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CLOUD GROWTH BASED PRECIPITATION ESTIMATION ALGORITHM FOR KALPANA-1 SATELLITE DATA

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Abstract: *In the present study,a novel algorithm is developed for precipitation estimation using Kalpana-1 data based on Thermal Infrared (TIR) and Watervapor(WV) measurements. Infrared (IR) rain rates are based on cloud top temperature which is indirectly related to surface rainfall whereas microwave (MW) measurements that sense precipitation in clouds are directly related to precipitation rates. For the few decades, estimation of precipation has been done utilizing hybrid algorithms, which uses both TIR and MW measurements. In this paper, TIR and WV measurements from Kalpana-1 geostationary satellite are used for determination of convective and non convective clouds. Rain rate is assigned for every rainy pixel using non linear power relationship. Brightness temperature(BT) of both TIR band and WV band are used for the determination of rainy and non rainy pixel. The obtained rainfall in this method is compared with high resolution multisatellite precipitation product namely TMPA 3B42v7 and IMD gridded rain guage dataset. Performance of the present technique is improved in terms of Correlation coefficients and RMSE values when compared with other rainfall products and IMD rain guage dataset.*

Keywords: *precipitation, TIR measurements, WV measurements,corelation coefficient, root mean square error, Kalpana-1*

I. INTRODUCTION

Rain is one of the major components of water cycle; extreme rain events can cause destruction and misery due to flash flood and droughts. Therefore, estimating rainfall at high temporal and spatial resolution is of great importance which can be successfully achieved by satellite remote sensing. Conventional method like rain gauges which are not uniformly distributed over the land increases the importance of remote sensing applications.Another conventional method are ground based radar (DWR) which is having high temporal resolution nearly 10 minutes but low spatial coverage and its maintainance are too expensive for developing countries. Now a days satellite data is freely available which makes the rainfall estimation using satellite remote sensing data a cost effective method. Hence meteorologists have come forward to utilize satellite data for estimations of rainfalls all over the world (e.g., Haile et al. 2010; Joyce et al. 2004). For Indian region a few algorithms were developed (e.g., Mishra et al. 2009, Prakash et al. 2010) to estimate rainfall utilizing data from Geo-Synchronous and Polar orbiting satellites. High temporal resolution (nearly 30-60 mins) can be achieved using geostationary satellite data but the spatial resolution is poor. In General, these satellites onboard carries visible (VIS; 0.4–0.7 μm), watervapor (WV; 6.2μm), and thermal infrared (TIR;10.8 μm) sensors. The techniques based on VIS/TIR images tried to develop a relation between the surface rain rate with cloudtop brightness temperatures provided by the satellite. The basic principle involved in using VIS and IR channels is cold clouds are likely to produce rainfall. In visible images, cold clouds are bright and thick which are responsible for convection. Similarly in Infrared images, convective clouds are large, tall and associated with cold brightness temperatures. The methods which are using TIR and WV measurements are indirectly related to surface rainfall since these measurements cannot penetrate through clouds. Several methods were developed based on VIS/IR and the techniques involved are Cloud indexing, Thresholding, Cloud growth techniques. Using thresholding technique (Arkin and Meisner, 1987) estimated rainfall for a 2.5^0 X 2.5^0 grid at monthly scale. Alder and Negri (1988) proposed a technique called Convective-Stratiform technique (CST), which segments cirrus clouds from convective core clouds. Based on cloud growth technique (Griffith et al., 1979 and Woddley et al., 1980), estimated rainfall which uses a principle growing clouds are associated with heavy rainfall.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. Spencer et al., 1989 proposed polarization corrected brightness temperature (PCT) using 85.5 GHz channel and determined a threshold of 255K for segmenting rainfall regions using simple threshold method. Over the last few decades, hybrid algorithms were proposed 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)). An efficient way of determining an empirical, nonlinear relationship between a number of ‘‘inputs’’ and one or more ‘‘outputs can be done using artificial neural network (ANN) . Now a days, an efficient way have been developed for estimation of rainfall using ANN techniques(e.g., Tsintikidis et al. (1997), and Bellerby et al.(2000)).

II DATA USED

1. Kalpana-1 data

Kalpana-1 satellite is the first dedicated meteorological geostationary satellite launched by Indian Space Research Organization (ISRO) using Polar Satellite Launching Vehicle (PSLV) on 12th September 2002. This geostationary satellite carries onboard a Very High Resolution Radiometer (VHRR) for three band images and a Data Relay Transponder (DRT). The VHRR sensor operates in three wavelengths band namely visible (VIS), TIR and WV. In WV and TIR, spatial resolution is 8 km where as inVIS band spatial resolution is 2 km.

