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ARIMA MODEL FOR RAIN FALL PREDICTION

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ABSTRACT

Rainfall prediction is important as heavy rainfall can lead to many disasters. The prediction helps people to take preventive measures and moreover the prediction should be accurate. There are two types of prediction short term rainfall prediction and long-term rainfall. Prediction mostly short-term prediction can give us the accurate result. The main challenge is to build a model for long term rainfall prediction. Heavy precipitation prediction could be a major drawback for earth science department because it is strongly associated with the economy and lifetime of human. It is a cause for natural disasters like flood and drought that square measure encountered by individuals across the world each year. Accuracy of rainfall statement has nice importance for countries like India whose economy is basically dependent on agriculture. The dynamic nature of atmosphere applied mathematics techniques fail to provide sensible accuracy for precipitation statement. The prediction of precipitation using machine learning techniques may use regression. Intention of this project is to offer non-experts' easy access to the techniques, approaches utilized in the sector of precipitation prediction and provide a comparative study among the various machine learning techniques.

Keywords: Rainfall prediction, machine learning, precipitation prediction.

1. INTRODUCTION

As an important part of water resource ecosystem, rainfall plays an important role in the field of hydrology and meteorology. General speaking, rainfall is the results of multi-scale air system interaction, and it is affected by many environmental factors, such as thermal power, flow field, and terrain. These complex physical mechanisms make forecasting rainfall very difficult. Furthermore, rainfall forecasting is closely related to resident life. Especially, short-time heavy rainfall is the main weather element that causes urban water-logging, and can also predict road water accumulation ahead of time. Consequently, due to the complex dynamic changes inside the atmosphere and the real-time requirement of short-term rainfall forecasting, a large-scale and high-precision forecasting model is urgently needed, which poses a big challenge to the field of meteorology and hydrology. Heavy precipitation causes serious losses of life and property, and often triggers natural disasters such as landslides and flash floods. In South Korea, a heavy rain advisory is issued when the expected amount of precipitation is over 70 mm in 6 h or 110 mm in 12 h (Korea Meteorological Administration, 2018).

Supervised learning is a machine learning method of creating a mapping between input and output from given examples. The mapping is used to predict the output of unseen data, and is called a classifier if the output is discrete or a regression function if the output is continuous. To illustrate the difference, consider a rainfall forecast problem. The classifier predicts whether or not it will rain, whereas the regression function predicts the expected amount of precipitation in millimeters. Recently, machine learning techniques have been used to forecast rainfall with the progress in the field of pattern recognition and artificial intelligence. Zhang et. al [1] proposes a novel solution called Dynamic Regional Combined short-term rainfall Forecasting approach (DRCF) using Multi-layer Perceptron (MLP). First, Principal Component Analysis (PCA) is used to reduce the dimension of thirteen physical factors, which serves as the input of MLP. Second, a greedy algorithm is applied to determine the structure of MLP. The surrounding sites are perceived based on the forecasting site. Finally, to solve the clutter interference which is caused by the extension of the perception range, DRCF is enhanced with several dynamic strategies. Experiments are conducted on data from 56 real-world meteorology sites in China, and they compare DRCF with atmospheric models and other machine learning approaches. The experimental results show that DRCF outperforms existing approaches in both threat score (TS) and root mean square error (RMSE).

