Prediction of Rainfall Distribution during the cyclone using Artificial Neural Network

Ramanathan, Nithish[1], Subramaniyan,Rajasirpi[1], RTS, Shakhithya[1]

Supervisor : Rajkumar,Kanmani shanmuga priya

[1]*Geoinformatics & Anna University*
Supervisor:Assistant Professor & IRS, Anna University

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Abstract - This study describes a proposed technique to predict rainfall using observations from the Indian National Satellite System (INSAT-3D) Imager. For the prediction, we use brightness temperature (TB) obtained from the thermal infrared, middle infrared and water vapor channels of INSAT-3D. A Multi-Layer Perceptron Neural Network (MLPNN) model is used to predict rainfall. Rainfall prediction from the brightness temperatures and INSAT-3D Hydro-Estimator (HE) product is used as the training reference. The model is trained and evaluated using data from one month (Oct 1, 2018 – Oct 31, 2018); 70 percent of data is used for training and the remaining 30 percent of data is used to evaluate the technique. The MLPNN model is configured using 6 inputs: TB of Thermal Infrared-1(TIR-1), Mid-Wave Infrared (MIR), Thermal Infrared-2(TIR-2) Water Vapor (WV) channels and the mean and the standard deviation (SD) of the TIR-1 TB over a 40 km x 40 km grid. The MLPNN is configured to estimate the rainfall values for each INSAT-3D pixel. We find that this technique predicts rainfall with the accuracy of 71%. Further verification metrics are provided in the manuscript. This study demonstrates the potential use of INSAT-3D observations for prediction of rainfall. The Predicted rainfall is compared and validated using the TRMM data available in GIOVANNI website. The rainfall is predicted during the Cyclone GAJA period (November 10, 2018 – November 21, 2018). The predicted half-hourly rainfall values are averaged into daily rainfall and then mapped. The spatial pattern and the movement of the Cyclone GAJA tracked with the help of the predicted rainfall map.

***Key Words*:** Prediction, Rainfall, Cyclone, MLPNN, Brightness Temperature

1.INTRODUCTION

Rainfall always play important role in forming of fauna and flora of natural life. It is not just significant for the human beings but also for animals, plants and all living things. It plays a significant role in agriculture and farming and undoubtedly; water is one of the most natural resources on earth. The sudden changes in climatic conditions and the increasing greenhouse emissions have made it difficult for the human beings and the planet earth to receive the necessary amount of rainfall that is required to satisfy the human needs and its contribution in everyday life. Hence, it has become significant to analyze the changing patterns of the rainfall and try to predict the rain not just for the human needs but also to predict for natural disasters like cyclone etc, that could cause by the unexpected heavy rainfalls. To be more specific and aware of the devastating changes in the climatic and also to stay updated; predicting rainfall has been the main focus of computer scientist and engineers. The rainfall prediction will not just assist in analyzing the changing patterns of rainfall but it will also help in organizing the precautionary measures in case of disaster mitigation and its management. The amount of rainfall received over a particular area is an important factor in assessing the amount of water available to meet the various demands of agriculture, industry, irrigation, hydroelectric power generation, and other daily human activities. The distribution of rainfall in time and space, therefore, is an important factor in determining the economic status of a region, or a state or a nation or a country. A cyclone is a general term used for a weather prediction system in which winds rotate inwardly to an area of low atmospheric pressure. For large weather systems, the circulation pattern is in a anticlockwise direction in the Northern Hemisphere and a clockwise direction in the Southern Hemisphere (Coriolis effect in ocean). Cyclones are given many names in different regions of the world – They are named as typhoons in the China Sea and Pacific Ocean; hurricanes in the West Indian islands in the Caribbean Sea and Atlantic Ocean; tornados in the Guinea lands of West Africa and southern USA; willy-willies in north-western Australia and tropical cyclones in the Indian Ocean.

2. STUDY AREA

The study region mainly covers the states of Tamil Nadu, Kerala, Karnataka, Andhra Pradesh, Telangana, Goa and some parts of Maharashtra, Madhya Pradhesh and Odisha and also the union territories of Andaman and Nicobar, Lakshadweep and Puducherry occupying area of about 19.31% of India It lies approximately between 4°N to 20°N and 65°E to 94°E. Southern part of India is a peninsula in the shape and almost it look like an inverted triangle bound by the Bay of Bengal in the east, the Arabian sea in the west direction and the Indian Ocean in the south direction. The geography this region is diverse with two mountain ranges - the Eastern Ghats and Western Ghats plays a vital role in distribution of the rainfall.

