International Journal of Engineering & Technology, 7 (3.29) (2018) 702-708

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

A Study of South-West Monsoon Over Indian Sub-Continent using Satellite Derived Precipitation Estimates

P Giri Prasad[1*], S. Varadarajan[2]

[1,2] Department of E.C.E., S.V.University College of Engineering, Tirupati, India.
**Corresponding Author E-mail : giri.svuce@gmail.com*

Abstract

In the present study, an investigation has been made over Indian Sub-Continent during South-West Monsoon for the years 2015-2016. The results show that no precipitation products are close to the gridded actual rainfall. But good correlation coefficients (CC) exist between the satellites derived precipitation product and actual rainfall. In this paper, multisatellite high-resolution precipitation products,namely Climate Prediction Center Morphing (CMORPH) version 1.0, TRMM Multisatellite Precipitation Analysis (TMPA)-3B42 V7 product are compared with India Meteorological Department (IMD) gridded rainguage data.
From the results, it is observed that south west monsoon during 2016 produces more rainfall compared to monsoon season of 2015. Five different regions with different climate zones are selected shows the variability of climate over Indian Sub-Continent. For the selected regions, monthly average rainfall(in mm) ,Correlation Coefficient(CC) and Root Mean Square Error (RMSE) are evaluated for satellite derived precipitation products and IMD gridded rain guage data.

Keywords:

1. Introduction

India, being an agricultural country, mainly depends on the rainfall during south west monsoon which has great importance (Prakash et al. 2014) receives 60%–80% of annual rainfall. India, due to its huge area, maintenance of network of manual meteorological observation is very difficult. Conventionally rainfall can be measured with the help of using rain gauges and ground radars. Rain gauges provide point measurements,so these measurements do not provide variation in spatial domain.Since rain gauges are not uniformly distributed, maintenance of ground radars becomes highly expensive for their continuous operation.Then Meteorologists have shown interest to utilize the satellite data forestimation of rainfalls across the world (e.g., Haile et al. 2010; Joyce et al. 2004).Some of few algorithms were developed for Indianregions (e.g., Mishra et al. 2009, Prakash et al. 2010) to estimate rainfall utilizing data from Geo-Synchronous and Polar orbiting satellites.Many algorithms have been developed by utilizing the various sensors has its own advantages and limitations.
Geostationary satellites offer continuous high temporal resolution (nearly 30-60 min) satellite data which are available from very high-resolution radiometer (VHRR) measurements.Generally, these satellites carriesvisible (VIS; 0.4–0.7 µm), watervapor (WV; 6.2µm), and thermal infrared (TIR;10.8 µm) sensors.
TIR measurements provide information of Cloud top brightness temperature. Therefore for estimation of rainfalls TIR measurements are widely used. By using simple cloud indexing technique,Arkin .et al. (1989) developed an algorithm for precipitation estimation over Indian region utilizing IR window channel observation of INSAT-1B.The rainfall obtained from TIR data are indirectly related to surface rainfall because these measurements cannot penetrate through hydrometeors.In contrary to TIR measurements, microwave measurements can penetrate through clouds provides direct relation with surface rainfall. But these measurements suffer with poor temporal resolution nearly twice a day.Over the few decades, hybrid algorithms were developed by merging microwave observations from polar-orbiting satellites and TIR-brightness temperature(TBs) from the geostationary satellite to estimate rainfall (e.g.,Gairola et al. (1992) and Todd et al. (1995)).
ANN approach is theefficient way of determining an empirical, nonlinear relationship between a number of inputs and one or more outputs. Aires et al. (2001) developed an ANN approach to retrieve information about surface temperature and watervapor from the satellite data. Now a days, the efficient way have been developed for estimation of rainfall using ANN techniques(e.g., Hsu et al.(1997), Tsintikidis et al. (1997), and Bellerby et al.(2000)).

2. Data

2.1 Climate Prediction Center Morphing Data (CMORPH)

To estimate rainfall, CMORPH uses motion based techniques. By observing the motion vectors continuously obtained from geostationary satellite IR images with conjugation of microwave (MW) measurements are used for rainfall measurements. In the presence of MW measurements,the features of rainfall such as shape and intensity are calculated using time-weighted linear interpolation method.In the absence of MW measurements, CMORPH estimates rainfall from available IR measurements.

Copyright © 2018 Authors. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Thus, CMORPH uses hybrid algorithms which use both MW and IR measurements. At Present,CMORPH version 1.0 was released which is the reprocessed version of earlier data. For the present study, this version of rainfall data is used.