Pham et. al [2] done the spatial prediction of rainfall-induced landslides at the Pauri Gahwal area, Uttarakhand, India using Aggregating One-Dependence Estimators (AODE) classifier which has not been applied earlier for landslide problems. Historical landslide locations have been collated with a set of influencing factors for landslide spatial analysis. The performance of the AODE model has been assessed using statistical analyzing methods and receiver operating characteristic curve technique. The predictive capability of the AODE model has also been compared with other popular landslide models namely Support Vector Machines (SVM), Radial Basis Function Neural Network (ANN-RBF), Logistic Regression (LR), and Naïve Bayes (NB). The result of analysis illustrates that the AODE model has highest predictability, followed by the SVM model, the ANN-RBF model, the LR model, and the NB model, respectively. Thus, AODE is a promising method for the development of better landslide susceptibility map for proper landslide hazard management. Yaseen et. al [3] proposed a new hybrid model integrated adaptive neuro fuzzy inference system with Firefly Optimization algorithm (ANFIS-FFA), for forecasting monthly rainfall with one-month lead time. The proposed ANFIS-FFA model is compared with standard ANFIS model, achieved using predictor-predictand data from the Pahang River catchment located in the Malaysian Peninsular. To develop the predictive models, a total of fifteen years of data were selected, split into nine years for training and six years for testing the accuracy of the proposed ANFIS-FFA model. To attain optimal models, several input combinations of antecedents' rainfall data were used as predictor variables with sixteen different model combination considered for rainfall prediction. The performances of ANFIS-FFA models were evaluated using five statistical indices: the coefficient of determination (R^2), Nash-Sutcliffe efficiency (*NSE*), Willmott's Index (*WI*), root mean square error (*RMSE*) and mean absolute error (*MAE*). The results attained show that, the ANFIS-FFA model performed better than the standard ANFIS model, with high values of R^2, *NSE* and *WI* and low values of *RMSE* and *MAE*. In test phase, the monthly rainfall predictions using ANFIS-FFA yielded R^2, *NSE* and *WI* of about 0.999, 0.998 and 0.999, respectively, while the *RMSE* and *MAE* values were found to be about 0.272 mm and 0.133 mm, respectively. It was also evident that the performances of the ANFIS-FFA and ANFIS models were very much governed by the input data size where the ANFIS-FFA model resulted in an increase in the value of R^2, *NSE* and *WI* from 0.463, 0.207 and 0.548, using only one antecedent month of data as an input (t-1), to almost 0.999, 0.998 and 0.999, respectively, using five antecedent months of predictor data (t-1, t-2, t-3, t-6, t-12, t-24). We ascertain that the ANFIS-FFA is a prudent modelling approach that could be adopted for the simulation of monthly rainfall in the present study region.

2. LITERATURE SURVEY

Danandeh Mehr et. al [4] approach is adopted to develop a hybrid regression model for 1-month-ahead rainfall forecasting at two rain gauge locations (namely: Tabriz and Urmia stations), in northwest Iran. The approach is based on the integration of support vector regression (SVR) and firefly algorithm (FFA) that results in truthful rainfall forecasts. The proposed hybrid model was trained and validated using weak stationary state of monthly rainfall data obtained from the gauges. The efficiency results of the model were also cross-validated with those of stand-alone SVR- and genetic programming-based forecasting models developed as the benchmarks in this study. For both rain gauge locations, the results showed that the hybrid model significantly outperforms the benchmarks. With respect to the average efficiency results at the gauge locations, the FFA-induced

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improvement in the SVR forecasts was matched by an approximately 30% decrease in root-mean-square error and around 100% increase in Nash–Sutcliffe efficiency. Such a promising accuracy in the proposed model may recommend its application at monthly rainfall forecasting in the present semiarid region.

Binh Thai Pham et. al [5] developed and compared several advanced Artificial Intelligent (AI) models namely Adaptive Network based Fuzzy Inference System optimized with Particle Swarm Optimization (PSOANFIS), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for the prediction of daily rainfall in Hoa Binh province, Vietnam. For this, meteorological variable parameters such as maximum temperature, minimum temperature, wind speed, relative humidity and solar radiation were collected and used as input parameters and daily rainfall as an output parameter in the models. Validation of the developed models was achieved using various quality assessment criteria such as correlation coefficient (R) and Mean Absolute Error (MAE), Skill Score (SS), Probability of Detection (POD), Critical Success Index (CSI), and False Alarm Ratio (FAR). The results showed that all the AI models provided reasonable predictions of daily rainfall but the SVM was found to be the best method for predicting rainfall. This method was also found to be the most robust and efficient prediction model while taking into account of input variability using the Monte Carlo approach. This AI based study would be helpful in quick and accurate prediction of daily rainfall.

Lingling Ni et. al [6] developed two hybrid models, based on long short-term memory network (LSTM), for monthly streamflow and rainfall forecasting. One model, wavelet-LSTM (namely, WLSTM), applied a trous algorithm of wavelet transform to do series decomposition, and the other, convolutional LSTM (namely, CLSTM), coupled convolutional neural network to extract temporal features. Two streamflow datasets and two rainfall datasets are used to evaluate the proposed models. The prediction accuracy of WLSTM and CLSTM was compared with that of multi-layer perceptron (MLP) and LSTM. Results indicated that LSTM was applicable for time series prediction, but WLSTM and CLSTM were superior alternatives.

