World Academy of Science, Engineering and Technology
International Journal of Aerospace and Mechanical Engineering
Vol:9, No:2, 2015

Satellite Rainfall Prediction Techniques - A State of the Art Review

S. Sarumathi, N. Shanthi, S. Vidhya

***Abstract*—**In the present world, predicting rainfall is considered to be an essential and also a challenging task. Normally, the climate and rainfall are presumed to have non-linear as well as intricate phenomena. For predicting accurate rainfall, we necessitate advanced computer modeling and simulation. When there is an enhanced understanding of the spatial and temporal distribution of precipitation then it becomes enrichment to applications such as hydrologic, climatic and ecological. Conversely, there may be some kind of challenges occur in the community due to some application which results in the absence of consistent precipitation observation in remote and also emerging region. This survey paper provides a multifarious collection of methodologies which are epitomized by various researchers for predicting the rainfall. It also gives information about some technique to forecast rainfall, which is appropriate to all methods like numerical, traditional and statistical.

***Keywords*—**Satellite Image, Segmentation, Feature Extraction, Classification, Clustering, Precipitation Estimation.

I. Introduction

RAINFALL carries the supreme vital role in the matter of human life in entire manners of weather conditions. For human cultivation the influence of rainfall is very massive. Rainfall is considered to be one of the most natural climatic wonders whose prediction is arduous and challenging. The exact information about to bring rainfall plays a main role in the development and management of water assets and similarly important for prevention from reservoir maneuver and floods. In the metropolitan areas, rainfall has a durable impact on traffic, sewer systems and also some more human undertakings. On the other hand, the hydrology cycle of rainfall is one of the most composite and problematic elements to recognize and to model. This is due to the complexity of the atmospheric processes which create rainfall and the significant range of variation over a wide range of scales mutually in time and space. In recent epochs, predicting the accurate rainfall seems to be extreme challenges in operational hydrology. Rainfall predicting is closely associated with the agricultural region, whereas in their term rainfall means crops and crops means life. Agriculture plays an important role to enhance the economy of the nation. By using diverse methods; the huge scale of efforts has been undertaken by various researchers and scientist for predicting the rainfall accurately and effectively over the universe. However the accurate rainfall prediction estimated by several techniques was not fully satisfied still now because the rainfall has nonlinear nature [1]. For the past era, there are many satellite sensor technology has simplified for the growth of innovative methods to global precipitation observations. In recent times various satellite-based precipitation algorithms have been established which produce precipitation products involving of higher spatial and temporal resolution that is useful for hydrologic researches and water resources applications [2].

Mrs.S.Sarumathi, Associate Professor, is with the Department of Information Technology, K. S. Rangasamy College of Technology, Tamil Nadu, India (phone: 9443321692; e-mail: rishi_saru20@rediffmail.com).

Dr. N. Shanthi, Professor and Dean, is with the Department of Computer Science Engineering, Nandha Engineering College, Tamil Nadu, India (e-mail: shanthimoorthi@yahoo.com).

Ms. S. Vidhya, PG Scholar, is with the Department of Information Technology, K. S. Rangasamy College of Technology, Tamil Nadu, India (phone: 9443960666; e-mail: vidhyapsubramani@gmail.com).

II. Different Satellite Prediction Techniques

A. Precipitation Estimation from Remotely Sensed Information Using Neural Networks (PERSIANN)

An automated system for Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks, the PERSIANN [3] has been established. This is mainly constructed for estimating the rainfall from geosynchronous satellite longwave infrared imagery. The Tropical Rainfall Measurement Mission (TRMM) data are responsible for large-scale estimates of tropical rainfall over the long term. The estimation of surface rainfall can be reported by several algorithms which use geostationary longwave infrared channel images (e.g., [4], [5]). The realistic high spatial and temporal resolution ($\sim 4 \times 4\ \mathrm{Km}^2$ every 30 min) can be undertaken by the measurements with wide coverage of the land turned over by the geosynchronous satellites which is taken to be the strong point of this overture. On behalf of monitoring the spatial and temporal development of clouds these measurements can be utilized, the measurements of cloud-top brightness temperatures are offered by the longwave infrared (IR) channels that they do not supply enough information to meet the real volume of rain occurring at the soil surface. Depend upon the multispectral microwave measurements made by polar-orbiting satellites several algorithms have been made to calculate approximately rainfall. The multispectral microwave sensors have the ability to penetrate into the clouds and therefore within the hydrometeor column the measured brightness temperature depends on the emission, absorption process. The building of the hydrometeor column can be obtained by using radiative transfer models of the emission-absorption process and rapid rain rates can be estimated by physically based algorithms. Shortly from both geosynchronous and polar-orbiting satellites, the study has been undertaken for the development of methods which abuse the assets of a variety of sensors.

Here one of the standard TRMM products such as adjusted geosynchronous precipitation index (GPI) method (AGPI) [6] are used for calculating a ratio of the coincident rapid microwave and geosynchronous infrared rainfall that can be estimated for a one-month period [7]. Depend on this ratio the adjustments for the estimation of monthly geosynchronous infrared rainfall is made. Though the infrared temperature threshold is used to define the cold clouds remain fixed at 235K, the rain rate is adjusted for the "cold" clouds in AGPI process.