2.2 TMPA-3B42v7

By utilizing the strengths of geostationary IR data and low-earth orbiting MW observations along with gauge-adjusted rainfall, TMPA–3B42 precipitation productis generated. In this algorithm, available passive MW and IR estimates are combined by calibrating IR measurements(Huffman et al. 2007, 2010).With the help of MW estimates, the rainfall is estimated for available grids and for remaining grids are estimated using IR measurements. By using the inverse variance weighting method, the rain gauge data which are available over land are combined with this multi-satellite product at a monthly scale and rescaled to a three-hourly scale. Presently, the TMPA 3B42v7 data is released by making major corrections in TMPA 3B42v6.Prakash, Mahesh, and Gairola (2013) finds the differences in error from V7 to V6 product at a monthly scale over the different regions of land and oceans.

2.3 IMD Gridded Rain Guage Data:

For the evaluation of three SRE's over India,data developed by the IMD (Rajeevan and Bhate 2009) are used.From the various rain gauges present around India, observations are taken into account for the establishment of this gridded rainfall data set .By using a standard interpolation method,the data from available AWS stations are interpolated into a regular grid of 0.25°latitude/longitude. Since the AWS stations are not placed uniformly, this method is considered to be more equivalent for the ground truth data.The temporal and spatial resolution of the rainfall products are listed in Table 1

Table 1: Temporal and spatial resolution of the rainfall products

Rainfall Product	spatial resolution	Temporal resolution
CMORPH	0.25°X 0.25°	Three hourly
TMPA 3B42v7	0.25°X 0.25°	Three hourly
IMD gridded guage	0.25°X 0.25°	Daily

3. Methodology:

Based on Koppen–Geiger system, India is divided into seven different dominant climate regions which represent the highly variableclimate.Fiveregions are selected asshown in figure 1 represents the nature of sub-continent climate. Statistical parameters such as Root Mean Square Error (RMSE) and Correlation Coefficients (CC) are used to validate the satellite estimated rainfall data (TRMM 3B42v7 and CMORPH) with observed gridded rainfall data

Root Mean Square Error, $RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(X_i - O_i)^2}$

and Correlation Coefficients$CC = \frac{\sum_{i=1}^{M}(X_i-\bar{X}_i)(O_i-\bar{O}_i)}{\sqrt{\sum_{i=1}^{M}(X_i-\bar{X}_i)^2\sum_{i=1}^{N}(O_i-\bar{O}_i)^2}}$

Where M is the total number of samples, i= 1, 2, … M and X is the satellite rainfall estimation and O is the actual observation at the grid.

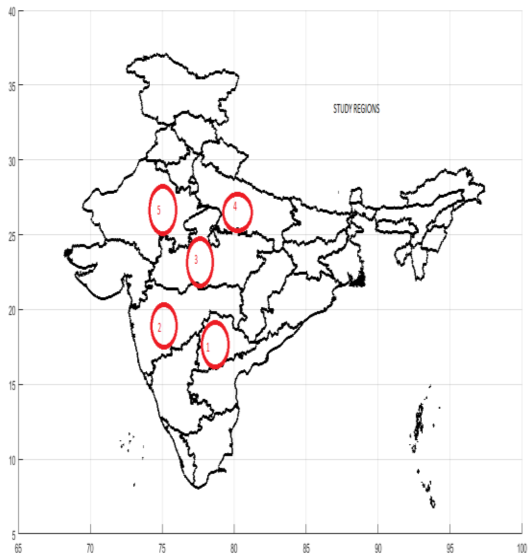


Figure 1: Regions considered in the study; I[78-800E,16-18oN], II[74-760E,18-20oN], III[76-780E,22-24oN], IV[79-810E,26-28oN], V[72-740E,26-28oN]

For the validation purpose of various satellite derived precipitation estimates such as TMPA 3B42V7, CMORPH, IMD gridded data (Pai et al. 2014) is used for the present study.

