) in 24-h Accumulated Rainfall



$$IP = \left(1 - \frac{RMSE_{ASSI}}{RMSE_{CNT}}\right) \times 100$$

- Even after assimilation rainfall prediction is not improved over the WG region
- Maximum improvement : Ocean Winds
- Maximum Deterioration : Satellite Profile

Skill Score Computation

Contingency table for skill score calculations

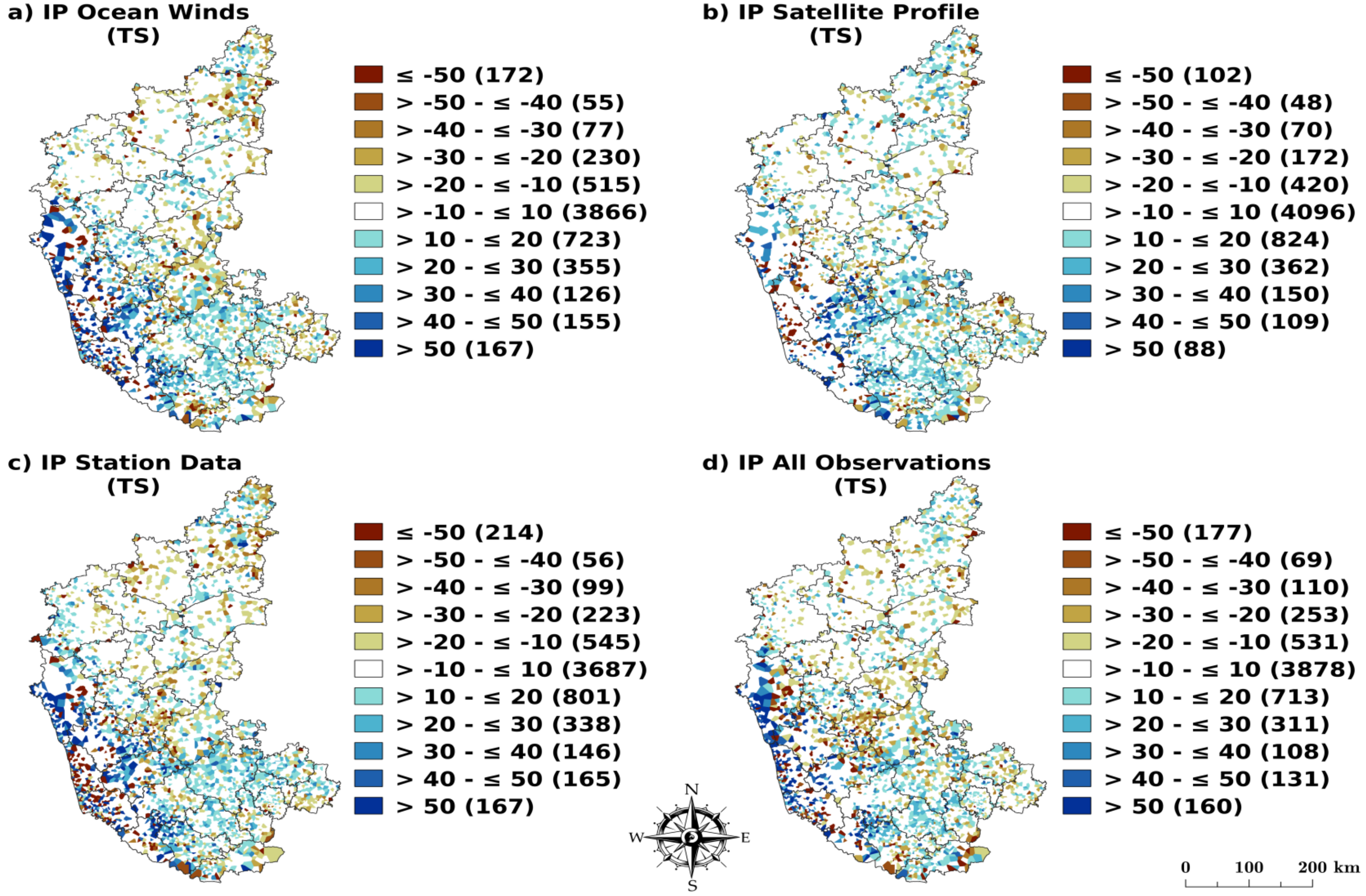
	Observation ≥ Threshold	Observation < Threshold
Forecast ≥ Threshold	a = Hits	b = False Alarms
Forecast < Threshold	c = Misses	d = Correct Negatives

$$\text{Threat Score} = \frac{a}{a+b+c}$$

Improvement Parameter in skill score:

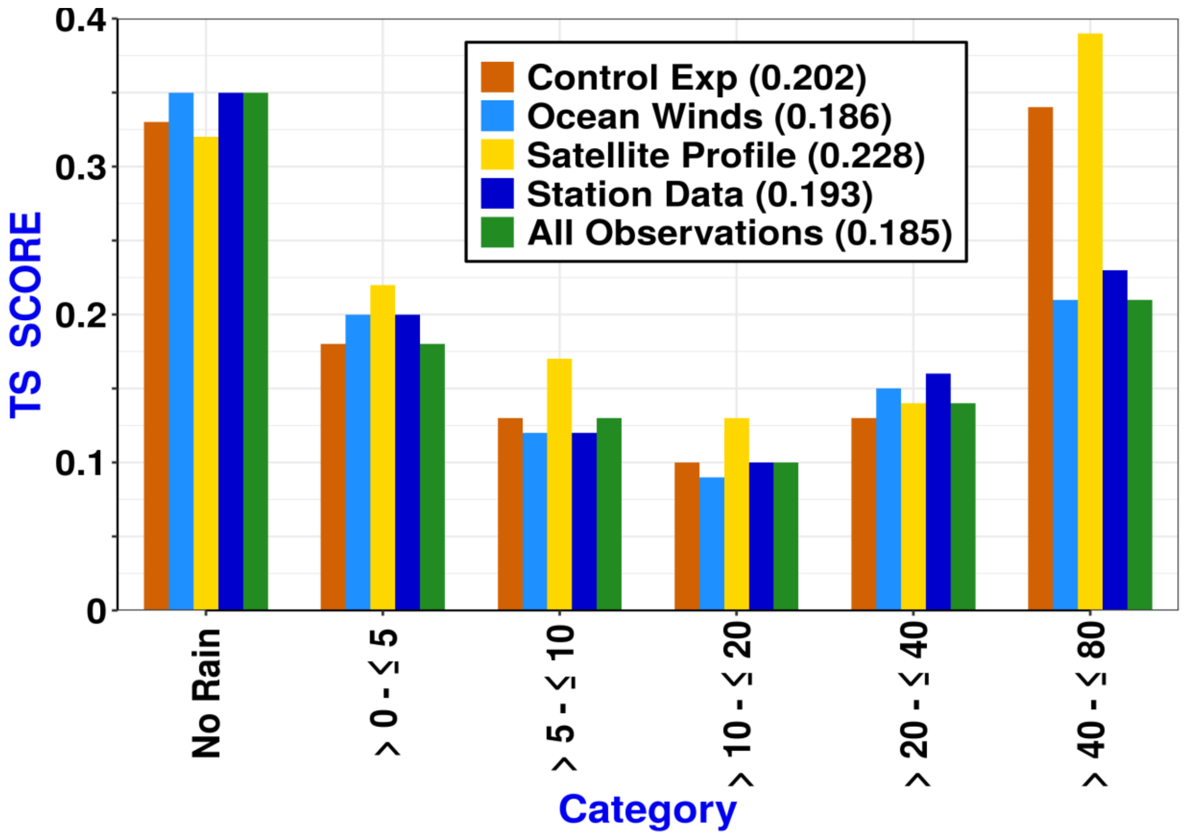
$$\text{IP} = \left(1 - \frac{|1-\text{SS}_{\text{ASSI}}|}{|1-\text{SS}_{\text{CNT}}|}\right) \times 100$$

Improvement Parameter based on Threat Score (TS)



- TS quantifies the skill of model in occurrence of the event of interest
- Assimilation with Ocean Winds & Station Data has shown maximum improvement
- Assimilation shown maximum deterioration over WG side with Station Data

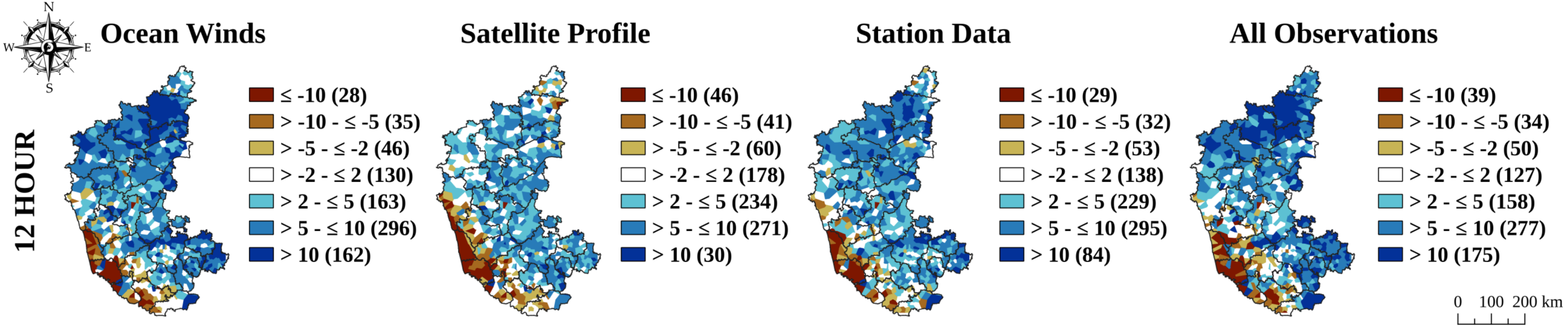
Error in Categorical Rainfall



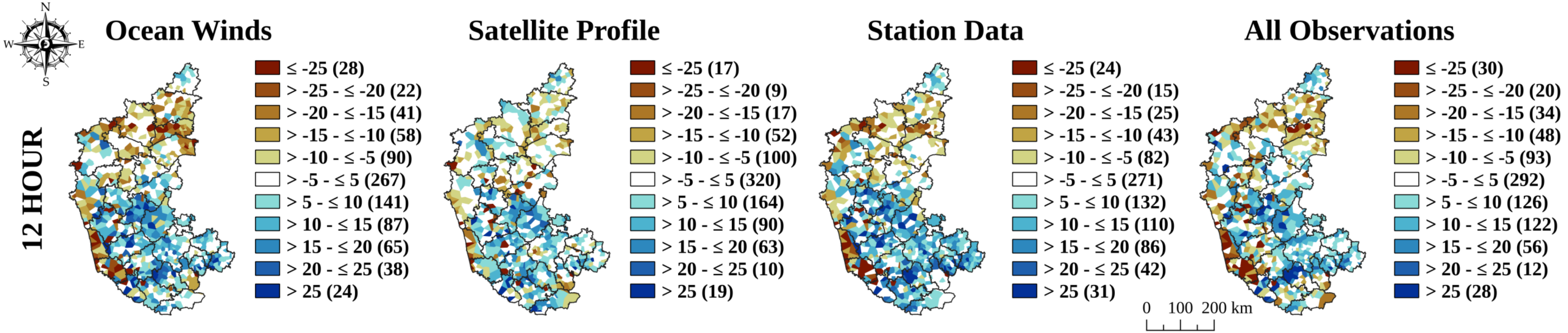
- Assimilation with Profile Data has improved area distribution of rainfall