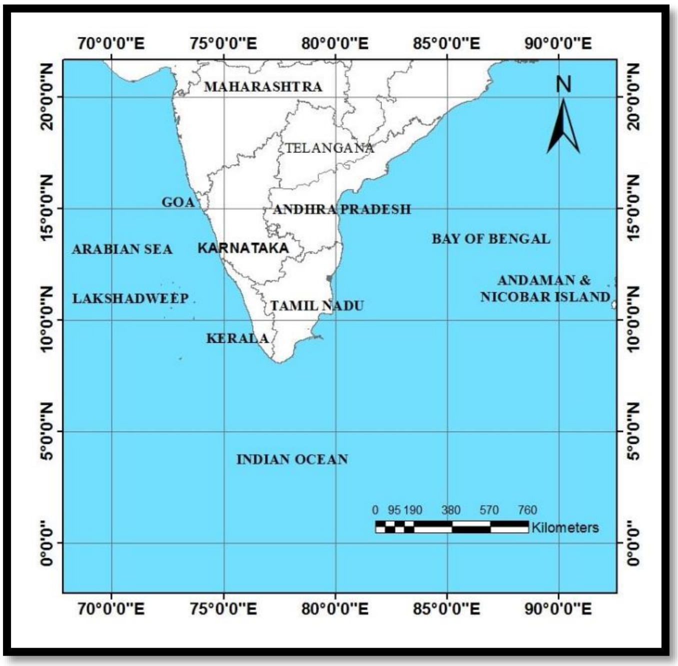
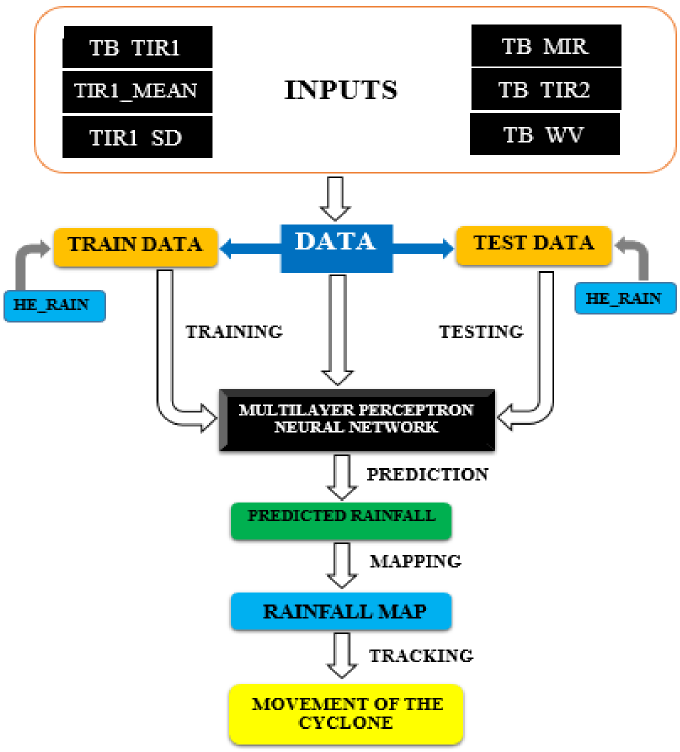


Figure .1 Study Area

3. DATA AND METHODOLOGY

INSAT-3D is a multipurpose geosynchronous spacecraft incorporates advanced Imager and Sounder instruments. The mission goal stated as "to provide an operational, environmental & storm warning system to protect life & property and also to monitor earth's surface and carryout oceanic observations and also provide data dissemination capabilities".. The INSAT-3D imager provides imaging capability of the earth disc from geostationary altitude in one visible (0.52−0.72 µm) and five infrared; 1.55 −1.70(SWIR), 3.80−4.00(MIR), 6.50−7.00 (water vapour), 10.2−11.2 (TIR-1) and 11.5−12.5 (TIR-2) bands with spatial resolution of 4 km and its temporal resolution is 30 minutes.