Seung-Hyun Moon et. al [7] various machine learning techniques were applied to the EWS for heavy rainfall nowcasting. The EWS that uses the logistic regression with selective discretization and PCA was proposed. The selective discretization method selectively discretized input variables that have a nonlinear relationship with the very short-term heavy rainfall, and the PCA reduced the dimensionality of input variables by creating a new coordinate system that provides an informative view of the data.

Yu Xiang et. al [8] proposed a combined model which applied different supervised learning methods for various scales according to their features. Unlike traditional methods to build prediction model that treat all the IMFs identically or ignore the shortest-period component, the proposed model proved to be more accurate in rainfall prediction area.

Manandhar et. al [9] proposed to perform the nowcasting of rainfall in the tropical region. The algorithm applies global positioning system-derived precipitable water vapor (PWV) values and its second derivative for the short-term prediction of rainfall. The proposed algorithm incorporates the seasonal dependency of PWV values for the prediction of a rain event in the coming 5 min based on the past 30 min of PWV data. This proposed algorithm is based on the statistical study of four-year PWV and rainfall data from a station in Singapore and is validated using two-year independent data for the same station. The results show that the algorithm can achieve an average true detection rate and a false alarm rate of 87.7% and 38.6%, respectively. To analyze the applicability of the proposed algorithm, further validations are done using one-year data from one independent station from Singapore and two-year data from one station from Brazil. It is shown that the proposed algorithm performs well for both the independent stations. For the station from Brazil, the average true detection and false alarm rates are around 84.7% and 37%, respectively. All these observations suggest that the proposed algorithm is reliable and works well with a good detection rate.

Shayea et. al [10] conducted to investigate the impact of rain on the propagation of millimeter waves at 26 GHz. The measurements were accomplished using a microwave fifth generation radio link system with 1.3 km path length implemented at Universiti Teknologi Malaysia Johor Bahru, Malaysia. The implemented system consisted of Ericsson CN500 mini-E-link, radio unit, rain gauge, and data logger. The measurements were attained and logged daily for a continuous year, with 1-min time intervals. Next, the MATLAB software was used to process and analyze the annual rain rate and rain attenuation, including for the worst month. From the analyzed results, it was found that at 0.01% percentage of time, the rain rate was 120 mm/hr; while the specific rain attenuation was 26.2 dB/km and the total rain attenuation over 1.3 km was 34 dB. In addition, the statistics acquired from the measurements for the worst month were lower than what was predicted by the international telecommunication union (ITU) model; around 51% and 34% for the rain rate and rain attenuation, respectively. The average percentage of error calculated between the measurements and predicted results for the rain rate and rain attenuation were 143% and 159%, respectively. Thus, it can be concluded that the statistics for the worst month in Malaysia is lower than what was predicted by the ITU model.

Yazid Tikhamarine et. al [11] focused on overcoming the common problem of data-driven models in identifying the internal parameters and the suitable selection for the input–output architecture of the model. Different data-driven models, namely, the least squares support vector machine (LSSVM) and multilayer perceptron (MLP), integrated with advanced optimization algorithms, such as particle swarm optimization (PSO) and Harris hawks optimization (HHO), were introduced.

Sulaiman et. al [12] applied an Artificial Neural Network (ANN) for prediction of heavy precipitation on monthly basis. For this purpose, precipitation data from 1965 to 2015 from local meteorological stations were collected and used in the study. Different combinations of past precipitation values were produced as forecasting inputs to evaluate the effectiveness of ANN approximation. The performance of the ANN model is compared to statistical technique called Auto Regression Integrated Moving Average (ARIMA). The performance of each approach is evaluated using root mean square error (RMSE) and correlation coefficient (R2). The results indicate that ANN model is reliable in anticipating above the risky level of heavy precipitation events.

Wang et. al [13] presented an initial investigation of a rainfall-induced slope failure with coupled MPM. The method has been able to simulate the slope failure from initiation through to the post-failure processes. A long slope on an inclined base has been analysed, and it has been shown that rainfall-induced failure may be characterised by a series of mainly superficial failures, as are often observed in practice.

