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Skill Evaluation of Extended Range Forecasts for Northeast Monsoon Rainfall across Smaller Spatial Domains of South Peninsular India

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Abstract

Reliable prediction of Northeast Monsoon (NEM) rainfall at extended range lead times is important for agricultural, water resources and disaster risk reduction over the south Peninsular India. In this paper an attempt has been made to evaluate the performance of the operational Extended Range Forecast (ERF) for smaller spatial domains for NEM rainfall. The real- time ERF forecast ,which is generated up to four weeks in advance, is verified over the south peninsular India using categorical rainfall forecast, which is Above Normal (AN), Normal (NN) and Below Normal (BN)for excess NEM 2015, deficient NEM 2016 and normal NEM 2017. Objective verification is carried out using the verification scores like Forecast Accuracy, Bias Score (BS), Probability of Detection(POD),False Alarm Ration (FAR), Critical success Index (CSI) and Equitable Threat Score (ETS) . The results show that the ERF system exhibits useful forecast up to 2-3 weeks lead time.Week-1 forecast demonstrate highest performance with accuracy exceeding 65-75%,while skill decreases to about 40-50 % by week -4.The NN category consistently shows the highest accuracy of 70 to 80 % at week-1, whereas BN category exhibits relatively lower skill especially at longer leads. Bias scores remain close to unity for NN forecasts, while AN forecast indicated slight overestimation and BN forecast shows underestimation. POD values are highest at short leads (0.7 to 0.8) and decline to (0.4 to 0.5) for longer leads. The decline is accompanied by a corresponding increase in FAR from (0.2-0.3) to (0.4 -0.5) reflecting growing forecast uncertainty at longer leads. The CSI attains peak values during week-1 and week-2 (~0.4-0.6) before declining with lead time, while ETS remains positive up to week-3. Interannual comparison reveals that forecast performance is highest during NEM 2016, followed by NEM 2017, whereas NEM 2015 exhibits relatively lower skill. ERF forecast over coastal region show better predictability compared to interior region. Overall, ERF system demonstrates reasonable skill for all contrasting NEM seasons of 2015,2016 and 2017 for smaller regions particularly up to 2-3 weeks lead time, highlighting its potential application in Agro-advisory services and impact-based forecasting

Keywords: Northeast Monsoon, Extended Range Forecast, Skill Scores, Forecast Verification

1. Introduction

The major rainfall season for south Peninsular India falls in October- December also known as northeast monsoon (NEM).The NEM rainfall constitutes majority ,particularly over Tamil Nadu, Kerala ,coastal Andhra Pradesh, Rayalaseema, and coastal Karnataka , almost all sub-division gets heavy rainfall during this period (Raj and Amudha 2023; Raj et al. 2025).Unlike the southwest monsoon ,which governs rainfall over the most of the Indian subcontinent, the NEM rainfall is largely confined to the south Peninsular India. The dependency on NEM rainfall varies markedly across all sub-division of South Peninsular India, namely Tamil Nadu is heavily dependent on NEM rainfall sustaining their water resources and agricultural operation, nearly half of its annual rainfall is received during NEM period.(Geetha and Raj 2008, 2014; Raj 2012; Rajeevan et al. 2012a, 2022).Although in case of some parts of Kerala and South Interior Karnataka, is observed to experience weaker NEM influence compared to rest of sub-division of Sub Peninsular India. This uneven spatial dependence highlights the need for region -specific analysis of NEM rainfall variability.

Analysis of Long-term observational records indicate that NEM rainfall is characterized by strong inter-annual and intra-seasonal variability(Rajeevan et al. 2022; Reba et al. 2022; Raj and Amudha 2023). It is also observed that over last 150 years ,no statistically significant long-term trend has been detected in NEM rainfall ,however pronounced epochs of excess and deficient rainfall are evident .(Raj et al. 2025).Such variability of NEM rainfall is related with a range of synoptic and large-scale drivers, including cyclonic disturbances over the Bay of Bengal, easterly waves and modulation of large-scale climate phenomena such as ENSO and Indian Ocean Dipole(Raj 2003, 2012; Geetha and Raj 2008, 2014; Raj and Amudha 2023; Raj et al. 2025).Another defining characteristic of NEM rainfall is its spatial heterogeneity. Coastal Tamil Nadu and South Coast of Andhra Pradesh frequently experience well defined onset and heavy rainfall events ,whereas Rayalaseema and South Interior Karnataka typically shows early withdrawal and reduced December rainfall .(Raj 2003; Raj and Amudha 2023)

Although previous research has sustainably advanced understanding of NEM rainfall climatology ,teleconnections and seasonal prediction(Rajeevan et al. 2012; Sreekala et al. 2012; Reba et al. 2022).Systematic diagnostic of Extended Range Forecast (ERF) of NEM rainfall remains limited. Improving this gap is essential for enhancing the seasonal forecasting skill, refining region-specific assessment for floods and droughts and support operation decision-making in agriculture and water resource management (Rajeevan et al. 2012).

In order to address this gap, we have taken consideration of 11 regions of South Peninsular India instead of 5 meteorological subdivisions. The detailed analysis also helps us to understand regions of high spatial and temporal variability. The finer regions also give us detailed understanding how ERF forecast performs in these regions. The study area covers 11 regions of South Peninsular India, as shown in the figure 1.Subdivision of Kerala is further divided into two regions: North Kerala (No_KL) and South Kerala (So_KL). Tamil Nadu subdivision is divided into four regions, namely South Coastal Tamil Nadu (Sc_TN), South Interior Tamil Nadu (Si_TN), North Interior Tamil Nadu (Ni_TN), and North Coastal Tamil Nadu (Nc_TN). Parts of Andhra Pradesh subdivision included in the study are North Coastal Andhra Pradesh (Nc_AP), South Coastal Andhra Pradesh (Sc_AP), and Rayalaseema (Rys_AP). Karnataka is not fully covered in the study area; only South Interior Karnataka (Si_Ka) and North interior Karnataka (Ni_Ka) are included. The figure 2 illustrates the daily rainfall variability during the NEM seasons of 2015, 2016, and 2017, representing excess, weaker, and normal monsoon conditions, respectively. During 2015, the excess monsoon condition is evident from the relatively higher and sustained rainfall activity observed throughout October and November, with several moderate to

intense rainfall events exceeding 3 mm/day. In contrast, 2016 experienced a weaker monsoon season, characterized by rainfall concentrated mainly during the first half of October, including a short-duration intense rainfall event, followed by prolonged dry conditions during November and December. The year 2017 represented a normal NEM season with comparatively balanced rainfall distribution and multiple moderate rainfall events during October, gradually decreasing towards the end of the season. The study by (Reba et al. 2022)highlighted the interannual variability associated with contrasting NEM seasons. Based on this classification, the present study considers the excess NEM rainfall year of 2015, the deficient NEM rainfall year of 2016, and the normal NEM rainfall year of 2017 for verification and analysis purposes.

2.Model Used and Methodology

2.1 Operational Extended Range Forecast System Model

The existing operational ERF modeling system of IMD was initially set up by IITM and utilizes the CFSv2 coupled model adopted from NCEP ((Sahai et al. 2015).The model is having two parts ,the ocean part is based on GFDL Modular Ocean Model V.4 (MOM4) and atmospheric model is based on Global Forecast System (GFS),Atmospheric and oceanic ICs are obtained from the Global Data Assimilation System (GDAS) and the Global Ocean Data Assimilation System (GODAS), operated by the National Centre for Medium Range Weather Forecasting (NCMRWF) and the Indian National Centre for Ocean Information System (INCOIS), respectively. Model forecasts are validated using daily precipitation analysis over India, derived from merged rain-gauge data and TRMM TMPA satellite-based rainfall estimates (Mitra et al. 2009).The model is run at different resolution (1) CFSv2 at T382,(2) CFSv2 at T126,(3) GFSbc (bias-corrected SST from CFSv2) at T382, and(4) GFSbc at T126, each with four members, totaling 16 members. The current ERF system of IMD operates weekly, using the initial condition (IC) from each Wednesday. It generates a four-week forecast, starting from the following Friday through Thursday. Additionally, a 17-year hindcast (2003–2019) is conducted alongside the operational run. The daily precipitation analysis over the Indian region, derived from merged rain-gauge data and TRMM TMPA satellite-based rainfall estimates, is used to verify the model forecasts (Mitra et al. 2009).

According to (Mitra et al. 2009) merged rainfall data performs well in the Indian region compared to other datasets available. It's also further noted that ,inclusion of gauge rainfall data, improved satellite measuring of rainfall ,also products matches well with IMD gauge only rainfall data (Pai et al. 2014).The present study uses IMD-GPM merged rainfall data at 1° resolution to compare the rainfall forecasts from ERP system.

2.2 Rainfall Categorization and Verification Scores

According to (Pattanaik and Alone 2024) to analysis ERF ,it is appropriate to use rainfall categories than using actual rainfall departures. This is because the rainfall variability tends to increases significantly at finer spatial scales, making the quantitative ERF departure forecast less reliable and meaningful particular in agriculture decision making. For the quantitative analysis, ERF verification for NEM rainfall is carried out by comparing forecast rainfall category with the observed rainfall category derived from observed rainfall departures. This paper analysis 11 regions of South Peninsular India which is more impacted by NEM rainfall (Figure 1).

Normally, as per India Meteorological Department (IMD) the weekly observed rainfall departures for each subdivision in a week is classified into 5 categories like Large Excess (LE), Excess(E), Norma(N), Deficient(D) and Large Deficient (LD) as shown in the table 2.