In the first phase of the work, we ordered the data from MOSDAC website required for this work. We started to download the half-hourly data from INSAT- 3D Imager in the H5 format. The data contains brightness temperature of all the bands of INSAT-3D and Hydro-Estimator Method rain (HEM rain). Downloaded sample data from MOSDAC is 3DIMG_15NOV2018_0030_L1B_STD & 3DIMG_15NOV2018_0030_L2B_HEM in which it consists of date (15), month (NOV), year(2018), time of observation (00.30), data level (L1- level 1, L2-level 2). The data is imported in Spyder (Python) with help of h5py module. The parameters from that file are extracted. These parameters are structured, inorder to train the neural network. In Spyder, the Artificial Neural Network model is constructed using the scikit learn module. The structured data is divided into two as 70 percent for training and 30 percent for training. The Multi-layer Perceptron model is trained with training data and evaluated with test data. The model predicts the test data which is compared with remaining data for determining its model accuracy. The model performs with 71% accuracy. In the second phase of the work, we download the L1B data from MOSDAC website to which L2B data is predicted using the Multi-layer perceptron neural network. The predicted rainfall values from the model are mapped using the Basemap module in python for easy understanding. Similarly, we predict and map the other downloaded data. The Layout is generated for the predicted rainfall values. The predicted half hourly rainfall values are accumulated and average to get the daily rainfall values. Using the daily rainfall values, the map is generated using python. The daily rainfall map is compared and validated with the help of the IMD report. In the third phase of the work to predict the movement/track of the cyclone GAJA, the predicted rainfall map is used. The coordinates of the eye of the cyclone is obtained from the rainfall map and noted in the MS Excel. The Shape file of India is downloaded from ESRI website. The shape file and the coordinates of the eye of the cyclone excel file is added to the Arc GIS. The coordinates are plotted as points. With the help of the points to line, we join the point to observe the movement of the cyclone GAJA. The images generated with help of the Multilayer Perceptron Neural network GIF file generated from python shows the movement of the cyclone GAJA. It is compared and validated with the help of the GIF file available in GIOVANNI website.



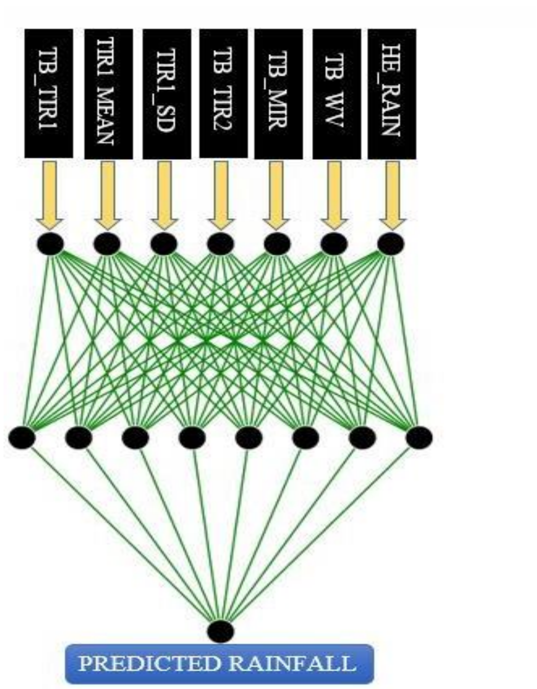


Figure .2 Multilayer Perceptron Neural Network

4. RESULTS AND DISCUSSIONS

Rainfall analysis can be done by different methods. One such type is statistical analysis which is component of data analytics. Statistical analysis can be broken down into five discrete steps: 1. Describe the nature of the data to be analyzed. 2. Explore the relation of the data to the underlying population. 3. Create a model to summarize understanding of how the data relates to the underlying population. 4. Prove (or disprove) the validity of the model. 5. Employ predictive analytics to run scenarios that will help guide future actions.

Contingency Table: A two – dimensional table that gives the discrete joint distribution of forecasts and observations.

Contingency Table

EVENTS	OBSERVED	NOT OBSERVED
FORECASTED	A	B
NOT FORECASTED	C	D

POD (Probability of Detection) is the ratio of the number of hit events to the total number of forecasted events.

POD = A / (A+C)

POFD (Probability of False Detection) is defined as the ratio of the number of false alarms to the sum of number of false alarms and true negatives.

POFD = B / (B+D)

PC (Proportion Correct) is the ratio of the number of correct forecasts to the total number of forecasted events

PC = (A+D) / (A+B+C+D)

ROC curve, is a graphical plot that illustrates the performance of the model. The curve is created by plotting the true positive rate (POD) against the false positive rate (POFD) at various threshold settings. ROC curve can be generated by plotting the true positive rate in the ordinate and the false positive rate in the abscissa. ROC curve is also known as a Relative Operating Characteristic curve, because it is a comparison of two operating characteristics (TPR and FPR) as the criterion changes.