Brunetti et. al [14] compared different satellite rainfall products to address the following question: how far are we from the use of satellite rainfall products in landslide forecasting? For the purpose, we developed a specific procedure that simulates the use of satellite (and observed) rainfall data in a hypothetical landslide warning system. Based on this procedure, we are able to infer the potential of the satellite rainfall products in predicting landslides occurrence.

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3. PROPOSED SYSTEM

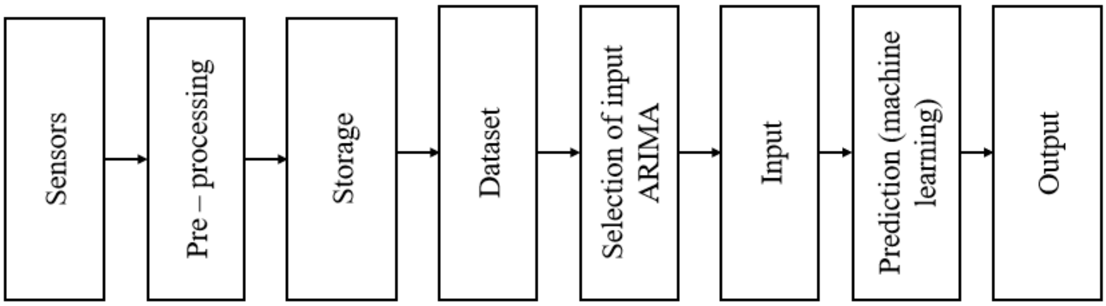

Fig. 1: Block diagram of proposed system.

WHAT IS TIME SERIES ANALYSIS?

What Is a Time Series?

A sequence of data points organized in time order.

- The sequence captures data at equally spaced points in time.
- Data collected irregularly is not considered a time series.

Time-series data is common across many industries.

- Finance: stock prices, asset prices, macroeconomic factors
- E-Commerce: page views, new users, searches
- Business: transactions, revenue, inventory levels

Time-series methods are used to do the following:

- Understand the generative process underlying the observed data.
- Fit a model in order to monitor or forecast a process.

Applications of Time Series

Time-series analysis is used in the following:

- Economic forecasting
- Stock-market analysis
- Demand planning and forecasting
- Anomaly detection

A time series has three components:

- Trend – long-term direction
- Seasonality – periodic behavior
- Residual – irregular fluctuations

Trend

Trend captures the general direction of the time series.

- For example, increasing job growth year over year despite seasonal fluctuations.

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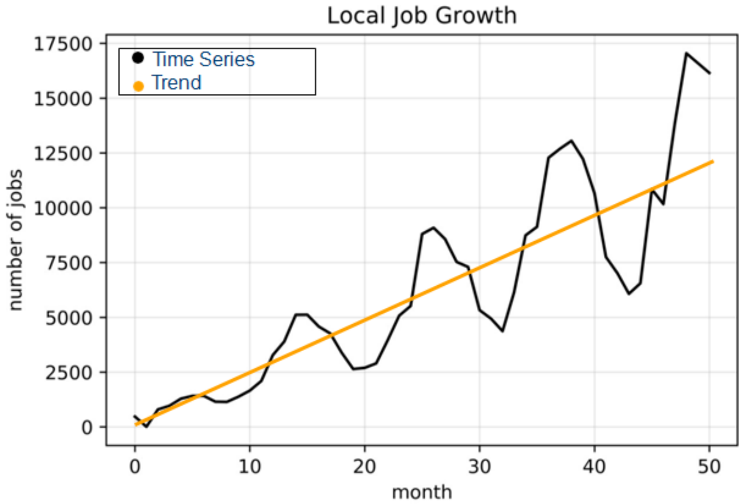
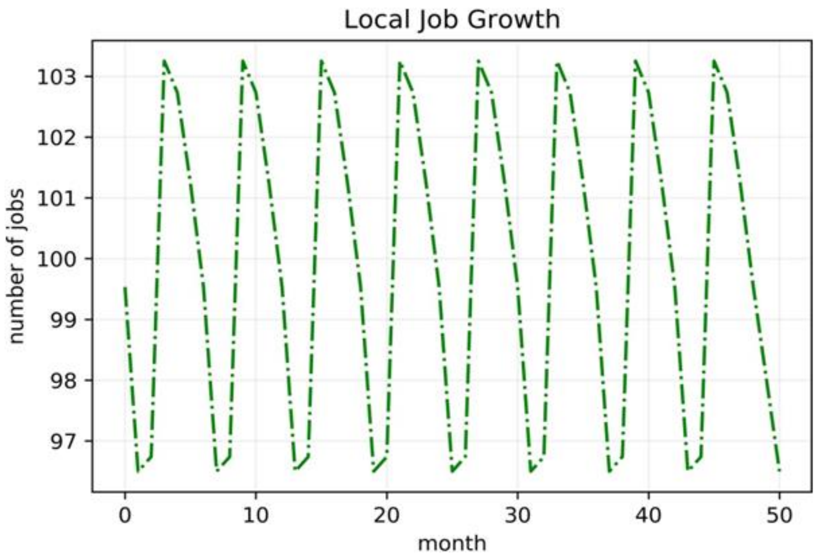
- Trend can be increasing, decreasing, or constant.
- It can increase or decrease in different ways (linearly, exponentially, or in other ways).