Table 1: Classification of subdivision as normal, above normal and below normal on rainfall departure in a week

Categories	Subdivision rainfall departure in a week (IMD classification)	Classification used in this study
Excess(E)	>20%	Above Normal (AN)
Large Excess (LE)	>60%	
Normal (NN)	-19% - +19%	Normal (NN)
Deficient(D)	<-20%	
Large Deficient (LD)	<-60%	Below Normal (BN)

From the study by (Pattanaik and Alone 2024),If you consider in case of application of ERF in agricultural activities, these 5 subdivsion rainfall departure in a week categories can be consolidated into 3 broader groups:- Above Normal (AN), Normal(NN) and Below Normal (BN) (Table 1)

Table 2: Contingency tables adopted for verification of ERF rainfall in this study

Forecast/Observed Categories	Above Normal (AN)	Normal (AN)	Below Normal (BN)
Above Normal (AN)	Correct (C)	Partially Correct (PC)	Wrong (W)
Normal (NN)	Partially Correct (PC)	Correct (C)	Partially Correct (PC)
Below Normal (BN)	Wrong (W)	Partially Correct (PC)	Correct (C)

Table 3: Schematic of the 2 X2 contingency table used to compute rainfall verification metrics.

Forecast/Observed	Observed (Yes)	Observed (No)	Total
Forecast (Yes)	Hits (H)	False alarms (F)	H+F
Forecast (No)	Misses (M)	Correct negatives(C)	M+C
Total	H + M	F + C	Total

Verification of NEM rainfall carried out using these three categories as shown in Table 1 and is used to construct contingency Table 2. A forecast is labelled Correct (C) when the forecast category matches with observed category, Partially Correct (PC) when it differs by one category and Wrong (W) when it differs by more than 1 category. In addition to categorical verification of NEM rainfall , several quantitative skill scores are employed to evaluate the forecast

performance more rigorously (Pincus et al. 2008) introduces metrics such as mean bias, centered RMSE, correlation coefficient and standard deviation ratio for CMPI3 and other models ,these metrics are considered to be more suitable for continuous variables In contrast, rainfall category forecast be treated as event-based , where the outcome is either ("yes") or ("no").For such forecasts, verification is done is using 2 X 2 contingency table(Table 3), which summarizes the frequency of ERF forecast during months of Oct-December.

Based on Contingency table approach, the calculation of standard verification scores is calculated as recommended by WWRP/WGNF Joint Working Group on Forecast Verification Research as part of their workshop available on following link https://www.cawcr.gov.au/projects/verification/#Methods_for_foreasts_of_continuous_variables

In order to understand the, observed and forecast weekly rainfall departures from climatological normal are classified into three categories. Above Normal (AN), Normal (NN) and Below Normal (BN)In order to carry out verification approach, we are adopting contingency-table analysis (Table 3) and the following metrics is used for verification approach

Forecast Accuracy (Fraction Correct)

Accuracy represents the proportion of forecast that are correct and varies between 0 and 1 indicating the perfect forecast,

$$Accuracy = \frac{Hits(H) + Correct\ Negatives}{Total\ Forecast}$$

Bias Score (BS)

Bias Score (BS) is also known as frequency bias, compares the number of forecasted events ("yes") to the number of observed events("yes")

$$Bias = \frac{Hits + False\ Alarms}{Hits + Misses}$$

The value greater than 1 often results in over-forecasting, while value below 1 indicates under-forecasting. This metrics only gives idea on relative frequencies of particular events

Probability of Detection (POD)

$$POD = \frac{Hits}{Hits + Misses}$$

POD measures the fraction of observed events("yes") which were correctly predicted, its sensitive to hits.The prefect score of POD is 1. POD is highly sensitive to the number of correctly predicted events (hits) but does not account for false alarms. In other words, it depends strongly on the climatological occurrence of the event, making it particularly useful for evaluating rare events. However, the score can be artificially increased by forecasting more "yes" events, which may also raise the number of false alarms. Therefore, POD should be interpreted together with the False Alarm Ratio (FAR)

False Alarm Ratio (FAR)

FAR quantifies the proportion of forecasted events ("yes")that didn't happen

$$FAR = \frac{False\ Alarms}{Hits + False\ Alarms}$$

FAR is sensitive to false alarms, as discussed earlier, FAR needs to be used in conjunction with POD. The ideal score of FAR is 0

Critical Success Index(CSI)

This metrics evaluate the how well forecasted events("yes") correspond to observed events("yes").

$$CSI = \frac{Hits}{Hits + Misses + False\ Alarms}$$

The score excludes correct negatives and penalizes both misses and false alarms.The values varies from no skill (0) to perfect skill(1)

Equitable Threat Score(ETS)

ETS is defined how well did the forecast "yes" events correspond to the observed "yes" events.

$$ETS = \frac{Hits - Hits_{random}}{Hits + Misses + False\ Alarms - Hits_{random}}$$

where

$$Hits_{random} = \frac{(Hits + Misses)(Hits + False\ Alarms)}{Total}$$

ETS score typically ranges from 0(no skill) to 1 (perfect skill) and values ranges around 1/3 to 1. (Krishnamurti et al. 2009)mentioned in his study that ETS score 0.12 could be considered as a skill forecast. The metrics ETS is often used for the verification purpose in NWP models.

3.Characteristics of Intra-seasonal Activity of NEMR in 2015,2016 and 2017

3.1. NEM Season during 2015

The NEM Season of 2015 was characterized by high intra-seasonal variability, marked by an exceptionally active NEM and enhanced cyclonic activity over the North Indian Ocean. The Southwest Monsoon withdrew from the entire country by 19 October, following which the NEM commenced over the south peninsular region on 28 October, about 8 days later than its normal onset.

Despite the delayed onset, the NEM rainfall over the south peninsular India was substantially above normal (132% of LPA). The intra-seasonal distribution revealed a suppressed phase during October, followed by a strongly active phase during November and early December. November 2015 emerged as one of the wettest months of the NEM since 1901, primarily due to persistent easterly wave activity and repeated low-pressure systems over the Bay of Bengal.

The enhanced synoptic-scale activity led to extreme rainfall events and flooding, particularly over Tamil Nadu, Puducherry, Rayalaseema, and parts of Kerala. The presence of two Extremely Severe Cyclonic Storms, CHAPALA and MEGH, over the Arabian Sea during October–November contributed to large-scale circulation anomalies, indirectly influencing moisture transport into southern India.

The season was also marked by intra-seasonal characteristics, especially over south peninsular India. The Southwest Monsoon withdrew from the entire country on 28 October, and the NEM commenced on 30 October, about 10 days later than normal.

The NEM rainfall over the core south peninsular region was severely deficient (around 35% of LPA), making it the lowest NEM rainfall since 1901. Intra-seasonally, all three months—October, November, and December—were dominated by weak convective activity, poor organization of easterlies, and an absence of sustained low-pressure systems over the Bay of Bengal.

Although a few cyclonic systems developed during the season, including the Very Severe Cyclonic Storm VARDAH in December, their contribution to seasonal rainfall was limited and highly localized. VARDAH made landfall over the Tamil Nadu coast and caused significant damage, but it did not result in widespread rainfall enhancement over the peninsula.

Large parts of south peninsular India experienced extended dry spells, while occasional rainfall was confined mainly to the Andaman & Nicobar Islands and parts of the eastern coastline. The NEM season of 2016 was also exceptionally warm, ranking among the warmest NEM seasons on record, with persistent above-normal surface temperatures.

Overall, the intra-seasonal activity during post-monsoon 2016 was characterized by prolonged inactive phases, poor synoptic support, and record-breaking NEM failure.

3.3. NEM Season during 2017

The NEM season of 2017 showed moderate intra-seasonal variability, lying between the extremes observed during 2015 and 2016. The Southwest Monsoon withdrew from the country on 25 October, and the NEM commenced on 27 October, close to its normal date.

Rainfall over the south peninsula during the season was below normal (about 86% of LPA), although significantly better than in 2016. Intra-seasonally, October and December recorded near-normal rainfall, while November was distinctly subdued, resulting in an overall negative seasonal anomaly.

The most dominant feature of NEM 2017 was the development of Very Severe Cyclonic Storm OCKHI during late November and early December. OCKHI originated over the southwest Bay of Bengal, traversed near Sri Lanka, and rapidly intensified over the Arabian Sea. Although it caused heavy rainfall and severe damage over Kerala, Tamil Nadu, and Lakshadweep, its impact was spatially uneven and did not substantially enhance seasonal mean rainfall over the entire NEM region.

Thermally, NEM 2017 ranked as the third warmest since 1901, with persistent positive temperature anomalies over most parts of the country. The intra-seasonal rainfall pattern reflected short active spells associated with cyclonic systems, interspersed with extended dry periods, particularly over interior peninsula.

4. Results and Discussion

The IMD operates a combination of weather forecasting framework spanning multiple temporal scales such as short-range, medium-range, extended-range and seasonal forecasts which supports strategic and tactical decision-making in agriculture(Pattanaik et al. 2013; Pai et al. 2014; Rao et al. 2015). These forecasts products form the scientific basis for operational agrometeorological services. Recently has also initiated the dissemination of ERF based agromet advisories on a weekly basis. These advisories are designed to deliver timely and user-friendly weather information to facilitate practical farm-level decisions such as sowing schedules, fertilizer application, irrigation management (Sharma 2015; Rathore et al. 2016). Disseminating is carried out through a multi-channel communication framework ensuring broad reach among farmers(Chattopadhyay et al. 2018; Pattanaik et al. 2020). Such advisories enable farmers to optimize their agricultural activities by capitalizing on favourable weather conditions while reducing losses arising from adverse weather events.(Rao et al. 2015; WMO 2020)

Previous studies like have highlighted the practical utility of weather-based advisories extreme monsoon conditions like,(Chattopadhyay et al. 2018) have demonstrated that real-time weather forecasts during 2015-2016 monsoon seasons were instrumental in managing the impacts of excess rainfall over the northeastern states of India, where timely village level alerts enabled the farmers to adjust the farm operation and minimize the crop loses.(Tyagi and Pattanaik 2010) in their study highlighted continuous real-time monitoring of intra-seasonal monsoon variability during drought year 2009 ,played important role in assessing both the spatial extent and severity of drought conditions across the country. From their study it was evident that ERF forecast reported prolonged dry spells during June, first half of August and the second half of September 2009 helped the authorities to take measure to drought preparedness and response strategies(Tyagi and Pattanaik 2010; Mooley et al. 2011).