The diagonal line represents POD is equal to POFD. The curved line represents POD and POFD at different thresholds. At a particular threshold, there will be good POD and POFD. That point will be very close to the upper-left corner, which says that accuracy is good.From ROC curve, the distance from the upper-left corner is a measure of skill of the technique. Given that the distance of the ROC curve to the upper-left corner is an efficient indicator of the general skill of the technique, it is easy to conclude that MLP techniques outperforms when more inputs are given to it.The rainfall is predicted using Multi-Layer Perceptron Neural Network by feeding voluminous input data. This model predicts with 71% of accuracy.

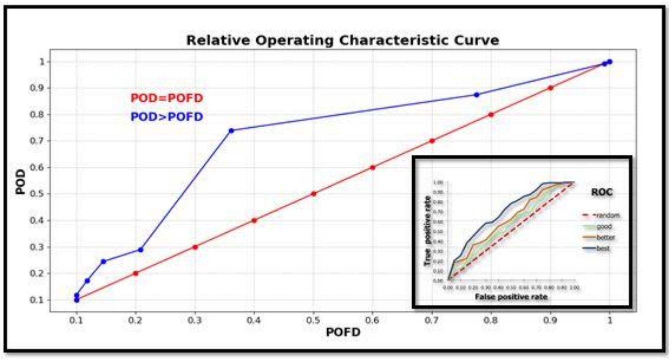


Figure.3 ROC curve

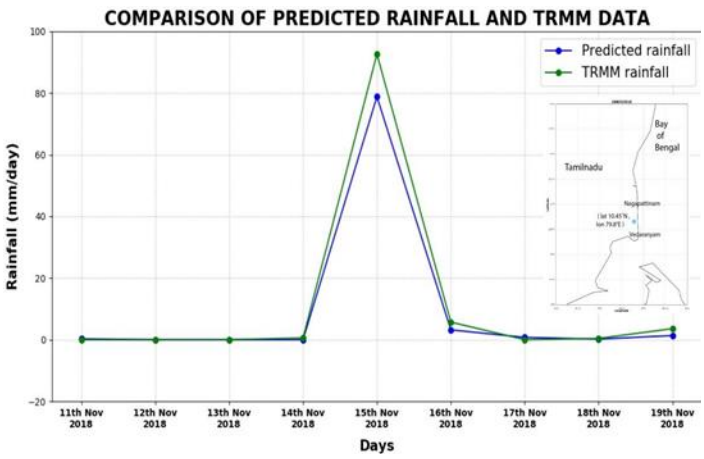


Figure.4 Comparison of Predicted Rainfall and TRMM data

The predicted rainfall is compared with TRMM rainfall data at a particular latitude and longitude (Latitude = 10.45˚N and Longitude =79.8˚E).This is the location of the cyclone Gaja which crossed land in between Nagappattinam andVedaranyam nearby Pushpavanam coast. The above graph represents the comparison of the predicted rainfall from the model and TRMM rainfall.

