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Comparison of Various Re-analyses Gridded Data with Observed Data from Meteorological Stations over India

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Abstract

Meteorological data such as precipitation and temperature are important for hydrological modelling. In areas where there is sparse observational data, an alternate means for obtaining information for different impact modelling and monitoring activities is provided by reanalysis products. Evaluating their behaviour is crucial to know their uncertainties. Therefore, we evaluated two reanalyses gridded data products, viz., Coordinated Regional Climate Downscaling Experiment (CORDEX) and National Centers for Environment Predictors and GCM (General Circulation Model) predictor variables (NCEP); two station based gridded data products, viz., Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation (APHRODITE) and India Meteorological Department (IMD) gridded data; one satellite based gridded data product i.e., Tropical Rainfall Measuring Mission (TRMM); and one merged data product, i.e., Global Precipitation Climatology Project (GPCP). These products were compared with IMD observed station data for 1971 to 2010 to evaluate their behaviour in terms of fitness by using statistical parameters such as NSE, CRM and R^2. APHRODITE and TRMM gridded data showed overall good results for precipitation followed by IMD, GPCP, CORDEX and NCEP. APHRODITE also showed good agreement for mean temperature. CORDEX and NCEP gave a promising result for minimum and maximum temperatures with NCEP better than CORDEX.

[*] Conceptualized the work and conference speaker
[†] Prepared the data and the manuscript
[‡] Helped in manuscript preparation
[§] Executed the work
[**] Checked and finalized the manuscript

1 Introduction

Estimating precipitation and temperature accurately on varying space and time scales are important for the weather forecaster and climate scientists, and also for a wide range of decision makers who deals with sectors like water resources and agriculture. However, measuring precipitation over the globe is not easy because of the limitations of surface-based observational networks and the large inherent variations in rainfall fields themselves. With a number of meteorological satellites in orbit and advanced computer processing of digital data, rainfall estimates can be derived at finer spatial and temporal resolutions for larger areas [1]. Satellites may have biases and random errors but they offer exciting opportunity to better understand the characteristics and variability of precipitation throughout the globe [2]. These reanalyses products are also widely used in climate research [3] [4] making it crucial to investigate their accuracy and limitations. Further, the result of comparing satellite data with observed data is relevant to the use of real-time rainfall data for flood warnings and river flow estimates or water management, and for pinpointing areas of likely agricultural impacts [5]. This will add to our understanding of the limitations and advantages of the use of satellites to overcome problems associated with global precipitation measurements [6]. In this study, various datasets were tested with the station observed data from 149 stations of India Meteorological Department (IMD) for 40 years (1971-2010) using various statistical indicators. The main objectives of this study were to extract point time series data from various station based and reanalyses gridded data products and to compare them with the observed point data.

2 Material and Methods

2.1 Data Acquisition

The point station data observed at 149 meteorological stations spatially distributed over entire India were acquired from India Meteorological Department (IMD), Pune. Monthly mean, minimum, maximum temperatures and rainfall for the period of 1971 to 2010 were used in this study. Six gridded datasets – two reanalyses gridded data products, viz., Coordinated Regional Climate Downscaling Experiment (CORDEX) and National Centers for Environment Predictors and GCM (General Circulation Model) predictor variables (NCEP); two station based gridded data products, viz., Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation (APHRODITE) and IMD gridded data; one satellite based gridded data product, i.e., Tropical Rainfall Measuring Mission (TRMM); and a merged data product, i.e., Global Precipitation Climatology Project (GPCP) were collected for the study. Table 1 and Table 2 show the characteristics of the gridded precipitation and temperature data, respectively.