4.1 Spatial Distribution of Forecast Skill during contrasting NEM 2015,2016 and 2017

The information on the NEM rainfall in advance is extremely useful in agricultural planning, particular to take decision on irrigation scheduling, fertilizer application and sowing. Reliable ERF prediction of the intra-seasonal fluctuation. As discussed by (Pattanaik et al. 2022) on ERF skill for 2020 southwest Monsoon across 36 meteorological subdivision of India, the results demonstrate that ERF system was able to reasonably capture the observed intra-seasonal variability of monsoon rainfall during different phases of monsoon, including its onset, active, break and withdrawal phases. Based on statistical analysis, significant correlation existed between observed and forecast rainfall departures indicating the ERF prediction retained useful skill up to about three weeks in advance.

From the Figure 3 (a-c) represents the spatial distribution of smaller region level ERF skill for the post monsoon season of 2015,2016 and 2017 respectively in terms of Correct (C), Partially Correct (PC) and Wrong(W) category forecasts at lead times from week 1 to week 4. From the figure it is evident that consistent and systematic evolution of forecast skill with lead time is evident across all three years for all 11 sub-divisions of South Peninsular India.

During NEM Rainfall 2015, the spatial distribution shows moderate forecast skill across most sub-divisions. Higher percentages of correct forecasts are observed during Week-1, particularly over Kerala and Andhra Pradesh regions, while forecast performance gradually decreases with increasing lead time. From Week-2 onward, several regions of Tamil Nadu and Karnataka exhibit increased partially correct and wrong forecasts, indicating larger forecast uncertainty at extended leads. The spatial variability during NEM 2015 is comparatively higher, suggesting unstable rainfall behavior and reduced predictability during the season.

In contrast, NEMR 2016 demonstrates improved spatial consistency and higher forecast skill over most regions of South Peninsular India. Correct forecasts dominate across many sub-divisions from Week-1 to Week-3, while the extent of wrong forecasts remains comparatively lower. Kerala and Andhra Pradesh subdivisions particularly show better spatial coherence and sustained predictability. Although forecast skill decreases slightly toward Week-4, the degradation is more gradual than in NEM 2015, indicating enhanced reliability of the ERF system during the 2016 post-monsoon season.

The spatial distribution during NEMR 2017 shows forecast performance intermediate between 2015 and 2016. Correct forecasts remain high during Week-1 and Week-2 across several sub-divisions; however, larger spatial variability emerges beyond Week-2. Some regions of Tamil Nadu and Karnataka display increased partially correct and wrong forecasts at longer lead times. Nevertheless, the overall forecast skill remains better than 2015 and reasonably consistent over Kerala and Andhra Pradesh regions.

Across all three years, the spatial analysis clearly indicates that forecast skill decreases progressively with increasing lead time from Week-1 to Week-4. Week-1 forecasts consistently exhibit the highest percentage of correct predictions and the lowest spatial extent of wrong forecasts. Among the three years, NEMR 2016 shows the best spatial forecast performance, followed by 2017, while 2015 exhibits the weakest spatial predictability and highest forecast uncertainty.

For all NEM season of 2015,2016,2017, the highest proportion of correct forecast at week 1, with several region exhibiting values exceeding 60-70%. As the lead time increases from week 2 to week 4, the proportion of correct forecast shows a gradual decline, in week 4 there is substantial fraction decreases in proportion of Correct (C) forecast in ERF time scale. In case of Partially Correct (PC) forecast increase with lead time across most regions and all years.

The Wrong(W) forecast category remains comparatively limited throughout all the lead times and years identified, It is also found that there is profoundly increase in the Wrong (W) forecast proportion from week 1 to week 4, the spatial extent and magnitude of these errors remain lower than those of Correct (C) and Partially Correct (PC) forecast combined.

Inter annual differences in forecast skill are also apparent. The 2016 and 2017 NEM seasons relatively higher spatial coherence and greater proportion of correct forecasts across all lead times compared to 2015, In contrast the NEM 2015 displays a larger Partially Correct (PC) forecast reflecting forecast uncertainty during that year

4.2 Verification Scores for ERF during Contrasting NEM season 2015,2016 and 2017

To comprehensively asses the performance of region level ERF of NEM rainfall ,additional verification metrics are examined for all 3 rainfall categories-Above Normal(AN),Normal(NN) and Below Normal(BN).The evaluation is carried out separately for post monsoon season (Oct-Dec) of 2015,2016 and 2017,covering a total of 18 NEM weeks for week 1 to week 4 forecast lead times and encompassing all 11 regions of south Peninsular India.

Using these contingency table(Table 3), suitable verification measures was computed for each rainfall category including Accuracy, Bias Score, Probability of Detection(POD), False Alarm Ration (FAR), Critical Success Index (CSI) and Equitable Threat Score (ETS) .The lead-time dependence of these verification is illustrated in the following discussion providing detailed quantitative evaluation of the skill, reliability and consistency of the sub divisional ERF category.

4.2.1**. Accuracy of ERF**

The smaller region level accuracy of ERF of NEM category forecasts shows a clear dependence on forecast lead time across all three monsoon seasons(2015-2017) as shown in the figure 4.For all rainfall categories ,the high accuracy is consistently observed at week-1 ,followed by a gradual systematic decline from week-2 and week-4.Among the three rainfall categories, the Normal(NN)category exhibits the highest accuracy at all lead times in all years, indicating that near -normal rainfall conditions are more reliably predicted at the sub-divisional scale. The AN category shows moderate accuracy with evident decline beyond week-2, while the BN category the generally displays the lowest accuracy, particularly at longer leads.

The NEM rainfall 2016 and 2017 consistently shows higher accuracy level than 2015 especially at week-2 to week-4 leads. The relatively lower accuracy during NEM 2015 suggests enhanced forecast uncertainty, likely linked to the dominance of synoptic-scale variability during NEM of 2015. Similar results were also reported by (Abhilash et al. 2018), who showed that the southwest monsoon season of 2015 had lower predictive skill in the extended range time scale due to the dominance of synoptic-scale disturbances. As discussed in their study, the lower predictive skill of the active phase during the 2015 monsoon season was associated with the dominant influence of synoptic-scale systems and the interaction between synoptic-scale disturbances and low-frequency modes, which contributed to reduced prediction skill at longer lead times. Thus, the comparatively lower predictive skill observed during NEM 2015 in the present study could also be attributed to the dominance of synoptic systems associated with NEM over the South Peninsular India. Similar observations were also discussed by (Pattanaik et al. 2020) where the performance of operational ERF during southwest monsoon seasons 2017 and 2018 indicated that forecast skill was strongly influenced by the evolution of synoptic-scale rainfall systems and the active rainfall phase over the southern peninsula during 10–16 August 2018 was slightly underpredicted by the ERF system.

4.2.2 Bias Score

The figure 5 presents the bias score, which provides insight into the under-estimating tendencies of the ERF of NEM rainfall at region level. Across all three years and lead weeks, the NN category maintains bias values close to unity, which shows the minimal bias in near-normal rainfall conditions. In contrast, the AN category exhibits a tendency towards over-estimating the ERF tendencies, particularly at longer lead times, which is evident by observing the bias values exceeding unity in several sub-division during 2016 and 2017. Conversely, the BN category shows persistent under-estimating especially beyond week-2. The bias pattern shows interannual differences with larger deviation from unity during NEM Rainfall 2015.

4.2.3 False Alarm Ratio (FAR)

The FAR score provides the measure of forecast reliability by quantifying the proportion of false events among all predicted events. From the figure 6, shows that FAR generally increases with lead time for all rainfall categories, indicating the growing uncertainty in forecasts as lead time increases from week-1 to week-4

The NN category consistently records the lowest FAR across all lead times and years, indicating fewer false near-normal rainfall predictions. The AN category shows moderate FAR values, while BN category exhibits comparatively higher FAR, particularly beyond week-2

Despite, the increase in FAR with lead time, FAR values for most categories remain within operationally acceptable limits up to week-3 especially during NEM 2016 and NEM 2017.The comparatively higher FAR is seen during NEM rainfall 2015 which further reflects the increased forecast uncertainty during that year. Overall, it is observed that FAR decreases with lead time gradually than abruptly.

4.2.4 Probability of Detection (POD)

Figure 7 illustrates the POD, which measures the ability of ERF to correctly identify the observed rainfall categories. Across all three NEM season 2015,2016 and 2017 considered in this paper , POD is highest at week -1 and decreases progressively with increasing lead time, which is consistent with declining forecast sharpness at longer leads

The NN category consistently exhibits the highest POD, followed by the AN category while BN category shows the lowest POD, particularly beyond week-2. This indicates that near-normal rainfall conditions are mostly reliably detected. POD values for all categories remains reasonably high up to week-3. suggesting ERF remains useful detection capability are sub-division level scale

Interannual comparison shows that NEM 2016 and NEM 2017 maintain higher POD values than NEM 2015 especially for AN and NN categories at longer leads, the reduced POD during NEM 2015 is consistent with lower accuracy and higher FAR observed in that year. Overall, the POD analysis demonstrates that the ERF system is capable of detecting rainfall regimes at extended leads with declining skill up to week-4.