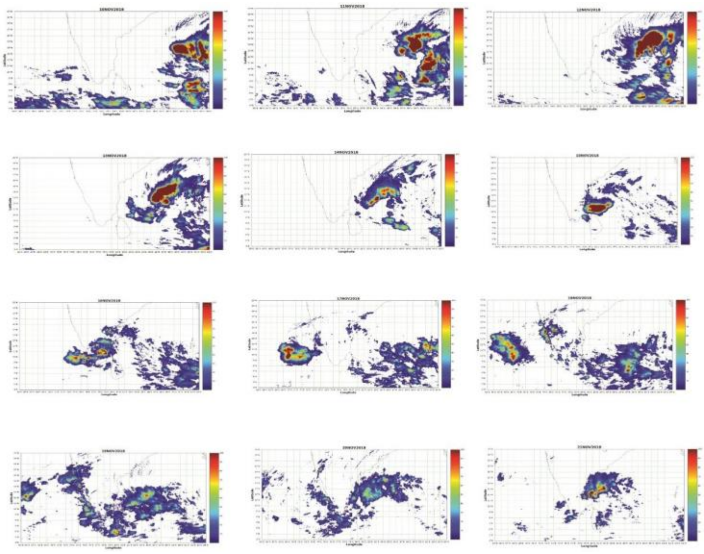


Figure.5 Predicted rainfall patterns of cyclone Gaja

The above figure consists of plots where the cyclone formed, dissipated and the step-by-step movement of the cyclone. Cyclone Gaja concentrated into depression over southeast Bay of Bengal nearby Andaman and Nicobar islands in the morning of 10th November. Moving west-northwards it intensified over east central and adjoining west central and southeast Bay of Bengal in the early morning of 11th November. It gradually moved westwards till early morning of 12th November after which it followed an anticlockwise looping track in the center of Bay of Bengal till 13th November morning. Subsequently, moving southwestwards, it intensified over southwest of Bay of Bengal on 15th November morning and further intensified severely in the same night . It crossed Tamil Nadu and Puducherry coast between Nagapattinam and Vedaranniyam near Pushpavanam coast (10.45°N and 79.8°E) on 15th November. After landfall, moving nearly westwards across interior Tamil Nadu and Kerala, it weakened in the same evening over central Kerala and subsequently it emerged into southeast Arabian Sea in the same midnight of 16th November, intensified into Deep depression by 17th November early morning and crossed Lakshadweep islands by the same afternoon. Subsequently, moving further northwestwards, it gradually weakened into depression over southeast Arabian Sea on 19th November noon. Associated with the movement of the system, widespread rainfall activity with isolated heavy to very heavyrain occurred over TN on 15th and 16th November. Cyclone gaja dissipated on 19th November from Arabian Sea.