IP in Wind Speed & Relative Humidity

IP in Wind Speed



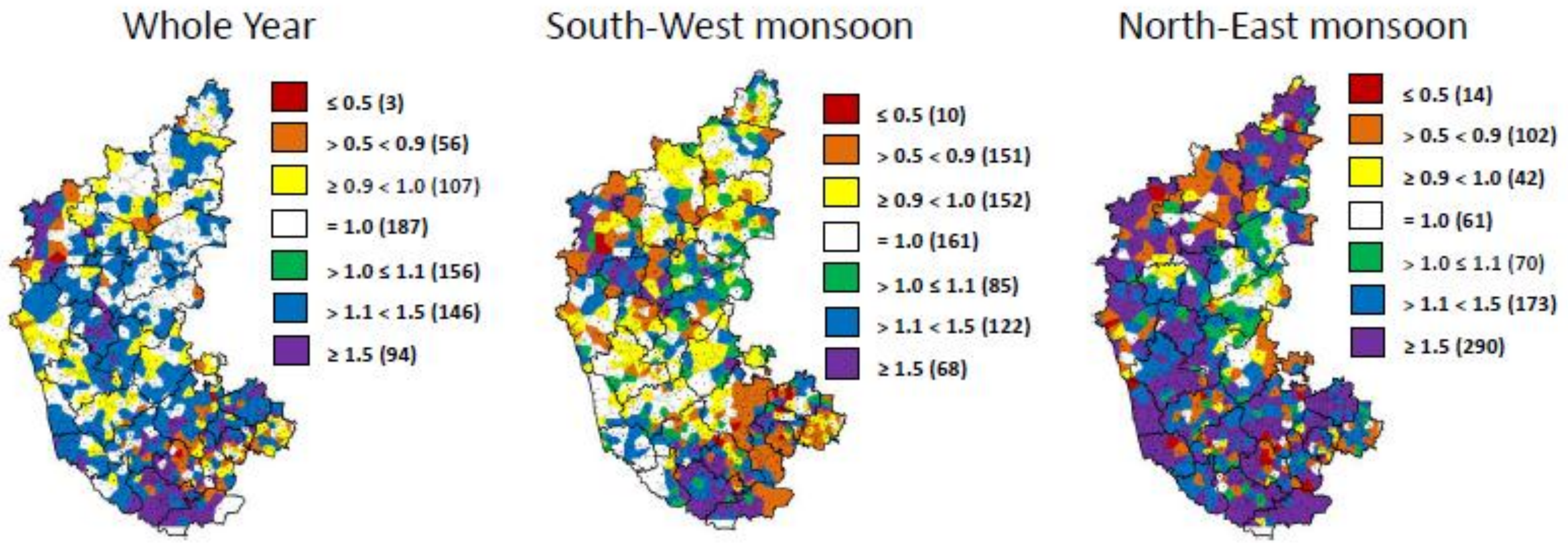
IP in Relative Humidity



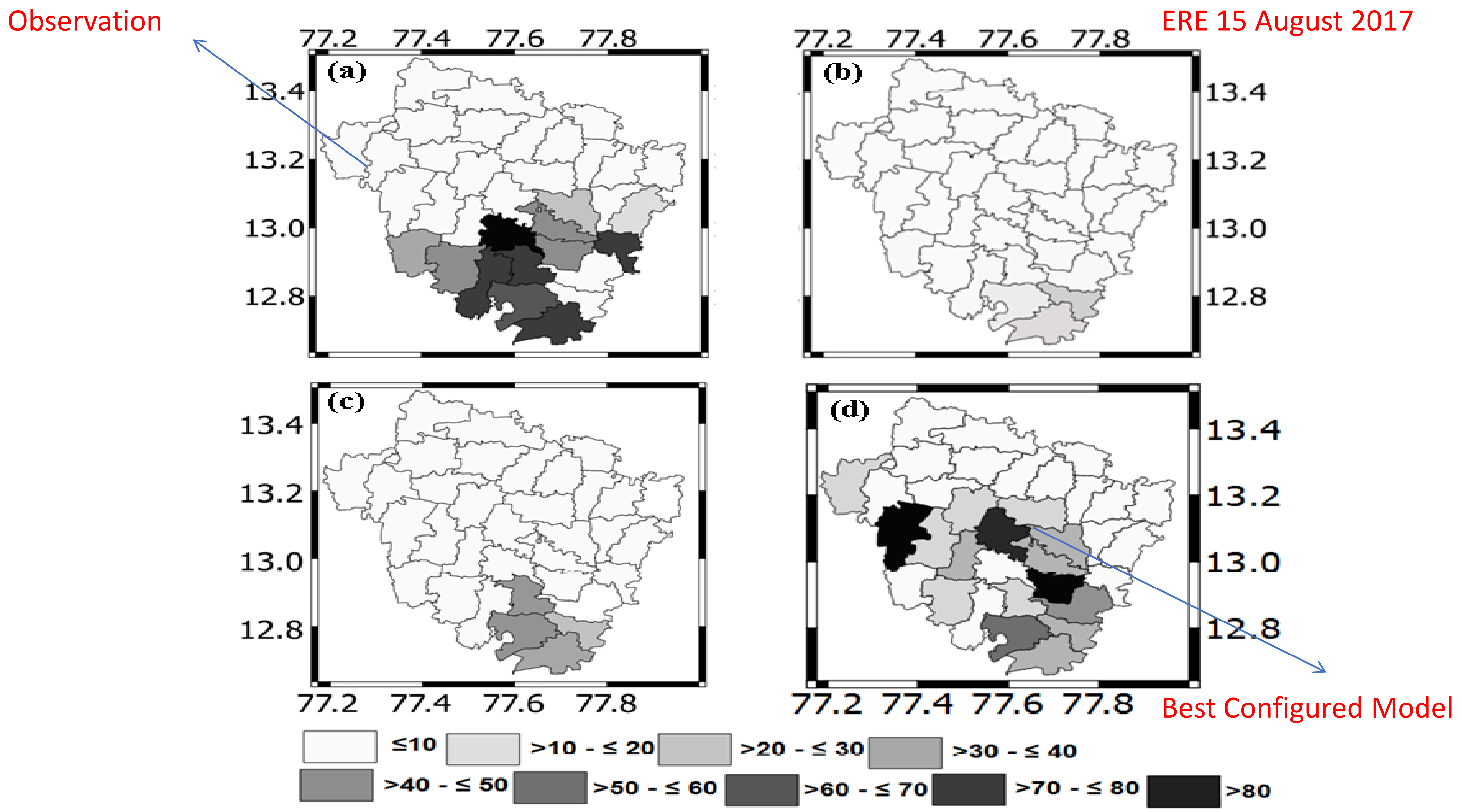
Impact of assimilation

Seasonality in assimilation impact

Impact Ratio: value 0, nether improvement nor degradation
values > 1, Improvement due to assimilation
values < 1, Improvement due to assimilation



Urban ERE simulation: sub-kilometer resolution



MAP, Springer, 2021

Forecast Skill of Urban localized and Non-Localized EREs

$$RI_i = \left[\frac{I_i + L_i + A_i}{3}\right] * 100$$

Here, i stands for EREs (i=1,15)

Quarterly journal of Royal Meteorological Society, 2018;143: 2340–2351

Where, $I_{(i))=}\frac{1}{N}P(i,k)$

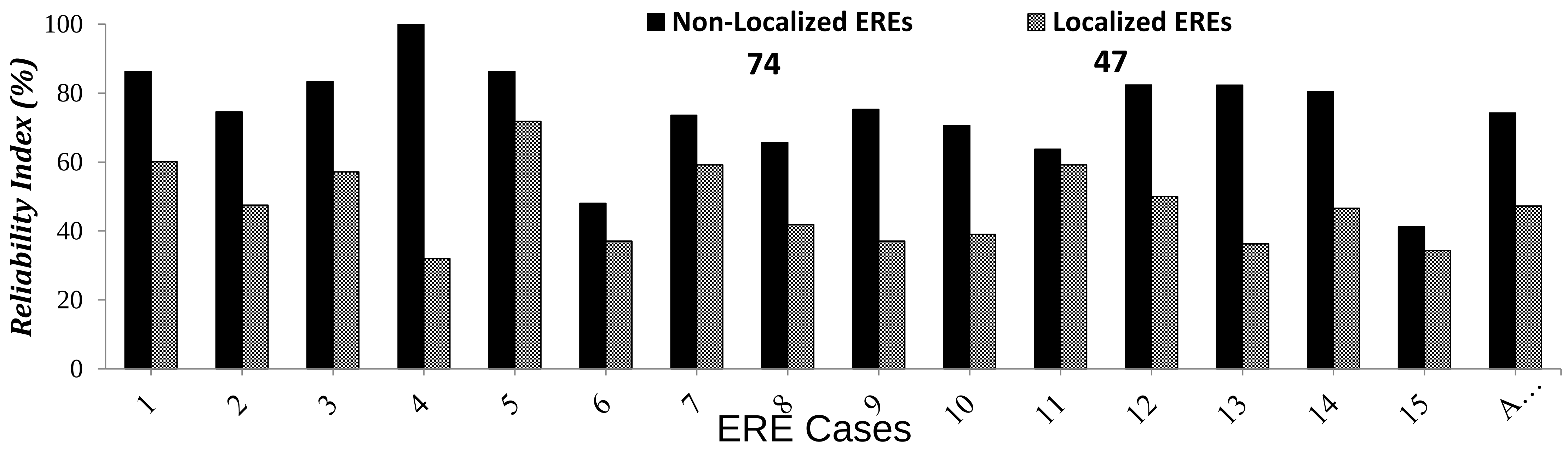
$,= 0, if\ relative\ error\ in\ magnituude\ of\ rainfall\ is\ above\ 50\%, k = ERE\ number,$ *k=1,34*

$$L_{(i))=}\frac{1}{N}\sum_{k=1}^{N} P(i,k)$$

$P(i,k) = 1, if\ rainfall\ is\ observed\ and\ forecasted\ over\ a\ hobli\ , else, P(i,k) = 0$

$$A_{(i))=}\frac{Nf(i)}{No(i)}$$

Where, Nf and No is the total number of hoblis where rainfall is forecasted and observed respectively



Cost Function for Hybrid-ETKF

$$J(x,a) = \beta_1 J_1 + \beta_2 J_e + J_o$$

$$= \underbrace{\beta_1 \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b)}_{\text{Background Term}} + \underbrace{\beta_2 \frac{1}{2}(a)^T A^{-1}(a)}_{\text{Ensemble Term}} + \underbrace{\frac{1}{2}(y_o - H(x))^T R^{-1}(y_o - H(x))}_{\text{Observation Term}}$$

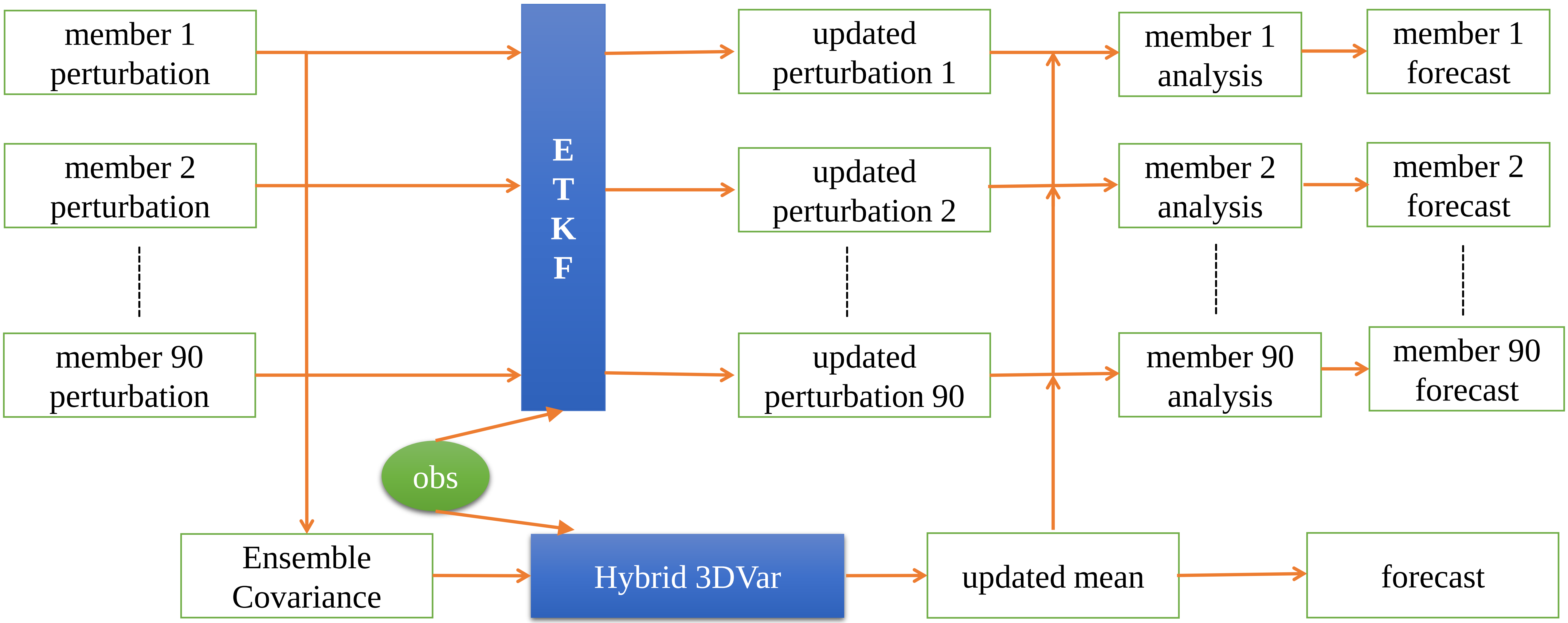
Where,

J_1 - Traditional 3DVar background term associated with static covariance B

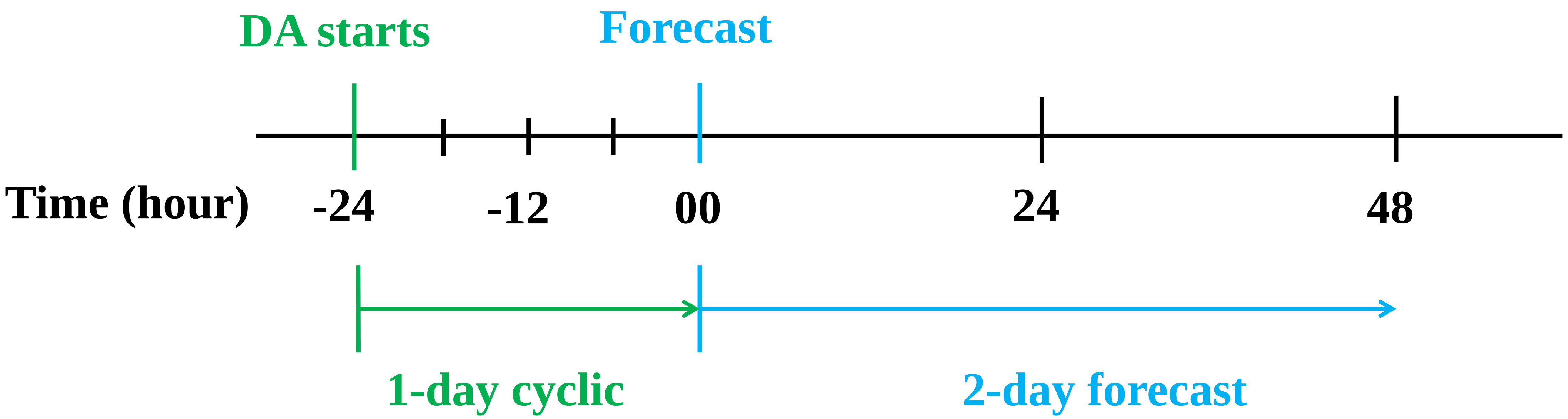
A – Defines spatial covariance of (a)

