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Article

AI-Enhanced Anomaly Detection with ARIMA Rainfall Forecasting

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Abstract: Finding anomalous patterns in large datasets that may indicate security risks or system malfunctions is a crucial task in cloud computing. Recent advances in machine learning, combined with the rapid growth of cloud computing, have enabled several cloud-based, data-driven approaches for autonomous anomaly detection. However, conventional anomaly detection methods are often resource- and time-intensive, particularly when processing massive volumes of data. The method proposed in this study addresses these challenges by providing a scalable and efficient mechanism for real-time identification of irregularities. Furthermore, the approach supports timely detection and resolution of system malfunctions, ensuring the continuous availability and effectiveness of cloud-based systems. The investigation utilizes a 50 GB NCEP (National Centers for Environmental Prediction) time-series dataset covering the period from 2010 to 2024 with a daily temporal resolution. The selected geographic region spans 77° longitude by 12° latitude, focusing on the Bangalore region. Since the Z-score is a key statistical measure for anomaly identification, it is computed to detect deviations from normal behavior. Monthly anomaly detection is performed for precipitation values from 2010 to 2024 to analyze temporal variations. In addition, a comparative analysis is carried out between ARIMA, SARIMA, and existing machine learning models to evaluate performance, accuracy, scalability, and robustness.
Keywords: Anomaly Detection, Z-score, ARIMA, SARIMA, CNEP, Time-Series

1. Introduction

Anomaly detection is the process of identifying patterns in data that diverge from expected behavior. These anomalies are known as outliers, discordant findings, exceptions, aberrations, surprises, oddities, or contaminants in a variety of application domains. In the context of anomaly identification, the terms anomalies and outliers are utilized most frequently, however they are Occasionally employed interchangeably. Anomaly detection is essential for numerous uses, including defense surveillance for enemy activity, cyber-security intrusion detection, credit card fraud detection, insurance or health care fraud detection, and safety essential system malfunction detection. Different sources of anomalies are Intrusion Detection Systems, Fraud detection and Data leakage. Anomaly detection is used in variety of areas in IOT domains such as smart cities, network security, Industries etc. [1], [2].

Anomaly detection is the process of identifying odd or surprising patterns in a time series. This task is difficult because time series data contains complex and frequently nonlinear relationships. Anomaly detection searches a time series for strange or unexpected patterns. Anomalies may indicate events or problems that need to be addressed, like fraud, malfunctioning machinery, or health risks. A critical problem with wide-ranging implications is time series anomaly identification in sectors such as banking, security, and healthcare [3], [4]. The fields of statistics, signal processing, and machine learning (ML) have given anomaly detection a lot of attention. Developing anomaly detection techniques for Deep Learning applications has gained a lot of attention lately [5], [6]. The challenge of anomaly detection has emerged as a well-known, quickly evolving area of data analysis [7]. The economy and well-being of millions of people in many nations, including India, depend heavily on rainfall. Because of this, either too much or too little rainfall can have a important effect, particularly if it happens regularly across an area namely a reservoir or watershed. Thus, it is essential to detect such spatiotemporally prolonged instances of either insufficient or excessive rainfall in both actual historical data and climate model predictions of future events. In our study, these events are called "anomalies".

Finding abnormalities with a vast spatiotemporal extent is crucial since they could be more consequential. Because it enables us to ascertain if some regions received roughly rainfall in a specific year, identifying these rainfall anomalies is essential for monitoring floods and droughts in India and other locations. Any technique for spotting these anomalies should be versatile enough to work at any time scale of interest, including "extreme rainfall events," which are distinct anomalies that are localized in place and time but depart greatly from the mean value [8].

Climate change may lead to a rise in the frequency of precipitation extremes in addition to changes in the spatial distribution of rainfall. Scientists use climate models, such as General Circulation Models (GCMs), that replicate global climate parameters like rainfall, to comprehend these changes. Due to the massive and increasing number of data and simulation results, such analysis cannot be performed manually; therefore, automated processes are needed. In data science, anomaly detection in general and spatiotemporal anomaly detection in particular are regarded as crucial fields of research [9].

