

1 Stochastic Time Series Analysis, Modeling, and Forecasting of Weekly Rainfall Using 2 SARIMA Model

3 4 5 Abstract

6 Rainfall holds critical significance for water resource applications, particularly in rainfed
7 agricultural systems. This study employs the Autoregressive Integrated Moving Average
8 (ARIMA) technique, a data mining approach commonly used for time series analysis and
9 future forecasting. Given the increasing importance of climate change forecasting in averting
10 unexpected natural hazards such as floods, frost, forest fires, and droughts, accurate weather
11 data forecasting becomes imperative. The objective of this study was to develop a Seasonal
12 Auto-Regressive Integrative Moving Average (SARIMA) model for forecasting weekly
13 rainfall in Junagadh Station, Gujarat. Utilizing 53 years of historical data (1963 to 2016), the
14 SARIMA model predicts weekly rainfall for the subsequent five years (2018 to 2022).
15 Through comprehensive evaluation using ACF and PACF plots, AIC, SBC, MAPE, and
16 MAE values, the study identifies SARIMA (0,0,4)(0,1,1)₅₂ as the optimal model, offering
17 the most accurate prediction. The robust results affirm that the SARIMA model provides
18 reliable and satisfactory weekly rainfall predictions. This research contributes valuable
19 insights into the precision and efficacy of SARIMA models for rainfall forecasting, aiding in
20 strategic water resource management in the Junagadh region.

21 **Key Words** :SARIMA, AIC, BIC, MAPE, SIC

22 1. INTRODUCTION

23 Efficient water resource management relies heavily on accurately forecasting rainfall
24 for a given area or station (Kumar et al., 2021; Kumar et al., 2021a; Kumar et al., 2022). In

25 the context of Indian agriculture, the southwest monsoon (June-September) plays a pivotal
26 role in the agrarian economy, with adequate rainfall being essential for robust crop
27 production (Kumar et al., 2021). Rainfall, among various hydrological parameters, is crucial
28 for tasks such as irrigation planning, runoff modeling, and drought and flood management.
29 The dynamic nature of rainfall patterns, influenced by changing climatic conditions, gives
30 rise to challenges like flooding, landslides, and drought (Shivhare et al., 2017), significantly
31 impacting agriculture and farming. In a country like India, where agriculture is a backbone,
32 the success or failure of crops is a primary concern, and even slight variations in seasonal
33 rainfall and temperature can have devastating effects on crops (Shivhare et al., 2018).The
34 runoff characteristics, both in terms of quantity and quality, in the majority of watersheds,
35 spanning from micro to macro scales, are significantly shaped and controlled by
36 spatiotemporal variations in rainfall. (Ram, Bhavin et.al, 2023a)

37 Accurately predicting future climate data is a challenging task (Nikam and Meshram,
38 2013). The accuracy and adequacy of rainfall data serve as the essential cornerstone for
39 determining the ultimate success of any progressive endeavors in natural resource
40 management (Ram, Bhavin et.al, 2023b). Despite the development of various algorithms,
41 achieving precise forecasting remains a challenge. Time series models, integral in
42 meteorology and hydrology, tackle the key problem of forecasting in statistics and Data
43 Science. Data transforms into a time series when sampled based on a time-bound attribute
44 like days, months, and years, inherently possessing an implicit order. Forecasting involves
45 predicting future values using this ordered data. Stochastic models, evolving over time (Box
46 and Jenkins, 1994), encompass autoregressive (AR) models, moving average (MA) models of
47 different orders (Gupta and Kumar, 1994, and Verma, 2004), and auto-regressive moving
48 average (ARMA) models of discrete orders (Katz and Skaggs, 1981; Chhajed, 2004; Katimon
49 and Demon, 2004) for annual streamflow. Two widely used forecasting algorithms, ARIMA

50 and SARIMA, address the challenge. ARIMA considers past values (autoregressive, moving
51 average) to predict future values, while SARIMA incorporates seasonality patterns, making it
52 more potent for forecasting complex data spaces containing cycles. The ARIMA model
53 emerges as a valuable tool, handling various dimensions related to univariate time series
54 model selection, parameter optimization, and prediction. In the current study, our focus was
55 on developing a seasonal rainfall forecasting model to predict the weekly rainfall time series
56 for Junagadh city in Gujarat, India, utilizing 58 years (1965-2022) of weekly rainfall data.