- Compared with a normal 3DVar, weighted sum of J_1 & J_e terms in Hybrid ETKF-3DVar cost function replaces the term J_b in 3DVar
- To conserve the total background error variance $\frac{1}{\beta_1} + \frac{1}{\beta_2} = 1$

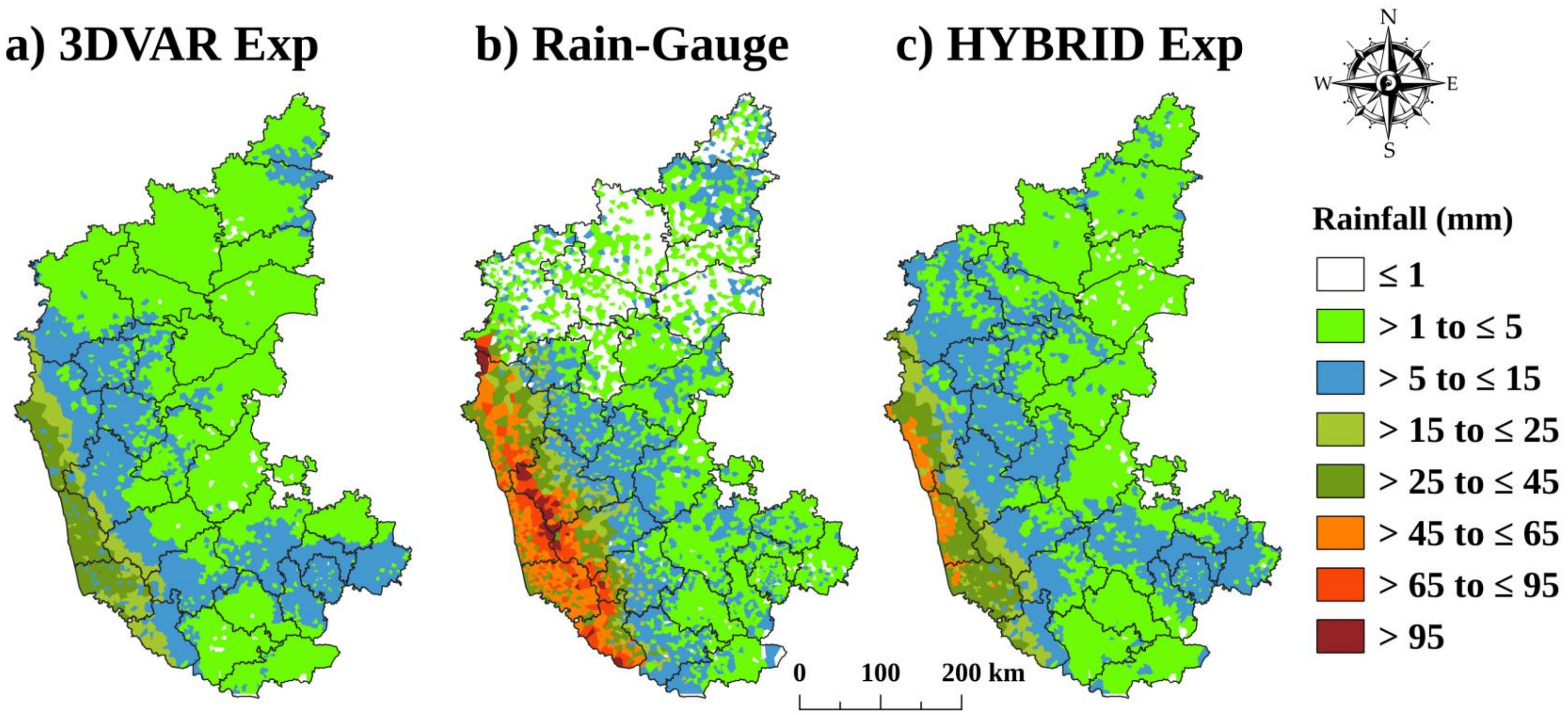
Flowchart of Hybrid ETKF-3DVar DA



Assimilation Experiment

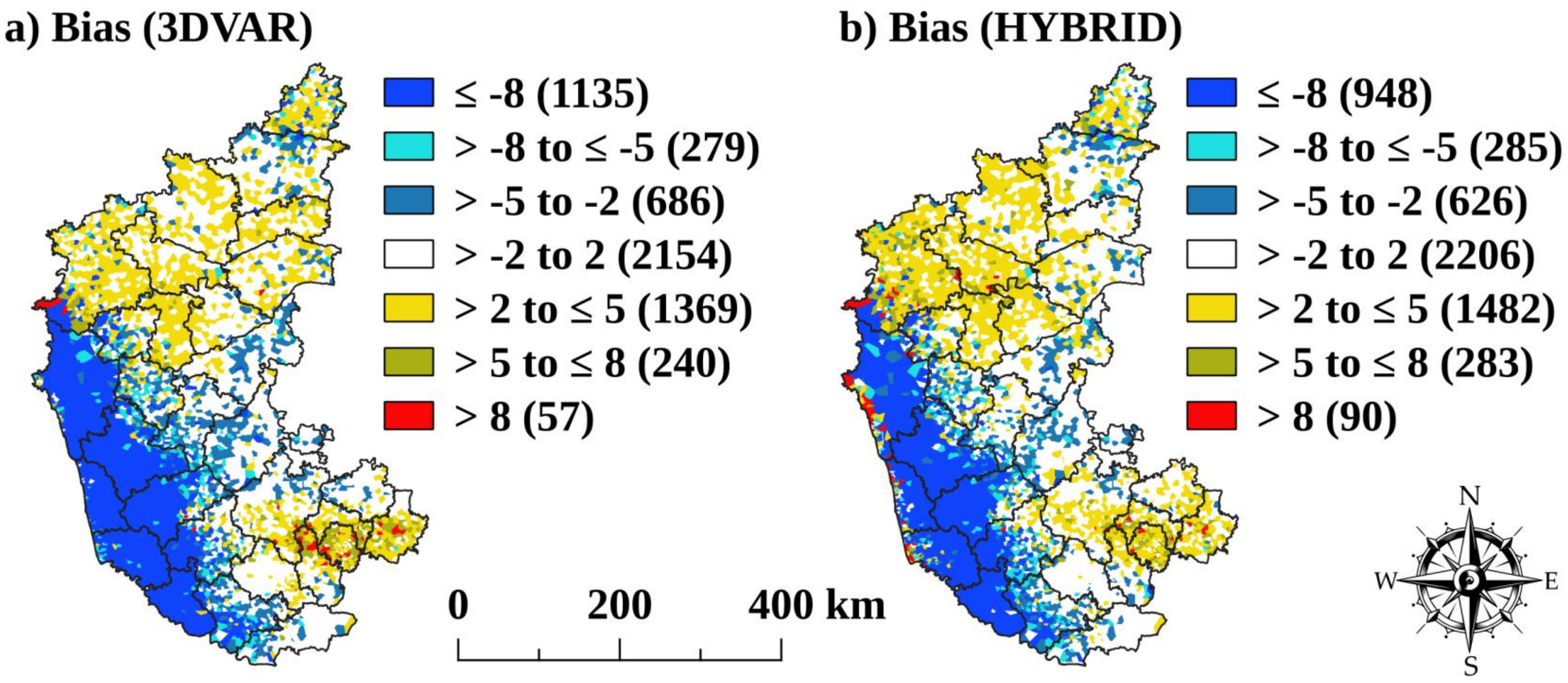


Spatial Distribution of Average Rainfall



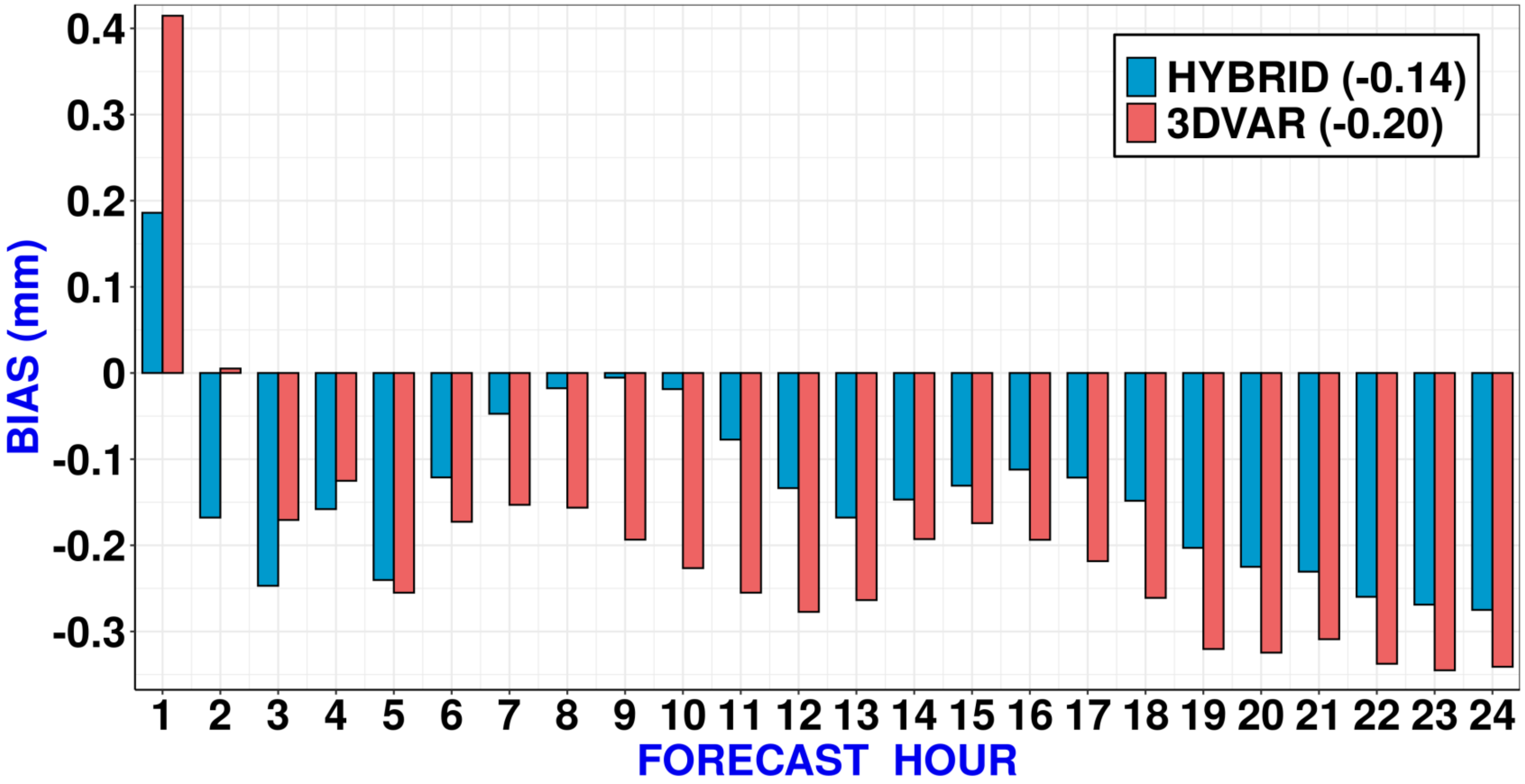
- ➢ Intensity of rainfall is improved in HYBRID experiment
- ➢ Both experiment shows underprediction over WG

