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# Improved Estimation of Radar Rainfall Bias over Tamil Nadu State of India Using a Kalman Filtering Approach

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**Abstract:** Bad weather, consisting of thunderstorms, normally causes the presence of strong winds and heavy rain that may develop into a storm over a certain area. Radar has been the most potential and powerful instrument used to detect and monitor the development of thunderstorms over a large area, however, it also has certain weaknesses. Weather radar can be affected by different sources of errors which have to be well considered and quantified for a proper interpretation of the collected data. We design a method that combines the Kalman filter with a multivariate analysis technique. The implementation of this technique is for the purpose of developing a formulation that may help to reduce error. These studies involved parameters such as temperature, humidity, point of gauge rainfall and weather radar reflectivity. The approach of using the Kalman filter combined with multivariate analysis is still a new way to improve radar rainfall estimates by prediction (time update) and correction (measurement update). This particular research was developed purposefully to reduce radar rainfall bias due to the uncertain sources of error seen in the weather radar and many studies have been developed but still did not achieve suitable values between radar readings with rain gauge returns.

**Key words:** Bias, radar rainfall, Kalman filter, time update, measurement, weaknesses

## INTRODUCTION

The implementation of filtering techniques for reducing radar rainfall error estimation is still new in Indian continental. Previously, the India Meteorological Department (IMD) (http://imd.gov.in) used conventional radar and also used the 3D-rapid program which provided virtually all of the features required for the operation of a radar network and distribution. India Meteorological Department was established in 1875. It is the meteorological service of the country and the principal government agency in all matters relating to Meteorology, Seismology and allied subjects.

Historically, it was placed for the purpose of aviation systems but was also able to be used for the purpose of weather estimation. IMD decided to use it because it is an advanced hardware and software system that can provide high spatial and temporal resolution rainfall information with a detailed view of the rainstorm and can detect air turbulence, called "wind shear" or "down burst". It is very useful for the purpose of aviation systems and hydrology in defining the weather characteristics and for the purpose of forecasting the weather over a large area. Besides that, radar rainfall data is affected by several errors. The normal factors in radar rainfall that contribute to errors are ground clutter, partial beam occultation caused by interception of terrain, beam blockage caused by irregular propagation as it passes through atmospheric layers with different densities and weakening effects. This is caused by atmospheric gases and weakening by the rainfall range which has an effect on radar measurement of rainfall (Oni *et al.*, 2012). Thus, a good understanding in the fundamental knowledge of radar rainfall is needed in order to improve and to enhance the algorithm and uncertainty analysis for the calculation of rainfall.

One of the main advantages of using radar for rainfall measurements because it can cover a large area in real time. On the other hand, getting accurate radar rainfall estimation for hydrological applications is not a simple task. The complexity of using radar in hydrological applications is mainly due to error characteristics. Removing the systematic error (bias) and enhancing the precision, accuracy and limitations of radar data sources will be the main issues in promoting accuracy in measurement for radar hydrology applications. It was reported by Villarini *et al.* (2010) and Wardah *et al.* (2011) about the procedure of bias correction. This study applies the Kalman filter equation in a way that will reduce the uncertainty in radar rainfall estimation. Weather radar sends off microwave pulses and measures various targets reflected by the atmosphere such as raindrops, hail and snow. The characteristics of weather contain elements

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such as humidity, temperature, wind direction, evaporation as well as birds need to be considered in collecting the radar echo.

The images are first filtered by the IRIS conversion software before the map of rainfall intensity appears to the user. These studies try to incorporate elements such as temperature, humidity and point of gauge rainfall into the Kalman filter techniques. The reason of choosing this particular element in weather systems is because the elements are situated at the point of sample location. The wind speed and wind direction are not involved because both of them are not permanently placed at any of the sample locations.