(a) Thermal IR band, TIR: 10.5–12.5 µm.

(b) Visible band, VIS: 0.55–0.75 µm.

(c) Water vapor band, WV: 5.7–7.1 µm.

In the present study we used the IR and WV data.

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 product is generated. In this algorithm, available passive MW and IR estimates are combined by calibrating IR measurements (Huffman et al. 2007, 2010). However, available MW estimates are taken and the rest of the empty grids are filled with IR measurements. By using the inverse variance weighting method, the rain gauge data which are available over land are combined with this multisatellite product at a monthly scale and rescaled to a three-hourly scale. This precipitation product is known as the research version monitoring product and is different from the real-time product. Presently, the TMPA 3B42v7 data is released by making major corrections in TMPA 3B42v6. Differences in error characteristics of this V7 product from V6 over tropical oceans with rain gauge data from the available moored buoys at a monthly time scale were recently reported by Prakash, Mahesh, and Gairola (2013).

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. Rainfall observations collected from more than 4000 gauge stations spread across India are used for the development 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. Although rain gauges used for the preparation of these data are not uniformly distributed in both space and time over India , this is assumed to be a more realistic representative of ground-truth and is hence widely used for various meteorological and climatological applications.

The temporal and spatial resolution of the rainfall products are listed in Table 1.

Rainfall Product	spatial resolution	Temporal resolution
Kalpana-1	0.25°X 0.25°	Half hourly
TMPA 3B42v7	0.25°X 0.25°	Three hourly
IMD gridded guage	0.25°X 0.25°	Daily

Table 1.temporal and spatial resolution of the rainfall products

III METHODOLOGY:

Rain is a highly randomly distributed quantity hence estimation within a spatial grid box can be done with utmost care(i.e determination of rainy and non rainy pixel). Determination of clouds are based on thermal IR and WV channels to identify the thin cirrus, deep convective and very deep convective clouds following Roca et al. (2002) and in conjugation with Upadhyaya and Ramsankaran (2014a). In the present technique, successive TIR and WV images are taken. If the coldest pixels in the first IR image are colder in the second image, that is, the cloud system is intensifying and the pixels in the first image are associated with the heaviest rainfall rates. Hence, Vicente et al. (1998) used an index, which is the difference in CTBT of the current image with the CTBT of the same pixel in the next image, indicating that the cloud growth is also as an important factor for rain area detection.

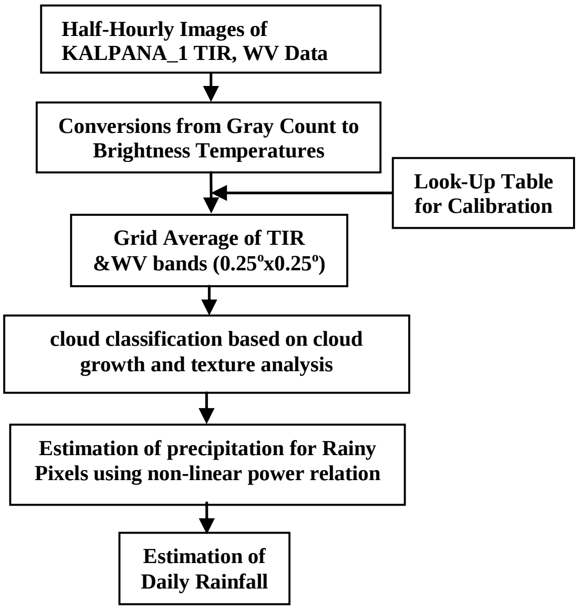

Fig .1. flow chart of the present algorithm

In the Present algorithm precipitation rates are computed based on non-linear power relation method. Figure. 1 explains the flow chart of the present algorithm. For the daily rainfall; each half hourly rainfall is calculated using this algorithm. Then these half hourly rainfall are cumulatively added to get the daily rain. Validations are made over land and ocean for heavy rainfall days using two global rainfall products (TMPA-3B42 v7 and CMORPH data) along with available AWS data provided by Indian Meteorological Department (IMD).
The comparisons are done over 0.25^ox0.25^o grid spatial resolution. In order to validate the Kalpana-1 data with global rainfall data products,Kalpana-1 data are regridded to 0.25^o X 0.25^o spatial resolution.