Data	Resolution	Frequency	Period
IMD	0.25°×0.25°	Daily	1901-2010
APHRODITE	0.25°×0.25°	Daily	1961-2007
TRMM (3B42 V6)	0.25°×0.25°	Daily	1998-2013
CORDEX	0.5°×0.5°	Daily	1970-2005
GPCP	1°×1°	Daily	1996-2015
NCEP	2.5°×3.75°	Daily	1979-2016

Table 1: Characteristics of gridded precipitation datasets used in the study

Data	Resolution	Frequency	Period
Mean temperature			
APHRODITE	0.25°×0.25°	Daily	1951-2007
Minimum temperature			
NCEP	2.5°×3.75°	Daily	1979-2016
CORDEX	1°×1°	Daily	1970-2005
Maximum temperature			
NCEP	2.5°×3.75°	Daily	1979-2016
CORDEX	1°×1°	Daily	1970-2005

Table 2: Characteristics of gridded temperature datasets used in the study

2.2 Methodology

The 'make netcdf table view' of the 'multidimension tools' under the 'Arc Toolbox' was used to first extract the data for the point stations from the raw data. The extracted .dbf file of single year from a single source was consolidated into contiguous year for the same source with complete yearly sequence (daily data for 1971-2010) in one spreadsheet file. The daily point time series data were further converted into monthly data. Certain statistical parameters such as Nash–Sutcliffe efficiency (NSE), coefficient of residual mass (CRM), and coefficient of determination (R^2) were used for comparison of various gridded data with observed station data.

The Nash–Sutcliffe efficiency is used to assess the predictive power of hydrological models. NSE can range from −∞ to 1. NSE = 1 corresponds to a perfect match of estimated value to the observed data. NSE = 0 indicates that the model predictions are as accurate as the mean of the observed data, whereas NSE < 0 occurs when the observed mean is a better predictor than the model. Essentially, the closer the model efficiency is to 1, the more accurate the model is. It is defined as:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}\left(X_{obs,i} - X_{model,i}\right)^2}{\sum_{i=1}^{N}\left(X_{obs,i} - X_{obs,avg}\right)^2}$$

Where, $X_{obs,i}$= observed value at i^{th} observation; $X_{model,i}$= model value at i^{th} observation; N = total number of observations; $X_{obs,avg}$= Average observed value.

CRM indicates overall under- or over-estimation. For perfect estimation, the value of CRM would be zero. A positive value indicates under-estimation, whereas, a negative CRM indicates over-estimation the observed values. CRM is estimated as:

$$\mathrm{CRM} = \frac{\sum_{i=1}^{N} X_{obs,i} - \sum_{i=1}^{N} X_{model,i}}{\sum_{i=1}^{N} X_{obs,i}}$$

The coefficient of determination is a measure of the proportion of variance of a predicted outcome. With a value of 0 to 1, R^2 is calculated as the square of the correlation coefficient (R) between the sample and predicted data. A value of 1 means every point on the regression line fits the data. R^2 is estimated as:

$$R^2 = \left[\frac{N\left(\sum_{i=1}^{N} X_{obs,i}X_{model,i}\right) - \left(\sum_{i=1}^{N} X_{obs,i}\right)\left(\sum_{i=1}^{N} X_{model,i}\right)}{\sqrt{\left\{N\sum_{i=1}^{N} X^2{}_{obs,i} - \left(\sum_{i=1}^{N} X_{obs,i}\right)^2\right\}\left\{N\sum_{i=1}^{N} X^2{}_{model,i} - \left(\sum_{i=1}^{N} X_{model,i}\right)^2\right\}}}\right]^2$$

