JJEES

JJEES (2025) 16 (1): 83-95
ISSN 1995-6681

Jordan Journal of Earth and Environmental Sciences

Time-Series Analysis for Forecasting Climate Parameters of Kashmir Valley Using ARIMA and Seasonal ARIMA Model

Khalid Hussain[1], Fahad Farooq J.[1], Mir Salim N.[1], Sheikh Umar Farooq[2], and Insha Altaf[1]

1Department of Computer Science and Engineering, University of Kashmir, North Campus, Delina, Baramulla, India
2Department of Computer Science, University of Kashmir, North Campus, Delina, Baramulla, India

Recieved on 28 December 2023, Accepted on 31 December 2024

Abstract

The Kashmir Valley, a sensitive ecological zone within the Indian Himalayan Region (IHR), demands urgent attention regarding climate change. Home to multiple rivers and glaciers, the region holds significant geopolitical and economic importance. This work presents an analysis of three major climate variables—precipitation, cloud cover, and temperature—in the Kashmir Valley by leveraging the CRU TS4.04 time series data from 1901 to 2021, thereby revealing some key and concerning trends. Further, this study aims to predict the future trends of these variables for the next 80 years (2020–2100) utilizing ARIMA and SARIMA models. The projections show a significant increase of approximately 2.0ºC in the mean temperature, compared to 2019 levels by the end of the 21st century. The projections also point to a substantial reduction in the frequency of winter months experiencing mean temperatures below 2.0ºC, potentially ceasing altogether by 2048, which could have devastating consequences for the region's ecosystem. The insights, gathered in this study, may serve as a presage for the concerned government and stakeholders and will pave the way for the development of robust and efficient plans to tackle climate change in the area. The findings also shed light on the limitations of the ARIMA model, particularly its inability to forecast erratic changes in climate variables, thereby emphasizing the need for more sophisticated approaches to capture the complexities inherent in regional climate systems.

Keywords: *ARIMA; Climate; Kashmir Valley; Analysis; Time-series Forecasting; Weather.*

1. Introduction

Climate change is a pervasive phenomenon, manifesting as prolonged alterations in diverse climate variables, notably temperature and precipitation, within a given region. The scope of the investigation may encompass a localized area or extend to dimensions as vast as a continent or the entire globe. Rigorous studies, dedicated to comprehending climate change, typically involve meticulous analyses of fluctuations in various climatic parameters, aiming to gauge the magnitude of alterations occurring within the specified region over defined periods. The climate time-series data can have trends (long-term changes in the data) and seasonality (changes and variations in the data that occur regularly at short intervals). Accurate predictions and estimations of the impending alterations in a region are indispensable for effective planning and management of natural disasters such as floods, droughts, and extreme temperature events. Recognizing the gravity of climate change, the United Nations Organization (UNO) underscores its significance, calling it a "defining issue of our time" and the present era as a "defining moment" (Nations Organization United, 2021), emphasizing the urgency for immediate global actions to analyze, prevent, and address climate change in diverse regions. A 2007 Intergovernmental Panel for Climate Change (IPCC) report by UNO highlights the potential damages associated with a 2.0ºC rise in global temperatures (IPCC, 2007). However, recent findings from a special report on global warming caution that adverse impacts may occur even with a 1.5ºC increase (IPCC, 2022). The IPCC's 2021 report amplifies concerns, branding the current global climate scenario as "code red for humanity" (IPCC, 2021). The dire consequences of climate inaction are expounded in the IPCC's Assessment Report-6 of the year 2023, which underscores the colossal risks and the imperative for unprecedented changes on a global scale. While the report provides unprecedented insights into the gravity of the climate emergency, it also highlights the critical need for immediate, substantial, and efficacious efforts to analyze, mitigate, and potentially reverse the climate change trajectory (IPCC, 2023).

Despite the global scale of efforts to combat climate change, certain regions warrant increased focus due to the potential catastrophic consequences, arising from adverse climate effects in these specific areas. A prime example is the Kashmir Valley, strategically positioned at an elevation of 1600 meters above sea level in the North-Western corner of the Himalayas, with an area ranging from (33.25◦N, 73.75◦E) to (34.5◦N, 75.25◦E) and geopolitically divided between India and Pakistan as shown in Figure 1. The region's environmental, geographical, and economic significance is substantial. The region is considered to have a sub-tropical climate, which is sometimes also classified as Sub-Mediterranean due to the rainfall distribution pattern (Meher-Homji, 1971). Mild summers and severe winters are considered characteristic features of the climate in the region. Multiple rivers such as Jhelum, Lidder, etc.,

* Corresponding author e-mail: suf.cs@uok.edu.in

originating from the glaciers located in the upper reaches of the valley, and then flowing through the valley, as well as towards other regions, such as Pakistan and Punjab, are acting as a source of irrigation. The high-altitude origins of these rivers confer a substantial hydroelectric potential of around 20,000 Megawatt, with an estimated annual export revenue of $13 billion. Nevertheless, only about 20% of this potential has been recently realized (Ahmad, 2019; Smith, 2010). Any drastic climate change can be disastrous to the hydroelectric potential of the region since it is directly dependent on the glaciers in the region. A glaring example of climate impact is evident in the saffron industry, an integral part of the region's heritage for over 2500 years. The industry has witnessed a substantial decline in the 2018 harvest to be merely half of that produced in 1998 (Chakravarty, 2022; Economic Times, 2020).

Numerous studies and reports on climate change in the region reveal alarming findings, including a 27 − 38% decrease in glacier sizes (Romshoo et al., 2020a), a 19.44% reduction in daily rainfall (Wani et al., 2015), and a projected 6.93 ºC temperature increase by 2100 in the RCP 8.5 Scenario (Romshoo et al., 2020b). Recent anomalous events, such as the exceptionally hot and humid summers of 2020 and 2021, the devastating floods of 2014, sporadic surges in rainfall, and shifts in horticulture practices (Das et al., 2011), underscore an apparent alteration in the region's overall climate. This necessitates thorough analysis, study, and forecasting to comprehend the extent of climate change, devise strategies for prevention, and develop measures to mitigate its impacts. While various machine learning-based forecasting methods, including ARIMA, S-ARIMA, ASTAR, SVM, and KNN, offer effective predictions of climate variables, studies in our region have predominantly relied on traditional forecasting methods (Zaz et al., 2019; Shafiqul et al., 2019).

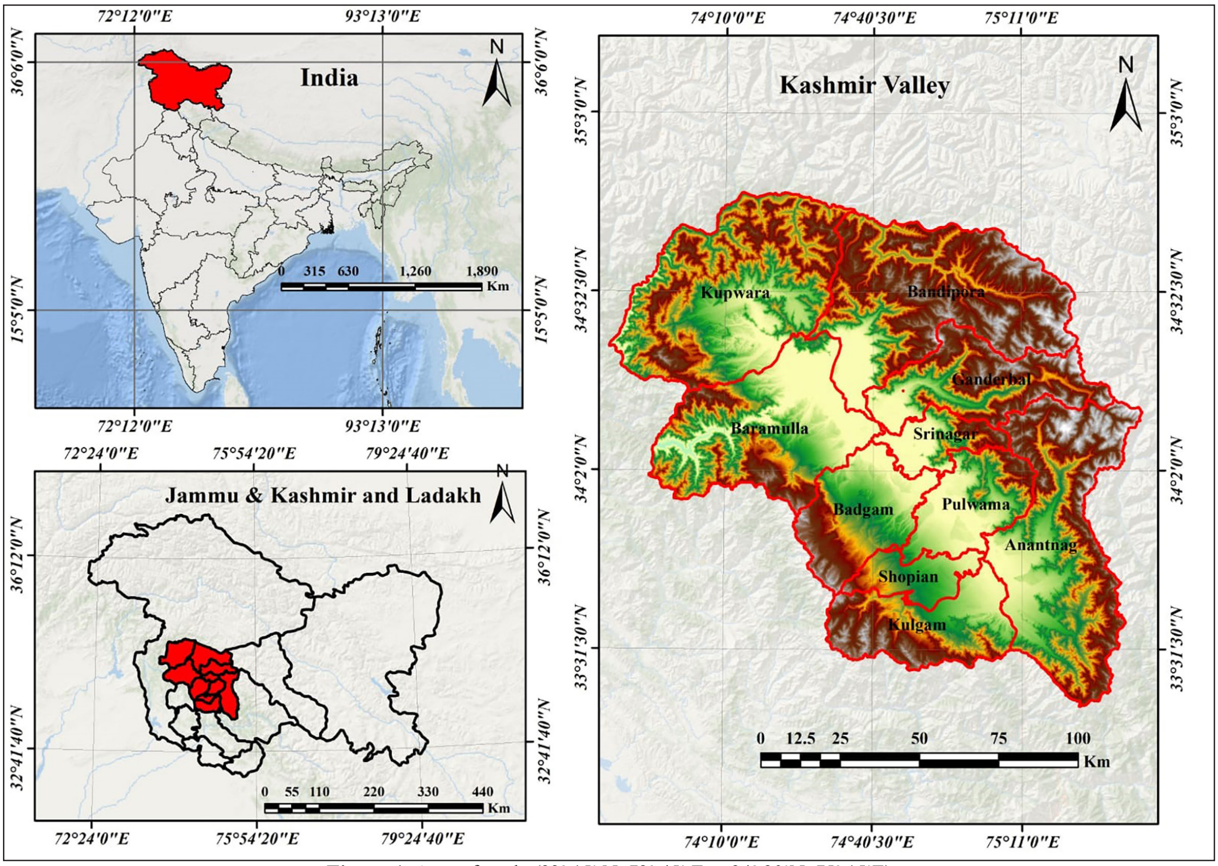

Figure 1. Area of study (33º 15' N, 73º 45' E to 34º 30'N, 75º 15'E)

