VALIDATION OF REANALYSING, SATELLITE AND GROUND BASED CLIMATE DATA OVER TAMIL NADU, INDIA

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Abstract. The utilization of satellite based and reanalysis climatic data has significantly advanced in hydro meteorological research in regions with limited observations. Before implementing satellite based and reanalysis-based data in specific locations, it is crucial to thoroughly assess their accuracy. This study focused on evaluating the accuracy of reanalysis climate data and Tropical Rainfall Measuring Mission (TRMM) satellite rainfall data compared to observed climate data in different agro climatic zones of Tamil Nadu, India. The evaluation was conducted on a monthly basis from 1981 to 2017. Furthermore, the performance of the precipitation product obtained from Tropical Rainfall Measuring Mission was also evaluated with reanalysis data at weekly basis from 1998 to 2017. Various statistical methods such as bias, root mean square error, index of agreement, and refined index of agreement were employed for this assessment. The results show that, the reanalysis and observed monthly data for rainfall, maximum and minimum temperature show a strong correlation in all zones of Tamil Nadu, except for the High rainfall and Hilly zone. TRMM rainfall values effectively capture rainfall data, but satellite data can overestimate and underestimate rainfall amounts, as revealed by the validation of satellite and reanalysis precipitation data.
Keywords: *reanalysis data, observed data, satellite product, evaluation, statistical analysis*

Introduction

Precipitation is a critical component of the earth hydrological cycle which plays a vital role in agriculture, water resource management and climate studies (Tabari, 2020). The accurate and reliable precipitation data are essential for understanding regional climate patterns, assessing water resources and planning for sustainable development (Buytaert et al., 2020). Tamil Nadu is a state in India highly dependent on monsoon rainfall for its agricultural activities, so rainfall observations are essential to monitor the climate in the basis of validation of climatic models, trend analysis, climatic shifts, detection, and attribution of changes in climate at regional scale (Sonali and Nagesh Kumar, 2020). Climate change has emerged as a significant and pressing threat. In order to effectively deal with temperature changes, it is important to analyze long-term trends and variations (Abbass et al., 2022). The analysis of long-term trends and variability is essential for accurately assessing the extent of temperature changes and formulating appropriate measures to combat climate change (Asfaw et al., 2018). Temperature data obtained from reanalysis is a valuable resource for filling in gaps where long-term data is unavailable (Lompar et al., 2019). Reanalysis data involves a method that merges physical models and observations to generate a complete and reliable dataset of atmospheric variables, such as temperature (Tapiador et al., 2012).

Precipitation data is commonly collected from different sources such as ground-based rain gauges, satellite observations, and reanalysis models (Sebastianelli et al., 2013). Each of these sources has its own strengths and limitations. Ground-based rain gauges provide direct measurements but have limited spatial coverage, especially in remote or sparsely populated areas (Moazami and Najafi, 2021). The quality of data from rain gauges cannot always be guaranteed, and there may be uneven distribution of gauges (Schreiner McGraw and Ajami, 2020). In areas with complex terrain, there are often fewer rain gauges due to the lack of human settlements (Li and Shao, 2010), making it difficult to obtain sufficient precipitation data for accurate future simulations (Ning et al., 2016). Satellite-based observations provide wide coverage but may have limitations in accuracy and resolution (Caroletti et al., 2019). However, in some cases, satellite data is used to fill gaps in station data, particularly in ungauged areas (Fan and Van den Dool, 2008). Reanalysis models combine observations at regular grids to generate data for various locations on Earth over a long period of time (Revilla-Romero et al., 2015). Climate models utilize past data to simulate previous situations that partly overlap with observations and reanalysis (Pfenninger and Staffell, 2016). These multiple sources of data are valuable for historical and long-term climate studies (Arkin and Xie, 1994), although they may contain biases that require validation.