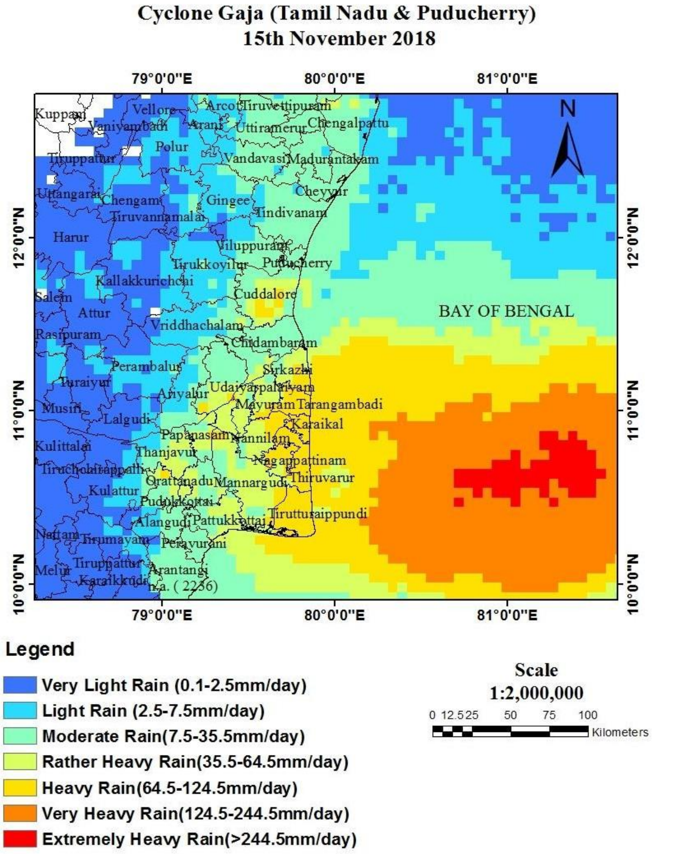


Figure.6 Influence of Cyclone Gaja on November 15, 2018 on Tamil Nadu

Cyclone Gaja made landfall over Tamil Nadu and Puducherry coast on 15th November 2018 between Nagapattinam and Vedaraniyam near 10.450N and 79.80E. The IMD has issued a red alert for Tamil Nadu and Puducherry on November 15, 2018. There will be heavy to very heavy rainfall in the region with extremely heavy downpour in some places. The IMD has also issued an orange alert for the region along with Kerala on November 16, 2018. As per IMD, the prediction is also shows similar rainfall patterns in Tamil Nadu and Kerala. On November 15, 2018 the eye of the cyclone Gaja lies in the Bay of Bengal, which influences the coast of Tamil Nadu and some interior districts of Tamil Nadu. The regions which received rainfall on 15 November, 2018 are Tirutturaippundi, Muthupet, Thiruvarur, Nagapattinam, Karaikal, Tarangambadi and some parts of Cuddalore, Thanjavur, Sirkazhi and Mayuram as heavy rainfall (64.5mm/day – 124.5mm/day).Mannargudi, Pattukottai, Nannilam, Orattanadu Udaiyarpalayam and some parts of Thanjavur and Cuddalore received rather heavy rainfall (35.5mm/day – 64.5mm/day) on November 15, 2018. The regions which received moderate rainfall (7.5mm/day – 35.5mm/day) are Peravurani, Arantangi, Alangudi,Adhirampatnam, Pudukottai, Papanasam, Mannargudi, Ariyalur,Sethiathope, Srimushnam, Kumbakonam, Chidambaram, Vriddhachalam, Tozhudur, Cuddalore, Neyveli, Viluppuram, Tindivanam, Cheyyar, Vandavasi, Madhurantakam, Chengalpattu and Pondicherry. Not only delta districts of Tamil Nadu, southern districts such as Ramanathapuram, Tuticorin, Tirunelveli and Kanyakumari also experiences rainfall due to Cyclone Gaja. Other than Tamil Nadu, some districts of south coastal Andhra Pradesh such as Nellore and Prakasam, Chittoor district in Rayalaseema and southern parts of Kerala experienced rather heavy to heavy rainfall.

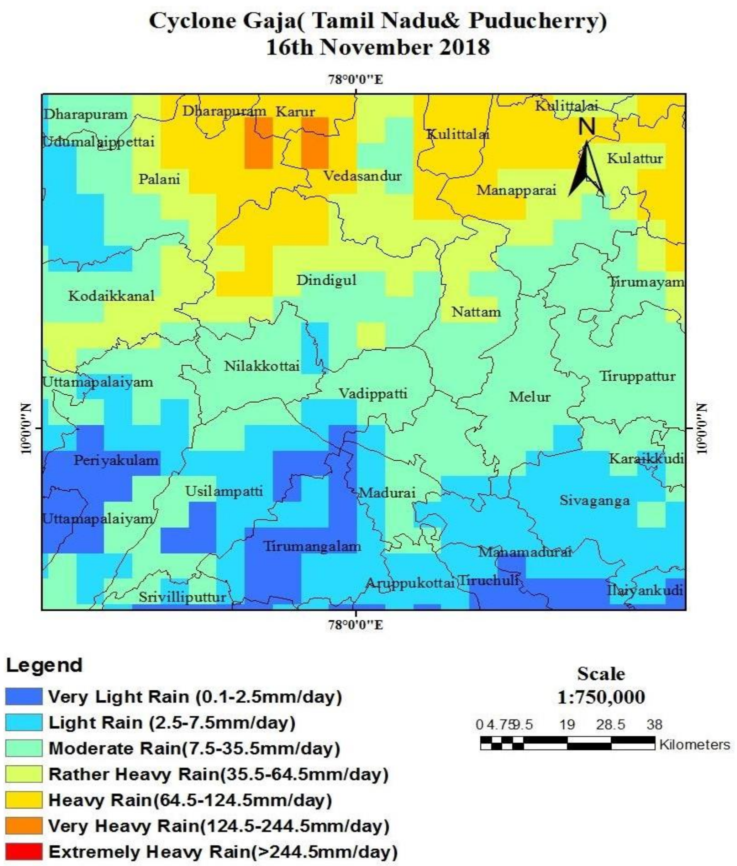


Figure.7 Influence of Cyclone Gaja on November 16, 2018 in Tamil Nadu

On November 16, 2018, Dharapuram, Karur, Palani, Vedasandur, Kulittalai, Manapparai received heavy rainfall. Kodaikkanal, Nilakkottai, Vadipatti, Melur, Tiruppattur, Nattam, Palani, Kulattur and some parts of Dindigul and Madurai received both rather heavy and moderate rainfall. Tirumangalam, Aruppukottai, Sivaganga, Manamadurai, Karaikudi Bodinaickanur, Usilampatti and Thammampatty received light rainfall.