Notably, limited exploration has been undertaken using machine learning and deep learning models, despite their demonstrated potential to yield superior results, compared to conventional mathematical models, as evidenced by several studies (Jebeile et al., 2021). This research aims to address this gap by leveraging advanced forecasting techniques to enhance the precision and reliability of climate predictions for the Kashmir Valley. The major contributions of this study are the following:

I. Forecasting future trends: One of the significant contributions of the study is forecasting the future climate trends of the valley for the next 80 years (2020−2100), based on a pre-processed large dataset ranging from 1901 to 2019. Despite being an ecologically sensitive and geographically important area, not enough efforts have been made to estimate the future trends of the climate variables such as temperature (mean, max, and min) and precipitation using machine learning models on the large high-quality dataset. This study aims to build upon the past results by using the proven ARIMA model for forecasting climate variables in the region. The validated forecasts will help in early planning and strategizing methods to tackle the changes in the future, which can prove beneficial to the surrounding regions, as well as, the rest of the world.

Identifying key trends: Apart from forecasting climate change for the future, we also performed some basic analysis to identfy key trends in climate change that have occurred over the years (1901-2019) in the region of interest.

In this study, analysis has been done on a much larger dataset, with some noteworthy findings that have been discussed, in detail, in section 4 of the study. The analysis would help us better visualize how climate has changed over the past decades. The analysis can pave the way for an immediate decision and policy-making regarding climate change in the region.

II. Providing ready-to-use data: A major hurdle in studying and analyzing climate change in Kashmir valley is the availability of ready-to-use, clean and readable data. The data used in the study is provided by the CRU (Climate Research Unit) and requires various pre-processing steps that may appear daunting to researchers of a non-technical background. The high-quality, processed, and ready-to-use CRU dataset has been made available publicly in a public repository (JK Climate Data Github repository (k3rnelpanik, 2022)). This repository can be used by further studies for replications or analyzing other variables such as potential evapotranspiration, vapor density, etc.

The paper is further divided into multiple sections, with section 2 discussing the previously undertaken research focusing on the subject matter. Section 3 follows, discussing the dataset used in the study, and section 4 discusses inferences and notable observations made from the historical data. Section 5 discusses the methodology followed in the study. Section 6 discusses the forecasting results for each of the climate parameters: temperature, precipitation, and cloud cover. The conclusion and future scope of the study are discussed in sections 7 and 8 of the study, respectively.

2. Related Work

Many studies in the past have been conducted to forecast and study climate change in Kashmir Valley. The studies conducted differ in terms of variables used to study climate change, the area used in the study, the dataset, and/or the technique(s) used to carry out the forecasting. The studies conducted in the region of Kashmir present varying findings and results.

Linear regression analysis was used to examine the rate of change of climatic indices using data from 1961-2005 and an overall increasing trend was found in the seasonal and annual average temperatures (Ul and Khan, 2013). Another study, including observational data from six stations within Kashmir Valley, used the Weather and Research Forecasting (WRF) model and ERA-Interim data. The main findings from the study were that the higher altitude stations exhibited a steep increase of 1.04ºC to 1.13ºC in the annual mean temperatures from 1980−2016 (Zaz et al., 2019). Investigation of future climate change trends for the 21st century was done under 3 emission schemes (AIB, RCP4.5, RCP8.5) with the baseline period of the data being 1961-1990. The study used the GFDL CM2.1 model and the conclusion was that the annual mean temperature was projected to increase by 4.5ºC, 3.98ºC, and 6.93ºC respectively under the 3 emission schemes. The study also found out that the different climatic zones would experience significant changes (Romshoo et al., 2020b). Changes in the glacier sizes have also been studied, by comparing satellite images from 1980 to 2018, showing a decrease of 27 − 38% in the sizes of different glaciers, suggesting increasing temperatures and a decline in winter solid precipitation in the region, which if continues in the future, would adversely affect the economy in the region (Romshoo et al., 2020a). Similarly, glacier behavior estimation has been performed under climate change using a GRASS GIS module in Italy, with the results showing that the module can be used for a large number of glaciers to obtain spatial simulations to assess future scenarios (Strigaro et al., 2016). Another study uses SDSM to make projections for maximum and minimum mean temperatures, showing an increase of 0.3ºC to 2.3ºC in future decades, from 2030−2100 (Shafiqul et al., 2019). A study by (Ahsan et al., 2021) focusing on climatic extremes in the valley uses IMD data, ranging from 1980−2010, with future projections being generated for 2006−2100, showing clear upward trends in temperature extremes, and a general decreasing trend in precipitation. Several studies have been conducted across different regions to analyze climate variable trends using basic statistical models (Baig et al., 2021; Hossain et al., 2014; Shama and Najim, 2014). The utilization of the ARIMA model has shown very promising results in various domains including climate change analysis. A study by Narayanan et al. (2013) used the ARIMA model for analyzing trends and modelinglk; pre-monsoon rainfall data with results indicating a significant rise in the pre-monsoon rainfall over the northwest part of the country. Air pollution modeling and forecasting have also been done using the ARIMA model, with findings showing that meteorological variables have a definite influence on the life cycle persistence of air pollutants (Naseem et al., 2018). Climate change has also been assessed along with a monthly rainfall forecast over Khordha District in Odisha, India, with outstanding accuracy using the ARIMA model (Swain et al., 2018). Precipitation and temperature changes in India's Bhagirathi River basin have been studied and forecasted using ARIMA, with the results showing an increasing trend for temperature in one station and a decreasing trend for another, while the precipitation is found to be over-predicted in case of extreme rainfall events (Dimri et al., 2020).

Other domains where the ARIMA model has been successfully applied and has produced exceptionally accurate results include stocks, the economy, and the COVID-19 Pandemic. ARIMA has been used for forecasting the GDP (Gross Domestic Product), which is a monetary measure of the market value of all the final goods and services produced in a specific time period by countries, for Portugal and Germany until the year 2031 with results suggesting a steady growth in both countries (Pires et al., 2021). The Nigerian economy has also been studied using the ARIMA model, with a study showing that the living standards in Nigeria would most likely worsen over the next decade unless the economic policy stance is not reviewed (Nyoni, 2019).

For analyzing and forecasting the COVID-19 pandemic, in terms of the spread and infection rates in different regions, ARIMA has produced acceptable and proven results. A study focused on analyzing the top five affected countries, with the resulting forecasts being found concurring the observed data and predictions of exponential curves in certain countries such as India, the US, and Brazil turning out to be true (Sahai et al., 2020). COVID-19 cases in India were also forecasted in another study using ARIMA, with data from the Ministry of Health and Family Welfare (MOHFW), with results showing an increasing trend of COVID-19 cases with approximately 1500 cases per day (Khan and Gupta, 2020). No studies focusing on the analysis of climate change in this specific region have harnessed the potential of machine learning approaches for forecasting future climate trends and variable values, such as temperature and precipitation despite the demonstrated superiority and stability of machine learning approaches over traditional models. Another aspect requiring improvement is the limited scope of data utilized in existing studies, as most have relied on small datasets with records spanning only a few decades (Ul and Khan, 2013). Additionally, certain studies have confined their investigation to narrower regions within the valley, excluding statistically and environmentally significant areas. This limitation diminishes the significance and applicability of their findings and conclusions. Addressing these gaps, the current study seeks to overcome these shortcomings by leveraging a substantial dataset covering the period from 1901 to 2019. Moreover, it aims to broaden the geographical scope by encompassing all regions of Kashmir Valley.

3. Dataset Description

The time series data used in the study is sourced from the CRU TS4.04 dataset (Centre for Environmental Data Analysis (CEDA), 2020), which is in the public domain of the Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia in Norwich, UK. The main motive of the division is to provide data to the general public for research purposes. The data is an interpolated high-resolution gridded dataset (0.5º x 0.5º grids) consisting of global monthly mean temperature, precipitation, cloud cover, potential evapotranspiration, etc. Itranges from 1901 to 2019. The 'Subsetter' tool from the web processing service (WPS) available on the CEDA web archive portal (Centre for Environmental Data Analysis (CEDA), 2025) was used to extract the monthly precipitation, average cloud cover, and mean temperature data for our region of study. While other datasets were available as well, such as the one from the Indian Meteorological Department (IMD) Pune which is available on the Open Governmental Data Platform and one from Berkeley Earth (Berkeley Earth Climate Data). These datasets have significantly a lower number of entries than the CRU dataset and in some cases, the datasets provided are derivatives of the CRU time series dataset itself like the data available on the Indian Water Portal. The CRU data is also well documented, credible, accurate, and used extensively in research (Dimri et al., 2020; Harris et al., 2020; Salvacion et al., 2018; Shi et al., 2017). Another reason for the selection of the CRU time series data in this study is that previous studies have used sparsely populated datasets, with data only available for the past 3-4 decades, and using an extensive dataset populated with data-points from over a century as is the case with the CRU dataset, provides the potential for better understanding of the past trends as well as more accurate forecasting.