4. Results and Discussions:

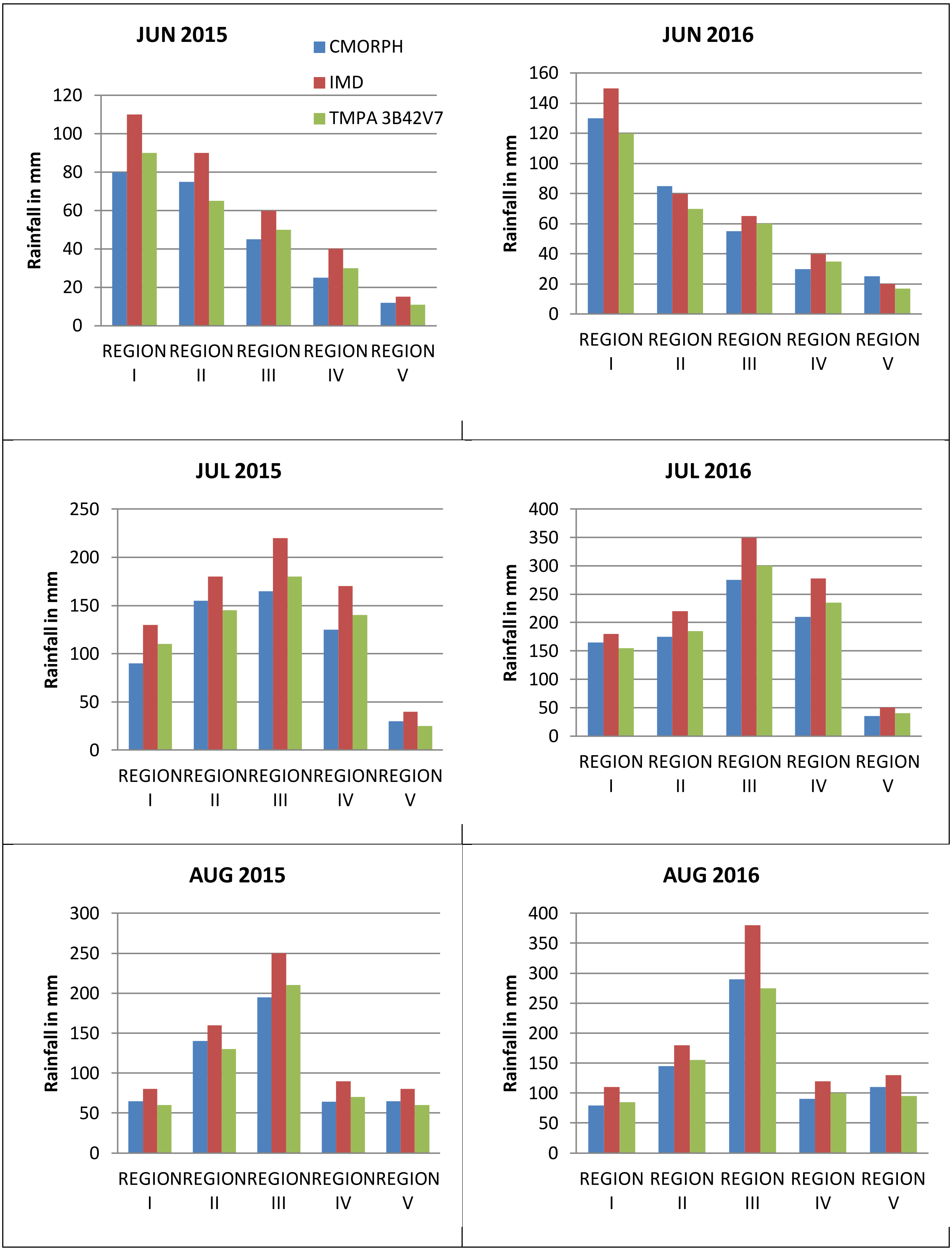
4.1. Monthly Rainfall Over the Selected Regions:

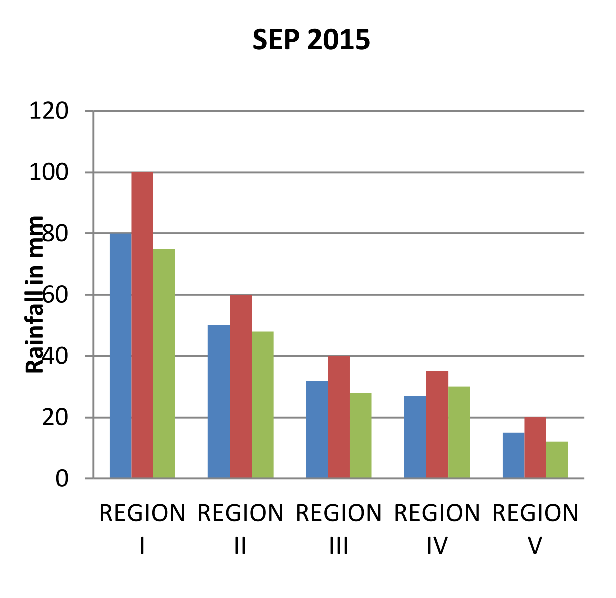
It is seen from figure 2(a-b) that in the month of June, the average rainfall is less for all the selected regions III, IV, V and more for region I and II which shows the onset of monsoon provides more rainfall for some parts in Maharastra and Telangana and less rainfall for Madhya Pradesh, Uttar Pradesh and East Rajasthan.
During the months of July and August, the south west(SW) produces more rainfall at regions of III,IV,V. During the month of September, all the selected region receives less rainfall except at Region I. From the results, it is clearly observed that region III(some part in Madhya Pradesh) receives more rainfall while region V (some part in Rajasthan) receives less rainfall compared to other region. It is observed that region V is located in arid desert hot climate zone hence receives less amount of rainfall. By observing the results, we can conclude 2015 is a deficit monsoon year while 2016 is normal monsoon year.