Seasonality

Seasonality captures effects that occur with specific frequency. It can be drive by many factors.

- Naturally occurring events, such as weather fluctuations caused by time of year.
- Business or administrative procedures, such as start and end of a school year.
- Social or cultural behavior, such as holidays or religious observances.
- Fluctuations due to calendar events, such as the number of Mondays per month for trading or holidays that shift from year to year (Easter, Chinese New Year).



Residuals

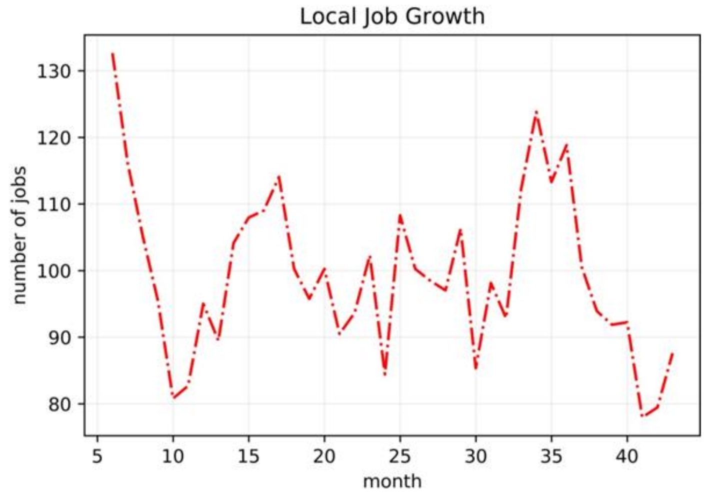
Residuals are the random fluctuations left over after trend and seasonality are removed.

- They are what is left over after trend and seasonality are removed from the original time series.

– You should not see a trend or seasonal pattern in the residual.

- They represent short-term fluctuations.

- They're either random or a portion of the trend or seasonality components was missed in the decomposition.



Decomposition Models

Time-series components can be decomposed with the following models:

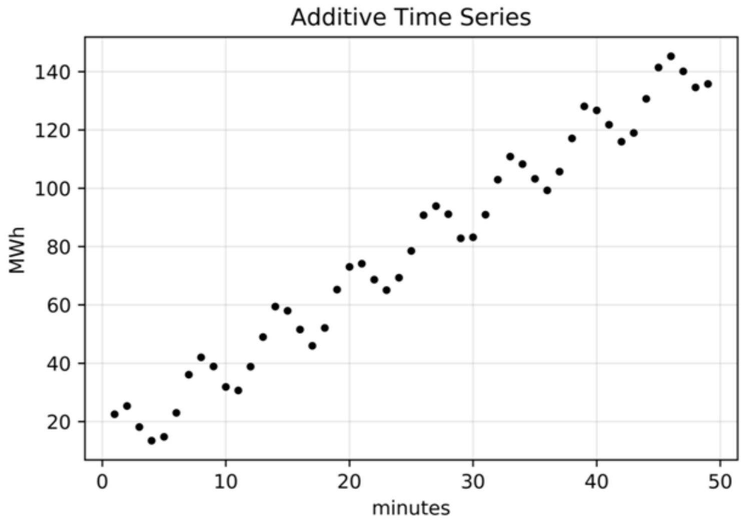
- Additive decomposition
- Multiplicative decomposition

Additive Model

Additive models assume that the observed time series is the sum of its components.