I. Pre-processing: The CRU data obtained in its original form required some pre-processing before being used for analysis and forecasting purposes. While the data is originally being provided a gridded time series, it needs to be averaged over the region of interest for each month, which is done by calculating the mean for cloud cover (%) and temperature (ºC). To convert the gridded time series data points to numeric values, the sum of the total precipitation (mm/month) is considered for each month.

II. Detection and removal of outliers: Detection and removal of outliers allow machine learning models to better understand the underlying trends in the data and to model them more accurately. The 'z-score' of the distribution is calculated for this purpose and any values that had a z-score greater than 3 or less than -3, as is the norm with Gaussian (Normal) distributions, were replaced by the mean of the immediately neighboring values.

$$z = \frac{x-\mu}{\sigma^2} \tag{1}$$

where μ denoting the mean of the distribution and , the standard deviation.

III. Training and testing values: The total collected data spanned over the time period of 1901 to 2019. The data (1901-2019) is split into two parts, with data from 1901-1999 being used for training the model and that from 2000-2019 used for validation of the forecasts made for the time period of 2000-2100.

4. Data Analysis and Notable Observations

A key part of our study was to analyze and visualize the extent of climate change that has occurred over the years up until now, especially since it has been a topic that has not received much attention when it comes to the Valley of Kashmir (Ahmad, 2018). The time series data was plotted using specialized software Seaborn and trend lines fitted upon the graphs to better visualize the direction and change in the temperatures, precipitation, and cloud cover over the period of study. Results are analyzed and discussed in the subsequent sections of the paper.

4.1 Drastic changes in temperature

The change in mean temperature over the period of 119 years in the region can be observed from the temperature (Figures 2 - 5), showing about 10 − 25% change in mean temperature in springs, summers, and autumns. The more worrying part is the gradual but extreme increase of about 200% in the mean temperatures over the past winters, as shown in Table 1 and Table 2. This is a worrying sign for the region, considering its ecologically sensitive nature. Such drastic and extreme increase in the mean temperature, especially for winters, can result in the accelerated melting of glaciers which may result in flooding and even affect the perennial nature of the rivers originating from them. The rise in mean temperature is also a problem for most of the fruit-bearing trees in the region such as apples, apricots, and walnuts, all of which have their own “Chilling hour” requirements, the insatiability of which can cause abnormalities in the yield (Salama et al., 2021; Patel et al., 2019; Das et al., 2011; Stafne, 2017).

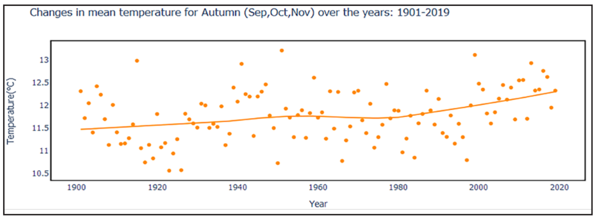

Figure 2. Changes in mean temperature over 1901-2019 in the autumn season (Sep., Oct., and Nov.)

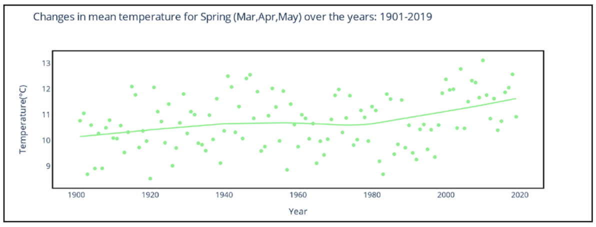

Figure 4. Changes in mean temperature over 1901-2019 in the spring season (Mar., Apr., and May)

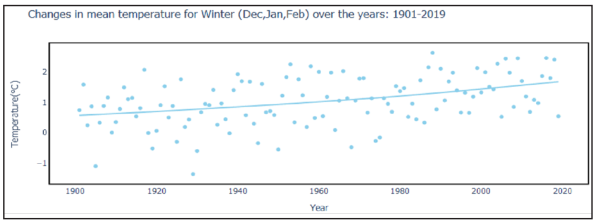

Figure 3. Changes in mean temperature over 1901-2019 in the winter season (Dec., Jan., and Feb.)

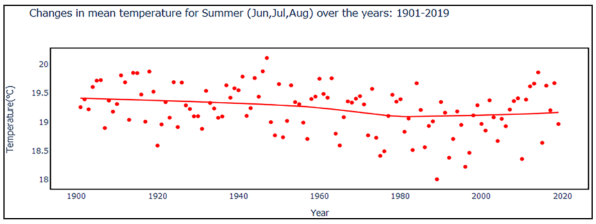

Figure 5. Changes in mean temperature over 1901-2019 in the summer season (June, July, and Aug.)

Table 1. Changes in mean temperature for winter (1901-1990) and (1991-2019).

Years	Mean	Standard Deviation	Min	25%	50%	75%	Max
1901-1990	0.870	1.509	-3.275	-0.266	1.003	1.942	4.488
1991-2019	1.506	1.420	-1.206	0.359	1.669	2.709	5.000

Table 2. Changes in mean temperature for autumn (1901-2000) and (1991-2019).

Years	Mean	Standard Deviation	Min	25%	50%	75%	Max
1901-1990	11.685	0.555	10.567	11.285	11.683	12.036	13.206
1991-2019	12.231	0.391	11.602	11.875	11.875	12.524	12.929

4.2 Precipitation spikes

Upon analysis of the precipitation data, extreme spikes in precipitation were noticed in summers and autumns, causing flash floods in localized areas such as that in 2010 (Guardian, 2010) and major floods like that of (Greater Kashmir, 2015) and that of 2022 in Pakistan which resulted in a loss of more than 1600 lives and estimated damage of $30 billion (Devi, 2022; Zhong, 2022; UNICEF, 2022). The precipitation data, when separately plotted for 1901-1990 and 1991-2019, shows a lower mean and deviation in the former time period and a higher mean and deviation, pointing to more erratic rainfalls. The precipitation keeps peaking in late summer and early autumn, as shown in Table 3 and Figure 6.

4.3 Potential for using temperature and cloud cover forecasts to predict heavy rainfall

Cloud cover is one of the most overlooked climate factors when it comes to analyses of the Valley’s climate. A trend line was fitted upon the data points to analyze the co-dependence of the variables. The trend line is a locally weighted polynomial regression line fit using weighted least squares giving more weight to points near the point whose response is being estimated and less weight to the points further away. Upon analysis of the data and the trend line, it was observed that the cloud cover usually sits around a small range of 41 − 47% and a relatively larger range of 23 − 34% in summers and autumns respectively, correlating to precipitations of 3000 − 8000 mm in summers and 1000 − 3000 mm in autumns. The deviances and spikes in precipitations can be correlated to cloud covers greater than 55% in summers and 40% in autumns, as shown in Figure 7 and Figure 8. A multi-variate approach, using the precipitation and cloud cover data, can thus be taken in early prediction of such spikes, which can thus aid in the prevention of catastrophic loss of property and life, such as the ones caused in 2010 and 2014.

Table 3. Total yearly precipitation compared over the years, (1901-1990) vs. (1991- 2019).

Years	Mean	Standard Deviation	Min	25%	50%	75%	Max
1901-1990	11960.7	2278.3	7490.7	10227	11651	13350	17319
1991-2019	13295.7	2427.7	10421	11490	12620	14761	18997

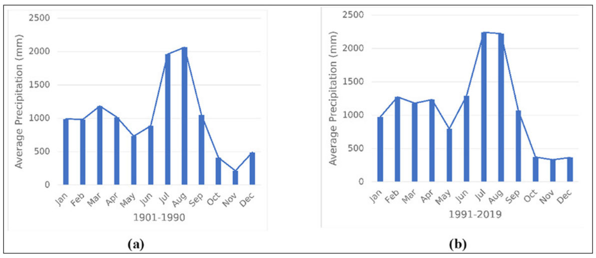

Figure 6. Comparison between mean monthly precipitation for 1901-1990 and that for 1991-2019.

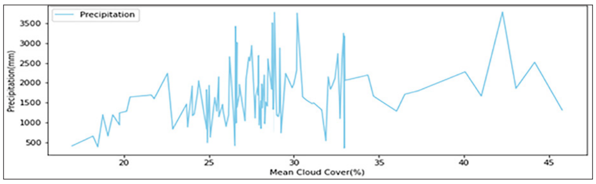

Figure 7. Correlation between cloud cover and precipitation spikes for the autumn season (Sep, Oct, and Nov).

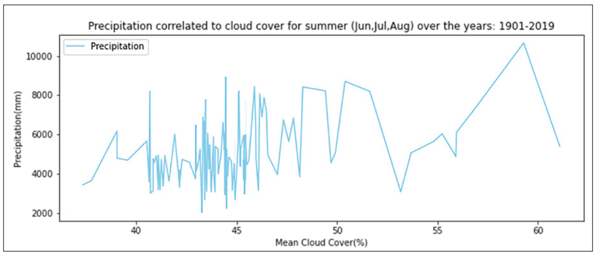

Figure 8. Correlation between cloud cover and precipitation spikes for the summer season (Jun, Jul, Aug).