Depending on how the rainfall volume deviates from the long-term average, anomalies can be either positive or negative. What defines a "anomaly," however, is a design-specific variance. The most straightforward method of detecting anomalies is based on a predetermined threshold; years that significantly deviate from the average could be identified by estimating the mean and variation of each grid location's yearly mean rainfall time series. However, this method does not account for its spatiotemporal neighbors. As a result, this method typically finds anomalies that are incoherent and localized. Large-scale spatiotemporal data have received a lot of interest lately. One of the most frequent needs nowadays is the analysis of such vast amounts of multidimensional data, and processing this data is thought to be the most difficult task. [10], [11].

Climate change has caused irregular and extreme rainfall patterns, making accurate rainfall anomaly detection a major research challenge. Traditional statistical models such as ARIMA face limitations in handling nonlinear and seasonal variations in rainfall data. Therefore, there is a need for intelligent AI-based frameworks that can efficiently analyze large-scale spatiotemporal climate data and improve anomaly prediction accuracy for disaster management and climate monitoring applications.

There are sections to this study. We examine the relevant works that are available in the literature in Section II. The issue formulation and description of the Z-score-based anomaly detection methods are provided in Section III. Results are discussed in Section IV. The performance of the SARIMA model is also shown in Section V, along with a relative comparison of the ARIMA model with other time series models. In Section VI, conclusions were finally discussed.

2.Background Study

A summary of anomaly detection strategies for various application domains has been outlined in this section.

Zhenlong Li, Das, M. et.al in [7] [14] have shown how the suggested indexing strategy could be used to real-world climate research and implemented an initial application to examine temperature anomalies on a NASA Goddard Space Flight Center (GSFC) Hadoop cluster. Conventional methods for identifying climate anomalies often compute and cache different mean values (e.g., monthly and annual means) for specific spatial regions, such as the globe or the northern and southern hemispheres, and then conduct investigations based on these aggregated figures. Because a user-defined, arbitrary spatial zone is not supported, this is not adaptable. The suggested indexing strategy addresses this by allowing us to: 1) apply different data analysis techniques (such as anomaly detection) directly on the original, raw data set while providing a timely response; and 2) use flexible spatiotemporal queries to subset and concentrate on the region of interest in the data set.

In order to differentiate among wet and dry state for sewage I/I analysis, Jingyu Ge et al. created a new technique based on sewer data in [9]. Apart from conventional methods that mostly depend on external information, this methodology makes help of the concept of time series anomaly detection, which is free of other data sources like rainfall. The method's adaptability goes beyond flow data to encompass the utilization of different in-sewer measurements. The approach greatly improves the precision and accuracy of assessing wet/dry conditions, according to simulation studies. By eliminating the substantial pre-processing and pre-analysis that traditional approaches usually require, it facilitates the procedure. This enhancement avoids the need for parameter modifications based on geography or other environmental factors, making the diagnostic procedure more straightforward and applicable. Additionally, the method works well for reducing I/I brought on by a variety of non-rainfall sources, such as snowmelt and ocean tides. The method greatly improves the quantitative analysis of I/I, according to empirical data.