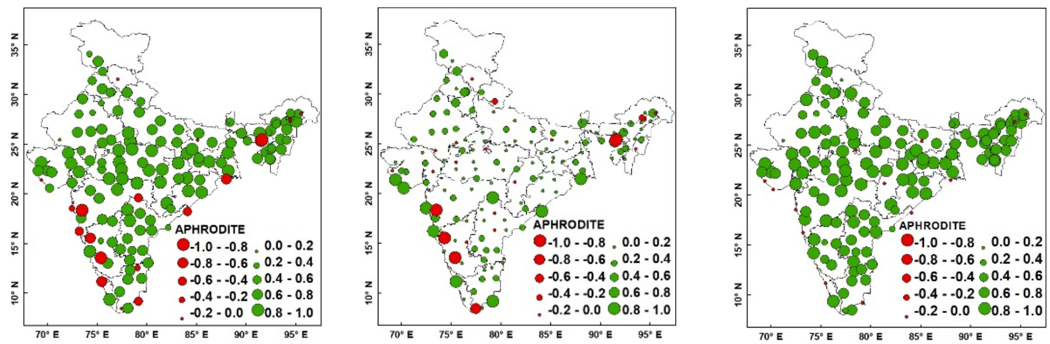
3 Results and Discussion

3.1 Precipitation

The results of the performance indicators of precipitation for APHRODITE (Figure 1) showed good correlation with observed data. About 98 stations showed NSE value greater than 0.5 from which 31 stations showed NSE value greater than 0.7 indicating high accuracy. Again, 128 stations showed CRM values in the range of -0.5–0.5 and 73 stations showed CRM values between -0.2–0.2 indicating a nearly perfect estimation. And 122 stations showed R^2 value greater than 0.5 agreeing with observed data in terms of R^2 and out of which 58 stations showed R^2 value greater than 0.8 indicating great correlation.

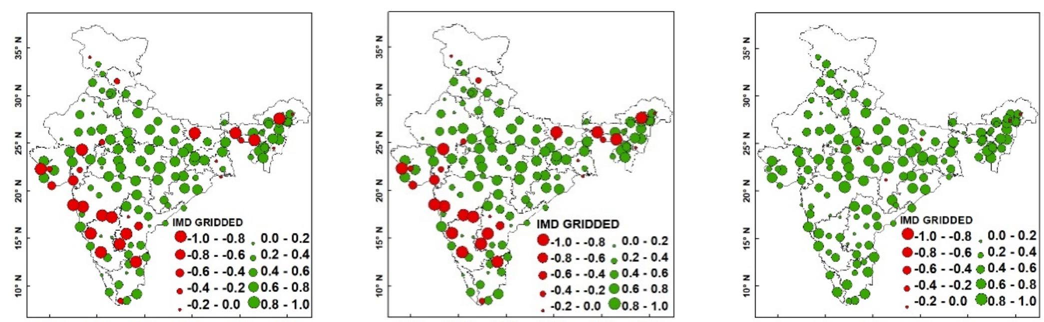
The performance indicators with IMD gridded precipitation data (Figure 2) showed that it performed well in terms of all the three indicators. About 69 stations have NSE values greater than 0.5 of which 49 stations showed NSE values greater than 0.7 indicating high accuracy. Again, 138 stations showed CRM values in the range of -0.5–0.5 and 101 stations showed CRM values between -0.2–0.2 indicating a nearly perfect estimation. In addition, 85 stations showed R^2 values greater than 0.5, although only three stations have values greater than 0.8 indicating great correlation.

The pictorial representation of the performance indicators for the precipitation data of TRMM (Figure 3) also showed good performance in all three statistical quantities. About 91 stations showed NSE values greater than 0.5, out of which 88 stations showed NSE values greater than 0.7, indicating high accuracy. Similarly, 106 stations showed CRM values in the range of -0.5–0.5 out of which 73 stations showed CRM values between -0.2–0.2 giving a nearly perfect estimation. And about 107 stations showed R^2 values greater than 0.5 of which 68 stations have values greater than 0.8 indicating a great correlation.