**About Regional Meteorological Department:** Regional Meteorological Centre at Chennai was started on 1 April, 1945 to supervise and coordinate meteorological services in the Southern region which now covers the states of Tamil Nadu Andhra Pradesh, Karnataka, Kerala and Union Territories of Pondicherry and Lakshadweep. Under the technical and administrative control of the Regional Meteorological Centre, Chennai three meteorological centres function at Hyderabad, Bangalore and Thiruvananthapuram to render meteorological services intheir respective states. Area Cyclone Warning Centre at RMC Chennai supervises and coordinates the non-aviation forecasting work at meteorological centres. Cyclone warning services are rendered through Area Cyclone Warning Centre, Chennai and Cyclone Warning Centre, Visakhapatnam. Meteorological office at Chennai Airport (Minambakkam) controls and coordinates the aviation weather forecasting activities of the region. Cyclone detection radars located at Chennai, Machilipatnam, Visakhapatnam, Karaikal and Kochi track tropical cyclones over the Bay of Bengal and the Arabian Sea with their S-band 10 cm radars. The S-band radar at Chennai has been replaced with a doppler weather radar recently. High Resolution Picture Transmission (HRPT) direct readout ground station was established at RMC Chennai during June 1995. This receives AVHRR satellite imageries and TOVS data from polar orbiting NOAA satellites. RMC Chennai also houses the Cyclone Warning Dissemination System (CWDS) unit from where the cyclone warning bulletins are disseminated to remote centres in coastal districts. Conventional Seismological observatories are functioning at Thiruvananthapuram, Visakhapatnam, Vijayawada, Minicoy and Salem under this RMC. Seismological observatories under Global Seismological Network (GSN) were established at Chennai, Thiruvananthapuram and Visakhapatnam during 1997. An observatory under World Wide Standardised Seismological Network (WWSSN) is functioning at Kodaikanal. A broad band system is functioning at Mangalore. Meteorological observations collected over a number of years form the basis of Climatology.

Climatological data have wide applications and are utilized for planning large-scale national development projects. Climatological sections at Regional Meteorological Centre and other meteorological centres in the region organise the scrutiny and archival of meteorological data and use them for answering various weather related enquiries. Accuracy of meteorological observations is ensured by periodical inspections of observatories by the inspectorate section at Regional Meteorological Centre and other meteorological centres. Calibrations of all instruments at observatories are checked at least once in 2 years. The state governments, railways and other organisations, maintain more than 2000 rain gauge stations. Periodical inspections of these rain gauge stations are arranged through hydrology sections at RMC Chennai and other MCs. A training unit to cater the basic meteorological training course was started at RMC Chennai during 1984. More than 1000 trainees in about 50 batches of 4 months duration each have already been trained so far. Agromet Advisory Units have started functioning at RMC Chennai and other MCs from 1978. These units are regularly issuing Agromet Advisory Bulletins twice a week for the benefit of the farming community in their respective states. RMC Chennai maintains 121 surface observatories (53 departmental and 68 part-time), 13 Pilot Balloon observatories, 10 Radiosonde/Rawin stations and 1 radiosonde station. Port Meteorological offices at Chennai, Kochi and Visakhapatnam liaison with masters of ships and shipping companies and other marine interests (Fig. 1).

**Literature review:** Badhiye *et al*. (2012) applied artificial neural network to make forecast of stock market in Nigeria using 4 different banks. Their results specify a measure of how well the variation in the output as described by the targets is very close to 1 for all the 4 bank stocks covered which indicates that the artificial neural network model is a good fit. The precision of their forecast was measured using the notion of relative error and the outcomes were quite due, even though it did not attain 100% level of precision. Since, artificial neural network are good in predicting stocks of the 4 banks in Nigeria, it is improbable that an artificial neural network will ever be the perfect forecasting method that is anticipated as the elements in a huge dynamic system like the stock market are too complex to be comprehended overtime.

Singh and Gill (2014) and Kalyankar and Alaspurkar (2013) asserts that the typical neural network method of executing time series forecasting is to prompt the function say f, by means of every feed forward function approximating neural network architecture using a set of n-tuples as inputs and a single output as the target rate of the network. They also demonstrated that the hybrid back propagation genetic method is a standard way to train neural networks for weather forecasts but shows that the