In [15], Adway Mitra and Ashwin K. Seshadri presented a coherent anomaly detection technique based on Markov Random Fields (MRFs), in which every node is linked to a place and a year. This restriction was established to find related components when anomalies are extended over a certain spatiotemporal size, emphasizing coherence, which is an intrinsic aspect of rainfall. However, because the method is adaptable enough to detect anomalies with a vast range of spatial and temporal scales, it is not limited to detecting huge anomalies. The approach can be modified to highlight both coherence and spatial extent in applications where a wider scale is relevant, such as droughts over a river basin or food-producing region. Although anomalies are particularly intrinsic because they are discovered by an analyst-selected strategy, the general characteristic of coherence is not specific to anomalies found using this way; it is also evoked by anomaly detection techniques like wavelets. The another merit of the suggested method is that it fails to favor any one size or shape. In this way, MRFs provide a way to deal with the heterogeneity and anisotropy that arise in anomaly occurrences, whereas more conventional techniques like wavelets might be imitated by specific size or shape assumptions. After testing the method on artificially created anomalies, the authors demonstrated that, for a range of anomaly statistics, the MRF-based approach outperforms location-wise thresholding-based solutions on a number of measures. All things considered, this analysis reveals on the variations in rainfall across the Indian subcontinent. The findings also make one wonder if the anomalies identified using this method are pertinent to the analysis of hydrological floods and droughts, which are based on taking into account a numerous factors, including soil moisture. Inferring anomalous states on the basis of addition of more meteorological and hydrological data would be a logical progression of this work. This technique may also be employed to other datasets for anomaly detection. For instance, the method is being used to detect heat waves that span many days and cover wide areas using a dataset of daily maximum temperatures. Here, node potentials are used to give preference to positive anomalies over negative ones.

A new method for identifying and characterizing anomalies in spatial time series data was published by Hesam Izakian et al. in [16]. It has been proposed that a sliding window of constant length can produce a set of spatiotemporal subsequences in successive time steps. The essential system that exists within each time window is then revealed using a spatiotemporal clustering technique. An anomaly score has been calculated on the basis of historical performance of each individual subsequence within each time window. The estimated anomaly scores are then combined to assign an anomaly score to each cluster within each time window.

A gradient-based technique for generating a fuzzy linkage among any two successively revealed structures has been presented to examine the nature of clusters and the spread of anomalies over time evolution. The Alberta temperature dataset, an outbreak scenario simulated over a number of farm stations in the province of Alberta using NAADSM, and an instructional synthetic dataset are adapted illustrate the method. The authors have shown that the presented technique aids in identify and characterize incident abnormalities in a clear and user-friendly way by offering significant support for the visualization and comprehension of the disclosed structures.

A method for forecasting river water levels and spotting abnormalities using the multivariate Gaussian distribution methodology and the Conv-GRU model was introduced by SCOTT MIAU et al. in [17]. In this potent time series prediction model, the long-term dependent features in a time series were learned using the GRU model, while CNN was utilized to extract features from the time series data. The data sets from the water level stations were utilized to forecast water levels using the CNN and GRU model. Lastly, the probability of anomalous water level behaviour was evaluated by modelling the resulting prediction error as a multivariate Gaussian distribution. The experiment first tested several deep learning-based models (ANN, CNN, LSTM, Seq2seq, and Conv-GRU) to predict water level. To get the same benchmark comparison, the authors looked at every model and found the best network parameter configuration. The results of the experiment showed that Conv-GRU performed better for water level prediction on several performance metrics, such as RMSE, MAE, and MAPE, than competing deep learning methods including ANN, CNN, LSTM, and Seq2seq. Conv-GRU networks were shown to be capable of learning more intricate temporal patterns with ambiguous pattern durations.

Conv-GRU networks might also be able to detect anomalies and replicate normal time series behaviour. The proposed Conv-GRU combined Gaussian statistical anomaly detection technique performed well when applied to real-world datasets involving both short-term and long-term temporal dependence modelling, especially when it was not immediately clear whether the normal behaviour involved the long-term dependence. In the future, evolutionary algorithms may be used to improve the performance of the Conv-GRU model and the river water level forecast model. To support the model being given, more river level forecast data sets could be collected. The forecast and anomaly analysis system's use in river level stations may eventually be extended to other parts of Taiwan, especially the central and southern regions, where major disasters frequently occur during the typhoon season (July–September), in order to develop disaster prevention plans and reduce casualties.