5. Methodology

The data considered for the study includes temperature (mean, maximum and minimum), precipitation, and cloud cover from the year 1901-2019. The data is provided in the gridded form and is prepared as monthly mean values, except for precipitation, which is taken as the sum total of precipitation observed in the entire region. Upon preparation of data files, the models that produce the best results in terms of forecast need to be identified, provide a factual background, clearly define the problem, propose a solution, and include a brief literature survey along with the scope and justification of the work done.

5.1 Model Description

Auto-Regressive Integrated Moving Average (ARIMA) model is used for time series analysis to better understand the underlying trends in the data and to produce forecasts based on the mean, deviation, and differences of the past values (Pires et al., 2021; Youssef et al., 2021; Sahai et al., 2020; Khan and Gupta, 2020; Ding et al., 2020; Nyoni, 2019). The usage of the ARIMA model involves three main hyper-parameters:

- p-term which denotes the order of the AR (auto-regressive) term i.e., the number of prior values the current value in a time series is regressed upon.
- d-term which denotes the I (integrated) term i.e., numbers of differencing required for the time series to make it stationary.
- q-term which denotes the order of the MA (moving average) term i.e., the number of error values occurring at various time intervals in the past that the regression error is a linear combination.

These p(AR), d(MA) and q(I) values need to be selected, so that the model fits the data in the best way possible. If the time series to be used is non-stationary, its trend is removed by differencing to obtain a stationary time series. Non-seasonal ARIMA models are denoted as ARIMA (p, d, q) and seasonal ARIMA models as ARIMA (p, d, q) (P, D, Q) m where "m" denotes the number of periods in each season. ARIMA is considered to be one of the best models to use, when dealing with long and stable time series data, especially for approximating historical patterns for the future (Jebeile et al., 2021; Rolnick et al., 2019; YoosefDoost et al., 2017). An ARIMA model can be mathematically described as:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \quad (2)$$

The equation follows the Box-Jenkins convention wherein the MA parameters (θ) are defined so that their signs are negative. Identifying the appropriate ARIMA model for some data begins by determining the order of differencing (d) required to make the time series stationary and remove any seasonality. Stationary series can still have auto-correlated errors, which is suggestive of the need for some number of AR terms (p≥1) and possibly some MA terms (q≥1) in the forecasting equation. Separate ARIMA models have been fitted to forecast mean temperature, maximum temperature and minimum temperature, and cloud cover following the methodology presented in Figure 9. Precipitation achieved a relatively higher RMSE value, due to the inability of the ARIMA model to adapt to extreme changes in the data, with values ranging from 60mm/month, all the way up to around 19000 mm/month. Identification of the best fit models was done using the metrics discussed in detail in section 5.2.

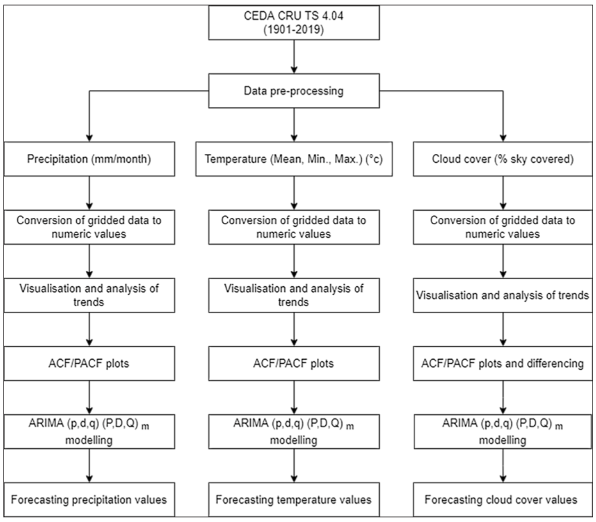

Figure 9. Methodology followed for forecasting three major climate variables

5.2 Evaluation Metrics

The results are graded using multiple evaluation metrics, such as RMSE, AIC, BIC as well as distribution metrics such as skew, kurtosis, and stationarity R2, all of which are inherent to the ARIMA model.

i. Akaike Information Criterion (AIC):

AIC is an estimator of prediction error. When a statistical model is used to represent the process that generated the provided data, the representation is never exact, some information is always lost. AIC simply estimates this relative amount of information such as a part of the climate observations lost by our model. A lower AIC value implies a better model:

$$AIC = 2 \times K - 2 \times \ln(\text{loglikelihood}) \quad (3)$$

where, K being the number of parameters in the data.

ii. Bayesian Information Criterion (BIC):

BIC tries to find the "True" model amongst a finite set of models. BIC introduces penalty terms into a model for each parameter that may increase the likelihood, thus preventing overfitting, i.e., preventing the model from simply repeating temperature or precipitation values instead of actually trying to understand the basis for the patterns. Similar to AIC, lower BIC values are preferred and considered to make for better models:

$$BIC = -2 \times loglikelihood + K \times \log(N) \quad (4)$$

where, K being the number of parameters in the data and N being the size of the dataset.

iii. Root Mean Square Error (RMSE):

The RMSE denotes how close the values predicted by the trained model are to the actual observed values. The differences between the observed and predicted values, such as temperature or precipitation, known as residuals, help in the determination of a model's quality.

$$RMSE = \sqrt{mean(forecast - observed)^2} \quad (5)$$

iv. R-squared:

The R-squared value denotes how well the model has fit on the training data, thus providing a measure for the model's evaluation instead of the forecasts, i.e., how well the model has understood previous trends from the weather data, the closer the value to 1, the better the model is considered.

$$R^2 = 1 - \frac{unexplained\ variation}{total\ variation} \quad (6)$$

v. Stationarity Tests

The first step while dealing with any time series data is to determine whether it is stationary or not, which can be done using multiple tests. In this study, we used one such test known as the Augmented Dickey-Fuller Test (ADF). The p- value from the test is used to test the null hypothesis and any values higher than the significant threshold of 0.05 (5%) deem the rejection of the null hypothesis false. The conclusion from the results thus reached was that only the cloud cover time series data was nonstationary, while the rest of the data were stationary. To make the cloud cover data stationary, first-order differencing was performed. As auto-correlated errors could still exist in the differenced time series, AR (p≥1) and MA (q≥1) terms could be added to compensate for any mild under-differencing or over-differencing respectively. The ADF test results are shown in Table 4 and the differencing plots in Figure 10.

Table 4. Augmented Dickey-Fuller Test results for the dataset.

	Mean Temperature	Avg. Min. Temperature	Avg. Max. Temperature	Precipitation	Cloud Cover
Test Statistics	-4.519	-4.186	-4.938	-5.494	-0.629
p-value	0.000	0.001	0.000	0.000	0.864
Lags	23	23	23	24	23
Observations	1404	1404	1404	1403	1404
Reject	True	True	True	True	False

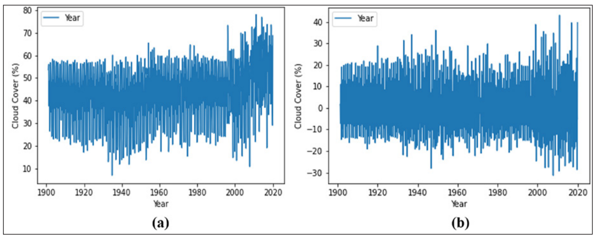

Figure 10. Differencing plots for cloud cover: (**a**). Before Differencing and (**b**). After Differencing

5.3 Determination of AR(p) and MA(q) terms

Auto-correlation function (ACF) and partial auto-correlation function (PACF) plots are used for determining the values for AR (p) and MA (q) terms. The ACF and PACF plots showing large values decomposing very slowly over time shows the need for differencing. The plots also show a confidence level (95%), towards which, if the values show a sharp cut-off in ACF, denotes some over differencing in the series and the need for an MA(q) term. In case of PACF, a sharp cut-off represents under differencing and the need for an AR (p) term. The ACF-PACF plots are shown in Figures 11-15. It is found that in case of mean temperature, maximum and minimum temperature, the ACF plot showed a sharp cut-off after the 3rd lag, thus providing the value for MA(q) term. The PACF plot shows a sharp cut-off after the 12th lag and a dip after the 4th lag, providing with a value of either 12 or 4 for AR(q) term. Both of them are used in the ARIMA model and the better performing AR(q) term is selected. The AR(p) term for mean temperature is 12 and that for minimum and maximum temperature is either 12 or 4, and MA(q) term for all the three temperature variables is 3. This results in the selection of ARIMA (12, 1, 3) for mean temperature, ARIMA (12, 1, 3) for maximum temperature, ARIMA (4, 1, 3) for minimum temperature. Similar steps are followed to determine the 'p' and 'q' terms for both cloud cover and precipitation, with ACF plots for cloud cover showing a cut-off after the 12th lag and the PACF plot also showing a cut-off after the 12th lag, resulting in the selection of ARIMA (12, 1, 12). The ACF plot for precipitation shows a repeating pattern, indicative of one of the pattern cut-offs being the ideal value for the 'q' term, while its PACF plot shows a cut-off after the 11th lag, and ARIMA (11, 1, 12).