57 **2. MATERIAL AND METHODS**

58 **2.1 Study location**

59 Junagadh is geographically situated between latitude 21°31'23.29" N and longitudes
60 70°27'17.90" E, at an altitude of 86 meters above mean sea level in the South Saurashtra
61 region of Gujarat state. The climate of the study area is subtropical and semi-arid,
62 characterized by an average annual rainfall of 929.81 mm, which is concentrated between
63 mid-June and mid-October. The average annual pan evaporation is 5.6 mm/day. The coldest
64 month is January, with a mean monthly temperature ranging from 7°C to 15°C. The
65 maximum monthly temperature is recorded in May, varying between 29.50°C to 39.40°C.
66 Relative humidity fluctuates between 45% and 89%, while wind speeds range from 2 to 9.70
67 km/h.

68 **2.2 Data**

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70 In this study, weekly rainfall data spanning 58 years (1965-2022) were collected from the
71 Agrometeorology Department of Junagadh Agricultural University, Junagadh. Forecasts were
72 made for the five years (2018-2022) using a seasonal ARIMA model.

73 2.3 Methodological Description

74 Seasonal ARIMA (SARIMA) modelling

75 An autoregressive model of order p is conventionally classified as AR(p), and a moving
76 average model with q terms is known as MA(q). A combined model that includes p AR-terms
77 and q MA-terms is referred to as an ARMA(p, q) model. To address non-stationarity, a
78 generally non-stationary time series is transformed into a stationary one by computing
79 differences shifted by d lags, where in most cases, $d=1$. Such a model is then categorized as
80 ARIMA(p, d, q), where the symbol "I" signifies "integrated." The general form of the above
81 model, describing the current value $y(t)$ of a time series by its own past, is expressed as:

$$82 \quad \phi_p(B)\phi_P(B^s)\nabla^d\nabla_s^D y_t = \theta_Q(B^s)\theta_q(B)\varepsilon_t(1)$$

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85 Where $\phi_p(B) = 1 - \phi_1 B - \dots - \phi_p B^p =$ Non Seasonal autoregressive (AR) operator;
86 $\theta_q(B) = 1 - \theta_1 B - \dots - \theta_q B^q =$ Non Seasonal moving average operator (MA)
87 operator; $\phi_P(B^s) = 1 - \phi_1 B^s - \dots - \phi_p B^{sP} =$ Seasonal auto regressive (SAR) operator;
88 $\theta_Q(B^s) = 1 - \theta_1 B^s - \dots - \theta_Q B^{sQ} =$ Seasonal moving average operator (SMA). Here, $B =$
89 backshift operator (i.e. $B^1 Y_t = Y_{t-1}$, $B^2 Y_t = Y_{t-2}$ and so on); $s =$ the seasonal lag; $\varepsilon_t =$ sequence of
90 independent normal error variables with mean zero and variance σ^2 ; p and q are orders of
91 non-seasonal auto-regression and moving average parameters respectively and P and Q are
92 that of the seasonal auto regression and moving average parameter respectively; d and D
93 denote the non-seasonal and seasonal differences respectively.

94 The main stages in setting up an ARIMA forecasting model include model
95 identification, model parameter estimation, and diagnostic checking for the identified model's
96 appropriateness for modeling and forecasting. The classical Box-Jenkins model describes
97 stationary time series. Thus, tentatively identifying a Box-Jenkins model requires verifying
98 the time series for stationarity. Stationary models assume that the process remains in

99 equilibrium around a constant mean level, indicated when the plotting shows that the data
100 fluctuates around its constant mean. A cursory examination of the graph of the data and the
101 structure of autocorrelation and partial correlation coefficients at various lags may provide
102 clues to the presence of stationarity. If the model is found to be non-stationary, stationarity
103 could mostly be achieved by differencing the series. The next step in the identification
104 process is to find the initial values for the orders of seasonal and non-seasonal parameters, p ,
105 q , and P , Q . These values could be obtained by looking for significant autocorrelation and
106 partial autocorrelation coefficients.

107 After choosing the most appropriate model (step 1 above), the model parameters are
108 estimated (step 2) using the least square method. In this step, values of the parameters are
109 chosen to minimize the Sum of the Squared Residuals (SSR) between the real data and the
110 estimated values. Generally, a nonlinear estimation method is used to estimate the identified
111 parameters to maximize the likelihood (probability) of the observed series given the
112 parameter values. The methodology uses the following criteria in parameter estimation:

113 a) The estimation procedure stops when the change in all parameter estimates between
114 iterations reaches a minimal change of 0.001.

115 b) The parameters estimation procedure stops when the SSR between iterations reaches a
116 minimal change of 0.0001.

117 In the diagnostic checking step (step three), the residuals from the fitted model are
118 examined for adequacy. This is typically done through correlation analysis using residual
119 ACF plots and goodness-of-fit tests via Chi-square statistics. If most of the sample
120 autocorrelation coefficients of the residuals are within the limits $\pm 1.96/\sqrt{N}$, where N is the
121 number of observations upon which the model is based, then the residuals are white noise,
122 indicating that the model is a good fit. Otherwise, if the autocorrelations are not white noise,

123 the model may not adequately represent our time series. In the last phase, i.e., forecasting, we
124 calculate the point extrapolated prognosis of the time series and eventually the confidence lag
125 of the prognosis.