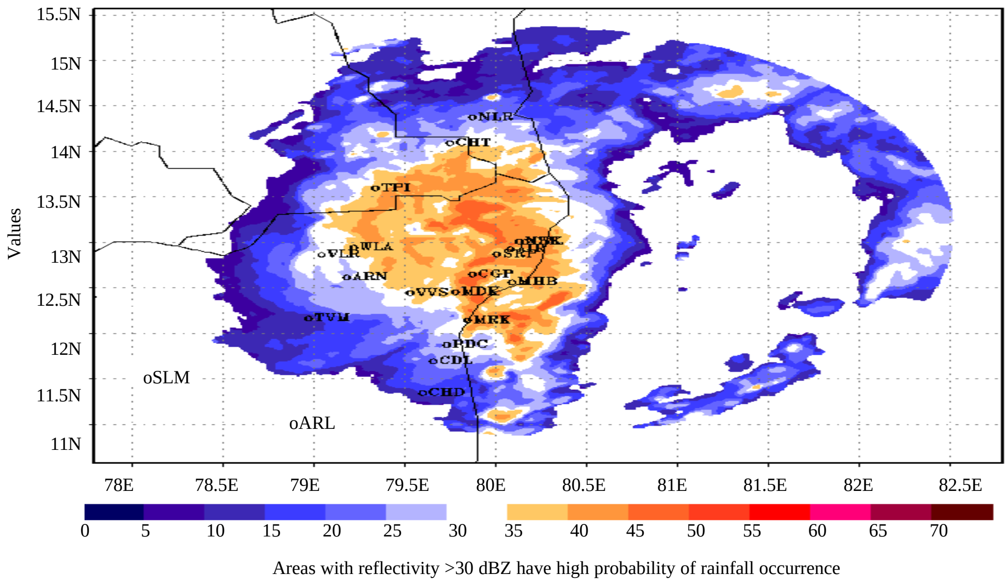


Fig. 1: WDSSII reflectivity forecast for Chennai and neighbourhood; IMD WDSS-II 30 min reflectivity forecast for Chennai and neighbourhood based on data at 20151201 at 1205 h IST adopted from NSSL., USA (based on Chennai radar data)

key weakness of this technique is that weather factors were supposed to be independent of each other and their sequential association with one another was not measured. They, however, anticipated an improved time series based weather forecast model to exclude the difficulties experienced by the hybrid back propagation/genetic algorithm method.

Kim *et al.* (2014) asserted that time series forecasting is a prodigious encounter in numerous fields. In finance, one can predict stock exchange courses or indices of stock markets while data dispensation consultants predict the flow of information on their networks. Globally, energy consumption is intensifying dissolutely for the reason that there is growth in human population, incessant pursuits for healthier living values, prominence on extensive industrialization in undercapitalized countries and the prerequisite to withstand constructive economic evolution charges. Sequel to this fact, a comprehensive forecasting method is vital for correct investment formation of energy generation and distribution. The shared tasks to the growth of dependable forecasts are the resolution of sufficient and necessary information for a respectable prediction. If the information level is inadequate, forecasting will be reduced; likewise if information is redundant, modeling will be difficult or lopsided. He further stated that it is a well-known fact that complex models gives precise forecasts but are difficult to accomplish but simple models gives less accurate forecast and are valued particularly if the forecasting segment is just a measure of an added composite formation device as frequently is the case. A mineral resource product which is vital to global economy is crude oil. Strictly speaking, crude oil is a key factor for the economic advancement of industrialized and developing countries as well as undeveloped countries respectively. Besides, political proceedings, extreme meteorological conditions, speculation in fiscal market amidst others are foremost events that characterized the eventful style of crude oil market which intensifies the level of price instability in the oil markets.

The crud oil industry in Nigeria is the largest industry. Oil delivered around 90% of Foreign exchange incomes, about 80% of Federal government proceeds and enhances the progress rate of the country's Gross Domestic Product (GDP). Ever since, the Royal Dutch Shell discovered oil in the Niger Delta in 1956, specifically in Oloibiri, Bayelsa State, the crude oil industry has been flawed by political and economic discord mainly due to a long antiquity of corrupt military governments, civilian governments and collaboration of multinational corporations, particularly Royal Dutch Shell. About six oil firm's namely: Shell, Elf, Agip, Mobil, Chevron and Texaco controls the oil industry in Nigeria. The aforementioned oil companies collectively dominate about 98% of the oil reserves and operational possessions. There are three key players in the Nigeria oil industry which include the Federal Ministry of Petroleum Resources, the Nigerian National Petroleum Corporation (NNPC) and the crude oil prospecting companies which comprise the multinational companies as well as indigenous companies as asserted by Singh and Gill (2014).

Jun *et al*. (2011) in their study predicted estimated rainfall in India using a complex statistical model ARIMA (1, 1, 1) and three different kinds of artificial neural network models namely Multilayer Perceptron (MLP), Functional-Link Artificial Neural Network (FLANN) and Legendre Polynomial Equation (LPE) in artificial neural network. They used the ARIMA (1, 1, 1) for the analysis of rainfall estimation data and effectively applied the three artificial neural network models stated before with the complex time series model. Their results revealed that FLANN exhibits very close and better forecasting outcomes as equated to ARIMA Model with a low Absolute Average Percentage Error (AAPE).

## MATERIALS AND METHODS

**Location of study area:** Regional Meteorological Centre at Chennai was supervise and coordinate meteorological services in the Southern region which now covers the states of Tamil Nadu, Andhra Pradesh, Karnataka, Kerala and Union Territories of Pondicherry and Lakshadweep (Fig. 2). Tamil Nadu is one of the 29 states of India. Its capital and largest city is Chennai (formerly known as Madras).

Tamil Nadu lies in the Southern most part of the Indian Peninsula and is bordered by the Union Territory of Puducherry and the South Indian states of Kerala, Karnataka and Andhra Pradesh. It is bounded by the Eastern Ghats on the North by the Nilgiri, the Anamalai Hills and Kerala on the West by the Bay of Bengal in the East by the Gulf of Mannar and the Palk Strait on the Southeast and by the Indian Ocean on the South. It also shares a maritime border with the nation of Sri Lanka.