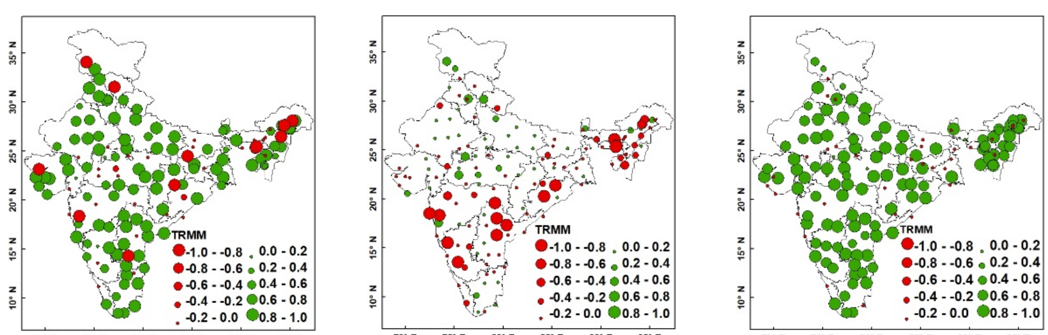
(a) NSE (b) CRM (c) R^2

Figure 1: Performance of APHRODITE precipitation data



(a) NSE (b) CRM (c) R^2

Figure 2: Performance of IMD GRIDDED precipitation data

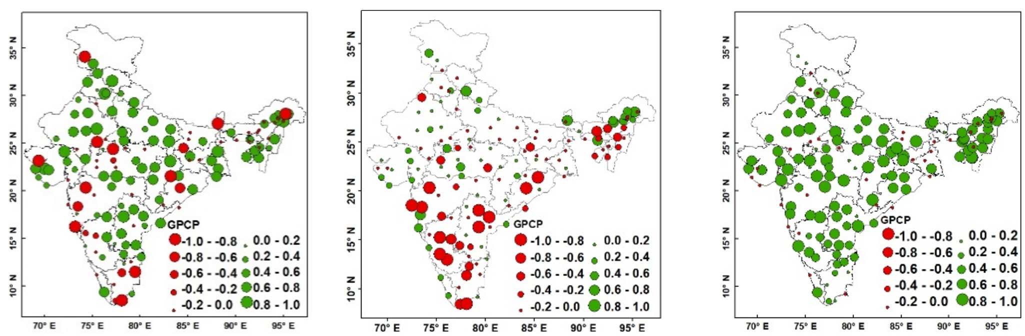


(a) NSE (b) CRM (c) R^2

Figure 3: Performance of TRMM precipitation data

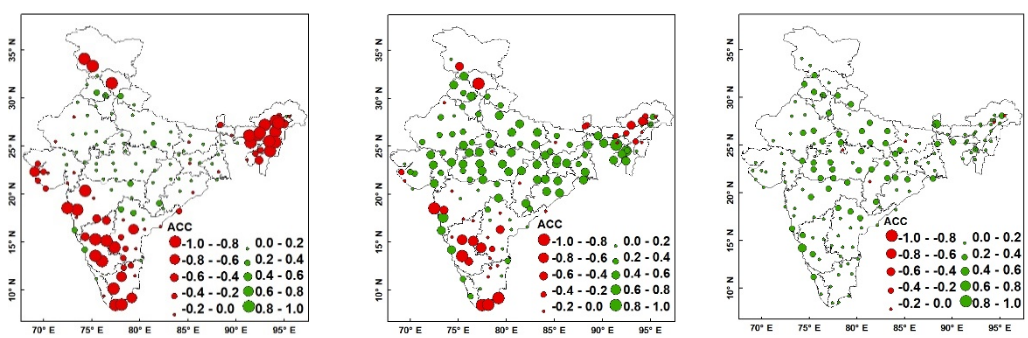
The performance indicators for the precipitation data of GPCP is shown in Figure 4. About 65 stations showed NSE values greater than 0.5, out of which 34 stations showed NSE values greater than 0.7 indicating high accuracy. Similarly, 91 stations showed CRM values in the range of -0.5–0.5, of which 57 stations showed a nearly perfect estimation (CRM values between -0.2–0.2). And about 91 stations showed R^2 value above 0.5, out of which only 28 stations had values greater than 0.8, indicating a good correlation.