The authors Dániel László Vajda1 et.al in[18] have presented a novel anomaly detection method, AnDePeD, capable of dealing with periodic data patterns and its improved version, AnDePeD Pro. They have demonstrated that the performance of suggested methods is enhanced by eliminating intrinsic mode time series from the scaled original data. When they tested the real-time pre-processing technique on seven periodic datasets corresponding to the use case of server farm telemetry, they found that AnDePeD Pro fared second among modern, well-known detectors. Because AnDePeD Pro not only performed among the best but also took first place in detection delay, indicating anomalies the fastest of all examined techniques, the initialisation delay and detection delay tests validate that it is the best detector tested. Although it wasn't the fastest, it ranked second among the best initialisation techniques. The anomaly detectors AnDePeD and AnDePeD Pro provide a suitable solution for real-time anomaly identification in the server farm telemetry domain. Other real-time scenarios can potentially make use of the proposed methods.

The authors C. Catalano et. al in [20] carried out work on anomaly detection systems so as to rise the security level of smart agriculture systems. Developing the initial anomaly detection prototype was the aim of the project. In order to achieve this, a machine-learning algorithmic architecture was created. To get the most out of MLR and LSTM, two different machine learning algorithms, they could be merged. In contrast to MLR, the results generated using LSTM networks on the experiment dataset are quite near to the observed data. It was feasible to find anomalies and confirm the necessity of an anomaly detection system in this specific domain based on the experiments that were carried out. The choice of a suitable threshold depending on the particular issue at hand also reflects the main component of the work. The conclusions are based on information gathered from a smart agriculture system provided by Apphia srl over a four-month period. To improve ML approach training and find more anomalies, a bigger dataset would surely be beneficial. It might need additional information to uncover hidden patterns. This work looked at three sensors, however anomaly detection can be used with other sensors as well. This system will be able to intervene before the system completely fails by monitoring the health of the sensors and identifying anomalies. Smart cities, smart grids, smart health, and smart fabric ecosystems can all benefit from the architecture created for anomaly detection in smart agriculture systems.

Research Gap

- Existing rainfall anomaly detection methods primarily focus on either anomaly detection or rainfall forecasting, with limited integration of both techniques into a unified analytical framework.
- Many existing approaches employ computationally intensive deep learning models that require large training datasets and high computational resources, limiting their practical applicability for large-scale climate data analysis.
- Most studies have evaluated anomaly detection models independently, with limited comparative analysis of conventional time-series models such as **AR, ARMA, ARIMA, and SARIMA** using standard performance metrics.
- Existing research provides limited investigation of long-term rainfall anomaly detection using **large-scale NCEP reanalysis datasets** for regional climate analysis, particularly for the **Bengaluru region**.
- Several anomaly detection techniques focus primarily on prediction accuracy but provide limited interpretability for identifying positive and negative rainfall anomalies over different temporal scales.

There is a need for a computationally efficient and interpretable framework capable of detecting rainfall anomalies while simultaneously evaluating forecasting performance for climate monitoring and disaster management applications.

3. Proposed Methodology

Finding outliers—abnormal patterns—in a dataset is the aim of anomaly detection. These patterns do not "fit" the dataset because they differ from the data's expected behavior. Finding trends in variables over time, such as changes in temperature and precipitation, is essential to climate research. To investigate precipitation anomalies, we set up a test application in a Google Colab environment. The study's geographic area was the 5 GB of NCEP (National Centre for Environmental Prediction) data. With a daily (24-hour) resolution and a geographic resolution of 77° longitude by 12° latitude, the time period spans 15 years, from 2010 to 2024.The z-score for each month (January through December) is calculated using Formula 1.

$$z_{ij} = \frac{x_{ij} - u_j}{s_i},$$

$$i \in [1,12], j \in [1,15] \quad (1)$$

where x_{ij} represents the mean temperature for month i and year j. u_j represents the month's mean temperature over a 15-year period and s_i represents the month's standard deviation.