**Data collection:** In this study, hourly rainfall data from RMC was used and covered from January to December of 2015. For this study, 4 stations were selected to demonstrate the application of the Kalman filter technique in the process of reducing error between weather radar rainfall and rain gauge. All the data input was gained by obtaining the sample of collected data from the rain gauge coordinates. The Kalman filter formulation was developed using MATLAB programing and it was applied to all stations for an interval of one year for measurements and predictions. Here, it is decided to use rainfall events in a year period to apply in the Kalman filter equation (Table 1).

**Humidity:** Table 2 shows the humidity of different stations in Tamil Nadu.

Table 1: Southwest monsoon forecast for Tamil Nadu 2015 (district wise)

| Agro climatic zones | Districts | Normal rainfall (mm) | Expected rainfall (mm) | Percent deviation | Expected quality scale |
|---|---|---|---|---|---|
| Western zone | Erode | 213.0 | 180 | -18.4 | Near normal |
| | Tiruppur | 192.9 | 166 | -16.4 | Near normal |
| | Coimbatore | 192.9 | 165 | -17.1 | Near normal |
| North Western zone | Salem | 380.0 | 350 | -8.6 | Normal |
| | Namakkal | 317.0 | 327 | 3.1 | Normal |
| | Dharmapuri | 361.0 | 390 | 7.4 | Normal |
| | Krishangri | 403.6 | 388 | -3.9 | Normal |
| Cauvery delta zone | Thanjavur | 342.0 | 335 | -2.0 | Normal |
| | Trichy | 270.3 | 291 | 7.2 | Normal |
| | Ariyalur | 349.6 | 327 | -7.0 | Normal |
| | Perambalur | 349.6 | 328 | -6.6 | Normal |
| | Karur | 249.7 | 212 | -17.7 | Near normal |
| | Thiruvarur | 301.8 | 224 | -34.7 | Below normal |
| | Cuddalore | 373.6 | 357 | -4.7 | Normal |
| | Nagapattinam | 274.1 | 222 | -23.5 | Below normal |
| Southern zone | Dindigal | 251.4 | 240 | -4.8 | Normal |
| | Virudhunagar | 181.8 | 145 | -25.8 | Below normal |
| | Thirunelveli | 92.6 | 71 | -30.7 | Below normal |
| | Theni | 178.4 | 155 | -15.2 | Near normal |
| | Sivagangai | 289.6 | 238 | -21.8 | Below normal |
| | Madurai | 305.4 | 263 | -16.0 | Near normal |
| | Tuticorin | 86.8 | 64 | -34.9 | Below normal |
| | Pudukkottai | 350.7 | 345 | -1.8 | Normal |
| | Ramanathapuram | 136.1 | 91 | -49.0 | Below normal |
| North Eastern zone | Thiruvallur | 449.5 | 444 | -1.3 | Normal |
| | Kancheepuram | 462.7 | 422 | -9.7 | Normal |
| | Vellore | 442.0 | 423 | -4.6 | Normal |
| | Thiruvannamalai | 465.8 | 425 | -9.6 | Normal |
| | Villupuram | 433.0 | 427 | -1.4 | Normal |
| | Chennai | 443.5 | 410 | -8.2 | Normal |
| High rainfall zone | Kanyakumari | 327.8 | 342 | 4.2 | Normal |
| Hilly zone | The Nilgiris | 1060.0 | 965 | -9.8 | Normal |