4.2.5 Critical Success Index (CSI)

From the figure 8 it is seen that NEM 2015 exhibits the moderate CSI values with a clear dependence on lead time. Across most regions of south peninsular India, CSI peaks at week-1 or week-2 and subsequently declines towards week-4 indicating reducing forecast skill at extended leads. The regional contrast is clear, with AN consistently exhibiting the highest CSI, followed by NN. The extended range forecast of NEM rainfall 2016 shows best results in terms of CSI. Values are systematically higher in both 2015 and 2017 and the decline with lead time is noticeably weaker. Most of south Peninsular India regions shows CSI maxima at week-2 and week-3, indicating enhanced sustained predictability. The NEM rainfall 2017 forecast performance lies intermediate between 2015 and 2016.Although short-lead skill remains robust, peak CSI values are generally lower in 2016 and several subdivision display more variable lead-week evolutions. The decrease in CSI beyond week-2 is more pronounced than in NEM rainfall forecast of 2016.

Equitable Threat Score (ETS)

NEM rainfall forecast of 2015 is characterized by relatively strong ETS at week-1 followed by a rapidly decline with increasing lead time as shown in figure 9. For many areas of South Peninsular India, it is observed that ETS values

approach near-zero by week-3 and week-4 especially for BN. It's also observed that AN retains ETS across the lead weeks, whereas NEM rainfall forecast of 2016 shows improvements in ETS compared to the other region. Positive ETS values persist up to week-3. The decline with lead time is more gradual beyond week-2 suggesting increased reliability of ERF of NEM rainfall 2016.

The NEM rainfall of 2017 more variability across all station, while week-1 ETS remains comparable to 2015 and 2016.The skill drop beyond week-2 is sharper than in 2016.Overall, ETS indicates that ERF predictability for NEM rainfall 2015 is lowest compared to NEM 2016 and NEM 2017.

5. Summary & Conclusion

Forecasting in the tropical regions and producing reliable forecast in ERF at lead times of 2-4 weeks remains a major challenge, particularly in finer scale. In this study, the performance of operational ERF is assessed for 11 regions of South Peninsular India during excess, deficient and Normal NEM season of 2015,2016 and 2017.The performance of the ERF systems over South Peninsular Indian during NEM seasons of 2015-2017 demonstrates a clear dependence on forecast lead time, spatial variability and interannual monsoon characteristics.

Spatial analysis shows week-1 forecast consistently achieve highest skill, with a large fraction correct forecasts across all regions. Forecast skill degrades systematically from the week-2 to week-4 reflecting in increasing partially correct and wrong forecasts

Interannual comparison indicate that NEM 2016 exhibits the highest predictability, followed by NEM 2017, while NEM 2015 shows the lowest skill. The lower predictive skill during NEM 2015 could be associated with enhanced synoptic-scale variability and stronger interaction between synoptic disturbances and low-frequency modes, which reduced forecast predictability at extended leads. Similar findings were reported by (Abhilash et al. 2018), who showed that lower ERF skill during the 2015 monsoon season was associated with dominant synoptic-scale disturbances and their interaction with low-frequency variability. (Pattanaik et al. 2020)also highlighted that the performance of operational ERF is strongly influenced by the evolution of synoptic-scale rainfall systems and active-break monsoon conditions. Coastal regions display relatively higher skill compared to interior regions, particularly at longer leads. Verification metrics further supports these finding. Forecast accuracy and POD are highest at shorter lead times and decrease progressively with increasing lead time, while FAR shows an increasing trend. The NN category consistently demonstrates highest skill across all metrics, whereas extreme categories like(AN and BN) shows reduced predictability, especially beyond week-2 Bias analysis reveals near-unity values for NN forecast , indicating minimal systematic errors ,while AN is overestimated and BN is underestimated ,Skill measures such as CSI and ETS confirms that forecast reliability is strongest at week-1 and week-2 with gradual decline seen thereafter. The NEM 2016 shows sustained skill up to week -3 whereas NEM 2015 exhibits rapid decline

Overall, from our analysis, the ERF system retains meaningful predictive skill up to 2-3 weeks further which forecast reliability decreases sustainably. The results demonstrate the utility of ERF forecasts to provide reliable rainfall forecasts and holds significant potential for operational application related to as agro-advisories and impact-based forecasting

Author Contributions Statement

The idea of writing this paper was conceptualized by RMR and DRP. The first draft of the manuscript was prepared by RMR, DRP, and PVSR. The figures were prepared by RMR. Critical review and editing of the manuscript were performed by PVSR. All authors reviewed and approved the final manuscript.

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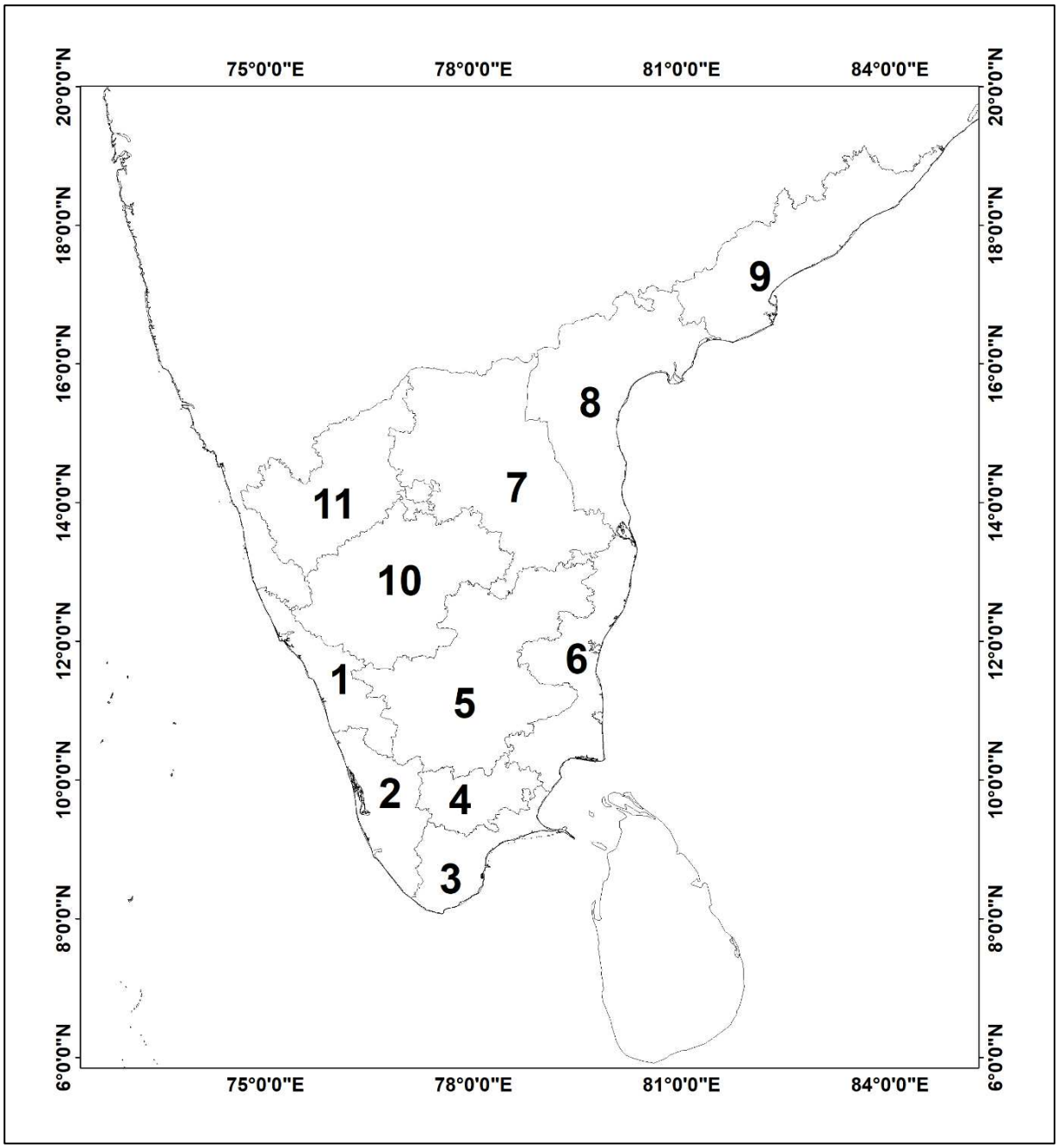

Figure 1: Shows 11 meteorological subdivisions of South Peninsular India: 1) North Kerala (No_KL) and South Kerala (So_KL) 3) South Coastal Tamil Nadu (Sc_TN), 4) South Interior Tamil Nadu (Si_TN), 5) North Interior Tamil Nadu (Ni_TN) 6) North Coastal Tamil Nadu (Nc_TN). 7) North Coastal Andhra Pradesh (Nc_AP),8) South Coastal Andhra Pradesh (Sc_AP), 9) Rayalaseema (Rys_AP). 10)South Interior Karnataka (Si_Ka) 11) North Interior Karnataka (Ni_Ka) .