Buarque et al. (2011), meteorologists and climatologists use both direct and indirect measurements to accurately determine precipitation and temperature in an area. Direct measurements are obtained from rain gauge networks, while indirect measurements are derived from satellite precipitation estimates (Prentice et al., 2000). However, obtaining accurate and representative precipitation measurements is challenging due to the difficulty in locating enough instruments to capture the spatial variability (Hirpa et al., 2010). Pombo and de Oliveira (2015) evaluated the performance of four products in Angola (2013-2014): the Tropical Rainfall Measuring Mission (TRMM) 3B43 (version 6), Global Precipitation Climatology Project (GPCP) Combined Precipitation Data Set (version 2.2), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), and the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Centre (CPC) Morphing Technique (CMORPH). They compared annual and monthly precipitation estimates from these products with ground observation measurements. The four remote sensing products provided information on the spatial and temporal variability of annual and monthly precipitation in Angola. The results

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showed that the TRMM estimates were more accurate than the other products. Satellite rainfall estimates are more cost-effective than ground-based weather stations and provide a more continuous and consistent data set (Han et al., 2011). Validation and uncertainty assessment are important for satellite data products from the end-user perspective (Otto et al., 2011).

The study area is Tamil Nadu, which is located in the southernmost part of India and covers an area of about 130,058 km^2. Conducting rainfall studies in India is challenging due to its complex geography and high vulnerability to climate change, as it is situated between the Arabian Sea and the Bay of Bengal (Narasimalu et al., 2018). This research aims to validate and assess the accuracy of different datasets in regions where both ground data and gridded data are available. This process can assist scientists and policymakers in determining which datasets are most suitable for future applications, even in areas with complex terrain and limited weather stations. Specifically, this study focuses on validating precipitation data in Tamil Nadu, India, by comparing and evaluating the reliability of three primary sources: ground-based rain gauge measurements, satellite-based observations, and reanalysis data.

Materials and Methods

Data generation and source

The monthly observed climate variables such as maximum temperature, minimum temperature and precipitation data from 1981 to 2017 for seven locations of different agro climatic zones of Tamil Nadu viz., North Eastern Zone (Tindivanam), North Western Zone (Yethapur), Western Zone (Coimbatore), Southern Zone (Madurai), Cauvery Delta Zone (Tiruchirappalli), High Rainfall Zone (Pechiparai), Hilly and High Altitude Zone (The Nilgiris) (*Fig. 1*) was collected from nearby research stations and colleges located in their respective zones under the Tamil Nadu Agricultural University, Tamil Nadu, India. The data collected was checked for quality using standard operating procedures for all study locations and throughout the entire study period.

Reanalysis climate data

In our study, the WRF model was implemented with two, two-way nested domains with 15 and 5 km horizontal resolutions and 51 vertical levels. In order to establish the initial and boundary conditions, the ECMWF reanalysis Interim (ERA-I) data was utilized, which is accessible at a horizontal resolution of 0.75° (Dee et al., 2011). All available satellite and in-situ observations in the region were assimilated into WRF using the consecutive re-initialization method as described by (Viswanadhapalli et al., 2017) to generate the data over a 38-year period (1980-2017) as shown in *Figure 2*. The simulations were performed for a 36-hour period, starting at 12:00 UTC each day. The first 12-hour period was neglected as a spin up time (time to stabilize the model) and the remaining 24-hour data were combined to generate a long-term high-resolution reanalysis for the monsoon regions including Arabian Peninsula.

Validation of reanalysis data and observed climate data

Validation of Reanalysis data with observed climate data at monthly basis from 1981 to 2017 for seven locations of different agro climatic zones of Tamil Nadu was done. The ArcGIS distance calculator was used to identify nearby points in our reanalysis data that

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corresponded to the observed data points. The Accuracy of the precipitation, maximum temperature and minimum temperature was assessed by statistical analysis Viz., bias, root mean square error (RMSE), Index of agreement (d) and Refined index of agreement (d_r).