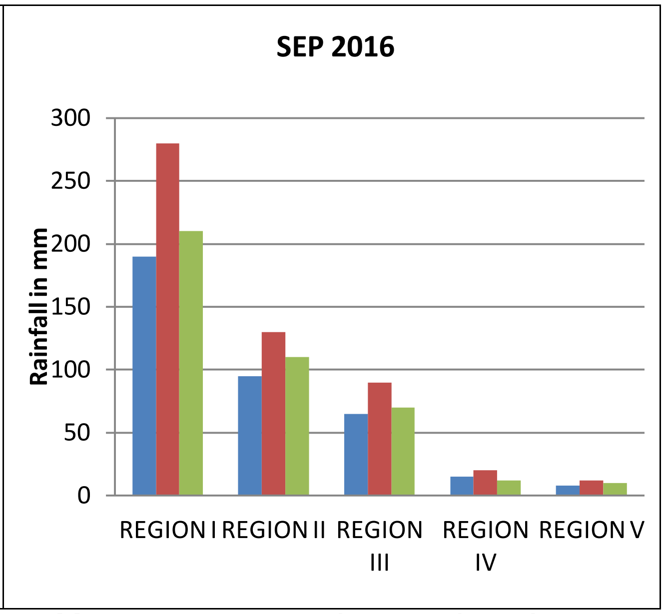
4.2. Correlation Coefficients for Daily Rainfall:

IMD Gridded Rainfall vs CMORPH: The correlation coefficient between IMD Gridded Rainfall and CMORPH rainfall has been presented in Fig.3(a). From the results, it have been observed that good correlation exist during normal monsoon year 2016 compared to deficit monsoon year 2015 for all the regions except for region V.

IMD Gridded Rainfall vsTMPA 3B42V7: The correlation coefficient between IMD Gridded Rainfall and TMPA 3B42V7 has been presented in Fig.3(b). From the results, it have been observed that good correlation exist during deficit monsoon year 2015 compared to normalmonsoon year 2016 for all the regions except for region V. TMPA 3B42V7 has better correlation with IMD compared to CMORPH because it is a rain guage adjusted rainfall product.


JUN 2015
CMORPH
IMD
TMPA 3B42V7
Rainfall in mm
REGION I
REGION II
REGION III
REGION IV
REGION V
JUN 2016
Rainfall in mm
REGION I
REGION II
REGION III
REGION IV
REGION V
JUL 2015
Rainfall in mm
REGION I
REGION II
REGION III
REGION IV
REGION V
JUL 2016
Rainfall in mm
REGION I
REGION II
REGION III
REGION IV
REGION V
AUG 2015
Rainfall in mm
REGION I
REGION II
REGION III
REGION IV
REGION V
AUG 2016
Rainfall in mm
REGION I
REGION II
REGION III
REGION IV
REGION V





TMPA 3B42v7 vs CMORPH: The correlation coefficient between TMPA 3B42v7and CMORPH rainfall has been presented in Fig.3(c).Since both are satellite derived precipitation estimates Good correlation exists between them for all selected regions.

4.3. Root Mean Square Error(RMSE) for Daily Rainfall

The Root Mean Square Errors (RMSE) between rainfall from satellite data and actual IMD daily rainfall was more in normal monsoon year 2016 compared to deficient monsoon year 2015. For the selected regions, RMSE is high for region III since it receives
large amount of rainfall during monsoon season compared to other regions. Region V receives less amount of rainfall hence it has less RMSE value. Comparisons of the daily rainfall (in mm) of the satellite derived precipitation products and IMD gridded rainfall data are shown in fig.4(a-c).