Observation = Trend + Seasonality + Residual

Additive models are used when the magnitudes of the seasonal and residual values are independent of trend.



Multiplicative Model

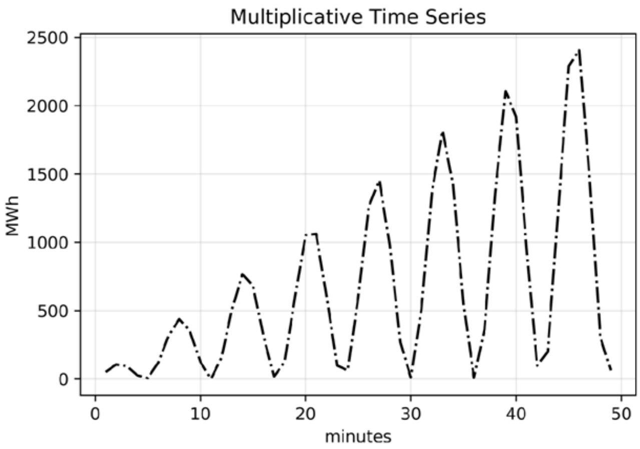
The observed time-series multiplicative models assume that the observed time series is the product of its components.

Observation = Trend * Seasonality * Residual

It is possible to transform a multiplicative model to an additive by applying a log transformation.

– log (Time*Seasonality*Residual) = log (Time) + log (Seasonality) + log (Residual)

Multiplicative models are used when the magnitudes of the seasonal and residual values fluctuate with trend.



How to Decompose a Time Series

Of the many ways to decompose a time series, these are the most common:

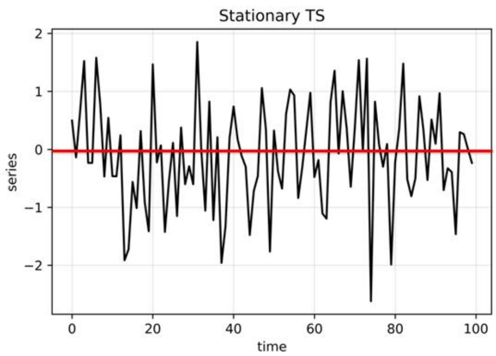
- Single, double, or triple exponential smoothing
- Locally estimated scatterplot smoothing (LOESS)
- Frequency-based methods common in signal processing
- More on these methods in future lessons!

What Is Stationarity?

A stationary time series is a time series where there are no changes in the underlying system.

- Constant mean (no trend)
- Constant variance (no heteroscedasticity)
- Constant autocorrelation structure
- No periodic component (no seasonality)

Assumption 1: Constant Mean



Assumption 2: Constant Variance

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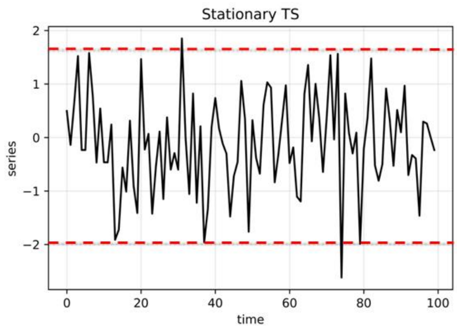
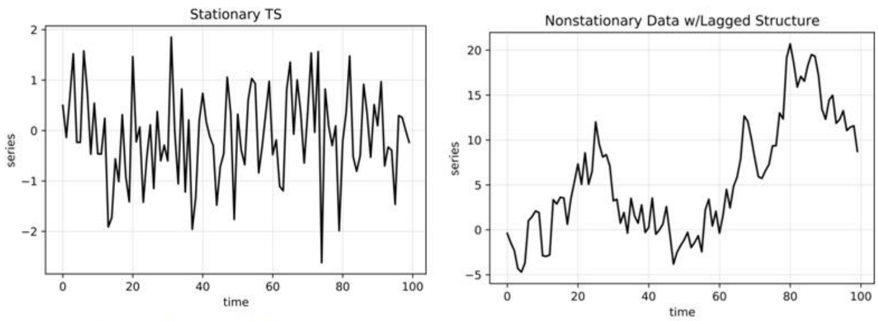


Autocorrelation

Autocorrelation is a key concept in time-series analysis.