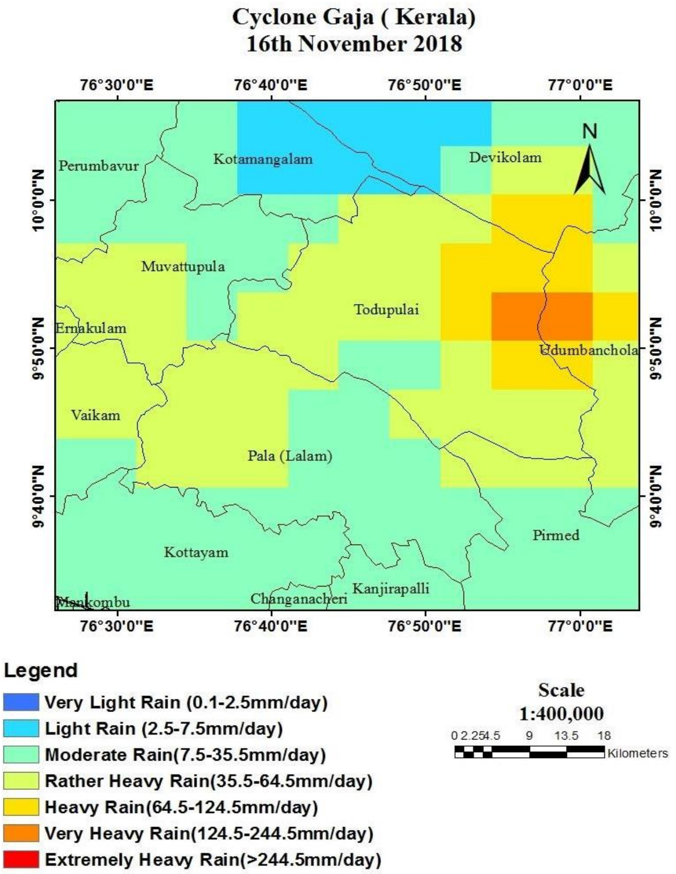


Figure.8 Influence of Cyclone Gaja on November 16, 2018 in Kerala

On November 16, 2018, Todupulai, Udumbancholai, Vaikam, Ernakulam and Pala received rather heavy rainfall to heavy rainfall. Changanacheri, Kottayam, Kanjirapalli, Mankombu, Perumbavur, Peermade, Idukki, Kumarakam and Munnar Kseb received moderate rainfall. Mostly, southern parts of Kerala received heavy rainfall due to Cyclone Gaja. Kandukur, Gudivada, Nellore and Prakasam districts of south coastal Andhra Pradesh received heavy rainfall on November 16, 2018. On November 17, 2018 Androth, Amini, Agatti, Cherium, Kalpeni, Kavaratti, Bangaram, Suheli Islands of Lakshadweep islands received heavy rainfall.