The fundamental algorithm of the PERSIANN system depends upon the neural network and when it becomes available it can be certainly modified to integrate the appropriate information. When autonomous estimates of rainfall are available, an adaptive training feature allows for hasty updating of the network parameters. Depend upon the geostationary infrared imagery the original system [8] was constructed and later they consist of both infrared and daytime visible imagery [9]. In various hydrologic and meteorological applications the artificial neural network models are beneficial and effective. The system functions in two modes such as simulation and update. In the simulation mode, from the geostationary satellites infrared images using the previously calibrated neural network mapping function, the surface rain rate at the $0.25^{\circ} \times 0.25^{\circ}$resolution is predicted for every 30 minutes. In the update mode, TMI immediate rainfall estimate is available at the simulation error at any pixel which is useful for adjusting the parameters of the associated mapping function. Subsequently, the regular rainfall rate output is generated by the simulation node and the quality of the product is enhanced by the update mode. Obviously, the correctness of the ultimate product depend on the efficiency of the input feature detection and classification scheme, the correctness of the individual input-output mapping functions, then finally the correctness and the frequency of the TMI rainfall estimate used for updating.

B. Precipitation Estimation from Remotely Sensed Information Using Neural Networks Cloud Classification Systems (PERSIANN CSS)

The PERSIANN cloud classification is an algorithm used for satellite-based rainfall estimation [10]. This algorithm is mainly used for extracting local and regional cloud features from infrared geostationary satellite imagery for estimating fine scale rainfall distribution. The fundamental process of this algorithm is to get the satellite cloud images can be separated into cloud patches. From those cloud patches from those cloud patches the feature extraction can be performed. Then cloud patches can be clustered into well-organized subgroups. Finally the temperature and rainfall relationship can be determined. For evaluating the PERSIANN CSS rainfall estimation at a range of temporal and spatial scales, the radar and gauge rainfall measurements were used.

1) Segmentation of Satellite Infrared Cloud Images

Newly proposed approach known as the incremental temperature threshold (ITT) and it succeeds segmentation by steadily increasing the temperatures of the threshold. Therefore the algorithm is used to place the first set of seeds and also locates the local minimum temperatureT_{min}. Until the border of other seeded regions or cloud-free regions are reached the threshold temperature is increased and from the seeded points it extends to the neighboring areas.

2) Extraction of Cloud-Patch Features

Entirely established convective clouds have different tight temperature gradients, higher local pixel temperature variations and overshooting tops. Stratiform clouds demonstrate more steady temperature gradients and lower temperature variations. Among several cloud categories such as coldness, geometry, and texture, the three kinds are used to differentiate. Between the selected cloud-patch features and the amounts of patch rainfall, there must be a possible interrelationship.

3) Classification of Cloud Patches

To categorize the cloud patch features into a number of groups [11] a clustering algorithm called self-organizing feature map (SOFM) was introduced. In previous work, this method has been already defined by [12] and now a brief description is provided. The SOFM project is used to outline from high-dimensional space into lower-dimensional space. In a two-dimensional coordinate, the number of clusters can be arranged from many variables of input patterns through classification which is all permitted by projection. There have been two stages involved, such as i) among patch features the distance can be calculated and also the SOFM cluster center ii) from the minimum distance between the input feature vector and the SOFM connection weights the best matching SOFM cluster center c can be identified.

4) Estimation of Patch and Pixel Rainfall

In different stages of its life cycle, the relationship of pixel temperature *Tb* and surface rainfall *R* of a cloud patch is likely to be fluctuating. Based on the classification resulting from the previous clustering stage, we allocate different *Tb–R* relationships to many cloud patches. By using the probability matching method [13], the *Tb–R* pixel pairs are initially redistributed in each classified cloud-patch group. This method can match the histograms of *Tb* and *R* observations where the proportion of the *R* distribution above a given rain rate is equal to the proportion of the *Tb* distribution below the associated *Tb* threshold value.

C. Climate Prediction Center Morphing Method (CMORPH)

A novel method is offered for half-hourly global precipitation estimates which are imitative from passive microwave, satellite scans that are propagated by motion vectors derived from geostationary satellite infrared data. For propagating the comparatively high quality precipitation estimates derived from passive microwave data, the Climate Prediction Center morphing method (CMORPH) uses motion vectors derived from half-hourly interval geostationary satellite IR imagery [14]. During the time between microwave sensor scans the shape and intensity of the precipitation features can be reformed additionally by the performance of a time-weighted linear interpolation. Therefore, this method produces spatially and temporal complete microwave-derived precipitation analyses which is self-determining of the infrared temperature field. While passive microwave information is inaccessible, CMORPH demonstrated considerable enhancements over both simple averaging of the microwave estimates and also in excess of techniques that blend microwave and infrared information however that derive estimates of precipitation from infrared data. In terms of daily spatial correlation with an authorizing rain gauge analysis CMORPH overtakes these blended methods in a specific manner.