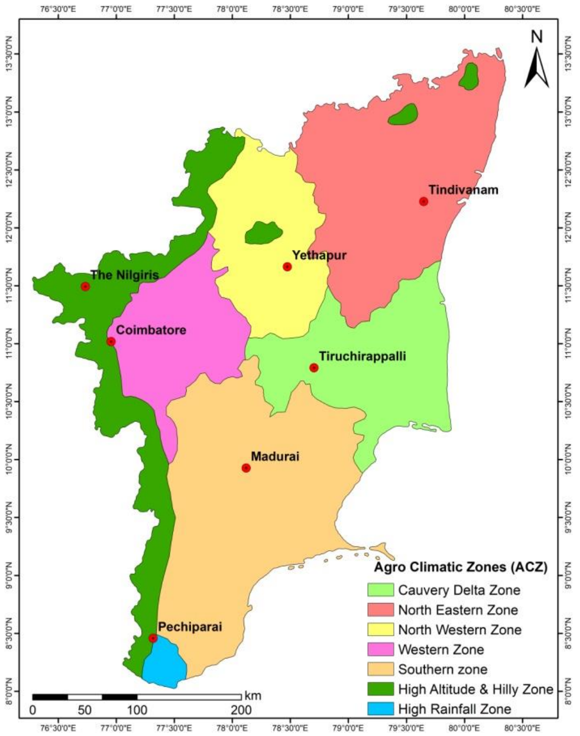

Figure 1. *Study area of Tamil Nadu with seven agro-climatic zones*

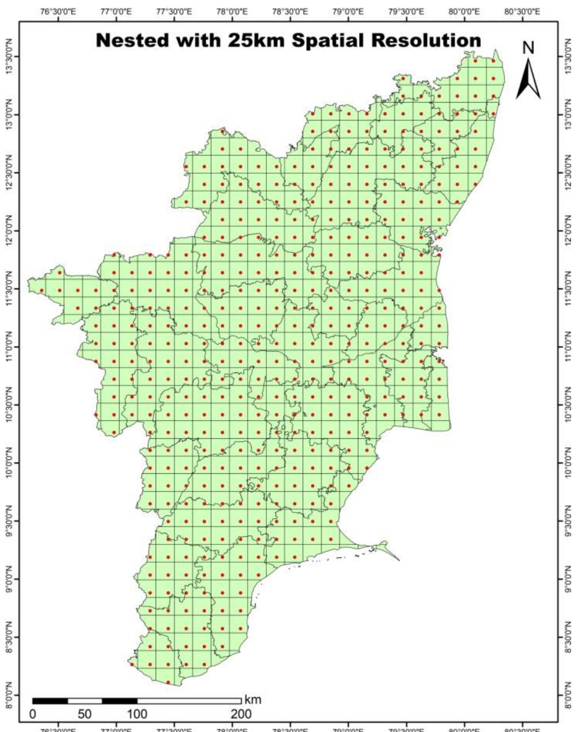

Figure 2. *Study area with nested points over Tamil Nadu*

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Tropical Rainfall Measuring Mission

Tropical Rainfall Measuring Mission satellite data generated jointly by the National Aeronautics and Space Administration of the United States (NASA) and the Aerospace Exploration Agency of Japan (JAXA) is one of the reliable source for meteorologists to collect precipitation estimates at relatively fine spatial and temporal scales. TRMM, one of the spacecraft in the NASA Earth Probe series of research satellites, low Earth orbit at an altitude of approximately 402 and had a inclination of 35 degrees. TRMM products derived from satellites can be extremely helpful in the study of historical natural disasters and in the analysis of variability of precipitation (Duncan et al., 2012).

The TRMM program was initially aimed at monitoring tropical and subtropical precipitation. Since the launch of TRMM on 27 November 1997, the satellite platform has collected various measurements related to precipitation rate and accumulation across the globe from 50 degrees north to 50 degrees south latitude. TRMM product 3B42 with 25 km spatial resolution data (1998 to 2017) for study area downloaded from the website of https://pmm.nasa.gov/data-access/ downloads /trmm.