5. Conclusions

For a deficit monsoon year 2015, RMSE between satellite estimates and actual daily rainfall was less compared to normal monsoon year 2016. Both the satellite derived precipitation products underestimates the rainfall during normal and deficit monsoon years but good correlation exists throughout the monsoon season.
Correlation between TMPA 3B42v7 and CMORPH were better for deficit monsoon year 2015 compared to normal monsoon year 2016.

Acknowledgments

We are thankful to "Atmospheric Remote Sensing and Advanced Signal processing", Centre of Excellence,Department of ECE, SVU College of Engineering, S VUniversity, Tirupati, Andhra Pradesh, India, for providing necessary resources and financial support to carry out the present work.

References

[1] SatyaPrakash,V. Sathiyamoorthy, C. Mahesh, and R. M. Gairola, 2014: An evaluation of high-resolution multisatellite rainfall products over the Indian monsoon region. Int. J. Remote Sens., 35, 3018–3035, doi:10.1080/01431161.2014.894661.

[2] Joyce, R., J. E. Janowiak, P. A. Arkin, and P. Xie, 2004: CMORPH:A method that produces global precipitation estimates frompassive microwave and infrared data at high spatial and temporalresolution. J. Hydrometeor., 5, 487–503, doi:10.1175/1525-7541(2004)005,0487:CAMTPG.2.0.CO;2.

[3] Prakash, S., C. Mahesh, R. M. Gairola, and P. K. Pal, 2010: Estimationof Indian summer monsoon rainfall using Kalpana-1VHRR data and its validation using rain gauge andGPCP data. Meteor. Atmos. Phys., 110, 45–57, doi:10.1007/s00703-010-0106-8.

[4] Mishra, A., R. M. Gairola, A. K. Varma, and V. K. Agarwal, 2009:Study of intense rainfall events over India using Kalpana-IRand TRMM precipitation radar observations. Int. J. Curr. Sci.,97, 689–695.

[5] Gairola, R.M., Krishnamurti, T.N., 1992. Rain rates based on SSM/I, OLR and rain gauge data sets. Meteorol. Atmos. Phys. 50, 165–174.

[6] Todd, M.C., Barrett, E.C., Beaumont, M.J., Green, J., 1995. Satellite identification of rain days over the upper Nile river basin using an optimum infrared rain/no rain threshold temperature model. J. Appl. Meteorol. 34, 2600–2611.

[7] Arkin, P. A., Krishna Rao, A. V. R. and Kelkar, R. R.,1989,Large scale precipitation and outgoing longwave radiation from INSAT-1B during the 1986 South West Monsoon season, J. Climate, 2, 619–128.

[8] Aires, F., C. Prigent, W. B. Rossow, and M. Rothstein, 2001: A newneural network approach including first guess for retrieval ofatmospheric water vapour, cloud liquid water path, surface temperaturesandemissivities over land from satellite microwaveobservations. J. Geophys. Res., 106 (D14), 14 887–14 907.

[9] Hsu, K., X. Gao, S. Sorooshian, and H. V. Gupta, 1997: Precipitation estimation from remotely sensed information using artificial neuralnetworks. J. Appl. Meteor., 36, 1176–1190.

[10] Tsintikidis, D., J. L. Haferman, N. Anagnostou, W. F. Krajewski, andT. F. Smith, 1997: A neural network approach to estimating rainfallfromspaceborne microwave data. IEEE Trans. Geosci. RemoteSens., 35, 1079–1092.