The data attractive can be done with the availability of IR data globally every single half hour, which is used for propagating PMW-derived precipitation features, generating a complete global precipitation analysis both spatially and temporally [14]. To determine and identify the cloud systems and their movements IR data can be used, meanwhile it offers good measurements of cloud-top properties. The process here defined, in which cloud system advection vectors (CSAVs) are derived. Over the worldwide, for propagating PMW-derived rainfall, it tends for every half hour of the day by using the CSAVs project. Therefore, it involves total automation and prevents the usage of visible imagery. For determining the cloud motion there was a method used which was parallel to the WINDCO method that uses the correlations among the collocated IR imagery by two diverse time intervals. The performance of cloud targeting is not done in order to decrease their complexity. The lower precipitating layer of the system doesn't have the capability to correlate efficiently with the direction and speed of cloud tops which was detected by satellite IR. Additionally, the direction of the wind goes up and downs and their speed also increase in magnitude with elevation from the earth's surface.

D.NRL Blended Technique

The simple view of the NRL blended-satellite precipitation technique is to initiate upon a real-time, from all operational geostationary VIS/IR imagers and LEO PMW imagers for underlying collection of time and space-matching pixels [15]. Since five operational geostationary satellites and the PMW data sets, it works in an autonomous, operational mode with a steadily arriving stream of near real-time data.

One of the beginning steps that demand to be considered before any satellite data sets are blended is to account for the characteristics of the PMW-estimated precipitation as retrieved by the individual PMW sensors within the satellite constellation. Due to diverse sensor frequencies, polarization states and scanning modes, diverse precipitation-retrieval algorithms can be applied to diverse sensors [16]-[19]. Among sensors this produces different precipitation retrieval characteristics and possible biases. One style to reconcile is by choosing one PMW sensor as a reference, and to frequency-match the satellite-derived rainfall histograms of the other satellite sensors to the reference histogram [20]. To the overall merged rainfall product this method assures that with sufficient observations over a necessarily long period of time and every sensor will contribute equivalent rainfall statistics. TRMM makes a good reference satellite in the meantime its tropical orbit is not sun-synchronous, permitting it to sample adjacent all local times during the course of any month, and its orbit often meets with the other sun-synchronous satellites. The over-ocean and over-land pixels are coordinated separately and binned into 3-h local observation times due to different PMW algorithms. The TRMM-PR is used as the reference estimate and the SSMI at latitudes above 40 N (below 40 S) where TRMM does not orbit in the NRL blended technique.

E. Tropical Rainfall Measuring Mission Multisatellite Precipitation Analysis (TMPA)

A calibration-based sequential scheme called as the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) is used for combining precipitation estimates derived from the multiple satellites and gauge analyses where possible, at accurate scales (0.25° × 0.25° and 3 hourly). TMPA is accessible over real time on the basis of calibration by the TRMM Combined Instrument and in real time on the basis of calibration by the TRMM Microwave Imager precipitation products [21]. The estimates of TMPA are generated in four stages: 1) calibration and combination of the microwave precipitation estimates, 2) creation of infrared precipitation estimates by calibrated microwave precipitation, 3) combination of the microwave and IR estimates, and 4) incorporation of rain gauge data.

1) Combined Microwave Estimates

First the conversion of existing passive microwave data to precipitation estimates on separate FOVs is done and then followed by averaging each dataset to the 0.25° spatial grid on the time range of 90 min from the minimal 3-hourly observation times (0000, 0300, . . . , 2100 UTC). The method gridding is "forward"— individual FOV is averaged into the grid box which comprises its center. The exception here is the AMSU-B gridding which is "backward"—each FOV is roughly apportioned to the grid box(es) which it normally occupies. The estimates are then adjusted to a "best" estimate using the probability matching of the precipitation rate histograms which are assembled from coincident data, comparable to the probability- matched method proposed by [22] and deployed, for example, by [23].

2) Microwave-Calibrated IR Estimates

For generating creating the complete record of 3-hourly 0.25° gridded $T_b's$, the research product makes use of two diverse IR datasets. Though the imagery amount distributed to CPC differs by satellite operator, the international agreements command that the complete coverage has to be provided at the 3-hourly synoptic times (0000, 0300 . . . 2100 UTC). The IR are converted into precipitation rates with the help of create spatially varying calibration coefficients. These coefficients are created by the monthly accumulation of histograms on a 1° × 1° grid, aggregated to overlapping 3° × 3° windows. The histograms accumulated here are the time–space matched combined microwave [or high quality (HQ)] precipitation rates and IR T_b's, each symbolized by the same 3-hourly 0.25° × 0.25° grid.

3) Merged Microwave and IR Estimates

The crucial aim of this project is to deliver the "best" estimate of precipitation in every grid box at every single observation time. It is normally pretty challenging task to associate diverse estimates of an irregular field like precipitation. The method of combining passive microwave estimates is moderately well performed because of the similar sensors and GPROF which is used for maximum retrievals.

4) Rescaling to Monthly Data

The usage of rain gauge data is the last step in the research product. The inclusion of rain gauge data from different combination datasets ([24], among others) is highly beneficial. Nevertheless, experience implies the gauge data shorter than a month are not reported with sufficient density or constant observational intervals in order to provide warranty for the direct inclusion in a global algorithm. This issue was solved by the authors using the GPCP One-Degree Daily combination dataset which scales the short-period estimates and adds them into a monthly estimate that contains monthly gauge data [25].

5) RT Algorithm Adjustments

The RT and research, product systems are developed in such a way that the consistency between the resulting datasets is endured properly. The main difference is that we make use of the TMI estimates from TRMM in the absence of TCI since this calibrator is not offered in real time.