Spatial Distribution of Bias in 24-h Accumulated Rainfall



- Underprediction of rainfall is improved in HYBRID experiment compared to 3DVar
- The improvement in rainfall prediction in HYBRID is implied by a more number of TRG stations in the -2 to 2 bias group

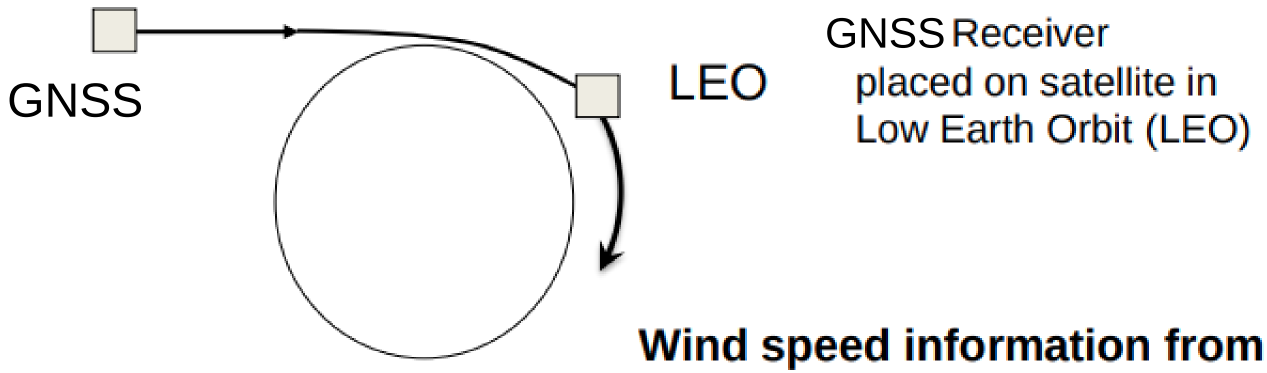
Temporal Variation of Bias in Predicted Rainfall



- After the early hours, HYBRID simulations had less bias in rainfall prediction than 3DVar simulations.

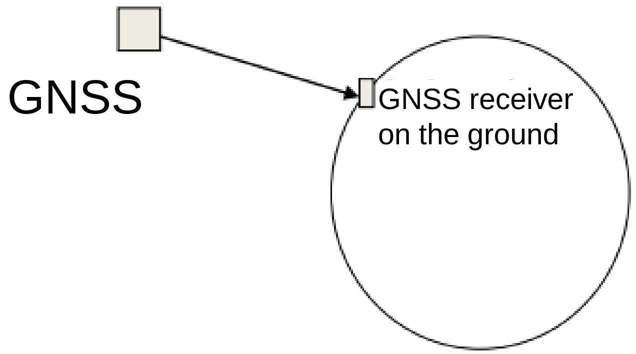
Assimilation of GNSS Observations

GNSS Radio Occultation (profile information from the atmospheric limb)

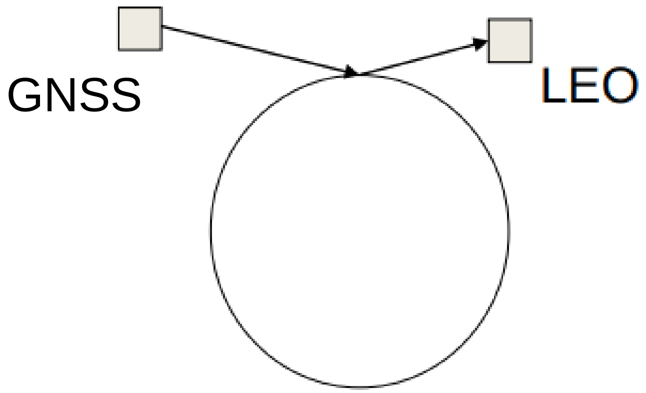


Ground-based GNSS

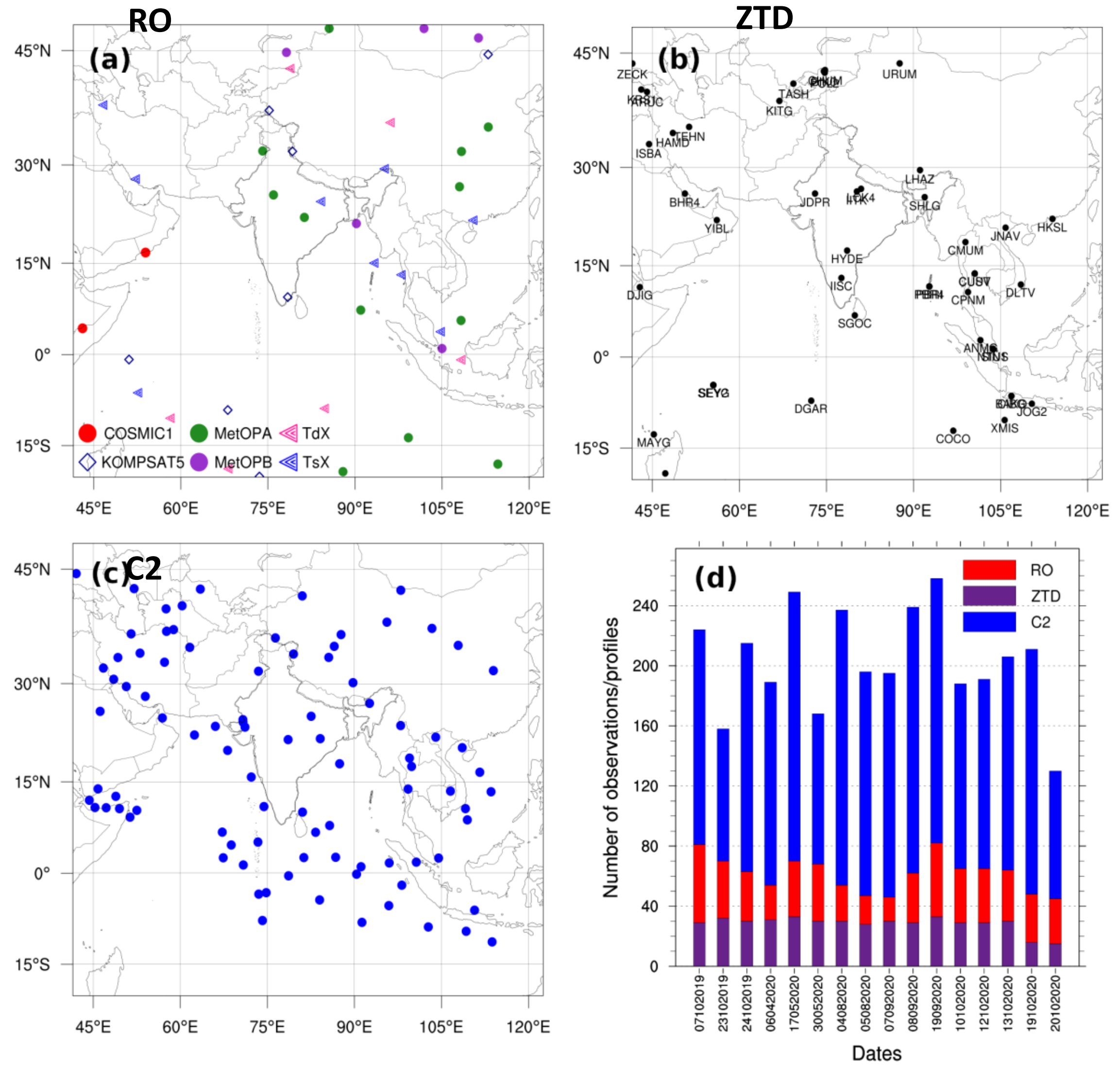
Zenith Tropospheric Delay (ZTD)



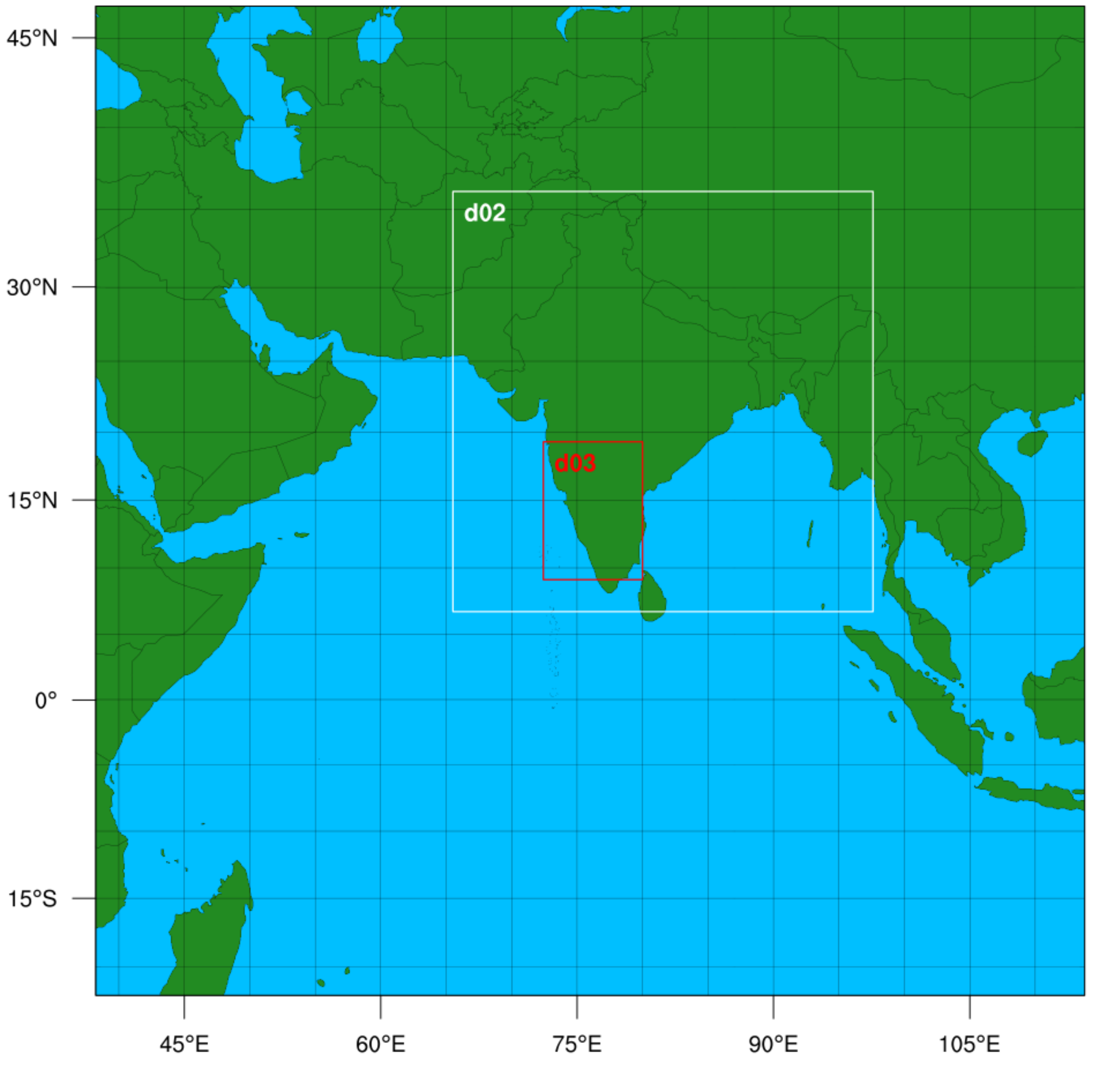
Wind speed information from signal reflected from ocean surface("GNSS-reflectometry")



Data and Model Domain



The location of (a) RO profiles (b) GNSS-GB (c) C2 profiles (d) Total number of GNSS observations used in study