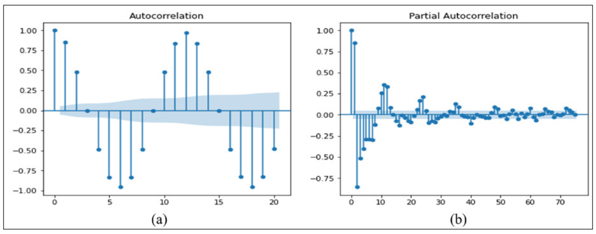

Figure 11. ACF and PACF plots for Mean Temperature.

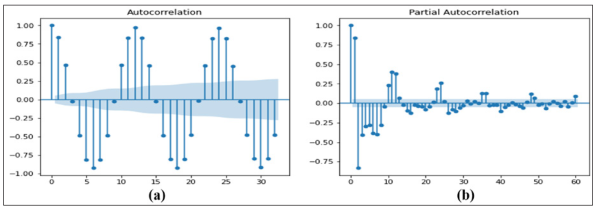

Figure 12. ACF and PACF plots for Average Minimum Temperature.

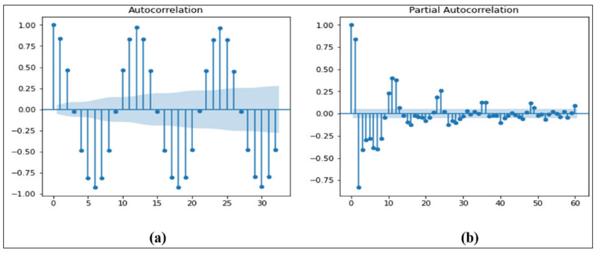

Figure 13. ACF and PACF plots for Average Maximum Temperature.

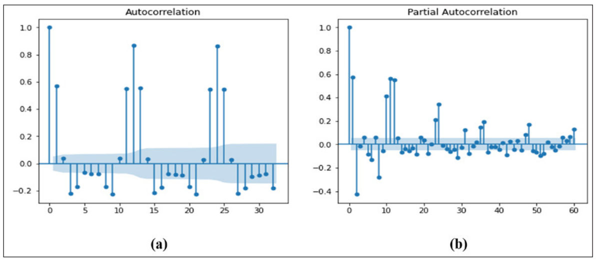

Figure 14. ACF and PACF plots for Cloud Cover.

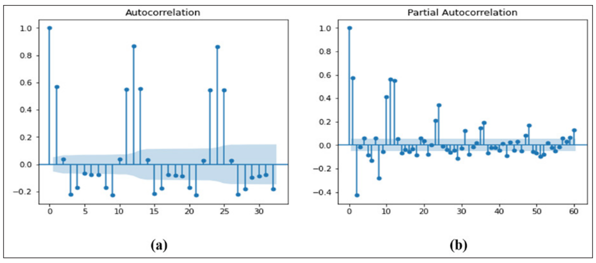

Figure 15. ACF and PACF plots for total precipitation.

5.4 Determination of the 'm' term

The 'm' term is used to remove seasonality in the time series. Since the data is a monthly dataset, with each year having 12 months, the same value was chosen, i.e., m = 12. Appropriate values for P, D, and Q are then chosen for m = 12 in a similar manner as the values for p, d, and q.

5.5 Selection of the best ARIMA model

Once the appropriate values for hyper-parameters (p, d, q) and (P, D, Q) are calculated, the best-fitting model is determined based on the residual values of ARIMA models. Data from the years 1901-2000 is used for training the models and forecasting is performed from 2001-2100, with the data from 2001-2019 acting as validation sets for the fitted models. The models are tested using the evaluation metrics described before in section 5.2. The most appropriate model for mean temperature is found to be ARIMA (12,0,3) (0,0,3)$_{12}$ and ARIMA (12,1,3) (0,1,3)$_{12}$ for maximum temperature and minimum temperature, ARIMA (4,1,3) (0,1,3)$_{12}$. The model selected for precipitation is ARIMA (11,1,12). In a similar manner, ARIMA (12, 1, 12) is selected for modelling the cloud cover data.

6. Results

Each variable's time-series data, encompassing mean temperature, maximum temperature, minimum temperature, precipitation, and cloud cover, underwent individual training and forecasting using distinct ARIMA models. The training dataset spanned from 1901 to 1999, with forecasts extending into the subsequent century (2000-2100). The validation of forecasts utilized data from 2000 to 2019. Despite the ADF tests confirming the stationarity of precipitation, mean temperature, minimum and maximum temperature data, certain seasonality was detected through ACF/PACF plots in the minimum and maximum temperature variables. These plots revealed the presence of seasonal properties, including sequentially recurring trends in lags and a gradual decay over time in the respective time series.

A computer system with an AMD Ryzen 5 4500U APU, 16 GB RAM and AMD Vega 8 GPU is used for training and visualizing the data, as well as making forecasts. The modeling and forecasting process is undertaken using Python 3.9 and Python libraries viz., as Matplotlib, Seaborn, Statsmodels, Pyplot, Plotly, NumPy, Pandas, SciKit Learn.

6.1 Temperature Forecasting Results

The results for mean temperature, minimum temperature, and maximum temperature show a very low RMSE value, considering the fact that average values of parameters in the region lies around 18-23°C. The mean temperature shows the most prominent change, doubling by the end of century for January and showing an increase of about 50% on average for the other two months of winter (December and February). Springs are also predicted to get hotter, which further worsens the issue regarding lack of "chilling period" required by fruit trees in the region, as discussed earlier in the analysis phase. The summers and autumns are seen to be getting cooler when looking at the mean temperature for Jun-Nov, whilst also seeing an increase in the minimum and maximum temperatures, pointing to an increase in the erratic behavior seen in the said seasons over recent years.

The models fit for each of the temperature variables (mean, maximum and minimum) have been shown in detail in Figures 16-18, and their evaluation results in Table 5. The forecast results have been made yearly and shown as values in 20-year intervals between 2020 and 2100 in table 6-8, and to better visualize the change predicted in the temperature, plots showing the same are provided in Figures 19-21.

Table 5. ARIMA model evaluation results for mean, minimum and maximum temperature.

Climate Variable	AIC	BIC	RMSE	Skew	Kurtosis	R^2
Mean Temperature	3442.07	3537.94	1.1296	-0.06	3.92	0.973
Minimum Temperature	3288.46	3343.84	1.1504	0.17	3.70	0.970
Maximum Temperature	3432.28	3527.93	1.1514	0.09	3.84	0.974

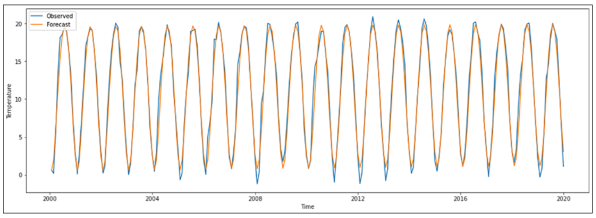

Figure 16. ARIMA (12,0,3) (0,0,3)12 model validation plot for mean temperature (°C).

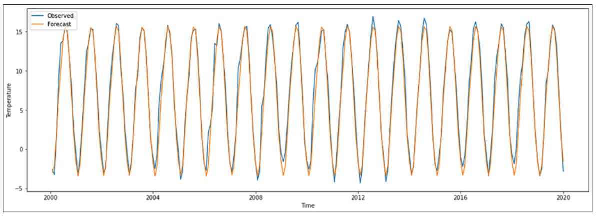

Figure 17. ARIMA (12,1,3) (0,1,3) 12 model validation plot for minimum temperature (°C).

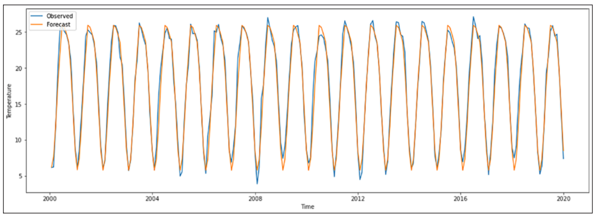

Figure 18. ARIMA (4,1,3) (0,1,3)12 model validation plot for maximum temperature (°C).

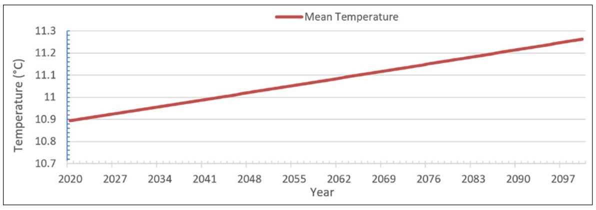

Figure 19. Yearly mean temperature (°C) changes over the years 2020-2100.

Table 6. Mean temperature (°C) forecasts for the years 2020-2100.