F. Cloud Detection from Satellite Imagery

Through remote sensing automatic cloud detection and tracking is an essential step in measuring global climate variation. Cloud masks, which specify whether distinct pixels depict clouds, are involved in several of the data products which are based on data developed on-board earth satellites. Numerous cloud-mask algorithms have the method for decision trees, which works as sequential tests that scientists planned depending on experimental astrophysics studies and simulations. Boundaries of current cloud masks confine our capability to exactly track changes in cloud patterns in excess of the period. In this paper, they discovered the potential advantages of automatically-learned decision trees by using the Advanced Very High Resolution Radiometer (AVHRR) for detecting clouds from images. They created three decision trees learning procedure provided which are used for comparing the accuracy of the decision trees to the accuracy of the cloud mask [26].Generally Cloud detection and its characterization is a demanding task. Cloud-detection algorithms must disambiguate clouds and further entities that have related appearance as clouds. From one region to another region the entities whose occurrence in satellite imagery may be related to that of clouds may vary. In the polar region, clouds and snow/ice are tough to distinguish since all three entities are reflective in the visible wavelengths and establish slight contrast in the thermal infrared. Because of spatially unresolved water bodies, or current rainfall the Sun glitter may affect with cloud detection in the tropics. In excess of volcanic areas, clouds and volcanic ash may seem to be related in the visible wavelengths. The clouds and dust may appear to be similar over the desert region. In forests areas, the clouds and fires appears to be similar. In the tropics the terrain shadows might also interfere with cloud detection. Researchers used a diversity of machine-learning methodologies to precede remote sensing data, for instance, Bayesian classification [27], support vector machines [28], decision trees [29], neural networks [30] and genetic algorithms [31]. The outcomes of these methods range from promising initial outcomes to validated algorithms that are positioned in high-level remote sensing data products [32].

The objective of this work was to discover the benefits of automatic-learned decision trees for cloud detection, and to define whether decision trees that are depend upon functional relationships among sensed data which were determined theoretically executed better than decision trees that were based on the sensor data only. For the results of three automatic-learned decision trees dependupon several degrees of physical modeling them compare cloud detection outcomes of the CLAVR expert produced decision tree [33], which is presently organized in the NOAA-14 AVHRR daily 8km global data products. The consecutive decision process in CLAVR is planned to distinguish among the clouds initially by their gross characteristics, and then by their delicate features. Here the algorithm guarantees that pixels that are unsuccessful of all the tests have a very small probability of having radiatively important clouds. This algorithm contains tests that are designed specially to decide before encountered ambiguities, for instance, ambiguities due to reflectance is superior than 44% in channel 1 or channel 2 for sun glint snow or ice. The CLAVR consist of four decision trees, respectively, for one of daytime land scene, daytime ocean scene, nighttime land scene, and the nighttime ocean scene. There are several limitations in CLAVR cloud mask. Initially, the mask undertakes that there is an illustrative sample of clear pixels in every image, though, this supposition does not hold when clouds are insistent at a particular pixel coordinate. Then Secondly, the CLAVR algorithm may create diverse outcomes for a given pixel based upon the neighborhood to which the pixel fits. Since the class that the algorithm allocates to a given pixel based on the consistency of neighboring pixels, the class of a pixel may vary if the pixel is assembled with pixels on the left, right, below or above. The capability of CLAVR to distinguish between clouds and other entities that seems as clouds in AVHRR images is limited. For comparing the cloud mask the estimation of cloud masks is challenging since there is no gold standard. A researcher evaluates the quality of cloud masks by relating their agreement with masks created by human analysis or by additional algorithms. The comparison was done among the results of CLAVR to classification results of a human-expert analyst [33]. Generally, for slight cloud amounts, CLAVR overvalued fractional quantities of 0.1 related to the analysis, interpretation, and for huge cloud amounts, CLAVR undervalued the cloud quantity by about 0.1. Estimation showed huge errors for definite geographical seasons and locations. In [34] the cloud quantities that resulted from new enhancements in CLAVR were in contract with cloud amounts from established satellite-derived cloud climatology's. The CLAVR algorithm is parallel to automatically well-educated decision trees in that it works a structure of sequential threshold-tests. Though, the test sequence and thresholds in CLAVR were resulting by scientists through theoretical and experimental analysis of definite AVHRR data (radiances from individual channels, or acquisition parameters), and not through analysis of the data space as a full.

G.EPSAT-SG: A Satellite Method for Precipitation Estimation

The EPSAT-SG is a frame for method design of new rainfall estimation which has two intermediate products such as rainfall probability and rainfall potential intensity. By a feed forward neural network the first product is computed and its evaluation results show better properties than any other direct precipitation intensity by geostationary satellite infra-red sensors. The Second product can be taken as a conditional rainfall intensity several implementation options are issued for rainfall estimation which illustrates the importance of properly managing the temporal discontinuity. This method could be easily adjusted to another geographical area and operational environment [35].