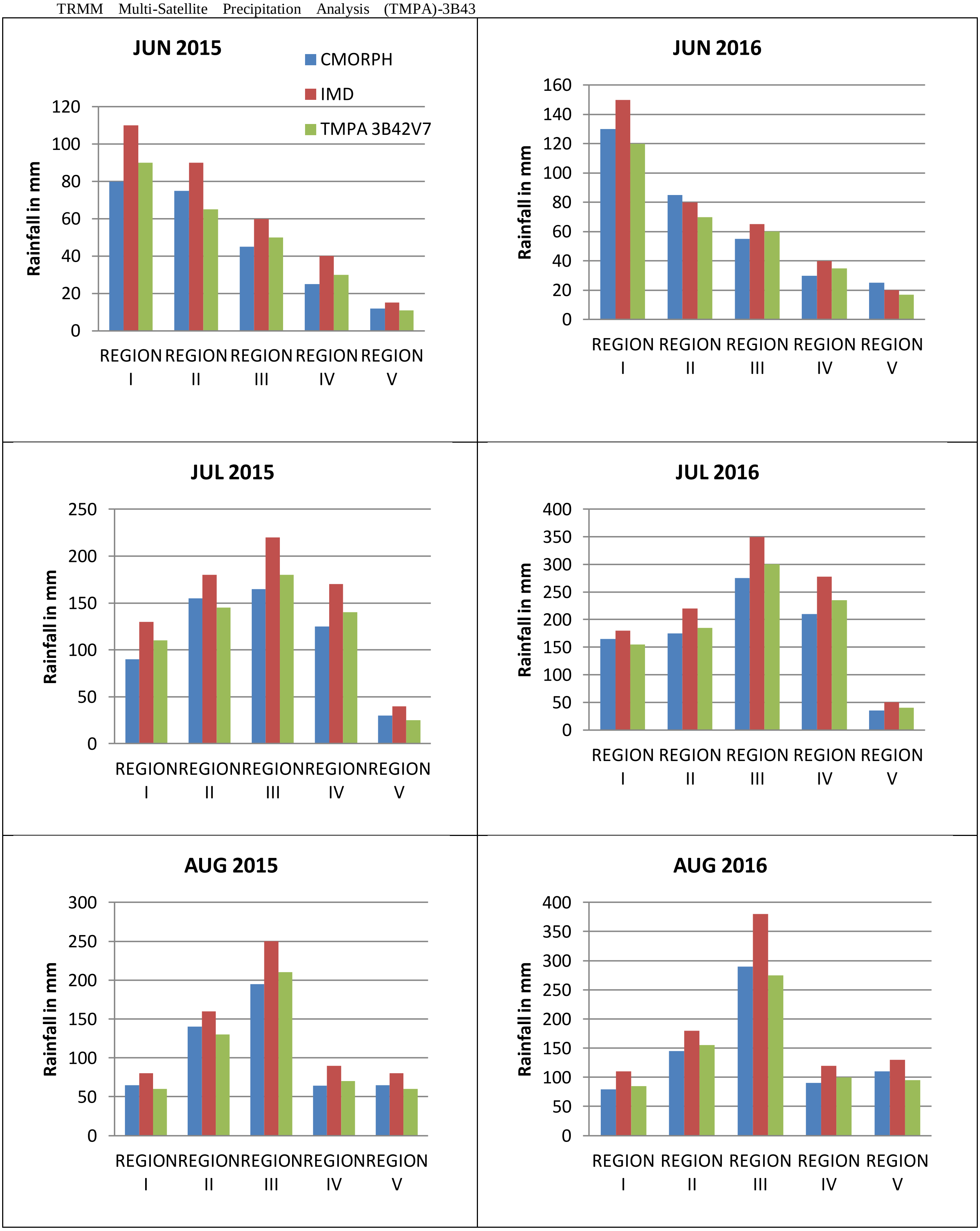
[11] Bellerby, T., M. Todd, D. Kniveton, and C. Kidd, 2000: Rainfall estimation from a combination of TRMM precipitation radar andGOES multispectral satellite imagery through the use of an artificialneural network. J. Appl. Meteor., 39, 2115–2128.