Validation of satellite derived precipitation data

Precipitation of TRMM 3B42 V6 and Reanalysis data were quantitatively (Weekly) compared on a point-by-point basis. The quantitative accuracy of the precipitation datasets was assessed from 1998 to 2017 using bias (*Eq.1*), root mean square error (*Eq.2*), Index of agreement (*Eq.3*) and Refined index of agreement (*Eq.4*).

Equations for statistical analysis

$$Bias = n^{-1} \sum_{i=1}^{n}(P_i - O_i) \quad \text{(Eq.1)}$$

$$\text{Root Mean Square error } (RMSE) = n^{-1} \left[\sum_{i=1}^{n}\left(P^i - O^i\right)^2\right]^{0.5} \quad \text{(Eq.2)}$$

$$\text{Index of agreement (d)} = 1 - \frac{\sum_{i=1}^{n}\left(P^i - O^i\right)^2}{\sum_{i=1}^{n}\left(|P^i - \bar{O}| + |O^i - \bar{O}|\right)^2} \quad \text{(Eq.3)}$$

Refined index of agreement (d_r):

$$\begin{cases} 1 - \dfrac{\sum_{i=1}^{n}|P_i - O_i|}{c\sum_{i=0}^{n}|O_i - \bar{O}|} \\ \sum_{i=0}^{n}|P_i - O_i| \leq c\sum_{i=0}^{n}|O_i - \bar{O}| \\ \dfrac{\sum_{i=0}^{n}|O_i - \bar{\bar{O}}|}{\sum_{i=0}^{n}|P_i - O_i|} - 1, when \\ \sum_{i=0}^{n}|P_i - O_i| > c\sum_{i=0}^{n}|O_i - \bar{O}| \quad with\ c = 2, \end{cases} \quad \text{(Eq.4)}$$

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where,
$\bar{\bar{O}} = Mean\ observed\ value,\ P_i = Model\ value$
$O_i = Observed\ value, n = Number\ of\ observations$

A value of 1 for the index of agreement (*d*) and refined index of agreement indicates a good agreement between the reanalysis and satellite data. Conversely, a value of 0 indicates poor performance that means reanalysis data doesn't align well with the satellite data. For the bias and root mean square error values lie in between $-\infty$ to ∞ and 0 indicate perfect score between reanalysis and satellite data.

Results and Discussion

Comparison of reanalysis data with observed weather data

Reanalyzed monthly rainfall data was validated with the observed data obtained from the seven agrometeorological observatory of Tamil Nadu Agricultural University representing the seven agro climatic zones of Tamil Nadu (*Table 1*).

Table 1. *Statistical analysis between observed and reanalysis climate data*

ACZ	RMSE			BIAS			d			dr		
	Tmax	Tmin	RF	Tmax	Tmin	RF	Tmax	Tmin	RF	Tmax	Tmin	RF
Western zone	2	1.1	136	-1.6	0.4	88	0.7	0.8	0.6	0.5	0.7	0.5
Southern zone	1.7	1.6	82.6	-1	-1.1	39.9	0.8	0.8	0.7	0.7	0.6	0.5
Hilly and high altitude zone	3.6	2.5	110.5	-1.2	1	-55.1	0.5	0.6	0.5	0.5	0.3	0.5
High rainfall zone	3.3	2.9	229.1	-1.2	-1.1	35.8	0.4	0.4	0.5	0.6	0.4	0.5
Northeastern zone	2.5	1.4	89.2	-0.3	-0.8	17	0.8	0.9	0.8	0.7	0.7	0.6
Cauvery Delta zone	1.6	2.2	85	-1.1	-1	49.2	0.8	0.3	0.7	0.7	0.7	0.4
North weatern zone	2.1	1.2	57.7	-1.4	-0.5	11.2	0.8	0.9	0.8	0.5	0.7	0.6