- Autocorrelation is the correlation between a measurement at two different times.
- The time interval between values is called the lag.
- For example, stock prices may be correlated from one day to the next with a lag value of 1.
- Autocorrelation often results in a pattern, whereas a time series without autocorrelation will exhibit randomness.



No autocorrelation Has autocorrelation

Why Is Stationarity Important?

Stationarity is a fundamental assumption in many time-series forecasting models:

- Without it many basic time-series models would break down.
- Transformations can be applied to convert a nonstationary time series to a stationary one before modeling.
- While there are more advanced time-series models that can handle nonstationary data, that is beyond the scope of this lesson.

How to Identify Nonstationary Time-Series Data

There are several ways to identify nonstationary time-series data:

- Summary statistics
- Augmented Dickey-Fuller test

Summary Statistics

Calculating the mean and variance over time is a useful way to discern whether the series is stationary.

- A simple but effective way to do this is to split your data into chunks over time and compute statistics for each chunk.

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- Large deviations in either the mean or the variance among chunks are problematic and mean that your data is nonstationary.

Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller test is a hypothesis test that tests specifically for stationarity.

- We generally say that the series is nonstationary if the p-value is less than 0.05.
- It is a less appropriate test to use with small datasets or when heteroscedasticity is present.
- It is best to pair ADF with other techniques, such as run-sequence plots, summary statistics, or histograms.

How to Transform Nonstationary Time-Series Data

There are several ways to transform nonstationary time-series data:

- Remove trend (constant mean)
- Remove heteroscedasticity with log (constant variance)
- Remove autocorrelation with differencing (exploit constant structure)
- Remove seasonality (no periodic component)
- Oftentimes you'll have to do several of these on one dataset!

Moving Average

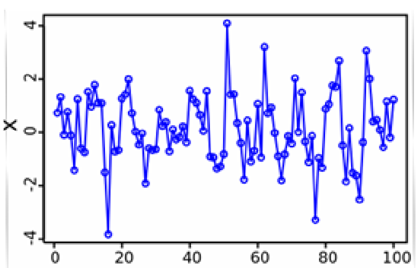
There is another technique called moving average that has greater sensitivity towards local changes in the data.

Moving average comes in two flavors:

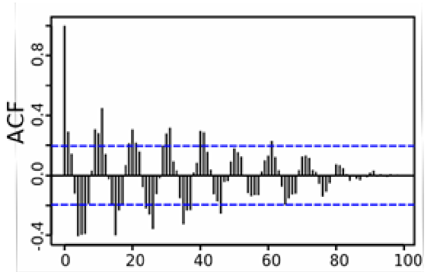
- Equally weighted
- Exponentially weighted

Autocorrelation Function (ACF)

- Measures the correlation of a signal with a delayed copy of itself.
- It is used to find repeating patterns in a signal, such as the presence of a periodic signal. Autocorrelation Function (ACF)



Observed Data



ACF Plot

Partial Autocorrelation Function

The partial autocorrelation at lag k is the autocorrelation between Xt and Xt-k that is not accounted for by lags 1 through k-1

where Pt, k(x) denotes the projection of x onto the space spanning xt+1, …. xt+k-1

Autoregressive Models (AR)

- A common approach to model univariate time series is to use autoregressive models (AR).
- An AR model is a linear regression of the current value of the series against one or more prior values of the series.
- Uses maximum likelihood estimators to determine coefficients instead of least squares.

Moving Average Models (MA)

- Another common approach to modeling univariate time series is the moving average (MA) model.
- MA models are conceptually a linear regression of the current value of the series against the white noise of one or more of the previous values of the series.
- The noise at each point is assumed to come from a normal distribution with mean 0 and constant variance.