The Z-score anomaly detection algorithm is used to identify anomalies in precipitation datasets. Z-score anomaly detection is one statistical method for identifying outliers in a dataset. Historical data can help identify anomalous weather patterns in the context of weather anomaly detection. The anomaly detection process is as shown in the figure 1. The following is an implementation of the Z-score anomaly detection algorithm for weather data:

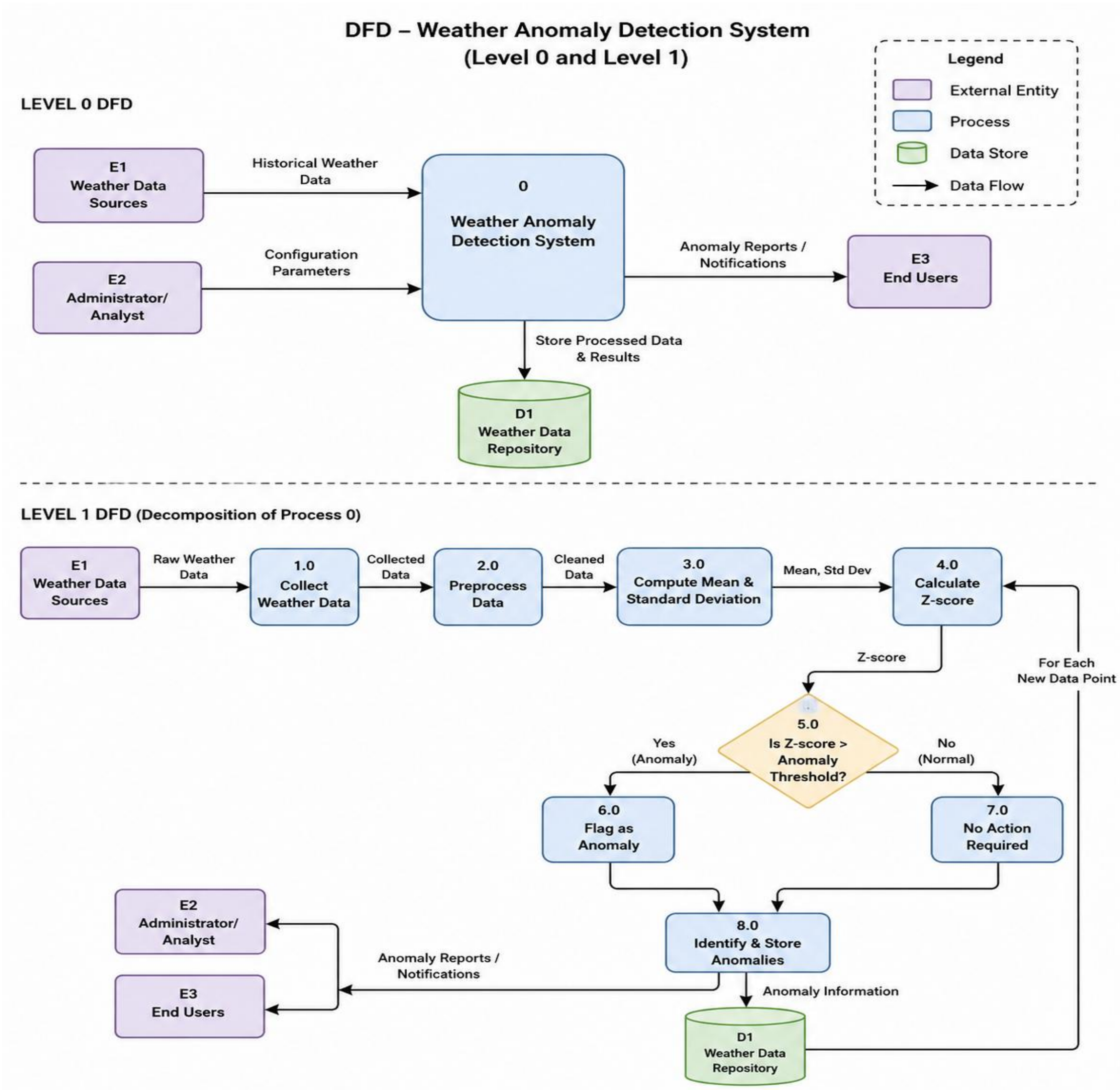

Figure 1: Intelligent Rainfall Anomaly Detection Workflow

Steps for Z-Score Anomaly Detection is as follows

1. To acquire historical weather data such as precipitation and temperature of Bangalore region from the year 2010-2024.

2. Calculate the Mean and Standard Deviation:For each weather parameter, calculate the mean (average) and standard deviation of the historical data.