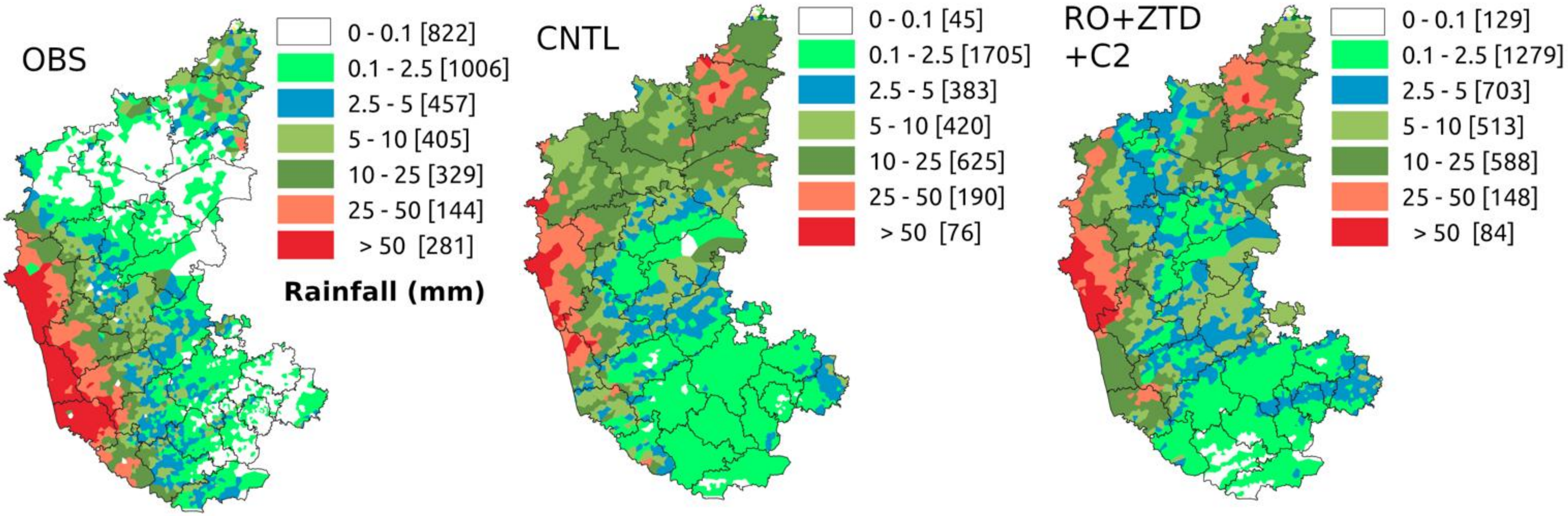
WPS domain configuration of three nested domain d01 (27km), d02 (9km) and d03 (3km) with elevation

Experiment Design

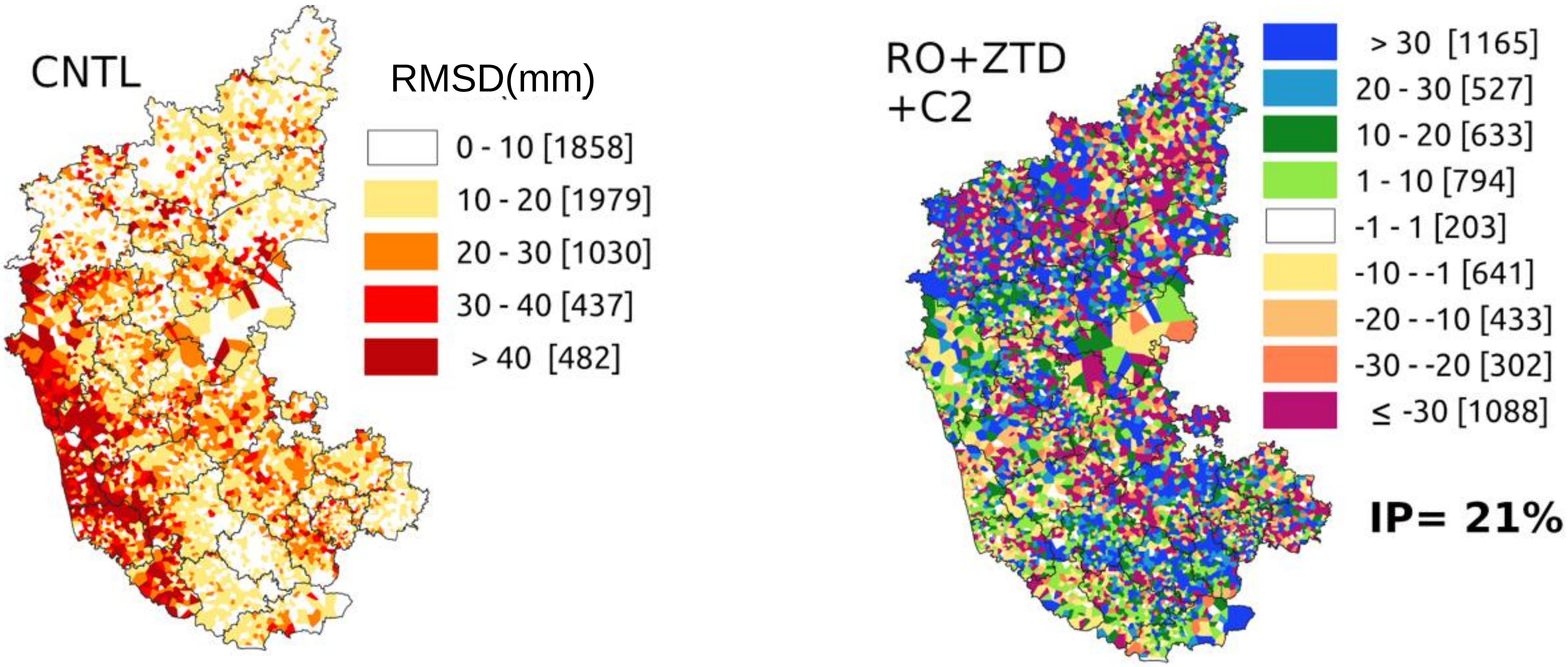
- For initial and boundary conditions, NCEP-GFS dataset at 0.25 degree, starting 1200 UTC on the day prior the ERE day is used
- PREPBUFR: ship, radiosonde, aircraft, satellite profile etc.

Experiments	PREPBUFR	GNSS-GB	GPS-RO	C2
CNTL	✓			
RO	✓		✓	
ZTD	✓	✓		
C2	✓			✓
RO+ZTD	✓	✓	✓	
ZTD+C2	✓	✓		✓
RO+ZTD+C2	✓	✓	✓	✓

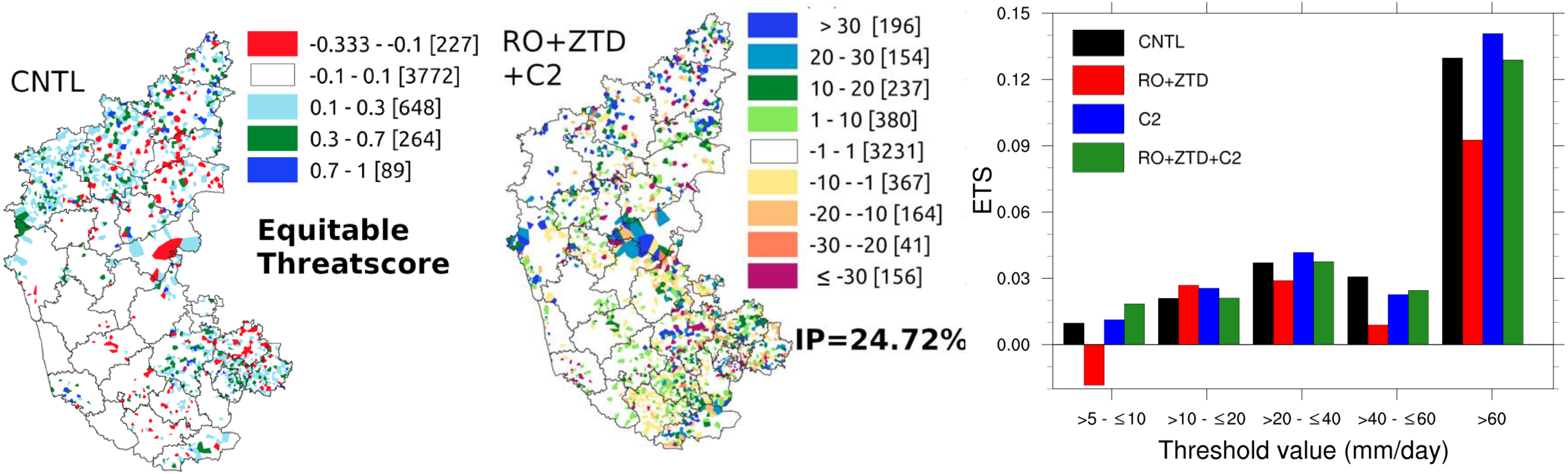
Physics suite	Configuration
Microphysics	New Thompson
Radiation(Sw/Lw)	Dudhia/RRTM
Land surface layer	Noah Land Surface
PBL	Mellor-Yamada-Janjic
Convection	Betts-Miller-Janjic



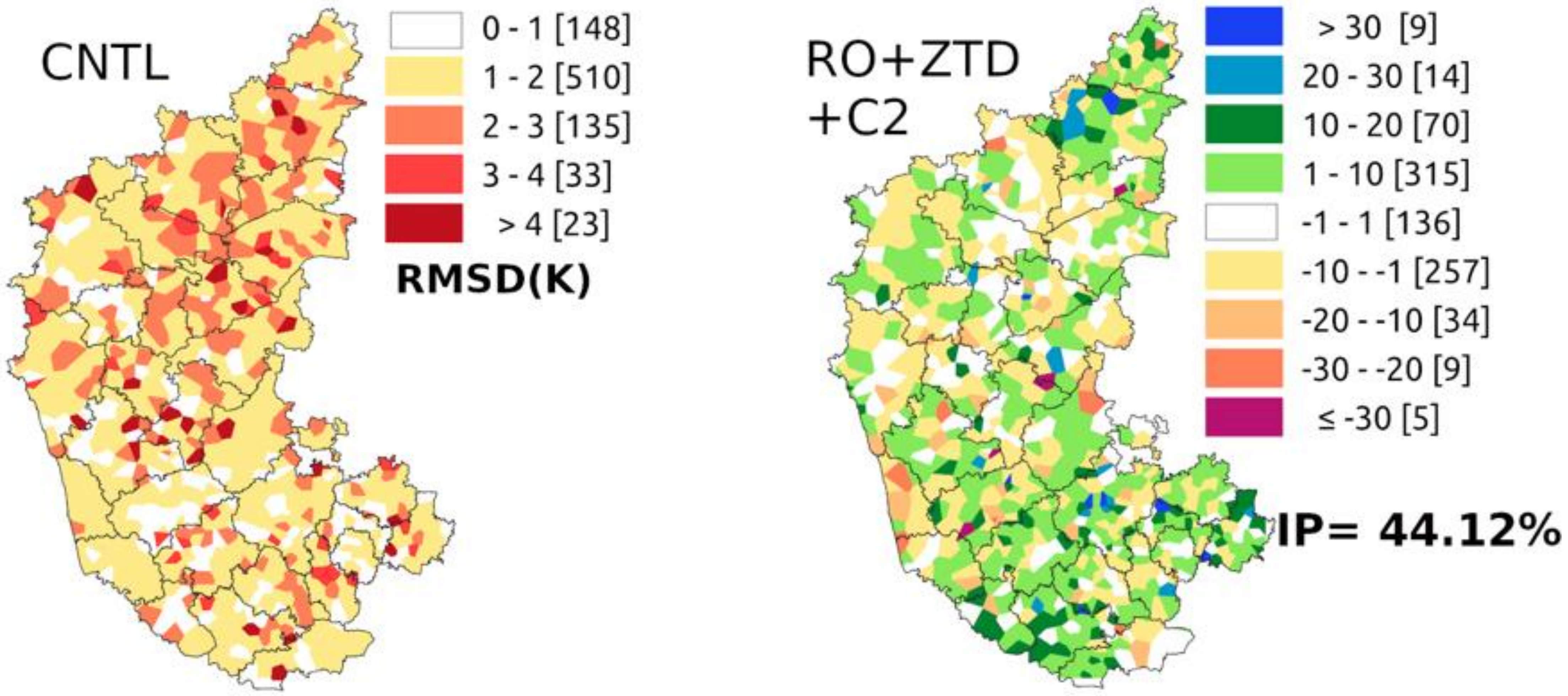
Spatial distribution of 24 hour accumulated observed and modelled rainfall for 25102019.