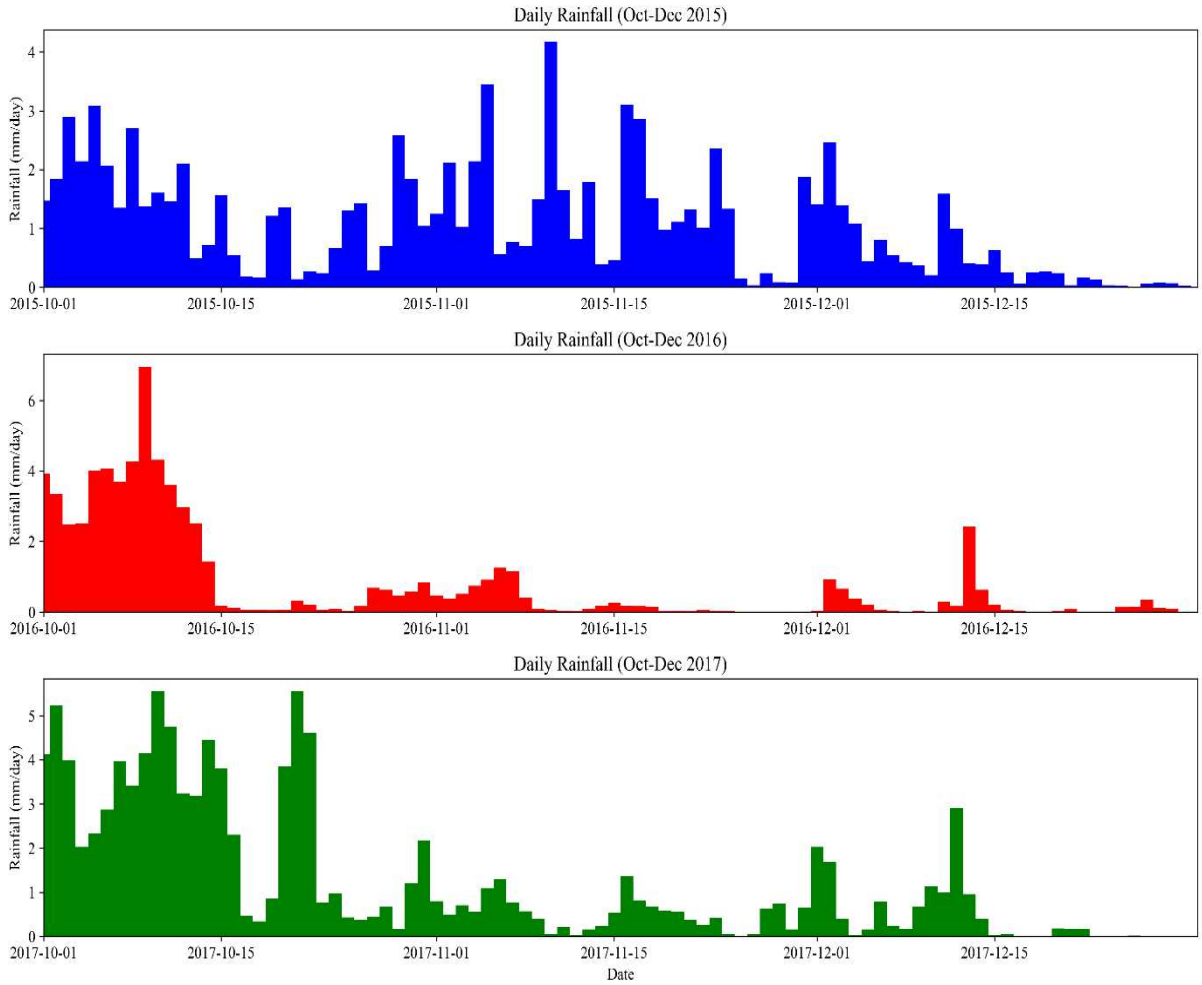

Figure 2: Daily observed rainfall (actual) averaged over the 11 regions of South Peninsular India during the post-monsoon seasons of 2015, 2016, and 2017.

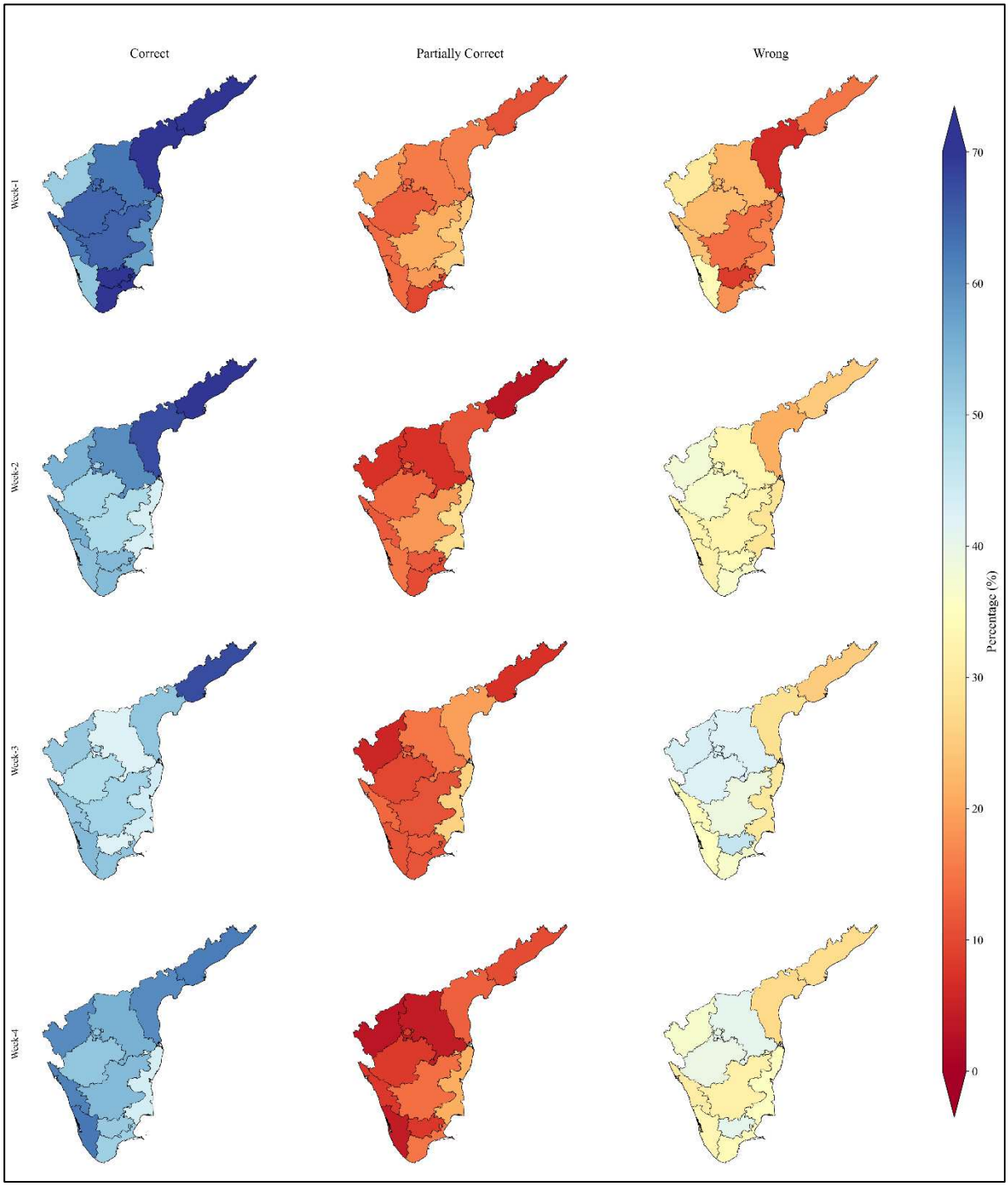

Fig 3a. Spatial distribution of sub-division level ERF skill for 2015 post monsoon season, shown in terms of Correct (C), Partially Correct (PC) and Wrong (W) category forecasts for week 1 to week 4 lead times

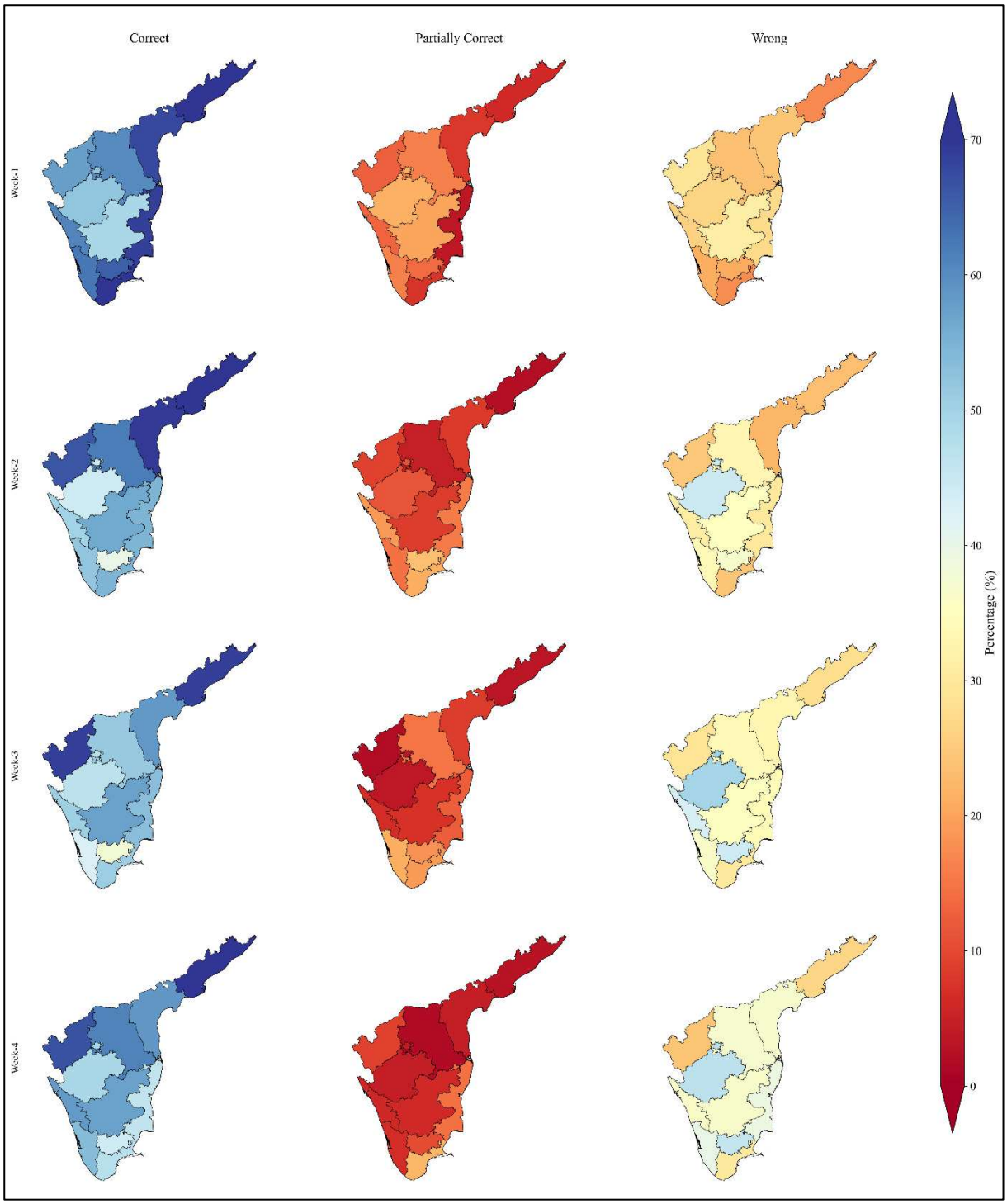

Fig 3b. Spatial distribution of sub-division level ERF skill for 2016 post monsoon season, shown in terms of Correct (C), Partially Correct (PC) and Wrong (W) category forecasts for week 1 to week 4 lead times