3. For each new data point, estimate the Z-score using the formula:

$$Z = (X - \mu) / \sigma$$

Where: X = observed rainfall value, μ = mean rainfall

σ = standard deviation

Higher $|Z|$ values indicate anomalies

4. Set a Threshold:

Define a threshold for the Z-score. Common thresholds are 2 or 3. If the absolute value of the Z-score is greater than the threshold, the data point can be considered an anomaly

5. Identify Anomalies:

Flag the data points that exceed the threshold as anomalies.

4. Results and Discussion

This application was used to analyze the 5 GB of data and it took only 32 seconds to calculate all of the mean values and identify the precipitation anomalies for each month. Table 1 shows the anomalies in June month precipitation during the last 15 years. Figure. 2 displays the relevant plot. A negative (positive) z-score value denotes an excess or shortfall in rainfall for that year. There have been instances of excessive rainfall in 2013, 2016, 2019, 2022, and 2024. In contrast, there was a rainfall deficit in 2012, 2014, 2017, 2018, and 2023. Compared to the last graph, this one displays a far more balanced image, with June showing both excess and deficit rainfall periods.

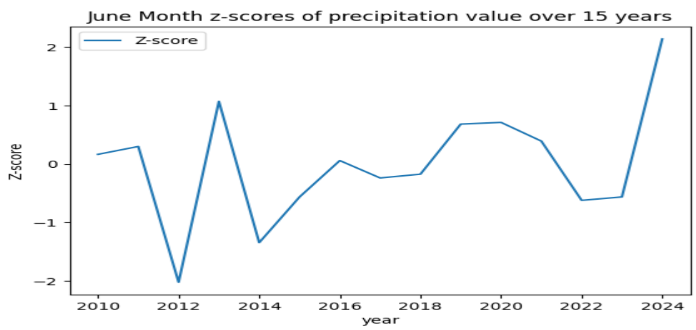

Figure 2. Z-scores for precipitation in June over a 15-year period

Table 1. Anomalies in June precipitation from 2010 to 2024

Year	z-score (Anomaly)
2010	0.16613
2011	0.30071
2012	-2.02353
2013	1.07203
2014	-1.34512
2015	-0.56396
2016	0.05930
2017	-0.23814
2018	-0.17342

2019	0.68345
2020	0.71270
2021	0.39265
2022	0.71270
2023	-0.56307
2024	2.14187

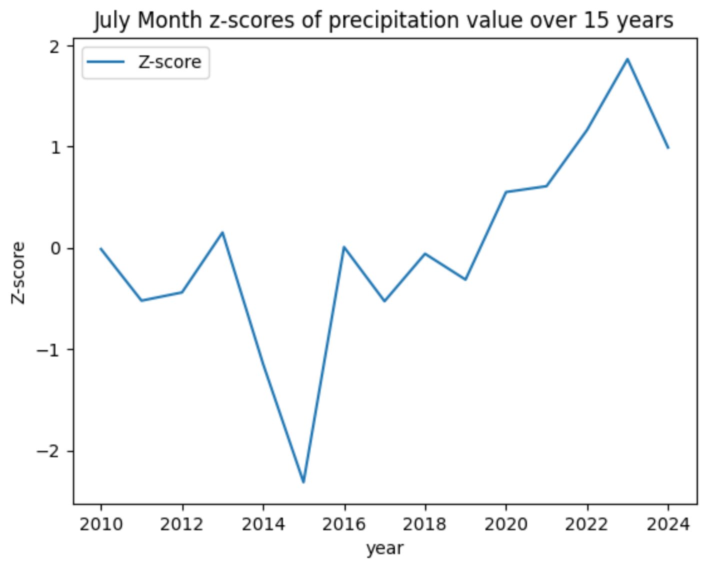

Figure 3. Z-scores for precipitation in July over a 15-year period

Table 2 displays the precipitation anomaly for the month of July from 2010 to 2024, and Fig. 3 displays the related plot. Excessive rainfall was recorded in 2013, 2015, 2019, 2020, 2021, 2022, 2023, and 2024. In contrast, the deficit years were 2010, 2011, 2012, 2014, 2016, and 2018. This graph displays a distinct rising trend in July rainfall over the past 15 years, interspersed with periods of excess and shortage. A change in regional climate patterns may be indicated by this trend.