The highest RMSE (3.6°C) for maximum temperature was noticed in high rainfall zone (HRZ) while Cauvery Delta zone (CDZ) showed the lowest RMSE (1.6°C). However, result showed that the reanalysis data consistently underestimated maximum temperatures across all agro-climatic zones (ACZ), as validated by the negative Bias (BIAS) values ranging from -1.6°C to -0.3°C. Among these, the western zone (WZ) showed the highest negative bias, while the northeastern zone (NEZ) had the lowest. There was a good agreement between the reanalyzed and observed maximum temperature as the index of agreement (d) value was higher than 0.5 in all ACZ except HRZ (0.4).

The RMSE of minimum temperature was more (2.6°C) in HRZ and less (1.1°C) in western zone (WZ). Similar to maximum temperature, the minimum temperature was also underestimated by the reanalysis data in all the ACZ expect WZ and Hilly Zone (HZ) where it was overestimated. The BIAS varied between -1.1°c (HRZ and SZ) and 0.4°C (WZ). The d value for minimum temperature was above 0.5 in all the places of Tamil Nadu expects HRZ (0.4).

Rainfall had the highest RMSE (229 mm) in HRZ and lowest (58 mm) in Northwestern Zone (NWZ). Over all, the RMSE for minimum temperature and rainfall found to be higher in HRZ. Reanalyzed dataset showed higher amount of rainfall for all the ACZ with

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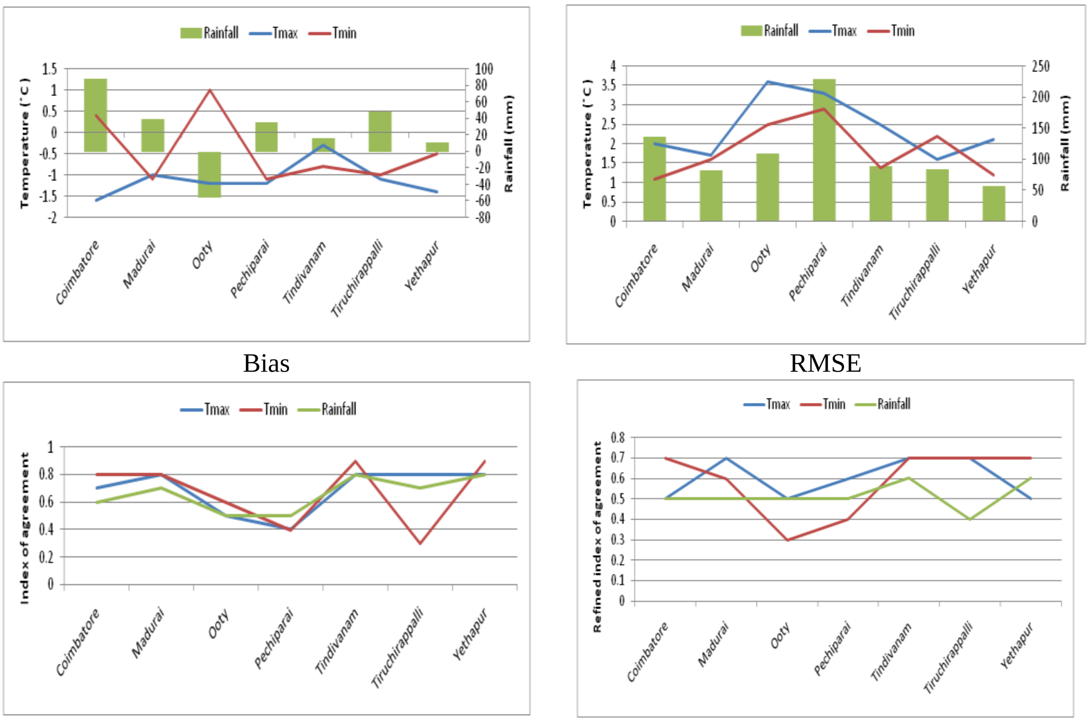
the exception of HZ (-55 mm). The overestimation found to be in the range of 11 mm (NWZ) to 88 mm (WZ). Rainfall data showed good comparison in all the places with the d value greater than 0.5. The larger (more than 0.5) refined index value (d_r) in most of the places indicated a good agreement between the reanalyzes with the observed maximum and minimum temperature as well as rainfall over Tamil Nadu (*Figure 3*). To check the usability of the reanalysis data, it is important to validate the same with the observed climate data. The results indicated that there is less variation between the two data sets in the agro climatic zones of Tamil Nadu except in high rainfall zone and hilly zone which showed high variability.