All the six models performed weakly in terms of R^2 while they showed a fair estimation in terms of NSE and CRM. About 72, 68, 75, 68, 76, and 69 stations showed positive NSE values less than 0.5 for ACC, CCS, CNR, GFD, MPI and NOR, respectively, while the rest showed negative NSE values indicating very less accuracy. Almost all R^2 values were found to be lesser than 0.5 indicating very weak correlation with the observed data. However, 111, 117, 113, 117, 111, and 116 stations were found to attain CRM values in the range of -0.5–0.5 for ACC, CCS, CNR, GFD, MPI and NOR, respectively, out of which 36, 37, 34, 30, 35, and 34 stations showed CRM values very close to zero (-0.2–0.2), respectively, indicating that CORDEX models gave a close to perfect estimation for few stations. Figure 5 shows the performance indicators for ACC precipitation data.



(a) NSE (b) CRM (c) R^2

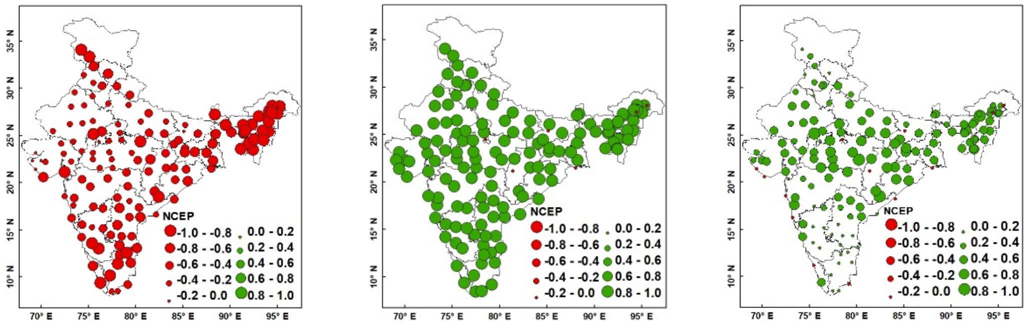
Figure 4: Performance of GPCP precipitation data



(a) NSE (b) CRM (c) R^2

Figure 5: Performance of ACC precipitation data

The performance indicators of NCEP precipitation data (Figure 6) showed that it does not agree well with the observed data as per any of the indicators. All stations showed NSE value less than zero (Figure 6a) indicating the observed mean as a better predictor than the model. Again, 143 stations showed CRM values higher than 0.5 indicating a tendency to underestimate precipitation. And only 56 stations were found to have R^2 values greater than 0.5, out of which only 4 stations have values above 0.8 indicating a weak correlation with the observed data.



(a) NSE (b) CRM (c) R^2

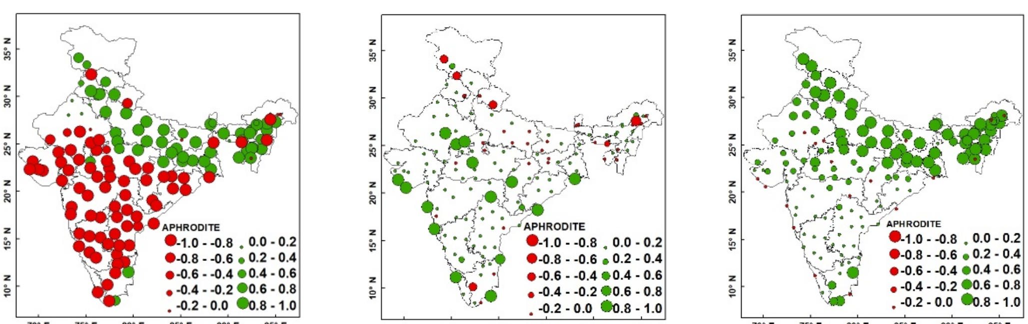
Figure 6: Performance of NCEP precipitation data

3.2 Temperature

For mean temperature, the APHRODITE data showed only 50 stations with NSE value greater than 0.5 indicating fair accuracy. Again, 128 stations showed CRM value in the range of -0.5–0.5 indicating a good estimation. And 51 stations obtained R^2 value above 0.8 (Figure 7) indicating a great correlation. It performed particularly well in the Ganga and Brahmaputra basins of North and North-East India, but performed poorly in the peninsular (South) India.