The concept of EPSAT-SG depend on the fact that where geostationary satellite infrared sensors are an appreciated tool for cloud classification. The statistical relation between rainfall intensity and top cloud temperature is weak and unbalanced as there is no straight relation between rain rates and IR satellites brightness temperatures. Though, there is a nearby relationship between IR information and occurrence of rainfall, particularly in excess of tropical area [36] where the furthermost part of the rainfall comes from convective clusters with cold tops. Extra straight measurements depend on microwave sensors or rain-gauge networks offer much improved estimations. Then the geostationary data sampling is remote longer both in space and in time and real-time acquisition of these data is informal to accomplish. The goal of a blended rainfall estimation technique is to consume this well scale information into a rougher scale and/or intermittent precipitation estimation. In certain extents this issue is much related to empirical downscaling of global circulation models on regional zones [37]. The foremost alteration lies in the nature of fine grid input limits. Supposing an adequate database size, an experimental relation can be calculated between infrared brightness temperatures and rainfall intensities. By a ground radar network, [38] fit an exponential exemplary through a logarithmic conversion. This used to raise the subject of the variance and also approximation error which is measured to be significant for high precipitation rates. The method to mitigate this result is to convey out the valuation on rainfall probability and not on rainfall intensity. In this paper the experimental relation among rain intensity and rainfall probability versus 10.8 μm temperature is demonstrated with a logarithmic scale. Simply the interval 200 K–273K has been considered in the calculations that have been carried out on the 2006 whole African area and, for sampling and significance deliberations. In this interlude, the shapes of these two curves appear as much related and are reliable with an exponential model for a temperature lesser than 260 K. The equivalent coefficient of variation, ratio of the standard deviation by the mean plots is defined in this paper. The non-dimensional coefficient permits to compare the signal to noise ratio in statistical relation. In the complete range of temperature the coefficient of variation related to the rainfall intensity is always superior to the probability coefficient and the least value of these two coefficient ratios is near to two. This feature proposes that, in their database, the approximation of rainfall probability from cloud temperatures is not as much of noisy as for precipitation intensity. Consequently the estimation is divided into three stages: the production of a rainfall probability depends upon IR channels, the approximation of rainfall potential intensities by a scale back process and the production of the assembled rainfall. The rainfall potential intensity is a mean precipitation intensity conditioned by rain probability. Should the implementation use individual reference data set for rainfall intensity, whereas the last stage is forthright? Else the many potential intensity fields have to be combined. In an algorithm very related to GPCP, the merging then in needs has on estimation variance.

H.Infrared Satellite Precipitation Estimate Using Wavelet-Based Cloud Classification and Radar Calibration

In this paper they have established a methodology to improve an infrared–based high resolution rainfall retrieval algorithm by intelligently standardizing the rainfall estimations by space based annotations. Their methodology includes the succeeding four phases: i) Infrared cloud images can be segmented into patches; ii) feature extraction by a wavelet-based method; iii) clustering and classification of cloud patches; and iv) dynamic application of brightness temperature (Tb) and rain rate relationships, derived by means of satellite observations [39].

On behalf of cloud classification and rain fall estimation the Cloud-top brightness temperature measurements from geostationary satellite (GOES-12), in combining with cloud-to-ground lightning data from the National Lightning Detection Networks (NLDN), are used. Furthermore, the 2A12-TMI algorithm, a precipitation product derived as of The Tropical Rainfall Measuring Mission's (TRMM) Microwave Imager (TMI), is used for standardization [40].These outcomes are also estimated with hourly precipitation from Nexrad Stage IV radar data [41]. For satellite based rainfall estimation is related to the PERSIANN methodology [42].Though, the algorithms are enhanced with lightning data and added superior with a wavelet-based feature extraction approach related to their earlier work then again with diverse reference and standardization [43]. For extracting information from features of cloud texture the Wavelet transforms is implemented in this method. Furthermore, certain studies demonstrate that lightning is in common correlated to rainfall quantities and cloud top temperatures [44]. Thus, they have used the number of lightning flashes which may happen in the corresponding cloud patch areas during -15 min to +15 min window of experimental infrared data from geostationary stages. For estimating rain rates at 0.04o x 0.04o spatial resolutions each 30 minutes this algorithm has been used to extract cloud features from GEOS-12 (Channel 4). For segmenting clouds from its background (the threshold is 253 K) the single thresholding method has been used. Additionally, morphological image processing methods are used to eliminate very small clouds in addition to label the clouds associated together as patches. In phase 2, also the feature used by PERSIANN algorithm, they have implemented one-scale decomposition 2D wavelet transform on the cloud patches and estimated the mean and the variance of the detail constants. Depend upon Daubechies filters and a sliding window (length-5) the Wavelet decomposition and reconstruction are executed. In phase 3, by Self Organizing Map (SOM) neural network classifier [45], they categorize the patches into 100 clusters (10x10-size). On behalf of the training they have used 400 cloud patches from 2007. In phase 4, an appropriate Temperature-Rain rate (T-R) curve is allocated to every cluster. Depend upon the coincidental images of top temperature, cloud patches (from GOES12) and its equivalent TMI rain rate; they can able to attain two vectors of brightness temperature and equivalent rain rate (TMI) examples. Subsequently, a nonlinear fitting exponential function is done in these examples in order to get (T-R) curve for every cluster. In testing method, as soon as a patch is segmented and feature extracted, the SOM specifies the most related cluster to the patch. Consequently, the rain rate for every pixel of the patch is allocated depends upon the corresponding (T-R) curve of the cluster. When the TMI radar permits the area of interest the parameters of (T-R) function are standardized and optimized.

III. Summarization of Satellite Prediction Techniques

Table I illustrates the relative aspects of the different Satellite Prediction techniques is to estimate the optimum technique where they are used to differentiate the methodology depend on their features. The main objective of this comparison is not to disparage which is the best technique, but to prove its usage and to create alertness in their fields.