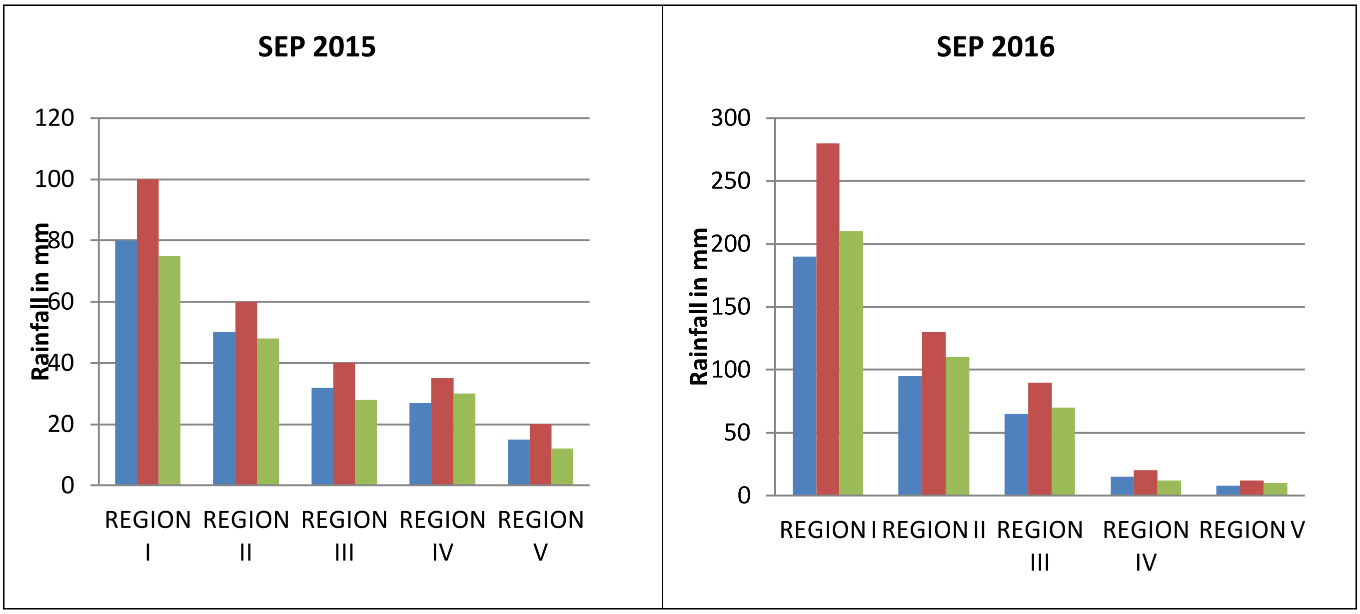
[12] Pai, D. S., et al. (2014). Development of a very high spatial resolution(0.250 9 0.250) Long period (1901–2010) daily gridded rainfalldata set over the Indian region. Mausam, 65(1), 1–18.

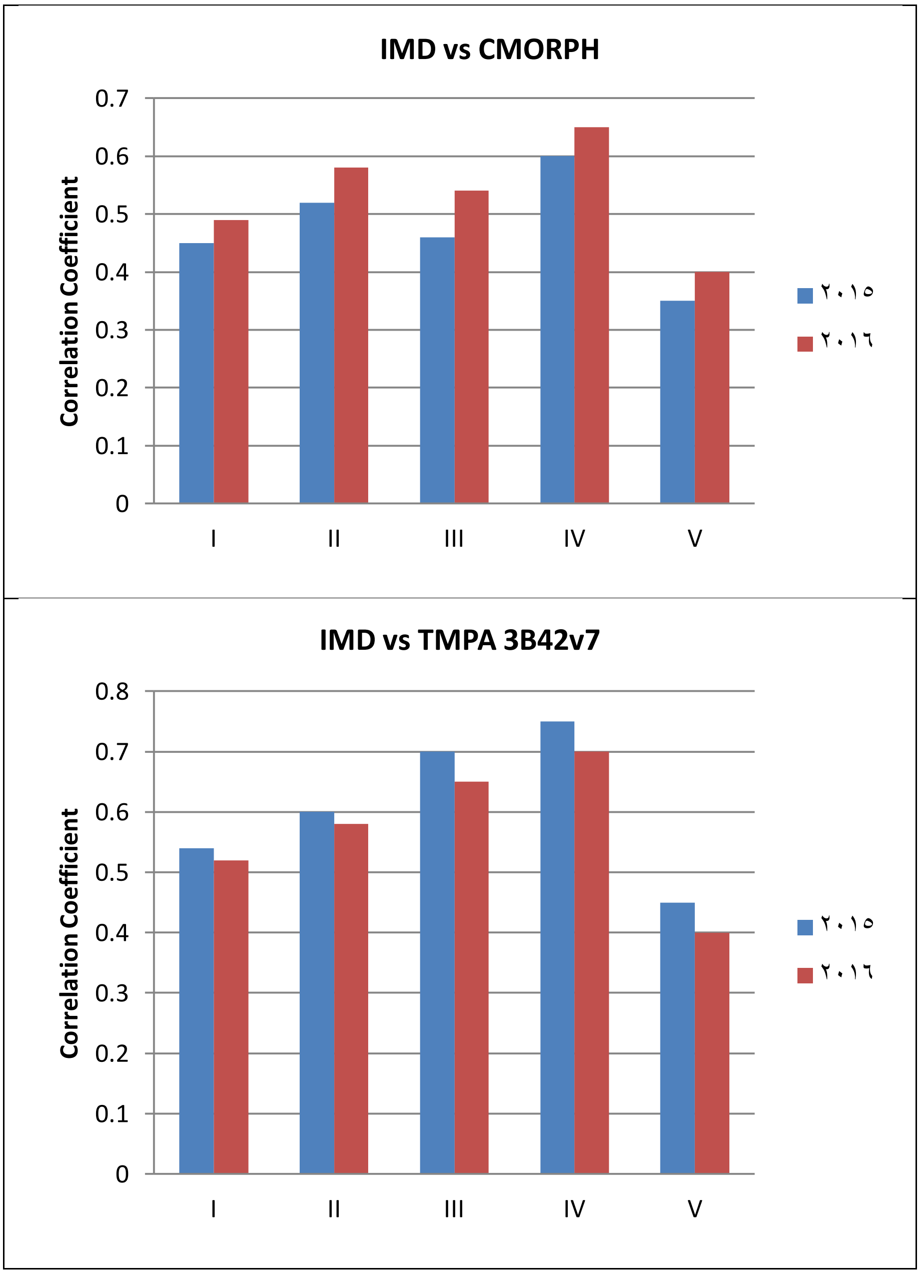
[13] Huffman, G. J., D. T. Bolvin, E. J. Nelkin, D. B. Wolff, R. F. Adler, G. Gu, Y. Hong, K. P. Bowman, and E. F. Stocker. 2007. “The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales.” Journal of Hydrometeorology 8 (1): 38–55. doi:10.1175/JHM560.1.