ARIMA Model Details

There are a few things you should know about ARIMA models:

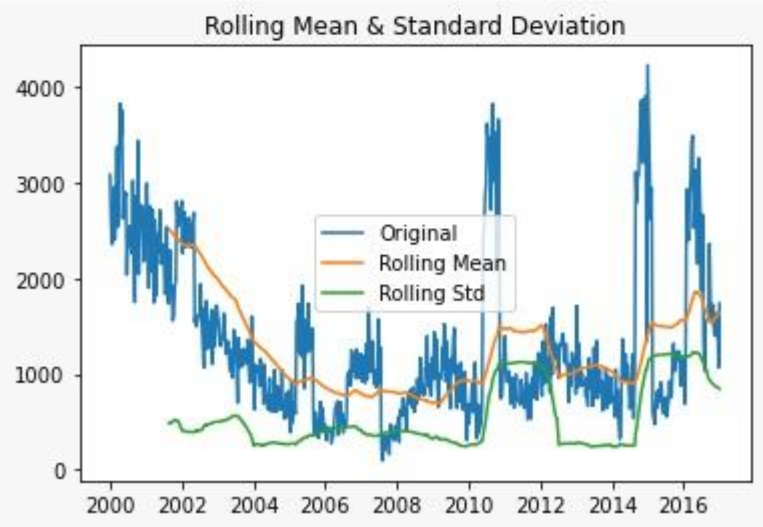
- The ARIMA model is denoted ARIMA (p, d, q).
- p is the order of the AR model.
- d is the number of times to difference the data.
- q is the order of the MA model.
- p, d, and q are nonnegative integers.

SARIMA Model

SARIMA is short for seasonal ARIMA. This model is used to remove seasonal components.

- The SARIMA model is denoted SARIMA (p, d, q)(P, D, Q).
- P, D, and Q represent the same as p, d, and q but they are applied across a season (for example, yearly).

4. RESULTS AND DISCUSSION



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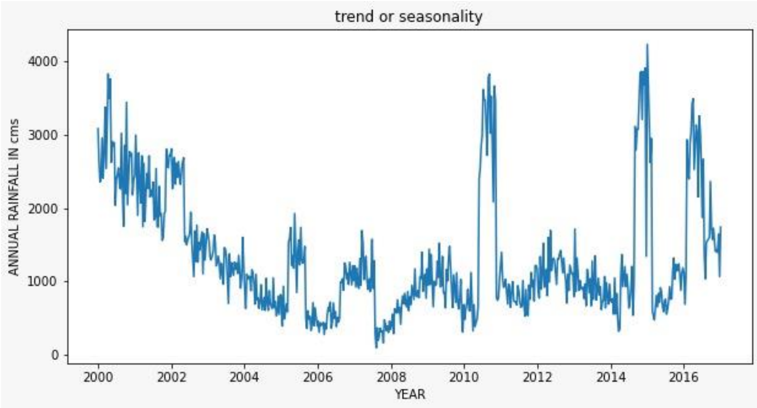

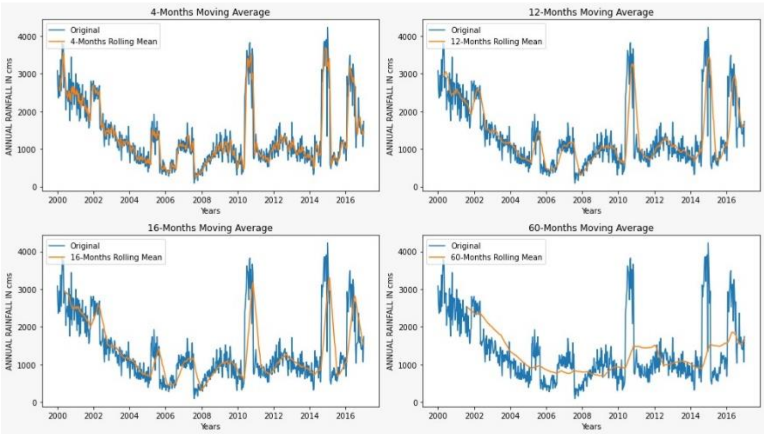

5. CONCLUSION

Precipitation and temperature are the main factors governing the dynamic structure of climate resulting in climate change. In the present study, precipitation and temperature data time series were studied and best ARIMA model is found after the removal of seasonality, and forecasting was done using the same model. The forecast results for precipitation are found to be overpredicting the values for extreme rainfall events, while it matches in case of other rainfall events. The data used is from the year 1901–2007 (107 years). The seasonal ARIMA (SARIMA) model was used, and forecasting was done for next 20 years (2001–2020). The auto-regressive (p) integrated (d) moving average (q) (ARIMA) model is based on Box Jenkins approach which forecasts the future trends by making the data stationary and removing the seasonality

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