IV. Conclusion

From this survey a detailed report can be obtained for predicting rainfall by using quite a lot of techniques over fifteen years. This paper provides an idea that maximum researchers and scientists use the above techniques for predicting rainfall and also they attain substantial results. Hence the upshot of this paper is to show the available techniques and therefore comparison table exposes the features and future scope of an individual methods used for predicting rainfall. This analysis creates an enhanced understanding of the readers. Moreover, in future this paper will lead a moral support for the researches to predict rainfall accurately and efficiently.

TABLE I
Comparison of Satellite Prediction Techniques

Techniques	Satellite data	Features	Future Scope
PERSIANN	TRMM TMI GOES-8 GOES-9/10 GMS-5	1. Improve the spatial and temporal resolution and accuracy of global scale precipitation estimation	1. Extend to cover almost the entire globe between 50°s and 50°w using the global gridded infrared imagery.
PERSIANN CSS	GOES	1. Improved spatial resolution. 2. Estimates rainfall based on cloud-patch scale. 3. Acts as an explanatory tool to analyze the cloud-rainfall system.	1. Evaluate PERSIANN CSS's performance over the ocean.
CMORPH	GOES-8 GOES-10 Metosat-7 Metosat-5 GMS-5	1. Perform better than PMW precipitation and radar.	1. Incorporate Advanced Microwave Scanning Radiometer for the Earth observing system.
NRL blended technique	GOES-9/10/12 Meteosat-5/7 Terra, Aqua PMW dataset	1. It is designed to operate during both daytime and nighttime conditions. 2. Improving the screening of falsely identified light rain over areas of thin cirrus clouds. 3. Extends the characterization of cirrus over a range of optical thickness during day and night	1. Optimize the use of other multispectral techniques and multiplatform observing systems for improving satellite precipitation estimation. 2. Use of other types of blended satellite technique.
TMPA	LEO DMSP NOAA	1. Increased rich constellation of satellite borne precipitation-related sensors in both post-real and real time.	1. Improve intercalibration of the microwave-based estimates. 2. Characterize the performance. 3. Explore climatological adjustments to the RT products to minimize its biases.
CLAVR	NOAA-14	1.The accuracy of automatically learned decision trees was greater than the accuracy of the cloud masks	NA
EPSAT-SG	GEO satellite data	1.Easily adapted to other geographical area &operational environment	1. This method can be easily extended to area covered by other GEO satellite than MSG 2.It can also be tuned to integrate other rainfall reference data sources than GPCP
2A12-TMI	GOES-12	1. It is enriched with lightning data and also Enhanced with a wavelet-based feature extraction methodology	NA