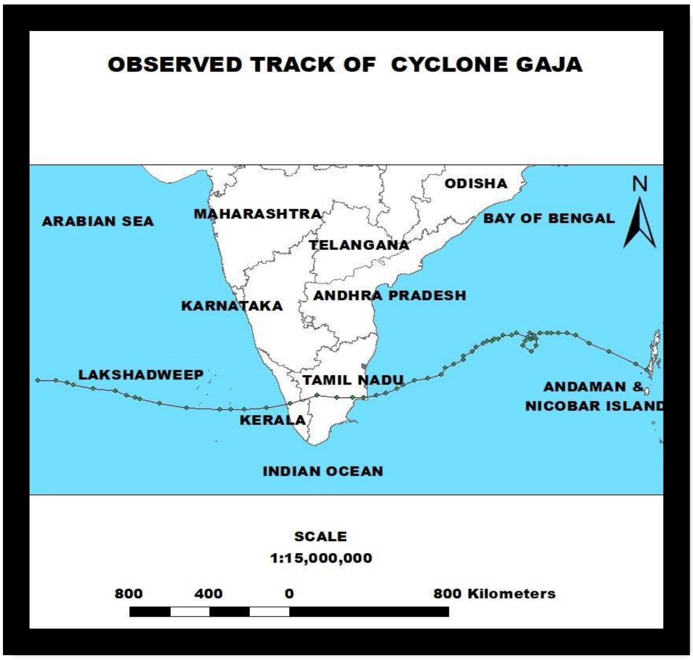


Figure.9 Observed track of Cyclone Gaja

5. CONCLUSIONS

The potential of using brightness temperature in the INSAT-3D imagery for rainfall was investigated in this study. An artificial neural network multilayer perceptron algorithm was used to develop the prediction of rainfall. During training procedure, MLP showed better performance. The additional use of input parameters works improving the prediction rainy pixels. All schemes clearly overestimate the rain occurrences.The constraints imposed by the indirect nature of the relationship between cloud top temperature and surface rain rate when infrared data are used to estimating rainfall. Infrared techniques based on geostationary IR data, however, offer a great potential for a 24-h operational application in midlatitudes. They are suitable for assessing precipitation regime over remote, undeveloped land areas and particularly over the sea. The findings of this study shows that the use of brightness temperatures in the INSAT-3D can be beneficial for the rainfall prediction. Artificial Neural Network models when properly trained showed encouraging and reliable performance, considering the highly spatial and temporal variable nature of precipitation. The developed rainfall prediction algorithm is expected to improve the accuracy of the satellite based rainfall retrieval algorithms. Moreover, the applicability of the schemes requires a more detailed analysis using different rainfall regimes, seasons, and areas. Predicted rainfall plays vital contribution in the field of agriculture, water reserve management, flood prediction and management with an intention to ease the people by keeping them updated with the weather and rainfall prediction. Accurate prediction for heavy monsoon rains during the cyclone will keep the authorities alert and focused for an upcoming event that of which the destruction could be minimized by taking precautionary measures.

REFERENCES

Amoo, O. T., & Dzwairo, B. (2016). Trend analysis and artificial neural networks forecasting for rainfall trends. Environmental Economics, 7(4), 1-10.

Abhishek, K., Kumar, A., Ranjan, R., & Kumar, S. (2012). A Rainfall Prediction Model using Artificial Neural Network. IEEE Control and System Graduate Research Colloquium

Biswas, S. K., Marbaniang, L., Purkayastha, B., Chakraborty, M., Singh, H. R., & Bordoloi, M. (2016). Rainfall forecasting by relevant attributes using artificial neural networks - a comparative study. International Journal of Big Data Intelligence, 3(2), 1-10.

Darji, M. P., Dabhi, V. K., & Prajapati, H. B. (2015). Rainfall Forecasting Using Neural Network: A Survey. International Conferences on Advances in Computer Engineering and Applications (pp. 1-5). Ghaziabad, India: IEEE.

Devi, S. R., Arulmozhivarman, P., Venkatesh, C., & Agarwal, P. (2016). Performance Comparison of Artificial Neural Network Models for Daily Rainfall Prediction. International Journal of Automation and Computing, 13(5), 1-9.

Hung, N. Q., Babel, M. S., Weesakul, S., & Tripathi, N. K. (2009). An artificial neural network model for rainfall forecasting in Bangkok, Thailand. Hydrology and Earth System Sciences, 13(8), 1-9.

Kumarasiri, A., & Sonnadara, D. (2006). Rainfall Forecasting: An Artificial Neural Network Approach. Proceedings of the Technical Sessions (pp. 1-9). Institute of Physics – Sri Lanka.

Lima, P. M., & Guedes, E. B. (2015). Rainfall Prediction for Manaus, Amazons with Artificial Neural Networks. Computational Intelligence (pp. 1-5). Curitiba, Brazil: IEEE

MuttalebAlhashimi, S. A. (2014). Prediction of Monthly Rainfall In Kirkuk Using Artificial Neural Network and Time Series Model. Journal of Engineering and Development, 18(1), 1-12.

Narvekar, M., & Fargose, P. (2015). Daily Weather Forecasting using Artificial Neural Network Neural Network. International Journal of Computer Applications, 121(22), 1-4.

Shaikh, L., & Sawlani, K. (2017). A Rainfall Prediction Model Using Articial Neural Network. International Journal of Technical Research and Applications, 5(2), 1-3.

Sharma, A., & Nijhawan, G. (2015). Rainfall Prediction Using Neural Network. International Journal of Computer Science Trends and Technology, 3(3), 1-4.

Heather M. Grams, Pierre-Emmanuel Kirstetter&Jonathan J. Gourley (2016), Naïve Bayesian Precipitation Type Retrieval from Satellite Using a Cloud-Top and Ground-Radar Matched Climatology. Journal of Hydrometeorology.

Giannakos, Apostolos&Feidas, Haralambos(2012), Classification of convective and stratiform rain based on the spectral and textural features of Meteosat Second Generation infrared data. Journal of Applied Climatology.

Giannakos, Apostolos&Feidas, Haralambos(2014), Rainfall estimation based on Meteosat multispectral infrared satellite data. Department of Meteorology and Climatology.

Daniel Sempere-Torres, Isztar Zawadzki (2005), An improved methodology for classifying convective and stratiform rain. Department of Atmospheric and Oceanic sciences.

Mounir Sehad, Ameur Soltane, Jean Michel Brucker & Fethi Ouallouche (2014), Image Segmentation Method for Identifying Convective and Stratiform Rain using MSG SEVIRI Data.