Statistics of Heavy Rainfall Events:

To validate the present technique for satellite estimated rainfall , a global precipitation product TMPA 3B42 is used for comparison. Also the above mentioned products are compared with IMD observed gridded rainfall data, the following statistical measures use Root Mean Square Error (RMSE) and Correlation Coefficients (CC) which are defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - O_i)^2} \quad \text{-------- (1)}$$

and Correlation Coefficients

$$CC = \frac{\sum_{i=1}^{N}(X_i - \bar{X}_i)(O_i - \bar{O}_i)}{\sqrt{\sum_{i=1}^{N}(X_i - \bar{X}_i)^2 \sum_{i=1}^{N}(O_i - \bar{O}_i)^2}} \quad \text{--------(2)}$$

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

IV Results and Discussions

Case Study : Rainfall Event over Chennai during 1st , December 2015:

For the present case, the daily rainfall on December,01,2015 has been examined using the present technique . Figure 2 shows the results of daily rainfall using TMPA 3B42 V7 fig. 2(a) , Kalpana -1 fig. 2(b), IMD fig. 2(c). The error between TMPA 3B42 V7 and Kalpana -1 is shown in fig. 2(d). In quick succession, two troughs of low pressure developed over Southeast Bay of Bengal during last week of November which move westwards towards Tamil Nadu coast. This causes very heavy rainfall at Tamil Nadu and adjoining Districts of Andhra Pradesh. From the results it is clearly observed that rainfall using kalpana-1 overestimates when compared with TMPA 3B42 V7. The correlation coefficients and RMSE obtained for the three rainfall products are listed in Table 2.

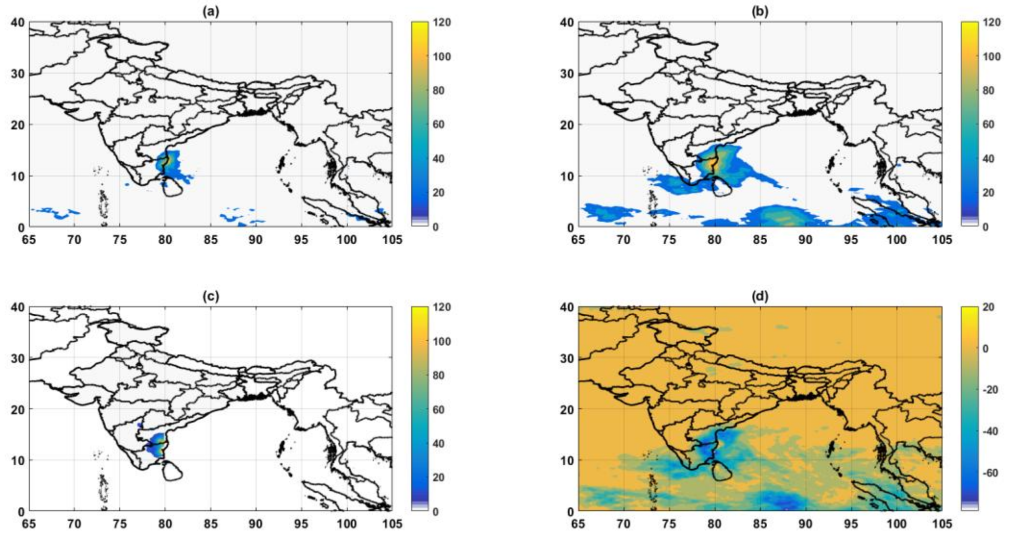

fig .2. Daily rainfall on 1st,December,2015 using (a)TMPA 3B42v7 (b) Kalpana-1 (c) IMD (d) error

Table 2. Comparisons of Correlation Coefficients and RMSE values

	Kalpana-1 vs TMPA 3B42 V7	Kalpana-1 vs IMD	IMD vs TMPA 3B42 V7
Correlation Coefficients	0.7157	0.6785	0.5782
RMSE(in mm)	8.9912	12.3523	15.6872

V. Conclusions

The present study evaluates the performance of the present rainfall estimation technique with the other satellite rainfall estimate(SRE) algorithm such as TMPA-3B42v7 and IMD gridded data. From the results, it is observed that the present algorithm has better correlation coefficient and RMSE values when compared to TMPA-3B42v7 . Based on the above results, we can conclude that the present technique using Kalpana-1 provides better evaluation when compared to TMPA-3B42v7 Rainfall product.

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