Table 2: Humidity in defferent Tamil Nadu stations

| Stations (Tamil Nadu and Puducherry) | Temperature (°C) Maximum Past 24 h | Maximum Dep. from normal | Minimum Past 24 h | Minimum Dep. from normal | Humidity (%) At 0830 h | Humidity Dep. from normal | Rainfall Millimeters Past 24 h | Millimeters Season's total from 01.01.16 | Millimeters Dep. from normal | Centimeters Year's total from 01.01.16 | Centimeters Annual normal | Weather remarks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Adiramapatnam | 32 | 2 | 24 | 3 | 81 | -6 | 0 | 0 | -35 | 0 | 124 | |
| Chennai | 30 | 1 | 25 | 5 | 78 | -4 | 0 | 0 | -20 | 0 | 140 | |
| Chennai AP | 30 | 1 | 24 | 3 | 78 | -6 | 0 | 0 | -25 | 0 | 138 | |
| Coimbatore AP | 30 | -1 | 23 | 5 | 83 | 4 | 0 | 0 | -7 | 0 | 59 | m* |
| Cuddalore | 31 | 2 | 25 | 5 | 87 | 1 | 0 | 0 | -35 | 0 | 134 | z* |
| Dharmapuri | 29 | 0 | 22 | 5 | 83 | 8 | 0 | 0 | -6 | 0 | 91 | |
| Kanyakumari | 33 | 3 | 24 | 1 | 76 | 9 | 0 | 0 | -11 | 0 | 75 | |
| Karaikal | 31 | 3 | 26 | 4 | 85 | 1 | 0 | 0 | -50 | 0 | 150 | |
| Kodaikanal | 18 | 1 | 12 | 4 | 79 | 24 | 2 | 2 | -33 | Tr | 158 | d |
| Madurai AP | 32 | 1 | 25 | 5 | 78 | 0 | 0 | 0 | -8 | 0 | 85 | z* |
| Nagapattinam | 31 | 3 | 26 | 4 | 76 | -6 | 0 | 0 | -80 | 0 | 143 | |
| Palayamkottai | 33 | 2 | 25 | 3 | 76 | -4 | 0 | 0 | -32 | 0 | 73 | |
| Pamban | 32 | 3 | 25 | 1 | 78 | 2 | 0 | 1 | -48 | Tr | 91 | |
| Parangipettai | 33 | - | 26 | - | 89 | - | 0 | 0 | -53 | 0 | 139 | |
| Puducherry | 31 | 2 | 25 | 3 | 87 | 5 | 0 | 0 | -15 | 0 | 134 | z* |
| Salem | 31 | -1 | 24 | 6 | 74 | 3 | 0 | 0 | -5 | 0 | 102 | z* |
| Thanjavur | 32 | 1 | 24 | 4 | 90 | 4 | 0 | 0 | -19 | 0 | 95 | |
| Tiruchirapalli AP | 32 | 2 | 24 | 4 | 85 | 4 | 0 | 0 | -16 | 0 | 87 | m* |
| Tirupattur | 30 | -1 | 21 | 4 | 83 | 0 | tr | 0 | -2 | 0 | 95 | d |
| Tiruttani | 32 | 1 | 23 | 7 | 87 | 7 | 1 | 1 | -15 | Tr | 101 | d |
| Tondi | 31 | 2 | 27 | 6 | 78 | -4 | 0 | 0 | -35 | 0 | 88 | |
| Toothukudi | 29 | 0 | 26 | 5 | 89 | 8 | 0 | 0 | -13 | 0 | 63 | |
| Uthagamandalam | 18 | -4 | 10 | 5 | 75 | 14 | 0 | 0 | -10 | 0 | 116 | |
| Vedaranyam | - | - | - | - | - | - | - | - | - | - | 148 | |
| Vellore | 30 | 0 | 23 | 6 | 93 | 7 | tr | 0 | -10 | 0 | 103 | m*d |

*Weather at 0830 h IST. Other remarks refer to preceding 24 h. D: Dust-storm, d: drizzle, f: fog, h: haill, l: lightning, m: mist, p: Shower, r-rain, s: snow, z: Hazet, t: thunderstorm, AP: Airport, tr-Rainfall 0.1-0.4 mm, Tr-Rainfall 0.01-0.49 cm. The plus sign is omitted when the departure are above normal