REFERENCES

[1] Deepak RanjanNayak, AmitavMahapatra, Pranati Mishra "A Survey on Rainfall Prediction using Artificial Neural Network" International Journal of Computer Applications (0975 – 8887) Volume 72– No.16, June 2013.
[2] SorooshSorooshian, Kuo-lin Hsu, Bisher Imam, and Yang Hong, "Global Precipitation Estimation from Satellite Image Using Artificial Neural Networks" Hydrological Modeling in Arid and Semi-Arid Areas, Edited by H.Wheater, S.Sorooshian and K.D.Sharma, Cambridge University Press, pp.21-28. 2008.
[3] S. Sorooshian, K. L.Hsu, X. Gao, H.V. Gupta, B. Imam, andD. Braithwaite, "Evaluation of PERSIANN system satellite based estimates of tropical rainfall," Bull. Amer. Meteorol. Soc., vol. 81, p. 2035, 2000.
[4] Arkin and P. Xie "The global precipitation climatology project: First algorithm intercomparison project" Bull. Amer. Meteor. Soc.,75, 401–419, 1994.
[5] Ebert, E. E., and M. J. Manton, "Performance of satellite rainfall estimation algorithms during TOGACOARE". J. Atmos. Sci., 55, 1537–1557.1998.
[6] Alder, G. J. Huffman, and P. R. Keehn, "Global rain estimates from microwave adjusted geosynchronous IR data". Remote Sens. Rev., 11, 125–152.1994.
[7] Arkin, P. A., "The relationship between fractional coverage of high cloud and rainfall accumulations during GATE over the B-scale array". Mon. Wea. Rev., 107, 1382–1387. 1979.
[8] Hsu, K. L., X. Gao, S. Sorooshian, and H. V. Gupta, "Precipitation estimation from remotely sensed information using artificial neural networks". J. Appl. Meteor., 36, 1176–1190. 1997.
[9] Hsu, H. V. Gupta, X. Gao, and S. Sorooshian, "Estimation of physical variables from multichannel remotely sensed imagery using neural networks: Application to rainfall estimation". Water Resour. Res., 35 (5), 1605–1618. 1999.
[10] Y. Hong, K. L. Hsu, S. Sorooshian, and X. G. Gao, "Precipitation estimation from remotely sensed imagery using an artificial neural network cloud classification system," J. Appl. Meteorol., vol. 43, pp. 1834–1852, 2004.
[11] Kohonen, T., "Self-organized formation of topologically correct feature maps". Biol. Cybernetics, 43, 59–69. 1982.
[12] Hsu, K., X. Gao, S. Sorooshian, and H. V. Gupta, "Precipitation estimation from remotely sensed information using artificial neural networks". J. Appl. Meteor., 36, 1176–1190. 1997.
[13] Atlas, D., D. Rosenfeld, and D. B. Wolff, "Climatologically tuned reflectivity–rain rate relations and links to area–time integrals". J. Appl. Meteor., 29, 1120–1135. 1990.
[14] R. J. Joyce, J. E. Janowiak, P. A. Arkin, and P. Xie, "CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution," J.Hydrometeorol., vol. 5, pp. 487–503, 2004.
[15] F. J. Turk and S. D. Miller, "Toward improved characterization of remotely sensed precipitation regimes with MODIS/AMSR-E blended data techniques," IEEE Trans. Geosci. Remote Sens., vol. 43, pp. 1059 1069, 2005.
[16] T. Wilheit, C. D. Kummerow, and R. Ferraro, "Rainfall algorithms for AMSR-E," IEEE Trans. Geosci. Remote Sens., vol. 41, no. 2, pp. 204–214, Feb. 2003.
[17] C. D. Kummerow, Y. Hong, W. S. Olson, S. Yang, R. F. Adler, J. Mc-Collum, R. Ferraro, G. Petty, D. B. Shin, and T. T. Wilheit, "The evolution of the Goddard profiling algorithm (GPROF) for rainfall estimation from passive microwave sensors," J. Appl. Meteorol., vol. 40, pp. 1801–1817, 2001.
[18] R. R. Ferraro, "Special sensor microwave imager derived global rainfall estimates for climatological applications", J. Geophys. Res., vol. 102, no. D14, pp. 16 715–16 735, 1997.
[19] F. Weng, L. Zhao, R. R. Ferraro, G. Poe, X. Li, and N. C. Grody, "Advanced microwave sounding unit cloud and precipitation algorithms," Radio Sci., vol. 38, no. 4, pp. 8068–8081, 2003.
[20] R. J. Joyce, J. E. Janowiak, P. A. Arkin, and P. Xie, "CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at 8-km, 1=2-hourly resolution," J. Hydrometeorol., vol. 5, pp. 487–503, 2004.
[21] G. J. Huffman, R. F. Adler, D. T. Bolvin, G. J. Gu, E. J. Nelkin, K. P. Bowman, Y. Hong, E. F. Stocker, and D. B. Wolff, "The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales," J. Hydrometeorol., vol. 8, pp. 38–55, 2007.
[22] Miller, J. R., "A climatological Z–R relationship for convective storms in the northern Great Plains". Preprints, 15th Conf. on Radar Meteorology, Champaign–Urbana, IL, Amer. Meteor. Soc., 153–154. 1972.
[23] Krajewski, W. F., and J. A. Smith,"On the estimation of climatological Z–R relationships". J. Appl. Meteor., 30, 1436– 1445. 1991.
[24] Huffman and Coauthors,"The Global Precipitation Climatology Project (GPCP) combined precipitation dataset". Bull. Amer. Meteor. Soc., 78, 5–20. 1997.
[25] Huffman, R. F. Adler, M. Morrissey, D. T. Bolvin, S. Curtis, R. Joyce, B. McGavock, and J. Susskind, "Global precipitation at one-degree daily resolution from multisatellite observations". J. Hydrometeor., 2, 36–50. 2001.
[26] SmadarShiffman "Cloud Detection from Satellite Imagery: a Comparison of Expert-Generated and Automatically-Generated Decision Trees" In Proceedings of the Eighth Workshop on Mining Scientific and Engineering Datasets, held in conjunction with the 2005 SIAM International Conference on Data Mining, April 21-23, Newport Beach, CA, 2005
[27] F. Murtagh, D. Barreto and J. Marcello, Decision boundaries using Bayes factors: the case of cloud masks. IEEE Transactions on Geoscience and Remote Sensing, 14, 2952-2958, 2003.
[28] Lee, Y., Wahba, G., Ackerman, S. A., Cloud classification of satellite radiance data by multicategory support vector machines, Journal of Atmospheric and Oceanic Technology Vol. 21 No. 2 pp. 159-169, 2004.
[29] Hansen, M., Dubayah, R., &DeFries, R, "Classification trees: an alternative to traditional land cover classifiers" International Journal of Remote Sensing, 17, 1075– 108, 1996.
[30] Promcharoen, S., Rangsanseri, Y., SuwitOngsomwang, S., Jaruppat, J., "Supervised Classification of Multispectral Satellite Images using Fuzzy Logic and Neural Network", Proceeding of the 20th Asian Conference on Remote Sensing, November 22-25, 1999, Hong Kong, China.
[31] A.B. Davis, S.P. Brumby, N.R. Harvey, K. Lewis Hirsch, and C.A. Rohde, "Genetic refinement of cloud-masking algorithms for the multi-spectral thermal imager (MTI)" in Proc. IGARSS 2001, Sydney, Australia, 9-13 July 2001.
[32] Zhan, X., Sohlberg, R.A, Townshend, J.R.G, DiMiceli, C., Carroll M.L., Eastman, J.C., Hansen, M.C. , DeFries, R.S. "Detection of land cover changes using MODIS 250 m data" Remote Sensing of Environment (2002), pp. 336–350.
[33] Stowe, L. L., P. A. Davis, and E. P. McClain, "Scientific Basis and Initial Evaluation of the CLAVR-1 Global Clear/Cloud Classification Algorithm for the Advanced Very High Resolution Radiometer" J. Atmos. & Oceanic Tech., 16, 6, 656- 681, 1999.
[34] Thomas, S., A. K. Heidinger, "Comparison of NOAA's Operational AVHRR Derived Cloud Amount to other Satellite Derived Cloud Climatologies"in press to the Journal of Climate, 2004.
[35] J. C. Berg`es, I. Jobard, F. Chopin, and R. Roca "EPSAT-SG: a satellite method for precipitation estimation; its concepts and implementation for the AMMA experiment" Ann. Geophys., 28, 289–308, 2010
[36] Arkin, P. A.: The relationship between the fractional coverage of high cloud and rainfall accumulations during GATE over the Barray, Mon. Weather Rev., 107, 1382–1387, 1979.
[37] Von Storch, H., Langenberg, H., and Feser, F.: A spectral nudging technique for dynamical downscaling purposes, Mon. Weather Rev., 128, 3664–3673, 2000.
[38] Vicente, G., Scofield, R. A., and Menzel, W. P.: The operational GOES infrared rainfall estimation technique, B. Am. Meteorol. Soc., 79, 1883–1898, 1998.
[39] M. Mahrooghy, V. G. Anantharaj, N. H. Younan, W. A. Petersen, F. J. Turk, and J. Aanstoos, "Infrared satellite precipitation estimate usingwaveletbased cloud classification and radar calibration," in Proc. 2010 IEEE Int. Geoscience and Remote Sensing Symp. (IGARSS), 2010, pp.2345–2348.
[40] C. Kummerow, Y. Hong, W. S. Olson, S. Yang, R. F. Adler, J. McCollum, R. Ferraro, G. Petty, D. B. Shin, and T. T. Wilheit, "The evolution of the Goddard profiling algorithm (GPROF) for rainfall estimation from passive microwave sensors", J. Appl. Meteor., 40, 1801-1820, 2001
[41] Y. Lin, and K. E. Mitchell "The NCEP Stage II/IV hourly precipitation analyses: development and applications. Preprints", 19th Conf. on Hydrology, American Meteorological Society, San Diego, CA, 9-13 January 2005, Paper 1.2., 2005