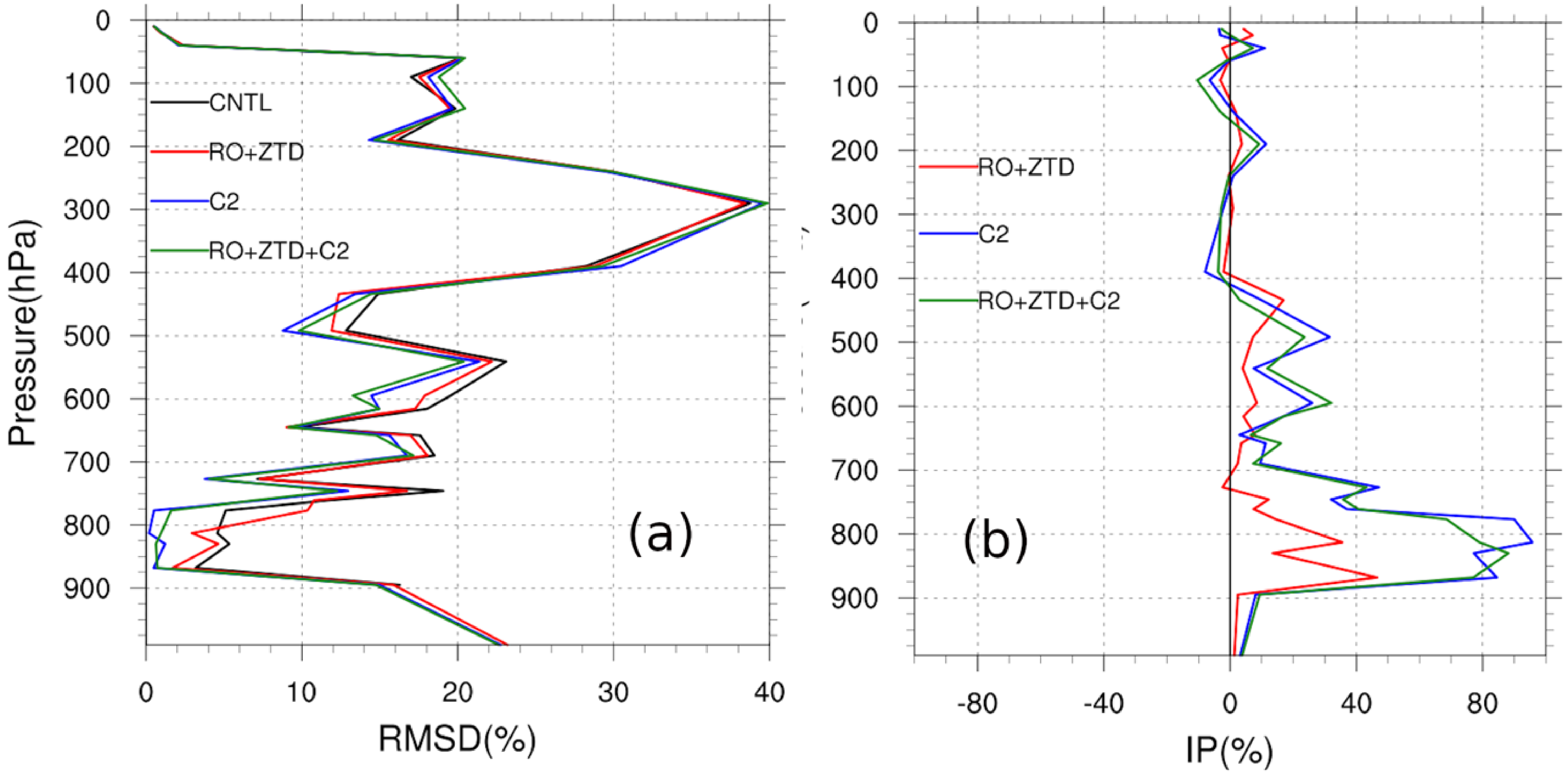
Spatial distribution of RMSD of control experiment (mm) and improvement (%) from GNSS observations



Spatial distribution of ETS of control experiment, improvement (%) for GNSS observations and ETS for different rainfall threshold over Karnataka

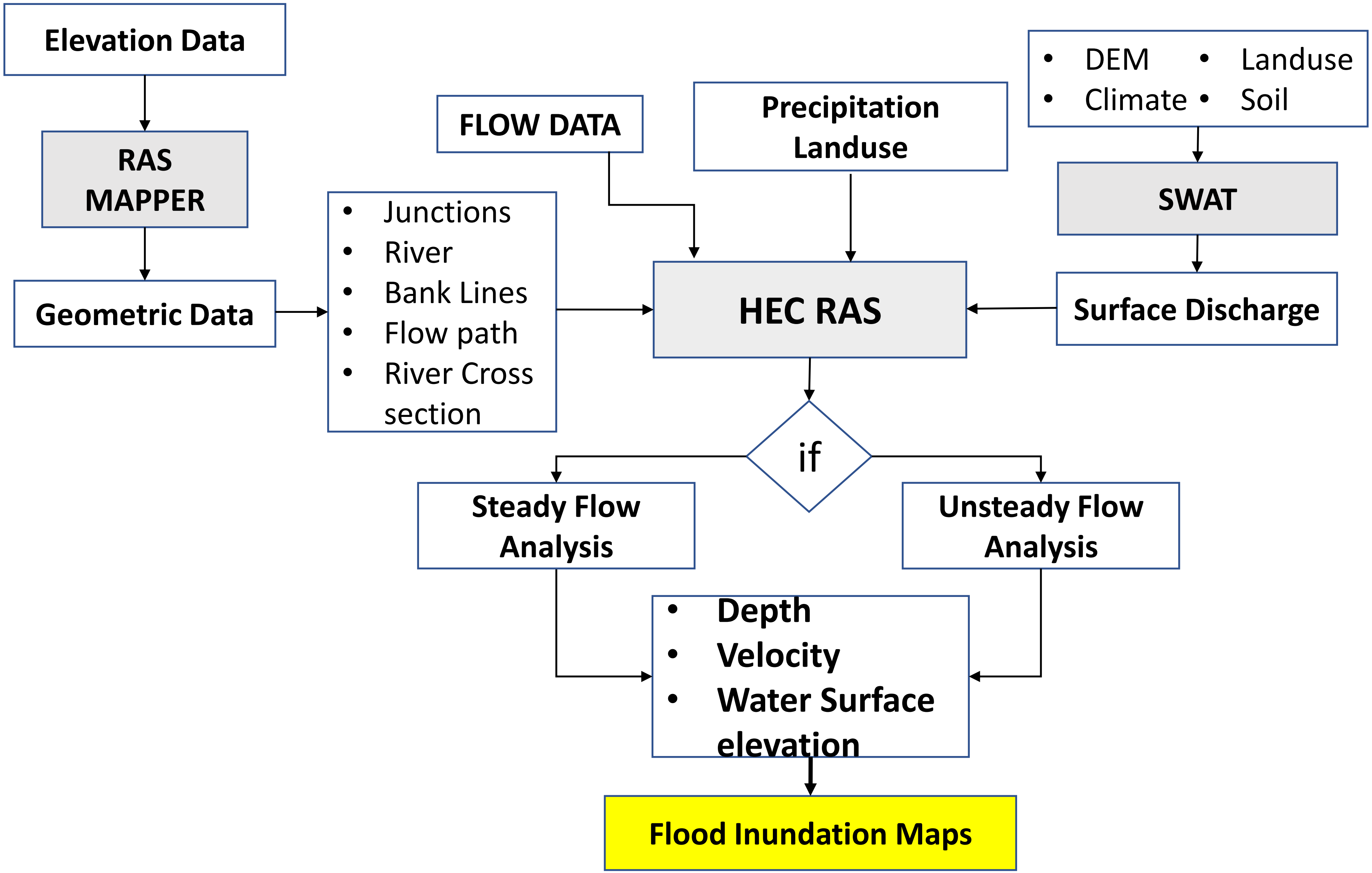


Spatial distribution of RMSD and improvement parameters (%) for surface temperature at 00UTC

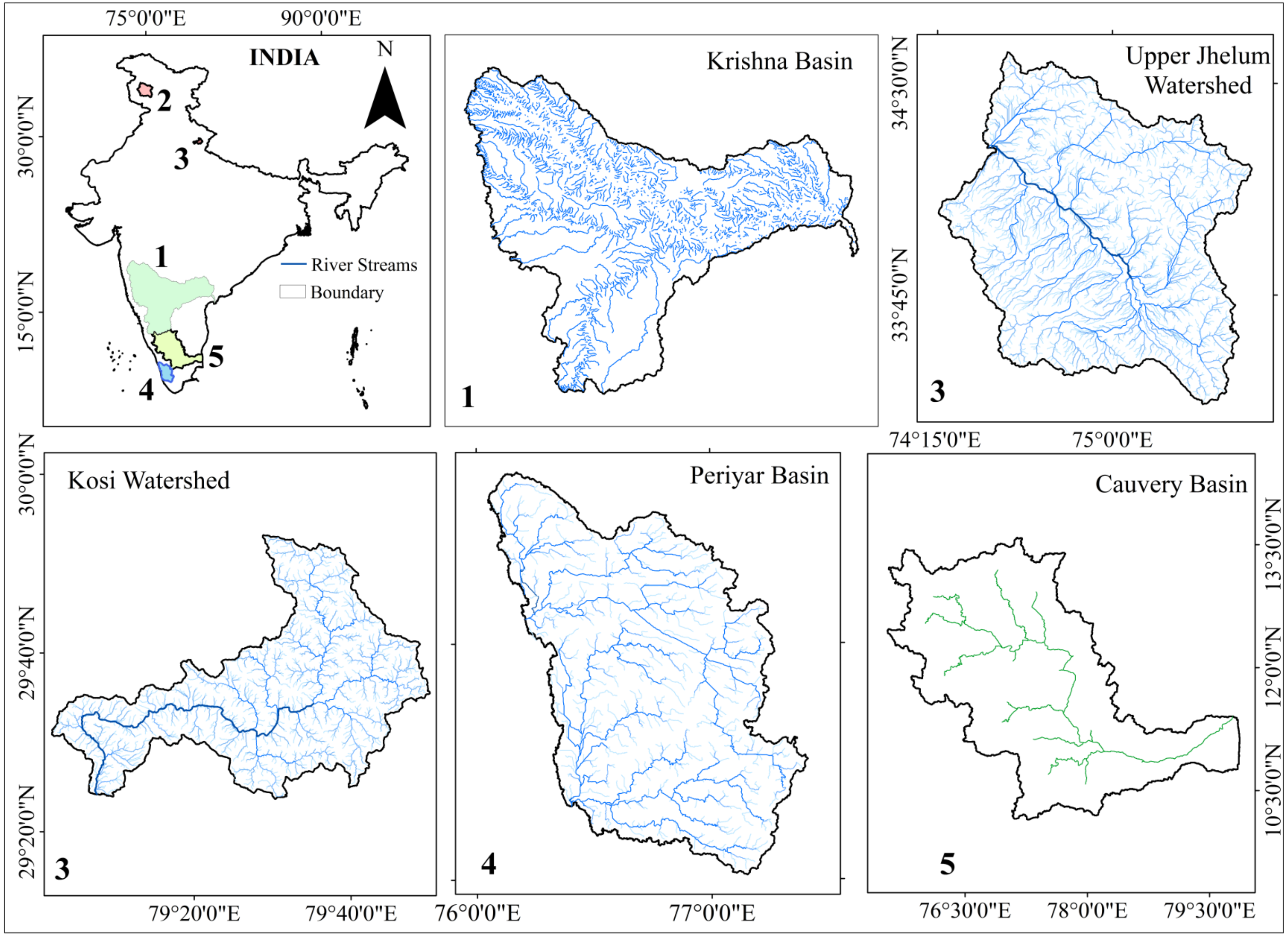


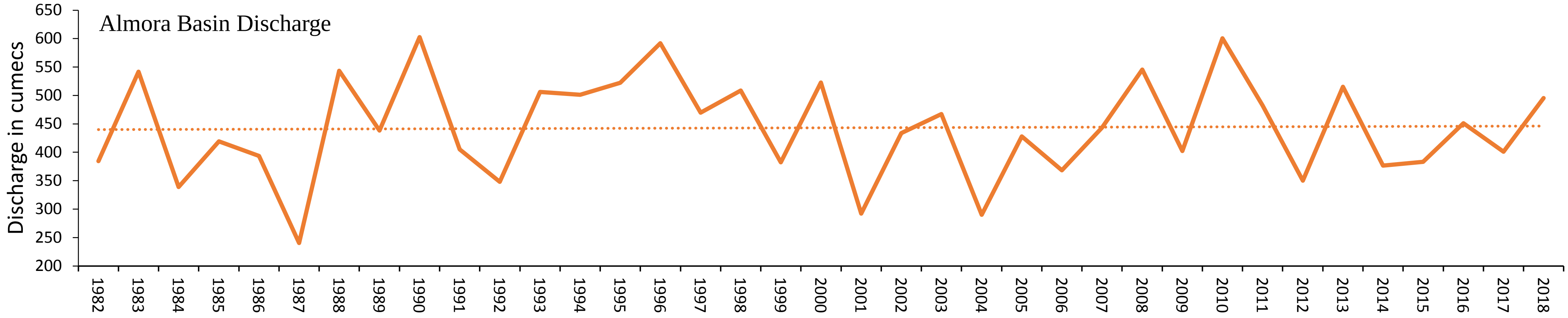
Vertical profile of RMSD (a) and improvement parameter (b) for relative humidity