126 **Evaluation Criteria**

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128 The other statistical criteria adopted in the study are:

129 **1) Akaike Information Criterion (AIC)**

131 The AIC is given by

$$132 \quad AIC = n \ln \sigma^2 + n + \frac{2(k+1)}{n-k-2} \quad (2)$$

133 Where n is the size of the sample used for fitting, k is the number of parameters
134 excluding constant terms, and $\sigma^2(\varepsilon)$ is the maximum likelihood estimate of the residual
135 variance.

136 **2) Schwarz information criterion (SIC)**

137 The SIC is given by

$$138 \quad SIC = n \ln \sigma^2(\varepsilon) + n + k \ln n \quad (3)$$

139
140 Where n , k and $\sigma^2(\varepsilon)$ are defined in the same way as for the AIC statistic.

141 **3) Mean absolute percentage error (MAPE):**

$$142 \quad MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{X_t - O_t}{O_t} \right| \times 100 \quad (4)$$

143 Where X_t = forecast value at time t ; O_t = actual value at time t ; N = number of weeks
144 considered for forecasting.

145 **4) Mean absolute error (MAE)**

$$146 \quad MAE = \frac{1}{N} \sum_{i=1}^N |X_t - O_t| \quad (5)$$

147 Where X_t = forecast value at time t ; O_t = actual value at time t ; N = number of weeks
148 considered for forecasting.

149 **3. RESULTS AND DISCUSSION**

150 In the present study the time series of weekly rainfall data from 1965 to 2017 were
151 used to develop the Seasonal ARIMA (SARIMA) model and the prediction was made for next

152 five years (2018-2022) using the developed model. The forecasted values than used for
153 validation of developed SARIMA model.

154 3.1 Analysis of Weekly Rainfall Time Series used for Model Development

155 Data of weekly rainfalls were analysed using Statistical Analysis System (SAS)
156 software. Auto correlation function (ACF) and Partial Auto correlation function (PACF) of
157 the original time series of weekly rainfall are shown in figure 1.

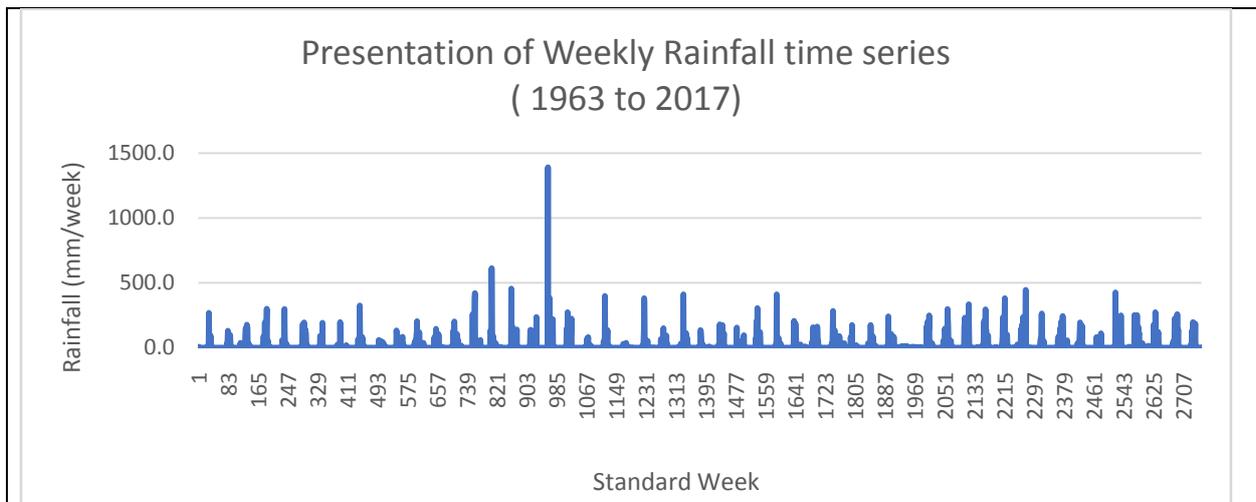


Figure:1 Graph of weekly Rainfall data series from 1965 to 2017

158 Key statistics summarizing the weekly rainfall time series data used for prediction
159 spanning the period from 1963 to 2017 were computed. The mean weekly rainfall is
160 calculated at 17.43, with a standard deviation of 56.75, indicating a notable variability in the
161 data. The dataset consists of 2743 observations (N). The Augmented Dickey-Fuller (ADF)
162 test results are presented, revealing significant negative values for the Zero Mean ADF (-
163 36.45), Single Mean ADF (-39.03), and Trend ADF (-39.06). These ADF test statistics
164 suggest a high likelihood of stationarity in the time series data, particularly with the
165 consistently low p-values associated with the ADF tests, indicating a rejection of the null
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167 hypothesis of non-stationarity. The negative values further reinforce the presence of a stable
 168 trend in the data, laying a foundation for the application of time series forecasting models.