[14] Huffman, G. J., R. F. Adler, D. T. Bolvin, and E. J. Nelkin. 2010. “The TRMM Multi-Satellite Precipitation Analysis (TMPA).” In Satellite Rainfall Applications for Surface Hydrology, edited by F.

Hossain and M. Gebremichael, 3–22. Dordrecht: Springer Verlag. ISBN: 978-90-481-2914-0.
[15] Prakash, S., C. Mahesh, and R. M. Gairola. 2013. “Comparison of TRMM Multi-Satellite Precipitation Analysis (TMPA)-3B43 Version 6 and 7 Products with Rain Gauge Data from Ocean Buoys.” Remote Sensing Letters 4 (7): 677–685. doi:10.1080/2150704X.2013.783248.




SEP 2015
Rainfall in mm
120
100
80
60
40
20
0
REGION I
REGION II
REGION III
REGION IV
REGION V
SEP 2016
Rainfall in mm
300
250
200
150
100
50
0
REGION I
REGION II
REGION III
REGION IV
REGION V


IMD vs CMORPH
Correlation Coefficient
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
I
II
III
IV
V
٢٠١٥
٢٠١٦
IMD vs TMPA 3B42v7
Correlation Coefficient
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
I
II
III
IV
V
٢٠١٥
٢٠١٦

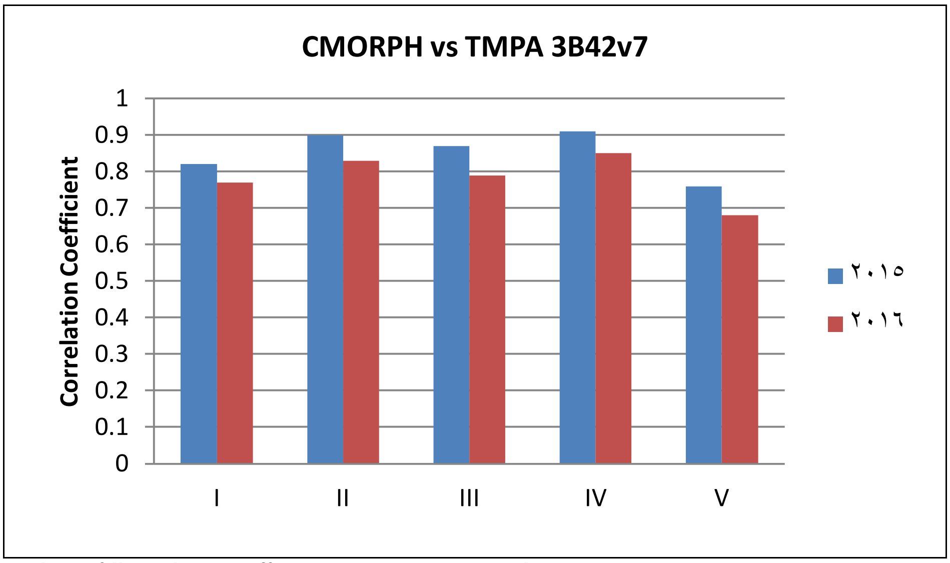


Figure 3: Daily rainfall correlation coefficients (a)IMDvs CMORPH (b)IMD vs TMPA 3B42v7 (c)CMORPH vs TMPA 3B42v7