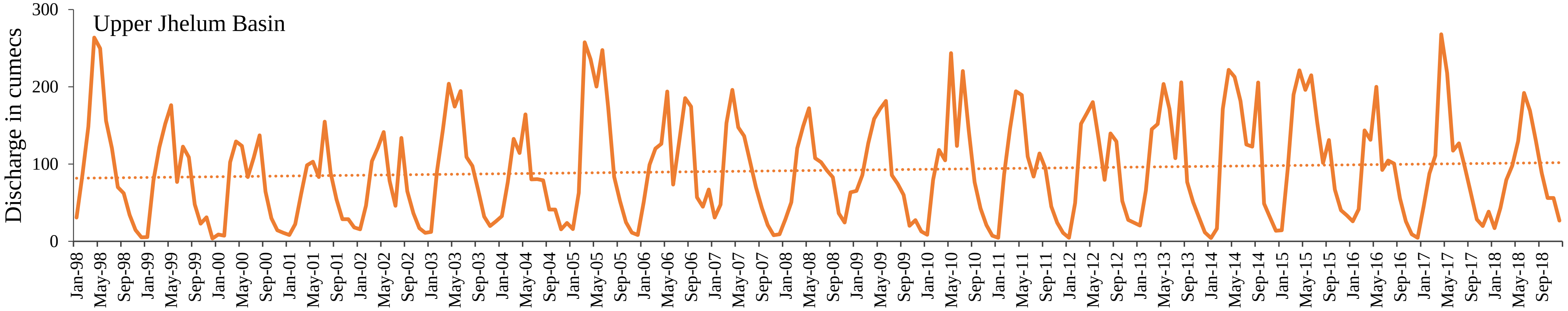
INTEGRATED HEC RAS & SWAT MODEL FOR FLOOD MODELLING

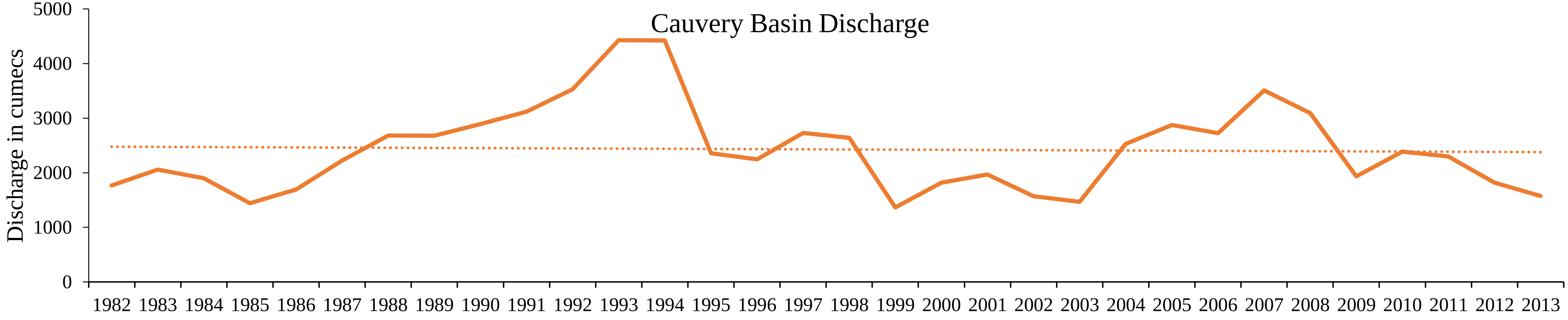


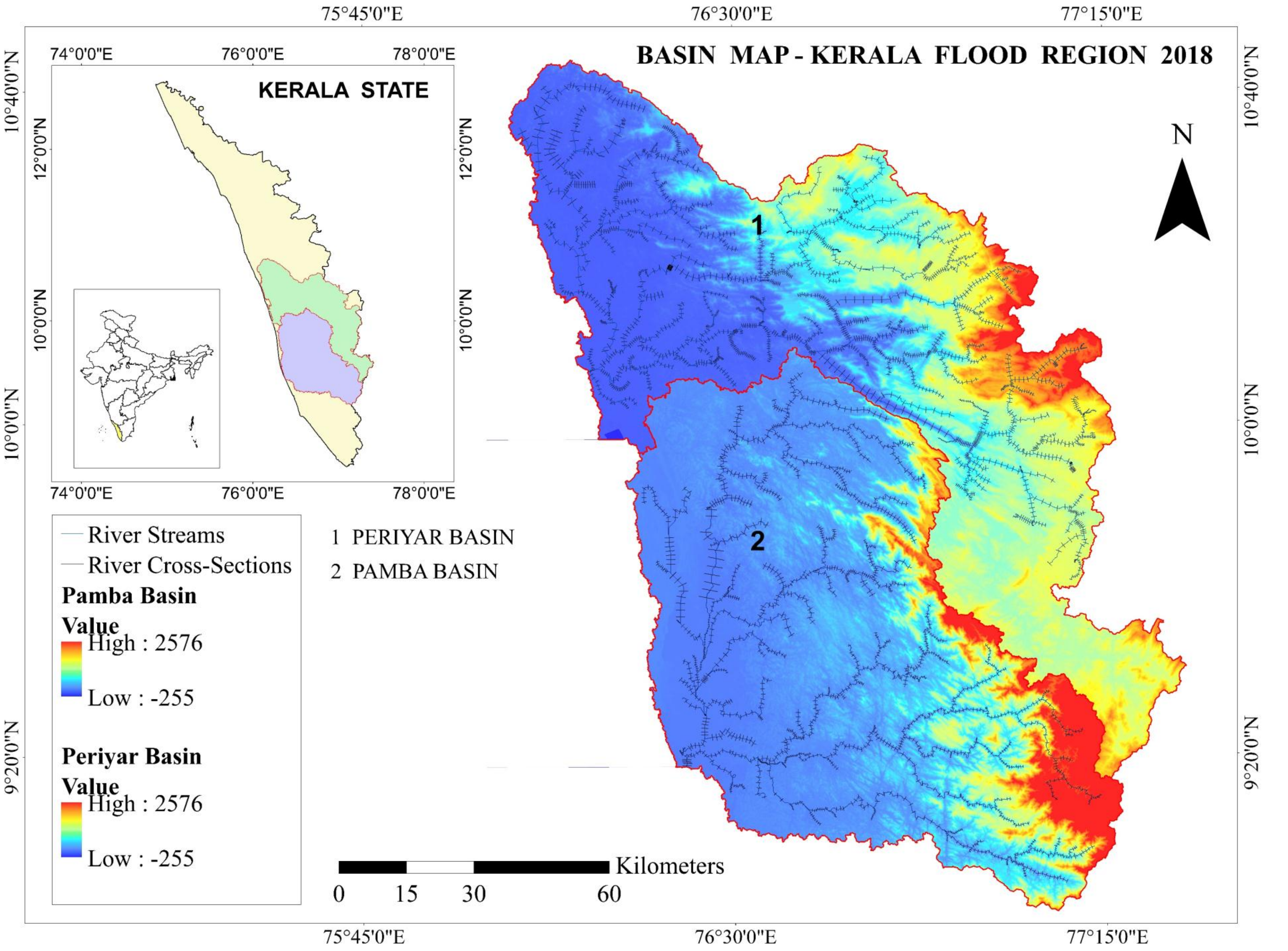
Basin scale hydrological simulations: Quantification of spatio-temporal variability and change




Almora Basin Discharge
Discharge in cumecs
650
600
550
500
450
400
350
300
250
200
1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018


Upper Jhelum Basin
Discharge in cumecs
300
200
100
0
Jan-98 May-98 Sep-98 Jan-99 May-99 Sep-99 Jan-00 May-00 Sep-00 Jan-01 May-01 Sep-01 Jan-02 May-02 Sep-02 Jan-03 May-03 Sep-03 Jan-04 May-04 Sep-04 Jan-05 May-05 Sep-05 Jan-06 May-06 Sep-06 Jan-07 May-07 Sep-07 Jan-08 May-08 Sep-08 Jan-09 May-09 Sep-09 Jan-10 May-10 Sep-10 Jan-11 May-11 Sep-11 Jan-12 May-12 Sep-12 Jan-13 May-13 Sep-13 Jan-14 May-14 Sep-14 Jan-15 May-15 Sep-15 Jan-16 May-16 Sep-16 Jan-17 May-17 Sep-17 Jan-18 May-18 Sep-18

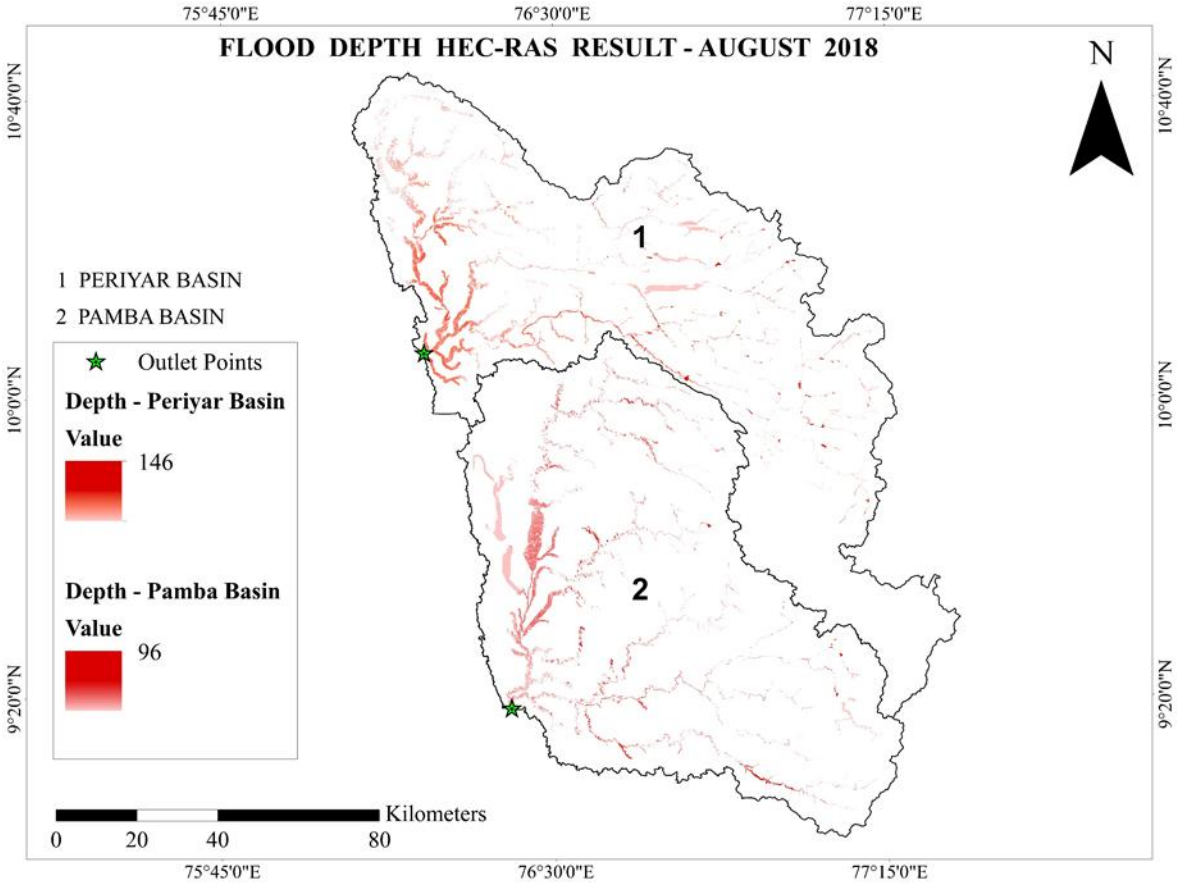

Cauvery Basin Discharge
Discharge in cumecs
5000
4000
3000
2000
1000
0
1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013