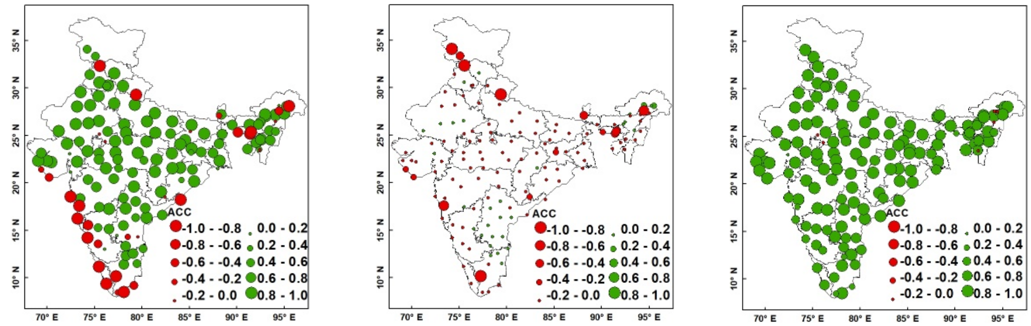
The six models of CORDEX and NCEP minimum temperature data showed 103, 103, 100, 103, 103, 101, and 84 stations with NSE values greater than 0.5 for ACC, CCS, CNR, GFD, MPI, NOR, and NCEP, respectively, indicating that both sources have high accuracy. About 135, 135, 134, 134, 135, 133, and 129 stations were found with CRM values in the range of -0.5–0.5 for ACC, CCS, CNR, GFD, MPI, NOR, and NCEP, respectively. And 99, 90, 84, 99, 91, 81, and 117 stations showed R^2 above 0.8 for ACC, CCS, CNR, GFD, MPI, NOR, and NCEP, respectively, indicating both sources have a great correlation with the observed data. Figure 8 and Figure 9 showed the performance indicators of ACC and NCEP minimum temperature data.

The six models of CORDEX and NCEP maximum temperature data showed 9, 8, 9, 9, 10, 9, and 66 stations with NSE values greater than 0.5 for ACC, CCS, CNR, GFD, MPI, NOR, and NCEP, respectively, indicating very poor performance of CORDEX and average performance of NCEP. However, 141 and 139 stations showed CRM value between -0.5 and 0.5 for all CORDEX models and NCEP, respectively, indicating no overall over- or under-estimation trends. That means, for CORDEX models, the inaccuracy was equally distributed in higher and lower estimates compared to observed maximum temperature. Accordingly, R^2 value above 0.8 was found only in 1 station for all