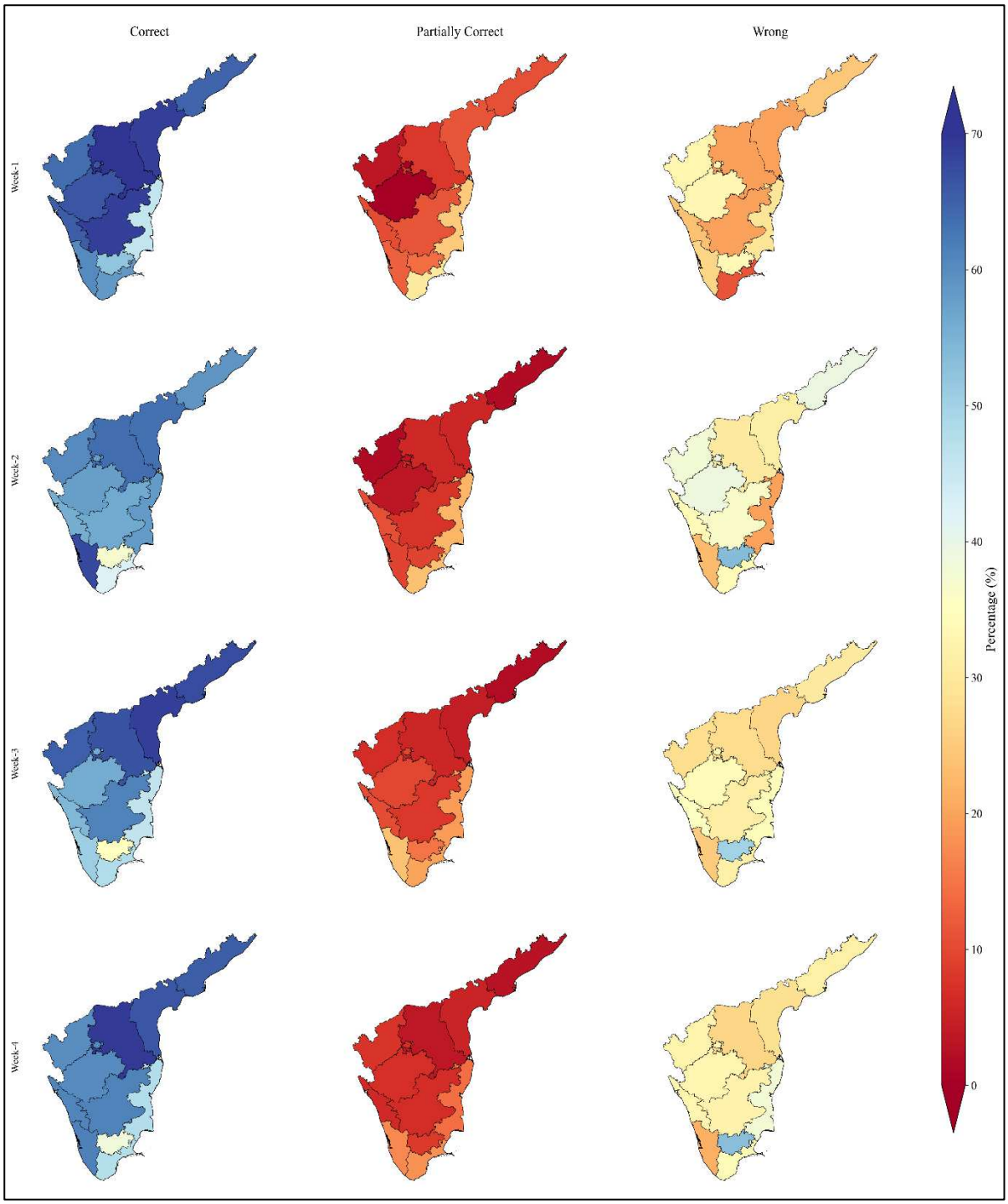

Fig 3c. Spatial distribution of sub-division level ERF skill for 2017 post monsoon season, shown in terms of Correct (C), Partially Correct (PC) and Wrong (W) category forecasts for week 1 to week 4 lead times

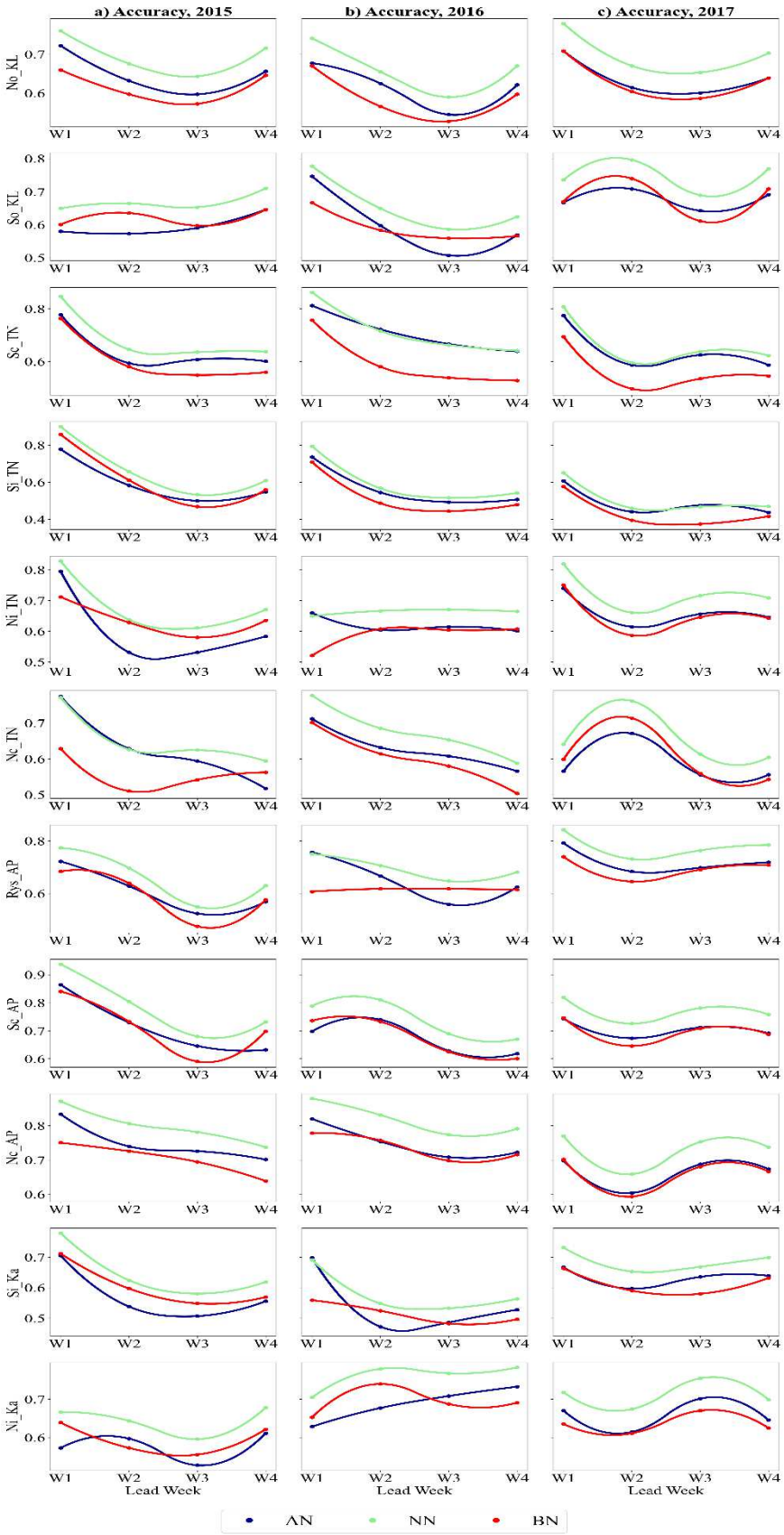

Figure 4. Accuracy scores for rainfall categories (AN: Above Normal, NN: Near Normal, BN: Below Normal) across lead weeks (W1–W4) for 11 homogeneous rainfall regions during 2015–2017. Columns represent individual years: a) 2015, b) 2016, and c) 2017.