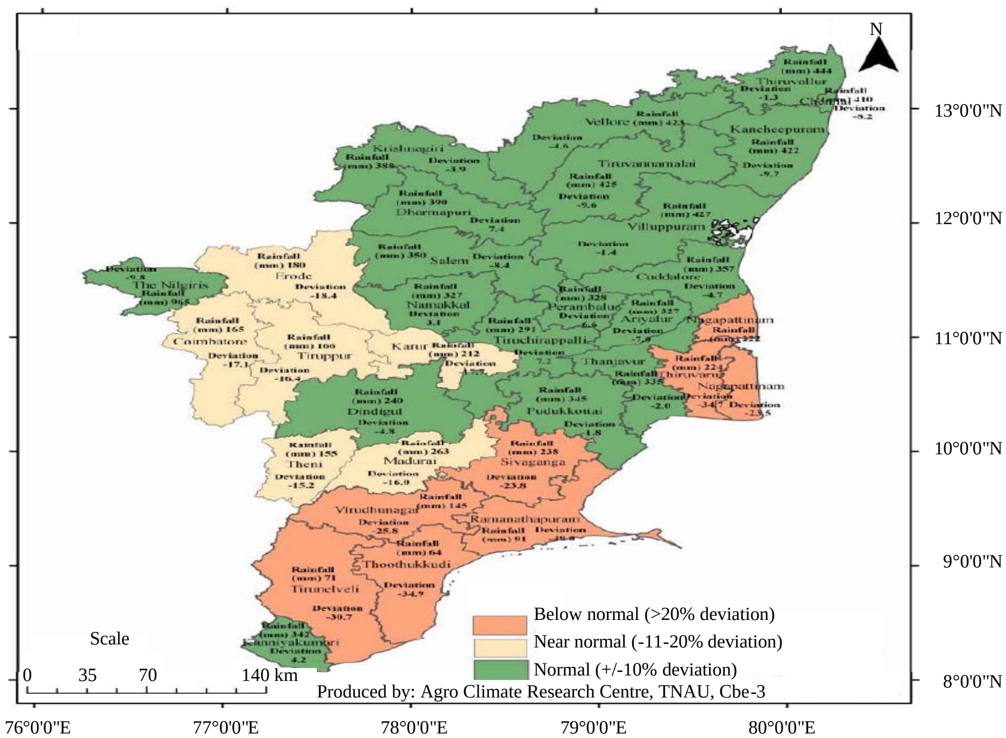


Fig. 2: Southwest monsoon forecast for Tamil Nadu 2015

## RESULTS AND DISCUSSION

**Experimental analysis:** The experiments were conducted on a HCL workstation with dual 3 Ghz Duo CPUs and 4 GB RAM. Here, it is conducted three sets of experiments to validate the use of Kalman filters for predicting rainfall prediction in data streams. The first experiment uses 5 different time series datasets for comparing Kalman filters with sampling and histogram based approaches discussed in related study. The second experiment quantifies the overhead of the KF operator on the query service time under normal executing conditions when the stream is available. The third experiment applies Kalman filter to rainfall observations over the Tamil Nadu state of India on a single calendar day.

**Comparative analysis:** The first set of experiments compare the prediction accuracy of Kalman filters with dynamic linear model against reservoir sampling and histogram based prediction techniques. Here, it is trained each approach with 2/3rd the input data sequence for training. Here, it is tested the predictions made for the remaining 1/3rd of the data sequence. The Root Mean Squared Error (RMSE) was computed by taking the sum of the squares of the errors (difference between the predicted and actual values), computing the average and then taking the square root as shown in Eq. 1:

$$\text{RMSE} = \sqrt{\frac{\sum(\text{Predicted value-actual value})^2}{\text{Number of elements predicted}}} \quad (1)$$

**Approaches:** Here, it is used Kalman filter, rainfall sampling and histogram approaches in our comparative analysis. Here, in this research selected sampling and histogram approaches to compare with Kalman filters as all three are generic approaches that can be used for any univariate stream. Wavelets are compression techniques that can store huge samples and histograms in less space. The results for sampling and histograms are thus extensible to the Wavelet domain.

**Kalman filters:** The Kalman filter state matrix was setup based on equation. $\Delta t$ is set to the difference in timestamp of the input data. For this experiment, all the input datasets are assumed to have discrete intervals of 1 time period. Hence, $\Delta t$ was set to 1. The process noise covariance was initialized to 0.01 multiplied by a $3\times3$ identity matrix. The observation size is 1 (a single integer or float value). The observation noise was also initialized to 0.01.

**Sampling:** In the rainfall sampling algorithm, when the (t+1) st record in the file is being processed, for $t\geq n$, the n candidates form a random sample of the first t records. The (t+1) st record has a n/(t+1) chance of being in a random sample of size n of the first t+1 records and so it is made a candidate with probability n/(t+1). The candidate it replaces is chosen randomly from the n candidates. The resulting set of n candidates forms a random sample of the first t+1 records. For the experiments, the sample size was set to 5, i.e., at any point of time the sample set had 5 elements which were the representative sample of the N elements in the training set seen so far. For the testing phase, a uniformly distributed random number generator was used to pick one of the 5 sample elements to replace the missing event. The RMSE was calculated using the predicted output and the actual value as shown.

**Histogram:** Histograms have been used widely for data approximation in the database literature. Here, it is leveraged them to be used for prediction. For each dataset, we built a histogram with 10 bins on the training dataset. The histogram was implemented in MATLAB. The MATLAB implementation stores the number of elements in each bin and its center point. After all the training data was entered, the percentage of total data in each bin was used to build a Cumulative Probability Distribution (CDF) of the histogram. During the testing phase when a data element had to be predicted, here, it is generated a uniformly distributed random number distributed between 0.0 and 1.0. Based on the histogram's CDF, a corresponding bin was then selected and its center used as the next predicted element. The RMSE was then calculated using the difference between the predicted and actual value.

**Prediction of meteorological data:** Meteorological data generated by the instrument sensors captures the rainfall characteristics like wind speed, temperature, cloud height and visibility, etc., from different gauge centres of Tamil Nadu. It is available from www.imdchennai.gov.in comprising of rainfall observations from Regional Meteorological Centre. The rainfall data is received from the rain gauge centre located in all over the Tamil Nadu. Here, focused on the data generated over Tamil Nadu state for a year. In this research streamed the data collected for this data into the Calder system and executed Select All queries on it. Table 3 lists the RMSE value of predicted values and the mean of the actual missing values for the two downtimes introduced in the meteorological data.