Month	Year				
	2020	2040	2060	2080	2100
JAN	**1.264**	1.837	2.246	2.574	**2.874**
FEB	**2.243**	2.723	3.165	3.544	**3.880**
MAR	5.773	5.951	6.251	6.565	6.856
APR	10.664	10.596	10.685	10.846	11.027
MAY	15.376	15.287	15.232	15.233	15.270
JUN	18.657	18.698	18.617	18.521	18.442
JUL	19.864	19.972	19.927	19.813	19.681
AUG	18.904	18.894	18.856	18.769	18.652
SEP	16.029	15.823	15.748	15.697	15.639
OCT	11.773	11.527	11.444	11.440	11.463
NOV	7.050	7.033	7.053	7.131	7.247
DEC	**3.132**	3.475	3.696	3.899	**4.114**

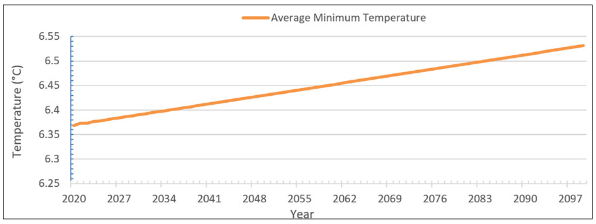

Figure 20. Yearly average minimum temperature (°C) changes over the years 2020-2100.

Table 7. Average minimum temperature (°C) forecasts for the years 2020-2100.

Month	Year				
	2020	2040	2060	2080	2100
JAN	-3.335	-3.289	-3.247	-3.206	**-3.165**
FEB	-2.127	-2.074	-2.034	-1.993	-1.952
MAR	2.133	2.163	2.203	2.244	2.284
APR	6.710	6.746	6.788	6.829	6.870
MAY	10.222	10.277	10.318	10.359	10.400
JUN	13.827	13.864	13.904	13.945	13.985
JUL	15.638	15.668	15.709	15.750	15.791
AUG	15.081	15.131	15.173	15.214	15.255
SEP	11.638	11.684	11.724	11.765	11.806
OCT	6.584	6.612	6.652	6.693	6.734
NOV	1.629	1.672	1.714	**1.755**	1.796
DEC	**-1.579**	-1.527	-1.486	-1.445	-1.404

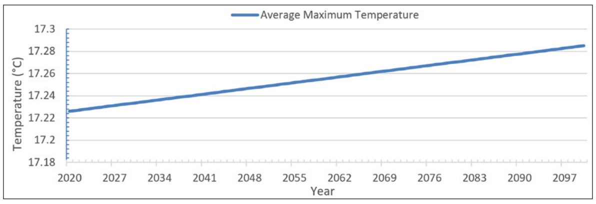

Figure 21. Yearly average maximum temperature (°C) changes over the years 2020-2100.

Table 8. Average maximum temperature (°C) forecasts for the years 2020-2100.

Month	Year				
	2020	2040	2060	2080	2100
JAN	5.799	5.814	5.829	5.844	5.858
FEB	7.324	7.339	7.354	7.369	7.383
MAR	11.890	11.905	11.920	11.934	11.949
APR	17.580	17.595	17.609	17.624	17.639
MAY	21.982	21.997	22.012	22.027	22.041
JUN	25.899	25.914	25.929	25.944	25.958
JUL	**25.623**	25.638	25.653	25.667	**25.682**
AUG	24.672	24.687	24.702	24.717	24.731
SEP	23.565	23.580	23.595	23.610	23.624
OCT	19.675	19.689	19.704	19.719	19.734
NOV	14.185	14.200	14.215	14.229	14.244
DEC	8.516	8.531	8.545	8.560	8.575

6.2 Cloud Cover Forecasting Results

The ARIMA model fitted for cloud cover showed an increase in the RMSE than that achieved for the model fitted for temperature values. The model thus tends to underestimate the peaks of the cloud and makes forecasts that are around 4-8% lower than what the actual values may be.

The evaluation metrics for the model are shown in Table 9 and the model fit values are compared to actual observed values for validation in Figure 22. The cloud cover values for different seasons have also been visualized in Figures 23-26, with springs showing a very slight decrease, winters showing a relatively larger decline in values, summers and autumns showing slightly increasing values as the years go on. The forecast results from the model are presented in table 10, in 20-year intervals.

Table 9. ARIMA model evaluation results for cloud cover.

	AIC	BIC	RMSE	Skew	Kurtosis	R^2
Cloud Cover	6262.51	6389.22	11.8918	-0.462	-0.967	0.2483

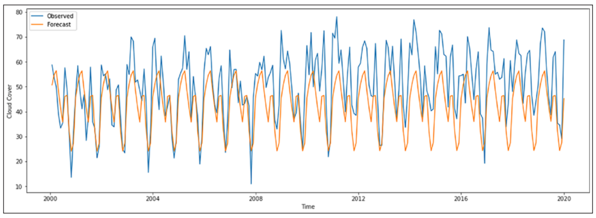

Figure 22. ARIMA (12,1,12) model validation plot for cloud cover (%).

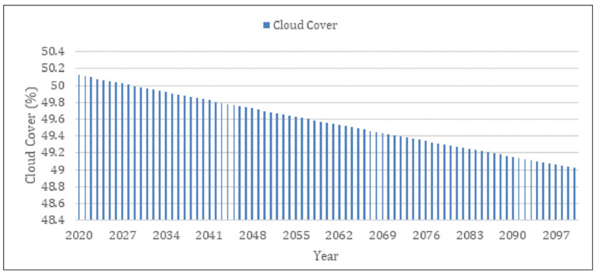

Figure 23. Cloud cover (%) forecast changes for winter (Dec, Jan, Feb) over the years 2020-2100.

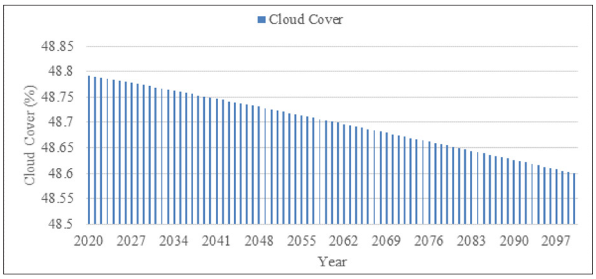

Figure 24. Cloud cover (%) forecast changes for spring (Mar, Apr, May) over the years 2020-2100.

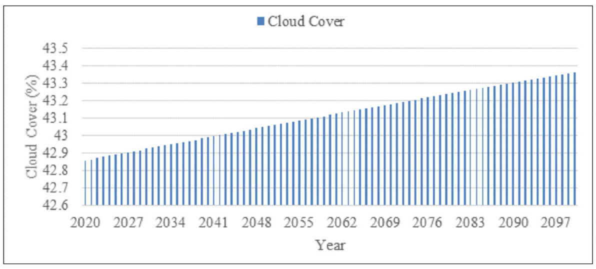

Figure 25. Cloud cover (%) forecast changes for summer (Jun, Jul, Aug) over the years 2020-2100.

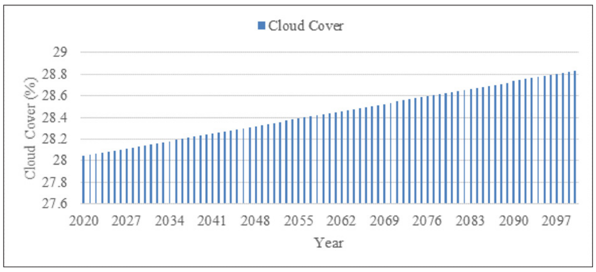

Figure 26. Cloud cover (%) forecast changes for autumn (Sep, Oct, Nov) over the years 2020-2100.

Table 10. Forecasts for average yearly cloud cover (%).

Month	Year				
	2020	2040	2060	2080	2100
JAN	50.845	50.598	50.356	50.122	49.894
FEB	54.339	54.054	53.778	53.509	53.247
MAR	56.310	56.225	56.127	56.020	55.904
APR	48.436	48.314	48.201	48.094	47.992
MAY	41.633	41.708	41.776	41.841	41.902
JUN	36.039	36.447	36.850	37.243	37.628
JUL	46.171	46.194	46.212	46.225	46.236
AUG	46.365	46.330	46.297	46.264	46.231
SEP	32.266	32.273	32.288	32.314	32.351
OCT	24.373	24.717	25.054	25.382	25.701
NOV	27.485	27.730	27.970	28.207	28.441
DEC	45.190	44.861	44.541	44.228	43.923

6.3 Precipitation Forecasting Results

The ARIMA model produces a high RMSE value for the precipitation dataset, mainly due to its inability to adapt to erratic changes in the precipitation which is essentially a high variance between the data points. The model is unable to replicate the peaks that are expected when comparing the forecasted values with the observed values and thus creates a curve with smaller peaks. The model evaluation results are discussed in Table 11. The validation fit for the model has been shown as a plot in Figure 27, and the values forecast using the model are presented in Table 12, with visualizations for the same in fig 28, showing an overall decrease in the total precipitation in almost all seasons, especially the summers, pointing to drier climates.

Table 11. ARIMA model evaluation results for precipitation.

	AIC	BIC	RMSE	Skew	Kurtosis	R^2
Precipitation	18005.49	18127.13	504.923	-0.073	-1.106	0.457

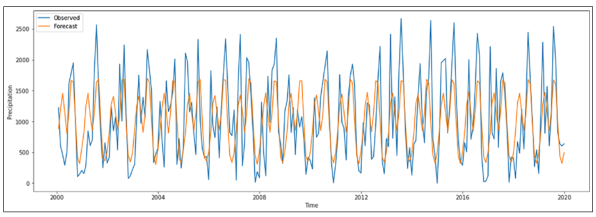

Figure 27. ARIMA (11,1,12) model validation plot for precipitation (mm/month).