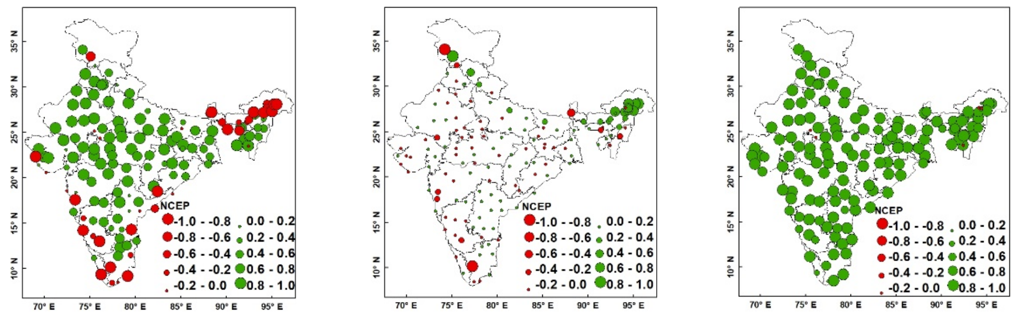
(a) NSE (b) CRM (c) R^2

Figure 7: Performance of APHRODITE mean temperature data



(a) NSE (b) CRM (c) R²

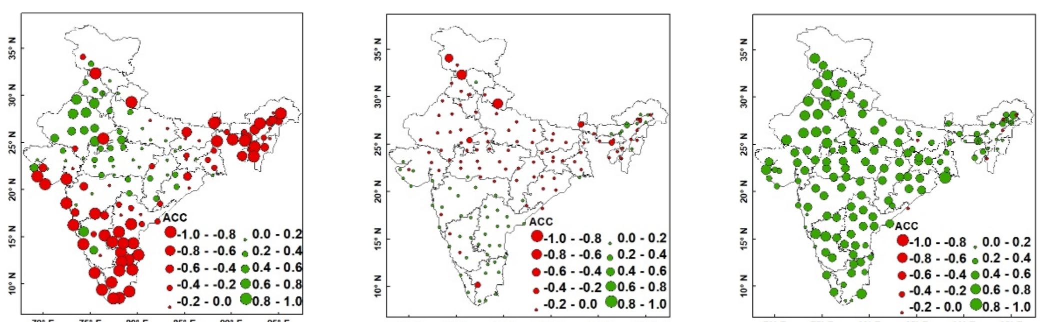
Figure 8: Performance of ACC minimum temperature data



(a) NSE (b) CRM (c) R²

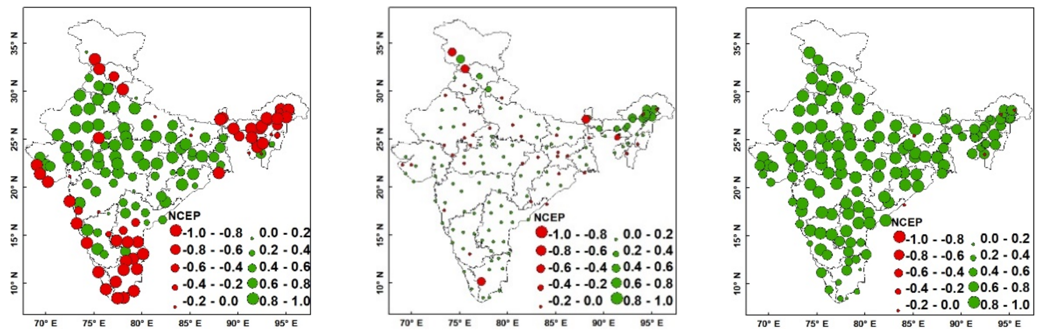
Figure 9: Performance of NCEP minimum temperature data

CORDEX models against 87 stations for NCEP indicating that NCEP has a better correlation with the observed data than CORDEX. Figure 10 and Figure 11 showed the performance indicators of ACC and NCEP maximum temperature data.



(a) NSE (b) CRM (c) R²

Figure 10: Performance of ACC maximum temperature data



(a) NSE (b) CRM (c) R^2

Figure 11: Performance of NCEP maximum temperature data

4 Conclusions

The APHRODITE dataset was found to be highly satisfactory for monthly precipitation but its mean temperature was found to have less correlation with observed data. IMD gridded, TRMM and GPCP precipitation data also showed satisfactory results. The NCEP data, however, showed very poor results for precipitation but gave fair results for maximum and minimum temperatures. The CORDEX products showed poor correlation for precipitation and maximum temperature but for minimum temperature data showed fair correlation. The ranking of the various products in case of precipitation data was in the order APHRODITE > TRMM > IMD > GPCP > CORDEX > NCEP. For maximum and minimum temperature data, the order was found to be NCEP > CORDEX. In case of mean temperature, only APHRODITE data was evaluated, and it showed fairly satisfactory result. Overall, APHRODITE data was found to have the most accurate estimation.

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