Table 3, it can be seen that the KF operator can predict the Meteorological data with low RMSE for the rainfall and humidity observations (within 10-20% of the corresponding mean). The predictions for the visibility observations have comparatively a greater RMSE (within 30-50% of the mean). Figure 3 plots the rainfall in mm from

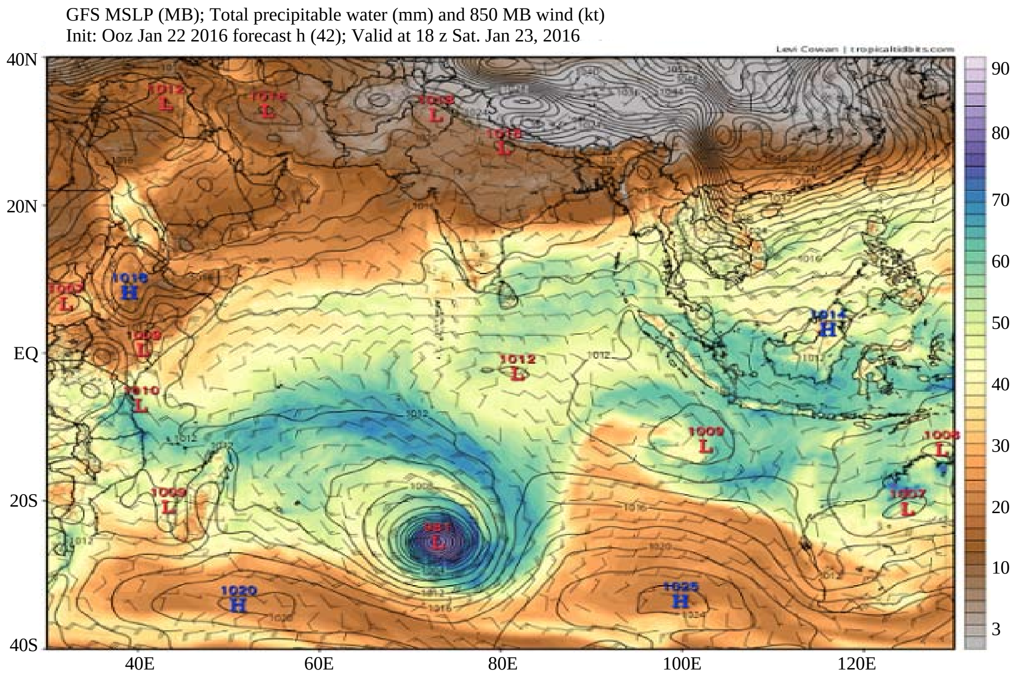


Fig. 3: Prediction of rainfalls/wind during data received from Chennai Meteorological Centre

Table 3: Lists the RMSE value of predicted values and the mean of the actual missing values for the two downtimes introduced in the meteorological data

Regional Meteorological Centre, Chennai; daily/seasonal rainfall distribution Tamil Nadu and Puducherry of date 23.01.2016