Table 12. Forecasts for total precipitation (mm/month) for the years 2020-2100.

Month	Year				
	2020	2040	2060	2080	2100
JAN	827.259	822.059	829.926	846.947	873.467
FEB	1292.45	1353.94	1408.87	1463.19	1515.35
MAR	1482.47	1513.28	1544.88	1571.42	1592.40
APR	1135.92	1144.92	1153.38	1163.77	1179.93
MAY	850.69	877.804	909.056	949.669	997.282
JUN	1163.02	1196.69	1236.43	1271.64	1298.92
JUL	1659.21	1655.83	1634.69	1600.16	1555.79
AUG	**1612.55**	**1547.77**	**1479.96**	**1415.04**	**1353.35**
SEP	983.912	945.346	921.974	904.800	891.905
OCT	434.783	458.288	471.460	478.244	478.894
NOV	336.650	317.251	290.615	258.438	220.468
DEC	483.213	427.805	381.267	**339.437**	**304.823**

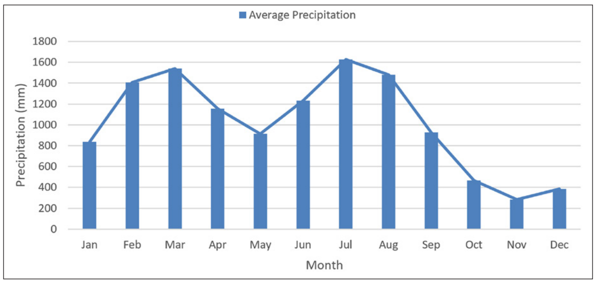

Figure 28. Forecasted average precipitation (mm/month) for the years 2020-2100.

7. Conclusion

The climatic attributes of a geographic area are fundamentally shaped by the observed variables of temperature, precipitation, and cloud cover. This research utilized the ARIMA model to conduct an in-depth analysis of these factors in the context of the Kashmir Valley, offering predictions for the region.

Across temperature variables, encompassing mean, maximum, and minimum values, the ARIMA model yielded predictions with low error values. A noteworthy observation is the discernible shift in mean temperatures, particularly evident during winter seasons, indicating an overall warming trend. The forecast points to an estimated temperature increase of approximately 2°C by the end of the century relative to 2019 levels, with a significant implication being the absence of winter months featuring temperatures below 2°C from 2048 onwards. Such alterations carry substantial ramifications for the local ecosystem and the economic landscape of the Kashmir Valley.

While minimum and maximum temperatures exhibit an ascending trend, the impact is comparatively less pronounced than that on mean temperatures. Projected outcomes suggest a marginal cooling effect during summers and autumns, compared with a relatively more substantial temperature increase during springs. These alterations may disrupt traditional low-temperature periods in spring, adversely affecting fruit and crop yields during autumn, thereby posing economic challenges for a considerable segment of the population dependent on agriculture.

Despite the ARIMA model's inherent limitations in predicting extreme precipitation events, mean precipitation forecasts demonstrated a closer alignment with actual observations. The study envisions a reduction in precipitation and an increase in cloud cover during summers, signaling a rise in humidity that could have adverse repercussions given the region's susceptibility.

A particularly disturbing finding is the cumulative impact of projected changes across all climate parameters, pointing towards potential catastrophes for vital economic sectors such as hydroelectricity, tourism, and agriculture. The projected temperature shifts and heightened cloud cover are anticipated to accelerate glacier melting, compounded by erratic precipitation, thereby elevating the risk of recurrent flooding. Urgent collaborative efforts involving governmental bodies, stakeholders, scientists, and researchers are imperative to formulate strategies and roadmaps addressing the foreseen climate changes. The proactive approach holds paramount significance in mitigating potential economic, environmental, and human losses in the region.

The primary purpose of this study is to bring attention to the imminent dangers of climate change in the region. Nevertheless, amidst the challenging projections, there remains a glimmer of hope. It is crucial to emphasize that these potential threats are not inevitable catastrophes. Meaningful and collective action can be taken to avert such scenarios. Recent global commitments, such as those emerging from The Paris Agreement signed in 2015 [45], UN Climate Change Conference (COP28) held recently in Nov-2023 [46] and other such inititaives exemplify the growing awareness and dedication to addressing climate change on a global scale. It is our fervent hope that governments across the country, and indeed the world, will take proactive initiatives inspired by these commitments, implementing effective policies and fostering international collaboration to secure a sustainable and resilient future for the world and to our region of interest.

8. Future Scope

While the mean, average minimum, and average maximum temperature variables exhibited precise results with minimal errors, the outcomes for cloud cover and precipitation diverged due to the ARIMA model's limitations in capturing and reproducing peaks and abrupt changes. Consequently, exploring alternative machine learning and deep learning models holds promise for enhancing prediction accuracy, especially for extreme events.

Another area that can be improved upon, is the use of higher-resolution datasets, which can allow for finer, cluster-wise analyses and forecasts. Such datasets can allow for the separation of data for planes, and mountainous regions, providing a clearer picture of the impact on glaciers and snow-caps in the region.

The utilization and integration of diverse datasets, including but not limited to the CRU dataset and satellite imagery datasets focusing on glaciers, within a unified research framework, present an opportunity to rectify potential shortcomings inherent in studies reliant on singular datasets. Expanding the scope of the investigation involves incorporating additional variables associated with greenhouse gas emissions, notably carbon dioxide (CO2) levels—a pivotal factor in regional climate health. This extended study aims to assess the magnitude of the region's climate degradation, particularly in light of the escalating industrialization trends in the area.

Enhancing climate forecasting accuracy and efficacy could be achieved through the incorporation of additional variables into the forecasting algorithm. While temperature and precipitation stand as pivotal factors in climate analysis, the inclusion of variables such as humidity, solar radiation, topography, latitude etc. holds the potential to yield substantial insights for region-specific climate forecasting.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability

The dataset used in the study and the codebase is available at https://github.com/fahad-farooq/climchange_jk

Disclaimer

The authors have no financial or non-financial conflicts of interest to declare

References

Ahmad, M. (2018). "It's High Time the Government Took Notice of Kashmir's Changing Climate". https://thewire.in/environment/high-time-government- took-notice-kashmirs-changing-climate (Jan. 13, 2025).

Ahmad, M. (2019). Development of hydropower projects in Jammu And Kashmir. International Journal of Trend in Research and Development, 6(1), 6–8.

Ahsan, S., Bhat, M. S., Alam, A., Farooq, H., & Shiekh, H. A. (2021). Evaluating the impact of climate change on extreme temperature and precipitation events over the Kashmir Himalaya. Clim Dyn, 1–19.

Baig, M. A., Zaman, Q., Baig, S. A., Qasim, M., Khalil, U., Khan, S. A., Ismail, M., Muhammad, S., & Ali, S. (2021). Regression analysis of hydro-meteorological variables for climate change prediction: A case study of Chitral basin, Hindukush region. Science of The Total Environment, 793, 148595. https://doi. org/https://doi.org/10.1016/j.scitotenv.2021.148595

Centre for Environmental Data Analysis (CEDA). (2020). " CRU TS 4.04: Climatic Research Unit (CRU) Time-Series Dataset Version 4.04". https://data.ceda. ac.uk/badc/cru/data/cru ts/cru ts 4.04 (Jan. 13, 2025).

Centre for Environmental Data Analysis (CEDA). (2025). " CEDA WPS User Interface". https://ceda-wps-ui.ceda.ac.uk/processes (Jan. 13, 2025).

Chakravarty, P. (2022). " Global warming forces Kashmir farmers to grow saffron indoors". https://rfi.my/8u1l.X (Jan. 13, 2025).

Das, B., Krishna, H., Attri, B. L., Ahmad, N., & Ranjan, J. K. (2011). Harvest maturity standards and fruit quality of some apple cultivars under high altitude conditions. Indian Journal of Horticulture, 68(2), 170–179.

Devi, S. (2022). Pakistan floods: Impact on food security and health systems. The Lancet, 400(10355), 799–800.

Dimri, T., Ahmad, S., & Sharif, M. (2020). Time series analysis of climate variables using seasonal arima approach. Journal of Earth System Science, 129(1), 1– 16.

Ding, G., Li, X., Shen, Y., & Fan, J. (2020). Brief analysis of the ARIMA model on the covid-19 in Italy. MedRxiv.

Economic Times. (2020). " Climate change ravages Kashmir's 'red gold' saffron crop". https://ecoti.in/4FoSLa (Jan. 13, 2025).

Greater Kashmir. (2015). " The 2014 Kashmir Flood: The Extreme of the Extremes". https://www.greaterkashmir.com/gk-magazine/the-2014-kashmir- flood-the-extreme-of-the-extremes (Jan. 13, 2025).

Guardian, T. (2010). " Kashmir flash floods leave dozens dead". https://www. theguardian.com/world/2010/aug/06/kashmir-flash-floods (Jan. 13, 2025).

Harris, I., Osborn, T. J., Jones, P., & Lister, D. (2020). Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Sci Data, 7(1), 1–18.