[42] Y. Hong, K. L. Hsu, S. Sorooshian, and X. G. Gao, "Precipitation Estimation from Remotely Sensed Imagery using an Artificial Neural Network Cloud Classification System," Journal of Applied Meteorology, 43, 1834-1852, 2004
[43] M. Mahrooghy, V. G. Anantharaj, N. H. Younan, W. A. Petersen, and F. J. Turk, "An Adaptive Methodology To Enhance Infrared Satellite Precipitation", 34th Conf. on Radar Meteorology, AMS, Williamsburg, VA, Paper 14.26., 4-9 October, 2009.
[44] T. Chronis, E. Anagnostou, and T. Dinku, "High frequency estimation of thunderstorms via Satellite Infrared and a long-range lightning network in Europe", Quarterly Royal Meteorological Society Vol.130 No. 599, 2004.
[45] T. Kohonen, "Self-organized formation of topologically correct feature maps". Biol. Cybernetics ,43, 59–69, 1982

Mrs. S. Sarumathi received B.E. degree in Electronics and Communication Engineering from Madras University, Madras, Tamil Nadu, India in 1994 and the M.E. Degree in Computer Science and Engineering from K. S. Rangasamy College of Technology, Namakkal Tamil Nadu, India in 2007. She is doing her Ph.D. programme under the area Data Mining in Anna University, Chennai. She has a teaching experience of about 15 years. At present she is working as Associate professor in the Information Technology department at K. S. Rangasamy College of technology. She has published 5 reputed International Journals and two National journals. And also she has presented papers in three International conferences and four national Conferences. She has received many cash awards for producing cent percent results in university examination. She is a life member of ISTE.

Dr. N. Shanthi received the B.E. degree in Computer Science and Engineering from Bharathiyar University, Coimbatore, Tamil Nadu, India in 1994 and the M.E. degree in Computer Science and Engineering from Government College of Technology, Coimbatore, Tamil Nadu, and India in 2001. She has completed the Ph.D. degree in Periyar University, Salem in offline handwritten Tamil Character recognition. Sheworked as a HOD in the department of Information Technology, at K. S. Rangasamy College of Technology, Tamil Nadu, India since 1994 to 2013, and currently working as a Professor &Dean in the department of Computer Science and Engineering at Nandha Engineering College Erode. She has published 29 papers in the reputed International journals and 9 papers in the National and International conferences. She has published 2 books. She is supervising 14 research scholars under Anna University, Chennai.She acts as the reviewer for 4 international journals. Her current research interest includes Document Analysis, Optical Character Recognition, and Pattern Recognition and Network security. She is a life member of ISTE.

Ms.S.Vidhya holds a B.Tech degree in Information Technology from N.P.R College of Engineering and Technology, affiliated to Anna University of Technology,Tiruchirappalli, Tamil Nadu, India in 2013. Now she is an M. Tech student of Information Technology department in K. S. Rangasamy College of Technology. She has published 3 international journalsand presented three papers in the National level technical symposium. Her Research interests include Data Mining, Web Mining, and Wireless Networks.