Table 2. Anomalies in July precipitation from 2010 to 2024

Year	**z-score(Anomaly)**
2010	-0.01234
2011	-0.52144
2012	-0.44019
2013	0.15116
2014	-1.14401
2015	-2.31340

2016	0.00759
2017	-0.52720
2018	-0.05867
2019	-0.31384
2020	0.55014
2021	0.60805
2022	1.16267
2023	1.86223
2024	0.98926

5.Comparison of ARIMA with Various Time Series Model

Rainfall data from the year 2010 to 2024 of Bangalore region was also trained using various time series models such as Autoregression (AR), Autoregression Moving Averages (ARMA) and Support Vector Machine (SVM). The metrics used for comparing ARIMA with these models are Mean Absolute Error(MAE) and RMSE(Root Mean Square Error).Comparision of the same is given in table below.

Table 3. Comparison of ARIMA with AR, ARMA and SVM models

	MODEL NAME				
		ARIMA	**AR**	**ARMA**	**SVM**
Evaluation metrics	**MAE**	6.35	19.54	21.36	8.57
	RMSE	7.32	20.45	22.49	10.82

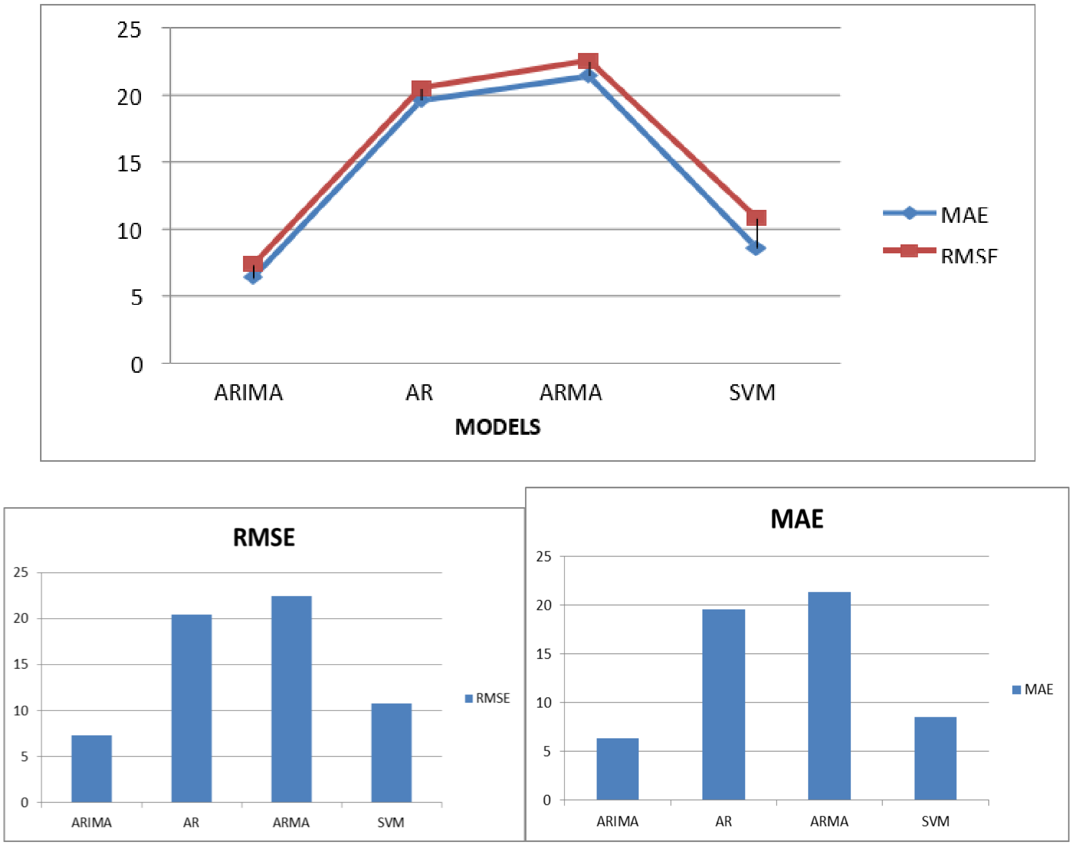

Fig 4(a-c): RMSE and MAE of ARIMA, AR, ARMA and SVM models

Recently comparison has been done with Seasonal ARIMA (SARIMA) and it shows that the accuracy in the prediction at a city scale using SARIMA outperforms the result obtained by ARIMA and other traditional statistical methods and dynamical model simulations. Results of the same is shown below.

```
RMSE for rainfall prediction: 3.45
3.452445264978084
```

(a)

```
sarima=SARIMAX(data['pr_wtr'],order=(1,0,1),seasonal_order=(1,0,1,12))
predicted=sarima.fit().predict();predicted
```

```
0        0.000000
1       32.538504
2       25.494328
3       28.407982
4       25.174698
          ...
3647    39.224797
3648    34.231168
3649    26.920711
3650    29.410031
3651    29.007457
```

(b)

```
resid=data['pr_wtr']-predicted;resid
mae=abs(resid.mean());mae
```

```
0.13112698000186787
```

(c)

Figure.5(a-c): SARIMA results

The above results state that SARIMA performs well when compared to ARIMA and other statistical models. SARIMA's MAE and RMSE are determined to be 0.13112 and 3.4524, respectively. When compared to ARIMA, these evaluation metrics were found to be good. The ARIMA model's limitations include the requirement that the input data contain at least 50 observations and considering that the ARIMA method is only appropriate for time series that are stationary. The ARIMA models are usually costly because of their large data requirements, the absence of updating procedures, and the requirement that they be estimated using nonlinear estimation procedures. Additionally, it is assumed that the estimated parameters' values remain constant over the course of the series