Hossain, M. Z., Mondal, M. N. I., Sarkar, S. K., & Haque, M. A. (2014). Seasonal variation of temperature in Dhaka metropolitan city, Bangladesh. Jor dan Journal of Earth and Environmental Sciences, 6(2), 93–97.

IPCC. (2007). Climate change 2007: Synthesis report. contribution of working groups I, II, and III to the fourth assessment report of the intergovernmental panel on climate change (C. W. Team, R. Pachauri, & A. Reisinger, Eds.) (Jan. 13, 2025). Intergovernmental Panel on Climate Change (IPCC). Geneva, Switzer- land. https://www.ipcc.ch/report/ar4/syr/

IPCC. (2021). Climate change 2021: The physical science basis. contribution of working group i to the sixth assessment report of the intergovernmental panel on climate change (V. Masson-Delmotte, P. Zhai, A. Pirani, S. Connors, C. P´ean, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. Matthews, T. Maycock, T. Waterfield, O. Yelek¸ci, R. Yu, & B. Zhou, Eds.) (Jan. 13, 2025). Intergovernmental Panel on Climate Change (IPCC). Cambridge, United Kingdom, New York, NY, USA, Cambridge University Press. https://www.ipcc.ch/report/ar6/wg1/

IPCC. (2022). Global warming of 1.5ºC: Ipcc special report on impacts of global warming of 1.5ºC above pre-industrial levels in context of strengthening response to climate change, sustainable development, and efforts to eradicate poverty. Intergovernmental Panel on Climate Change. Cambridge, Cambridge University Press.

IPCC. (2023). Summary for policymakers. in: Climate change 2023: Synthesis re- port. contribution of working groups i, ii and iii to the sixth assessment re- port of the intergovernmental panel on climate change (C. W. Team, H. Lee, & J. Romero, Eds.). Intergovernmental Panel on Climate Change. Geneva, Switzerland. https://doi.org/10.59327/IPCC/AR6-9789291691647.001

Jebeile, J., Lam, V., & Ra¨z, T. (2021). Understanding climate change with statistical downscaling and machine learning. Syntheses, 199(1), 1877–1897.

k3rnelpanik. (2022). " Climate Data for The Valley of Kashmir (1901-Present)". https://github.com/k3rnelpanik/climchange jk (Jan. 13, 2025).

Khan, F. M., & Gupta, R. (2020). Arima and nar based prediction model for time series analysis of covid-19 cases in india. Journal of Safety Science and Resilience, 1(1), 12–18.

Meher-Homji, V. M. (1971). On the mediterranean climatic regime of west Pakistan. Archive for Meteorology, Geophysics und Bioclimatology, Serie B, 19, 277– 286.

Narayanan, P., Basistha, A., Sarkar, S., & Kamna, S. (2013). Trend analysis and arima modelling of pre-monsoon rainfall data for western India. Comptes Rendus Geoscience, 345(1), 22–27.

Naseem, F., et al. (2018). An integrated approach to air pollution modeling from climate change perspective using ARIMA forecasting. Journal of Applied Agri- culture and Biotechnology, 2(2), 37–44.

Nathaniel, A., Jacob, A., Joshua, A., & Solomon, A. (2024). Estimation of global solar radiation, sunshine hour distribution and clearness index in three geopolitical regions of Southern Nigeria. Jordan Journal of Earth and Environmental Sciences, 10(2), 97–103.

Nations Organization United. (2021). “ Global Issues - Climate Change”. https://www.un.org/en/global-issues/climate-change (Jan. 13, 2025).

Nyoni, T. (2019). Is Nigeria’s economy progressing or backsliding? implications from arima models (MPRA Paper No. 91396). University Library of Munich, Germany. https://ideas.repec.org/p/pra/mprapa/91396.html

Patel, N. R., Akarsh, A., Ponraj, A., & Singh, J. (2019). Geospatial Technology for Climate Change Impact Assessment of Mountain Agriculture. Springer Singapore.

Pires, F., Gouveia, J., Perestrello, F., Melo, A., & Gomes, M. (2021). “ Using an ARIMA Model to Forecast GDP Until 2031 for Portugal and Germany”. https://ssrn.com/abstract=3855082 (Jan. 13, 2025).

Rolnick, D., et al. (2019). Tackling climate change with machine learning. arXiv preprint arXiv:1906.05433.

Romshoo, S. A., Fayaz, M., Meraj, G., & Bahuguna, I. M. (2020a). Satellite-observed glacier recession in the Kashmir Himalaya, India, from 1980 to 2018. Environ Monit Assess, 192(9), 1–17.

Romshoo, S. A., Bashir, J., & Rashid, I. (2020b). Twenty-first century-end climate scenario of jammu and Kashmir Himalaya, India, using ensemble climate models. Clim Change, 162(3), 1473–1491.

Sahai, A. K., Rath, N., Sood, V., & Singh, M. P. (2020). Arima modelling & forecasting of covid-19 in top five affected countries. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14(5), 1419–1427.

Salama, A.-M., et al. (2021). Temperate fruit trees under climate change: Challenges for dormancy and chilling requirements in warm winter regions. Horticulturae, 7(4), 86.

Salvacion, A. R., Magcale-Macandog, D. B., Cruz, P. C. S., Saludes, R. B., Pangga,

I. B., & Cumagun, C. J. R. (2018). Evaluation and spatial downscaling of cru ts precipitation data in the philippines. Model Earth Syst Environ, 4(3), 891–898. https://doi.org/10.1007/s40808-018-0450-6

Shafiq ul, M., Ramzan, S., Ahmed, P., Mahmood, R., & Dimri, A. P. (2019). Assessment of present and future climate change over Kashmir Himalayas, India. Theoretical and Applied Climatology, 137(3), 3183–3195.

Shama, L. F. Z., & Najim, M. M. M. (2014). Analysis of rainfall trends in three selected rain gauging stations from wl3, il1a, and dl1f agroecological regions in Sri Lanka. Jordan Journal of Earth and Environmental Sciences, 14(3), 175–181.

Shi, H., Li, T., & Wei, J. (2017). Evaluation of the gridded CRU TS precipitation dataset with the point rain gauge records over the three-river headwaters region. J Hydrol (Amst), 548, 322–332.

Smith, G. (2010). “ In Kashmir, water treaty means less power to the people”. https://www.theglobeandmail.com/news/world/in-kashmir-water-treaty-means-less-power-to-the-people/article1389907/ (Jan. 13, 2025).

Stafne, E. T. (2017). Chilling-hour requirement of fruit crops (Jan. 13, 2025). Missis- sippi State University Extension. http://extension.msstate.edu/publications/chilling-hour-requirements-fruit-crops

Strigaro, D., Moretti, M., Mattavelli, M., Frigerio, I., Amicis, M. D., & Maggi, V. (2016). A grass GIS module to obtain an estimation of glacier behavior under climate change: A pilot study on Italian glacier. Comput Geosci, 94, 68–76.

Swain, S., Nandi, S., & Patel, P. (2018). Development of an ARIMA Model for Monthly Rainfall Forecasting over Khordha District, Odisha, India. In P. K. Sa, S. Bakshi, I. K. Hatzilygeroudis, & M. N. Sahoo (Eds.), Recent Findings in Intelligent Computing Techniques (pp. 325–331). Springer Singapore.

Ul, I. Z., & Khan, R. L. A. (2013). Climate change scenario in Kashmir Valley, India, based on seasonal and annual average temperature trends. Disaster Advances, 6(4), 30–40.

UN Climate Change Conference. (2023). “ UAE-2023: COP28”. https://unfccc.int/ cop28 (Jan. 13, 2025).

UNFCCC. (2018). “ Paris Climate Change Conference - November 2015, Session COP 21”. https://unfccc.int/documents/184656 (Jan. 13, 2025).

UNICEF. (2022). “ Devastating floods in Pakistan”. https : //www . unicef . org / emergencies/devastating-floods-pakistan-2022 (Jan. 13, 2025).

Wani, M. H., Baba, S. H., Bazaz, N. H., & Sehar, H. (2015). Climate change in Kashmir Valley: Is it initiating transformation of mountain agriculture? Indian J Econ Dev, 3(2), 142–154.

YoosefDoost, A., Sadeghian, M. S., NodeFarahani, M., & Rasekhi, A. (2017). Com- parison between performance of statistical and Low Cost ARIMA Model with GFDL, CM2.1 and CGM 3 Atmosphere-Ocean General Circulation Models in assessment of the effects of climate change on temperature and precipitation in Taleghan Basin. American Journal of Water Resources, 5(4), 92–99.

Youssef, J., Ishker, N., & Fakhreddine, N. (2021, June). GDP Forecast of the Biggest GCC Economies Using ARIMA (MPRA Paper No. 108912). University Library of Munich, Germany. https://ideas.repec.org/p/pra/mprapa/108912. html

Zaz, S. N., Romshoo, S. A., Krishnamoorthy, R. T., & Viswanadhapalli, Y. (2019). Analyses of temperature and precipitation in the Indian Jammu and Kashmir region for the 1980–2016 period: Implications for remote influence and extreme events. Atmos Chem Phys, 19(1), 15–37.

Zhong, R. (2022). “ In a First Study of Pakistan’s Floods, Scientists See Climate Change at Work”. https://www.nytimes.com/2022/09/15/climate/pakistan- floods-global-warming.html (Jan. 13, 2025).