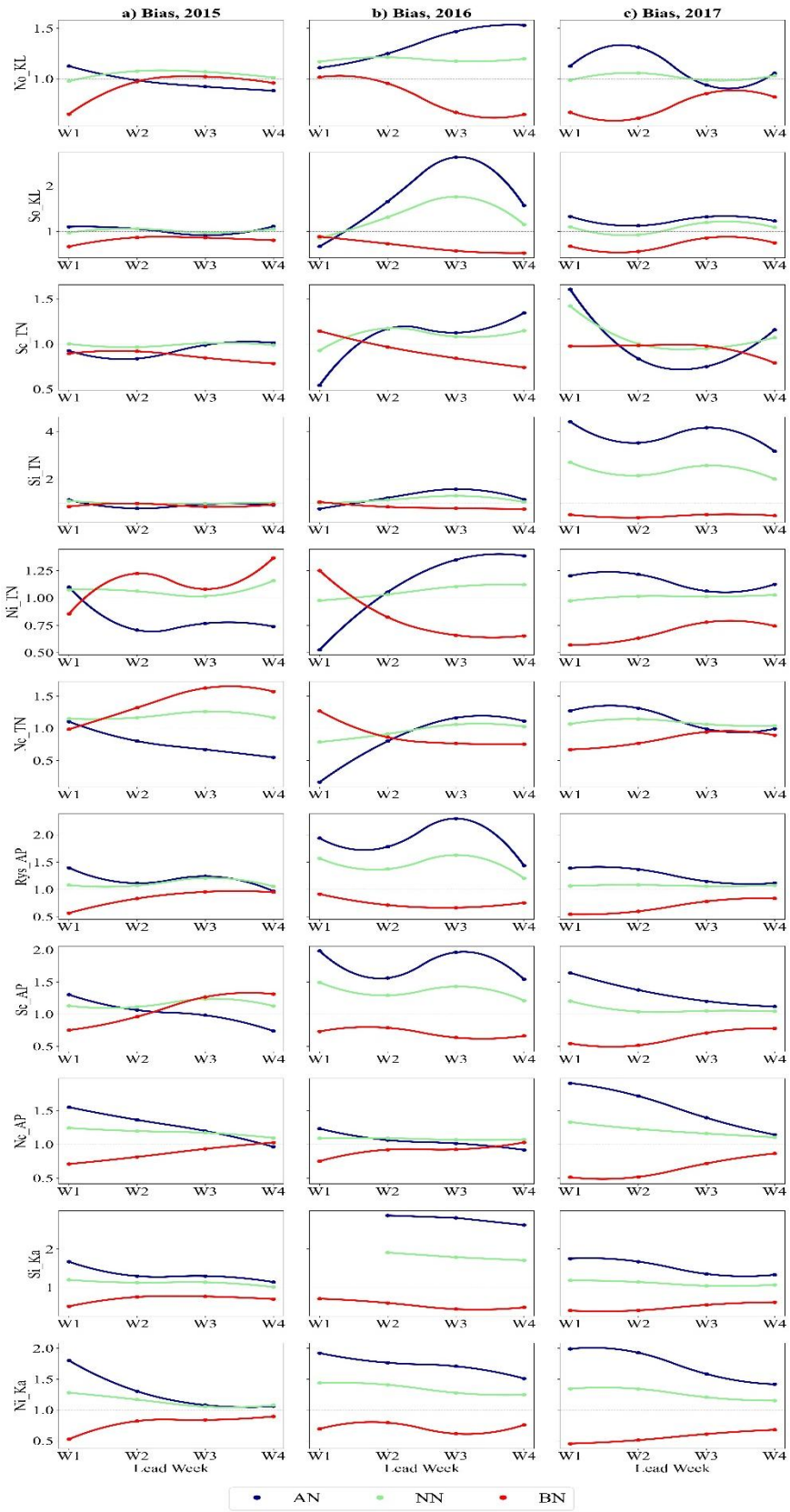

Figure 5. Bias Score for rainfall categories (AN, NN, BN) across lead weeks (W1–W4) for 11 homogeneous rainfall regions during 2015–2017. The dashed gray line indicates the perfect bias score of 1.0. Columns represent individual years: a) 2015, b) 2016, and c) 2017.

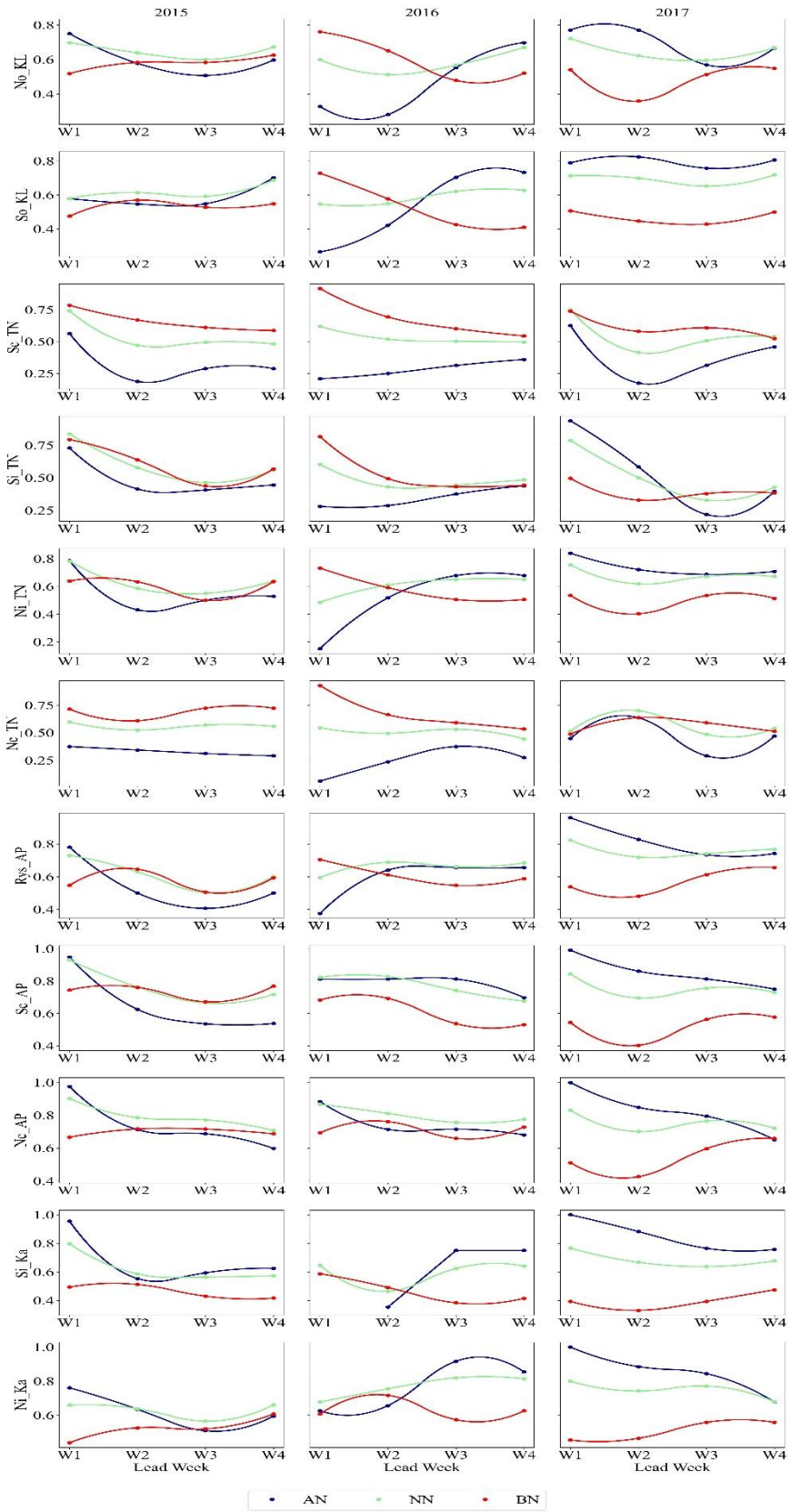

Figure 6. Probability of Detection (POD) for rainfall categories (AN, NN, BN) across lead weeks (W1–W4) for 11 homogeneous rainfall regions during 2015–2017. Columns represent individual years: a) 2015, b) 2016, and c) 2017.