5. Conclusion

Anomaly detection has been used to identify outliers or unusual patterns in spatiotemporal data. For climate research, it is essential to identify patterns in variables over time, such as variations in temperature and precipitation. The 50 GB NCEP dataset served as the source for the study's geographic region. The time period is 15 years, from 2010 to 2024, with a daily (24-hour) resolution. The geographic resolution is 77° longitude by 12° latitude. The Z-score is a crucial metric for identifying anomalies. Variations in precipitation values between 2010 and 2024 have been determined using monthly anomaly detection. Z-score values are recorded that indicate whether the selected area receives enough or too little rainfall.

A negative z-score value indicates a deficiency of precipitation in the selected area. The application calculated all the mean data and identified the precipitation anomalies for each month in just two seconds. The ARIMA model has also been compared in relation to other time series models. We also tested the SARIMA model on our dataset, and it performed better than ARIMA and other time series models.

The current research findings can be extended in the future for different regions for seasonal and temporal analysis, in addition to adding additional input features like humidity, wind speed, etc. for the climatic parameter prediction and utilizing deep learning techniques for increased accuracy. The precision of the model can still be improved by sophisticated statistical models for time series analysis, such as Vector Autoregression (VAR) Models and Vector Autoregression with Exogenous series (VARX). The application of AI/ML to cloud management and climate data analysis must be the primary focus of future research.

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Chandrakala B M	✓		✓	✓			✓			✓	✓		✓	

S Mercy					✓		✓			✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors state no conflict of interest.

Data Availability

The data supporting the findings of this study were obtained from the NCEP (National Center for Environmental Prediction) repository (https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.html).

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