Bias | RMSE

Index of agreement | Refined index of agreement

Figure 3. *Statistical analysis between observed and reanalysis climate data*

Comparison of satellite derived precipitation (TRMM) with observed data

The validation results showed that TRMM was able to well capture the rainfall (*Figure 4*) over Tamil Nadu and the BIAS was in the acceptable range in most of the places. A key factor contributing to the superior performance of TRMM data, is the availability of Special Sensor Microwave Imager/Sounder (SSMIS) sensor data. This inclusion of SSMIS sensor data enhances the quality of passive microwave information, consequently leading to a substantial increase in the accuracy of precipitation estimates derived from TRMM data (Wang et al., 2018). The Bias value from -15 mm to +15 mm was observed over maximum parts of Tamil Nadu. Southeastern part of Tamil Nadu showed negative bias value between -5 to -20 mm and northeastern part exhibited the BIAS between -5 to 0 mm. Positive bias was observed at western part of Tamil Nadu with different magnitude which varied in the range of 10 to 20 mm. RMSE values were higher (35 to 40 mm) in the areas near coastal line. Inaccurately predicted the rainfall quantity in coastal line was observed by Macharia et al. (2020). When move to the interior regions,

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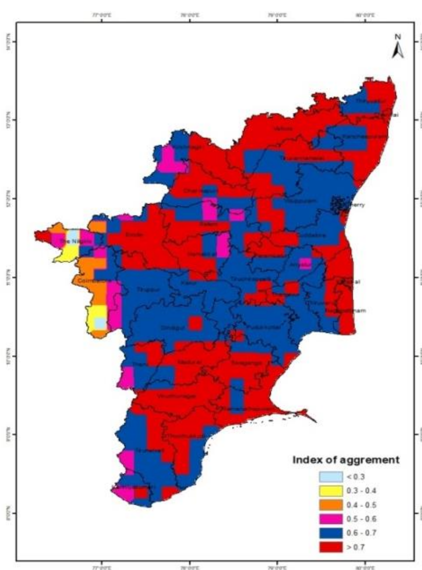
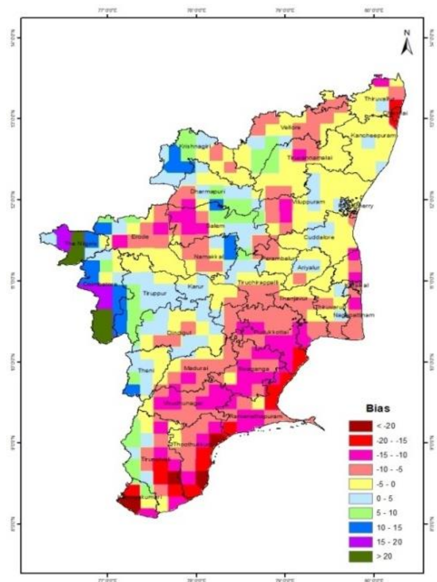
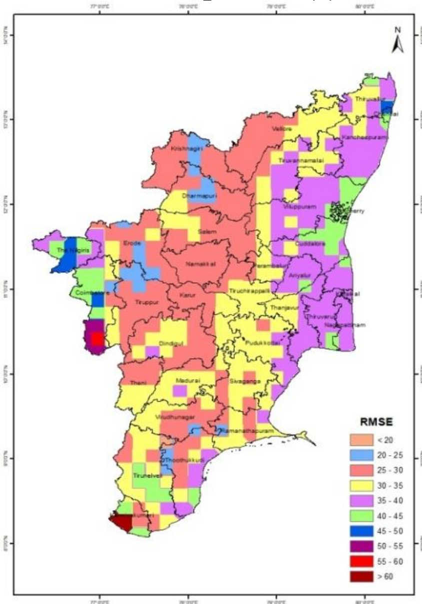
the RMSE got reduced up to 25 mm. In the western parts of Tamil Nadu, 25 to 30 mm of RMSE was observed and northeastern part had the RMSE between 35 and 40 mm. However, according to Shrivastava et al. (2014), the TRMM data captures rainfall distribution qualitatively, but there exist differences in the quantities of predicted rainfall with respect to the ground observations.