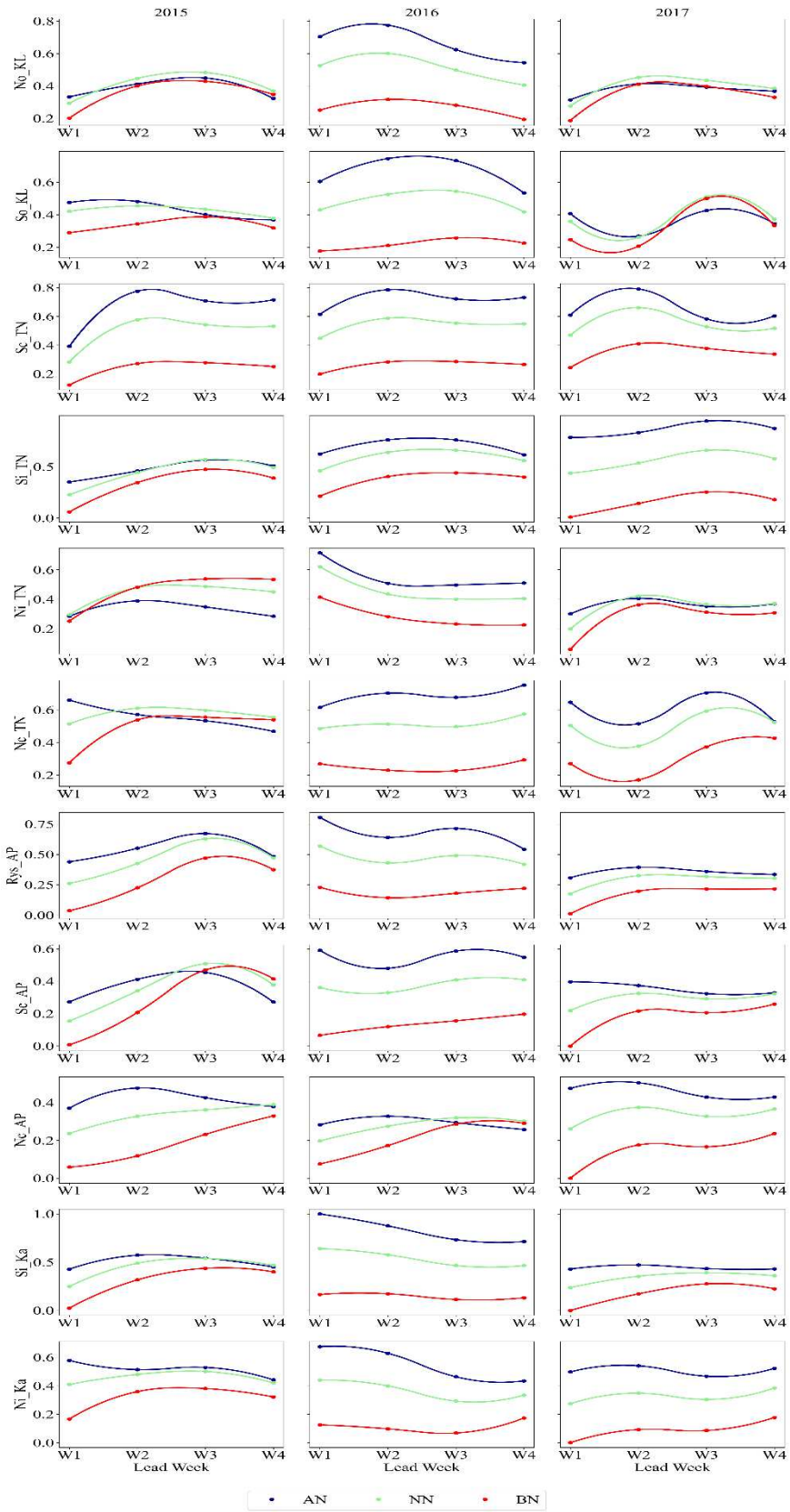

Figure 7. False Alarm Ratio (FAR) for rainfall categories (AN, NN, BN) across lead weeks (W1–W4) for 11 homogeneous rainfall regions during 2015–2017. Columns represent individual years: a) 2015, b) 2016, and c) 2017.

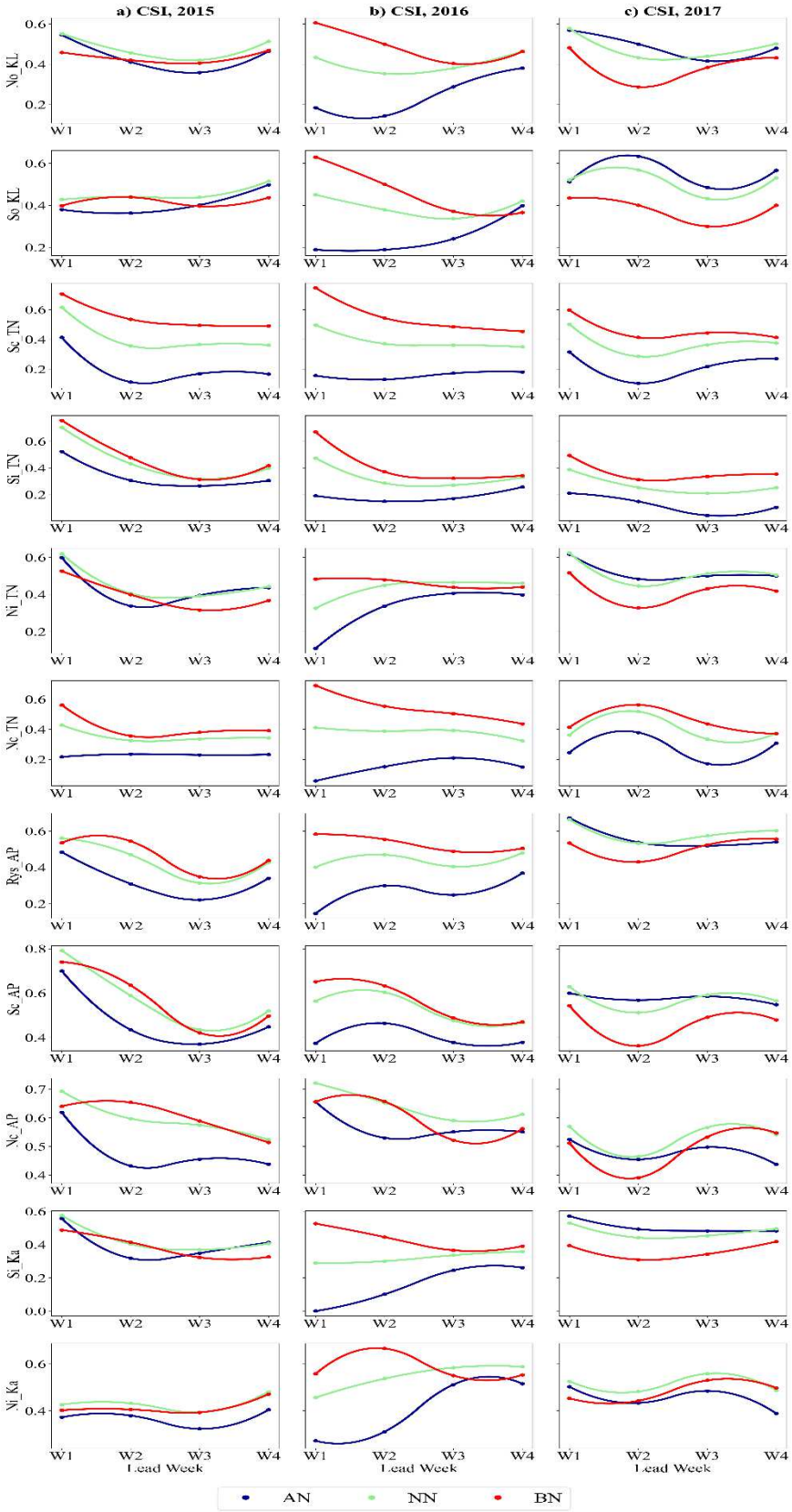

Figure 8. Critical Success Index (CSI) for rainfall categories (AN, NN, BN) across lead weeks (W1–W4) for 11 homogeneous rainfall regions during 2015–2017. Columns represent individual years: a) 2015, b) 2016, and c) 2017.

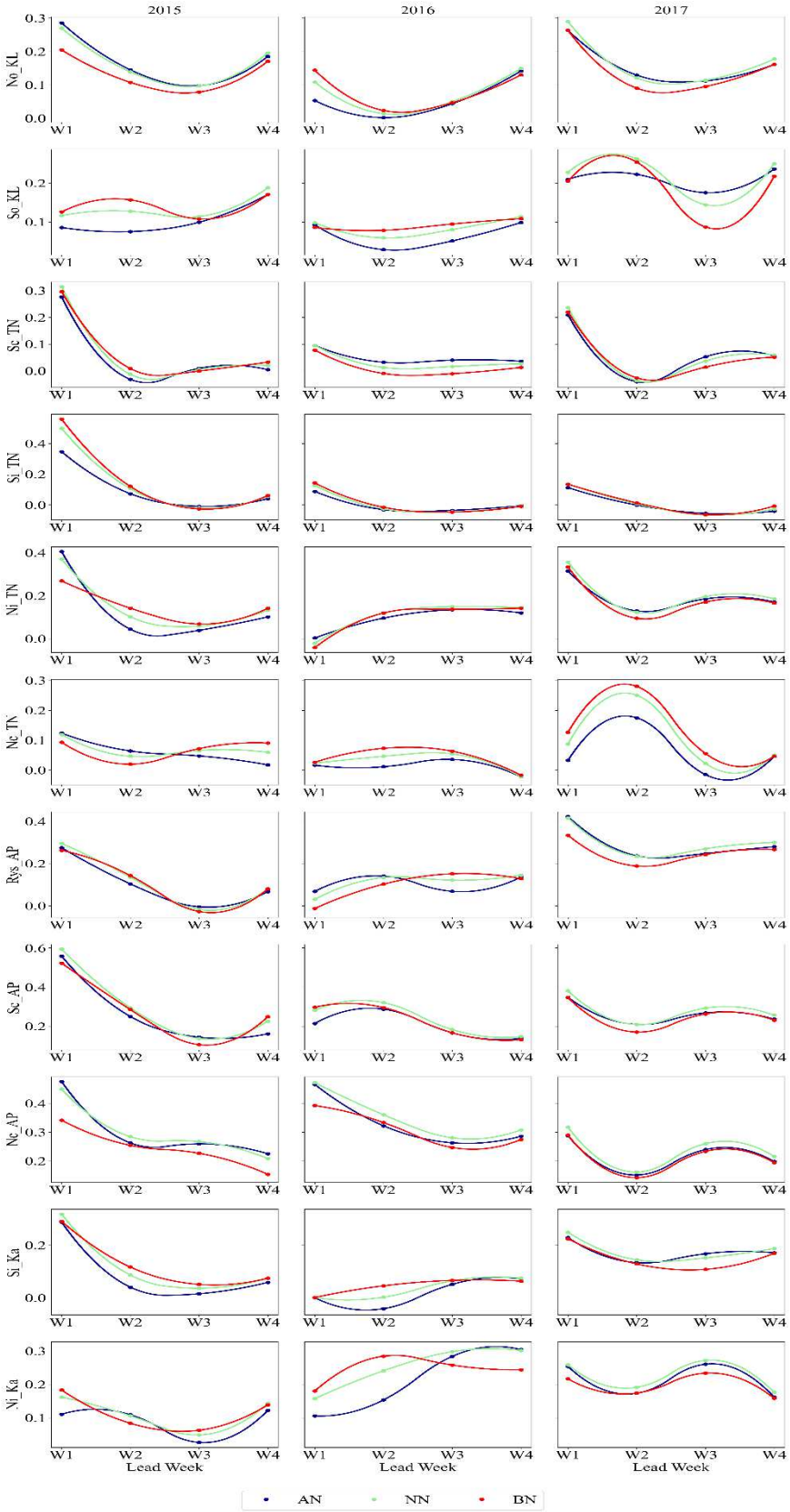

Figure 9 Equitable Threat Score (ETS) for rainfall categories (AN, NN, BN) across lead weeks (W1–W4) for 11 homogeneous rainfall regions during 2015–2017. Columns represent individual years: a) 2015, b) 2016, and c) 2017