| Winter 2016 rainfall | | 23.01.2016** | | | From 01.01.2016 to 23.01.206 | | |
|---|---|---|---|---|---|---|---|
| Code | Name | Actual (mm) | Normal (mm) | PDN* | Actual (mm) | Normal (mm) | PDN* |
| | States | | | | | | |
| 32 | Puducherry (UT) | 0.1 | 0.2 | -74 | 0.1 | 27.8 | -99 |
| 31 | Tamil Nadu | 0.3 | 0.2 | 55 | 1.8 | 16.0 | -89 |
| | Met. Subdivisions | | | | | | |
| 31 | Tamil Nadu and Puducherry | | | | | | |
| 534 | Ariyalur | 0.0 | 0.0 | -100 | 0.0 | 19.5 | -100 |
| 461 | Chennai | 0.5 | 0.1 | 433 | 0.5 | 19.7 | -97 |
| 462 | Coimbatore | 0.0 | 0.0 | -100 | 22.8 | 7.3 | 212 |
| 463 | Cuddalore | 0.1 | 0.1 | 45 | 0.1 | 25.5 | -99 |
| 464 | Dharmapuri | 0.0 | 0.0 | -100 | 0.0 | 6.9 | -100 |
| 465 | Dindigul | 0.0 | 0.1 | -100 | 0.6 | 17.6 | -96 |
| 466 | Erode | 0.0 | 0.0 | -100 | 0.0 | 5.9 | -100 |
| 467 | Kancheepuran | 0.2 | 0.2 | 0 | 0.2 | 15.2 | -99 |
| 468 | Kanyakumari | 0.0 | 0.6 | -100 | 0.0 | 13.5 | -100 |
| 436 | Karaikal | 0.0 | 0.7 | -100 | 0.0 | 50.9 | -100 |
| 469 | Karur | 0.0 | 0.0 | -100 | 0.0 | 9.3 | -100 |
| 470 | Krishnagiri | 0.0 | 0.0 | -100 | 0.2 | 4.7 | -96 |
| 471 | Madurai | 0.0 | 0.1 | -100 | 0.0 | 12.4 | -100 |
| 472 | Nagapattinam | 0.0 | 1.0 | -100 | 0.0 | 58.6 | -100 |
| 473 | Namakkal | 0.0 | 0.0 | -100 | 0.0 | 6.4 | -100 |
| 474 | Nilgiris | 3.0 | 0.4 | 655 | 12.2 | 19.7 | -38 |
| 475 | Perambalur | 0.0 | 0.0 | -100 | 0.0 | 12.1 | -100 |
| 476 | Puducherry | 0.1 | 0.0 | 200 | 0.1 | 15.2 | -99 |
| 477 | Pudukottai | 0.0 | 0.1 | -100 | 0.0 | 21.9 | -100 |
| 478 | Ramana Thapuram | 0.0 | 0.3 | -100 | 0.1 | 30.1 | -99 |
| 479 | Salem | 0.0 | 0.0 | -100 | 0.0 | 7.8 | -100 |
| 480 | Sivaganga | 0.0 | 0.2 | -100 | 0.0 | 14.4 | -100 |
| 481 | Thanjavur | 0.0 | 0.2 | -100 | 0.0 | 25.0 | -100 |
| 482 | Theni | 0.0 | 0.4 | -100 | 1.6 | 13.4 | -88 |
| 483 | Tirunelvell | 0.0 | 0.9 | -100 | 1.1 | 31.1 | -97 |
| 535 | Tiruppur | 0.0 | 0.0 | -100 | 0.0 | 6.7 | -100 |
| 484 | Tiruvallur | 0.5 | 0.1 | 374 | 0.9 | 16.4 | -94 |

Table 3: Continue

Regional Meteorological Centre, Chennai; daily/seasonal rainfall distribution Tamil Nadu and Puducherry of date 23.01.2016

| Winter 2016 rainfall | | 23.01.2016** | | | From 01.01.2016 to 23.01.206 | | |
|---|---|---|---|---|---|---|---|
| Code | Name | Actual (mm) | Normal (mm) | PDN* | Actual (mm) | Normal (mm) | PDN* |
| 485 | Tiruvannamalai | 4.3 | 0.5 | 763 | 9.0 | 13.3 | -33 |
| 486 | Tiruvarur | 0.0 | 0.5 | -100 | 0.0 | 38.2 | -100 |
| 488 | Toothukudi | 0.0 | 0.2 | -100 | 0.0 | 20.6 | -100 |
| 487 | Tiruchirapall | 0.0 | 0.0 | -100 | 0.0 | 12.6 | -100 |
| 489 | Vellor | 0.0 | 0.0 | 200 | 0.8 | 7.0 | -88 |
| 490 | Villupuram | 0.0 | 0.0 | -100 | 0.0 | 16.7 | -100 |
| 491 | Virudhunagar | 0.0 | 0.3 | -100 | 3.0 | 16.2 | -81 |
| | Subdivision rainfall | 0.3 | 0.2 | 55 | 1.8 | 16.0 | -89 |

Legend; PDN*; Percentage Departure from Normal; **Rainfall for the 24 h ending at 0830 h of date

the rain gauge meter measurements under consideration. The graph shows the prediction (vertical dotted lines) and the predicted and actual values during that time. In this research can see that for this example, the predicted values follow the pattern in actual values.

## CONCLUSION

In this study, investigated the use of Kalman filters with dynamic linear model for prediction of actual and predicted rainfalls in sensor data streams. Here, it is evaluated the Kalman filter approach by applying it to many time series datasets and showed that they perform better than sampling and histogram based approaches in most cases. In our research implemented Kalman filters as a one-pass streaming operator as part of the Calder system. The implementation resulted in a low overhead operator that when applied to meteorological data gives us results with good accuracy. Here, it is conclude by stating that the Kalman filter is a viable approach for predicting actual and predicted values in streams.

## RECOMMENDATIONS

In future, we would like to extend the Kalman filter based prediction approach to include the seasonal and cyclical trends in datasets thus making them suitable for varied applications. Here, it would also like to extend our comparative analysis to include the neural network (27) and rule mining (Kim *et al*., 2014) approaches.

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