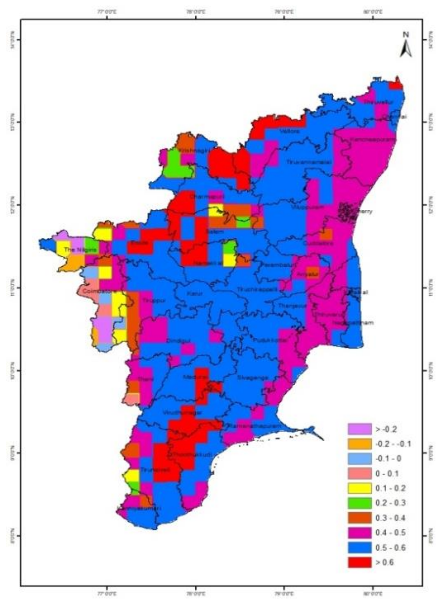
Index of agreement (d)



Bias



Root Mean Square Error (RMSE)



Refined index of aggrement (d_r)

Figure 4. *Comparison of satellite derived precipitation (TRMM) with reanalysis data*

Index of agreement (d) ranged between 0.1 and 0.9 over Tamil Nadu. However, maximum parts (95 % of area) of Tamil Nadu showed d value greater than 0.6. Among the ACZ, western zone recorded less d value (<0.5). The d_r values also followed the same pattern as d value in most parts of Tamil Nadu. The d_r ranged between -0.2 and 0.6 in Tamil Nadu and it was above 0.4 in most parts of Tamil Nadu. There was low agreement

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between the reanalysis and observed rainfall in western part of Tamil Nadu where the satellites cannot detect some low-level clouds due to large cloudage and the complexity of the terrain in high-altitude regions, their retrieval accuracy is affected (Wang et al., 2017). Along the coastal parts of Tamil Nadu, the d_r value fell between 0.4 and 0.5 while the d_r values got increased towards the interior parts of Tamil Nadu. These findings are in agreement with the outcomes of the study conducted by Dorninger et al. (2008), who assessed various precipitation products derived from satellites throughout Ethiopia and Zimbabwe and found that satellite data were more accurate in a generally flat landscape compared to rough terrain.

Conclusion

The study used statistical analysis techniques such as bias, square root mean square, index of agreement, and refined index of agreement to assess and evaluate the climatic parameter. These measures were employed to compare and analyze the agreement between the reanalysis data and observed data, as well as between satellite rainfall and reanalysis rainfall. Regarding validation of reanalysis and observed climatic monthly data of rainfall, maximum and minimum temperature, there is a significant agreement between the climate data with the observed maximum and minimum temperature as well as rainfall over all the zones of Tamil Nadu except High rainfall and Hilly zone. Tropical Rainfall Measuring Mission rainfall values have been found to effectively capture rainfall data. However, it is important to note that the validation of satellite and reanalysis precipitation data still reveals that satellite data can both overestimate and underestimate the amount of rainfall.

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