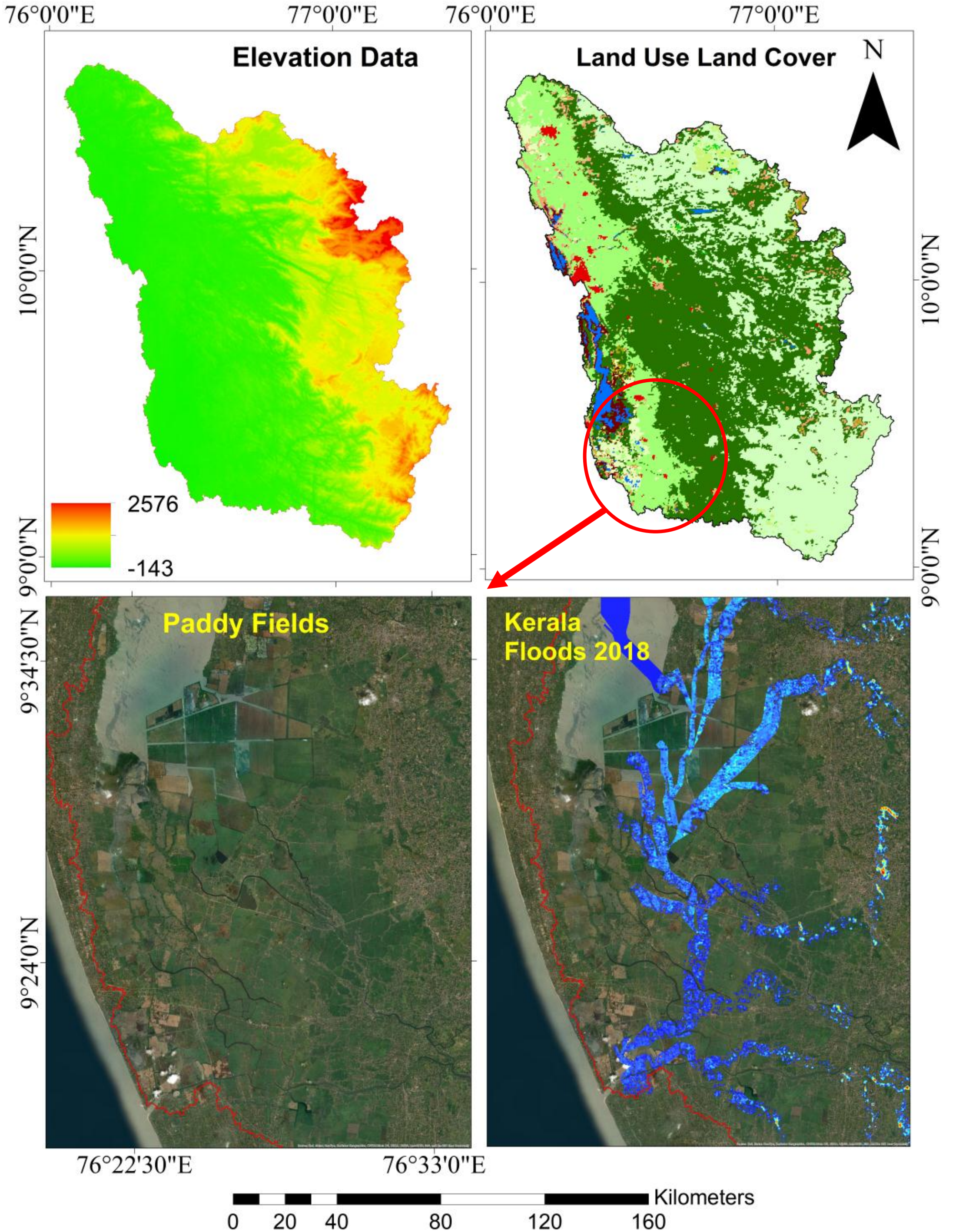


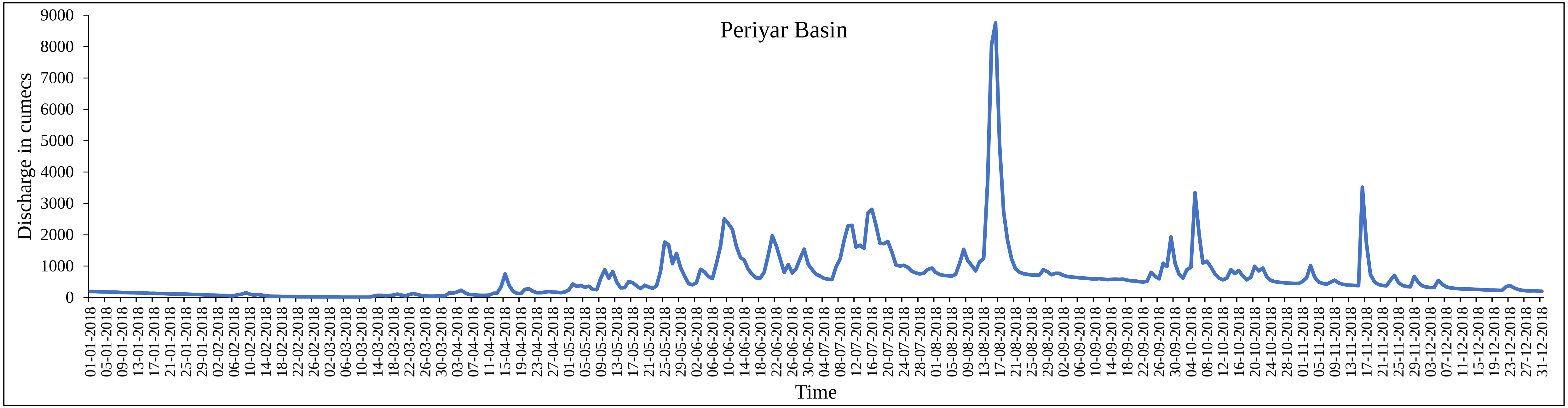
BASIN MAP - KERALA FLOOD REGION 2018
75°45'0"E
76°30'0"E
77°15'0"E
10°40'0"N
10°0'0"N
9°20'0"N
KERALA STATE
74°0'0"E
76°0'0"E
78°0'0"E
12°0'0"N
10°0'0"N
N
1
2
River Streams
River Cross-Sections
Pamba Basin
Value
High : 2576
Low : -255
Periyar Basin
Value
High : 2576
Low : -255
1 PERIYAR BASIN
2 PAMBA BASIN
Kilometers
0
15
30
60

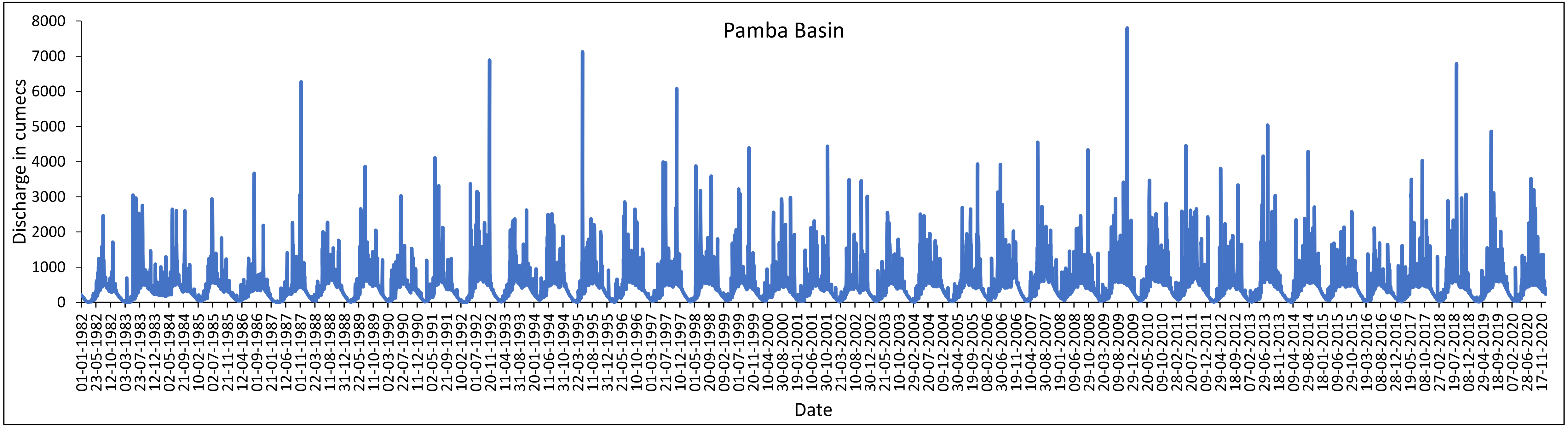
Flood simulations:

1. Basin scale flood simulation (Periyar & Pamba basin)
2. Flood simulation in paddy fields (Kuttanadu)

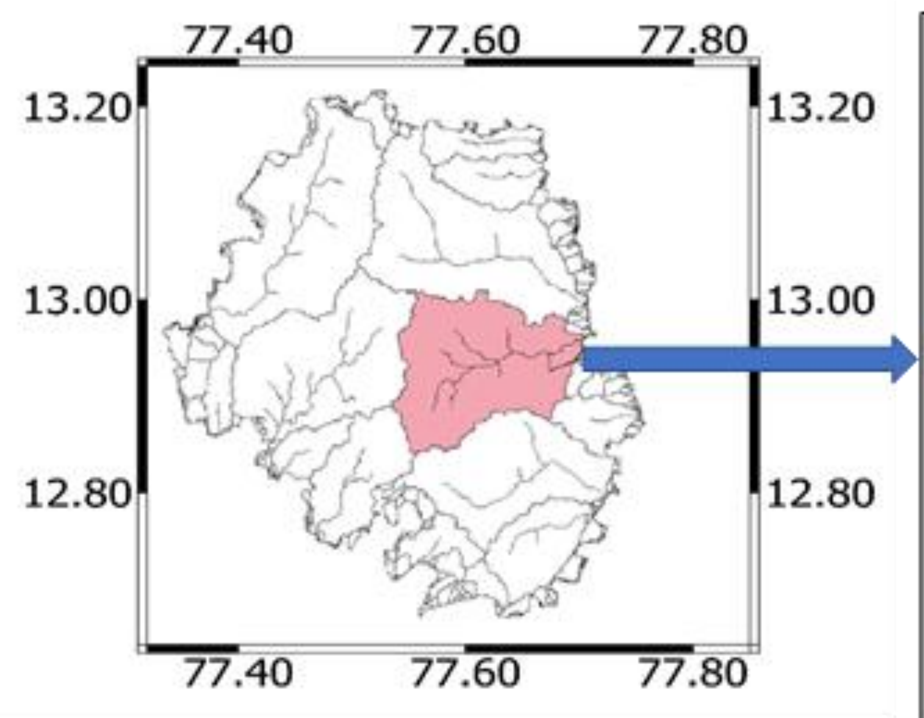


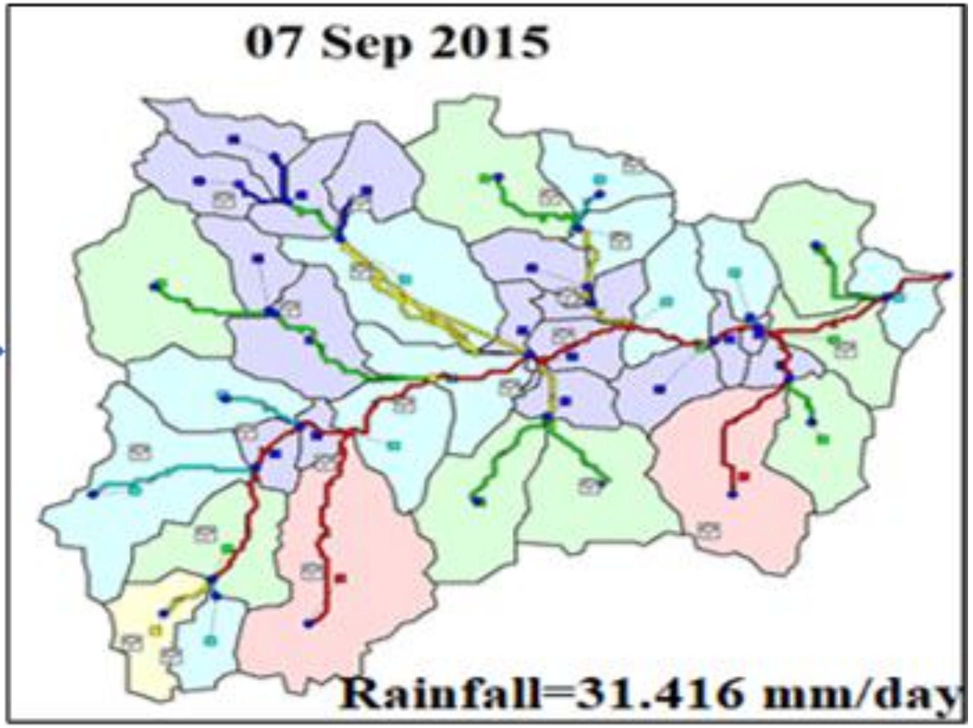



Periyar Basin
Discharge in cumecs
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
Time

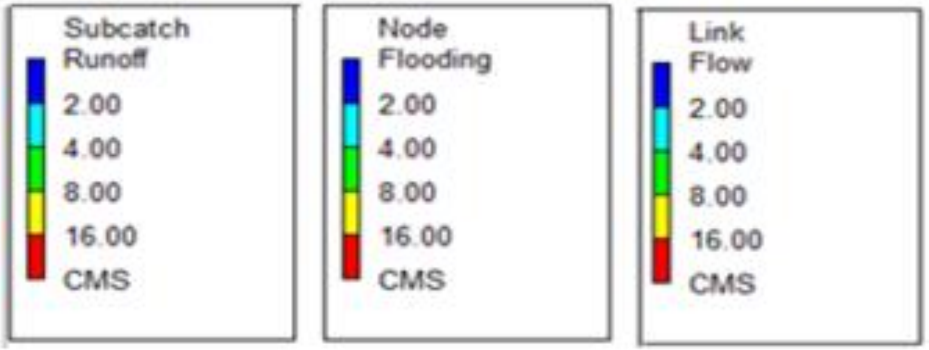

Pamba Basin
Discharge in cumecs
8000
7000
6000
5000
4000
3000
2000
1000
0
Date

Storm Water Management Model (SWMM) simulation for sub-catchment, Node flooding and link flow over **Koramangala, Challaghatta watershed valley** as a result of extreme rainfall events on **7th September 2015**. (KSNDMC Rainfall data)





Urban Bengaluru Storm water Drainage: Koramangala Challaghatta Valley




THANK
YOU