169 **The table 1 provides diagnostic** measures for a time series, showcasing
 170 autocorrelation (AutoCorr) and partial correlation (Partial) coefficients at different lags. The
 171 Ljung-Box Q statistic with associated p-values is used to test the null hypothesis of no
 172 autocorrelation in the residuals. Notably, all autocorrelation coefficients at various lags are
 173 significant, as indicated by the low p-values (<0.0001). The decreasing pattern in
 174 autocorrelation coefficients with increasing lags suggests a declining influence of past
 175 observations on the current one. The negative partial correlation coefficients imply that the
 176 effect of past observations is adequately captured by the model. These results support the
 177 suitability of the model for forecasting as they align with the assumption of white noise
 178 residuals, essential for robust time series modeling.

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Table:1 Time series Basic diagnostics					
Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	-	-	0	1.0000
1	0.2847	222.561	<.0001*	1	0.2847
2	0.1443	279.741	<.0001*	2	0.0688
3	0.1365	330.972	<.0001*	3	0.0861
4	0.1840	424.070	<.0001*	4	0.1294
5	0.1233	465.845	<.0001*	5	0.0310
6	0.1141	501.685	<.0001*	6	0.0489
7	0.1304	548.496	<.0001*	7	0.0638
8	0.0290	550.819	<.0001*	8	-0.0650
9	0.0099	551.092	<.0001*	9	-0.0261
10	-0.0099	551.362	<.0001*	10	-0.0429
11	-0.0133	551.851	<.0001*	11	-0.0339
12	-0.0289	554.157	<.0001*	12	-0.0245
13	-0.0032	554.185	<.0001*	13	0.0130
14	-0.0651	565.877	<.0001*	14	-0.0637
15	-0.0477	572.147	<.0001*	15	0.0020
16	-0.0668	584.453	<.0001*	16	-0.0352
17	-0.0785	601.493	<.0001*	17	-0.0396
18	-0.0778	618.215	<.0001*	18	-0.0214
19	-0.0813	636.475	<.0001*	19	-0.0338

Table:1 Time series Basic diagnostics					
Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
20	-0.0868	657.292	<.0001*	20	-0.0355
21	-0.0848	677.179	<.0001*	21	-0.0150
22	-0.0872	698.220	<.0001*	22	-0.0334
23	-0.0869	719.121	<.0001*	23	-0.0216
24	-0.0885	740.823	<.0001*	24	-0.0265
25	-0.0880	762.299	<.0001*	25	-0.0295

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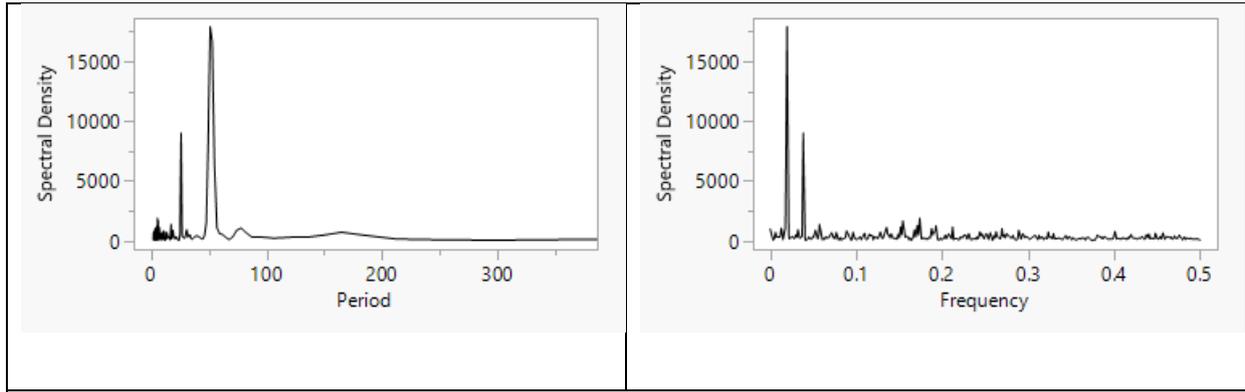


Figure:2 Spectral density plots of weekly rainfall time series

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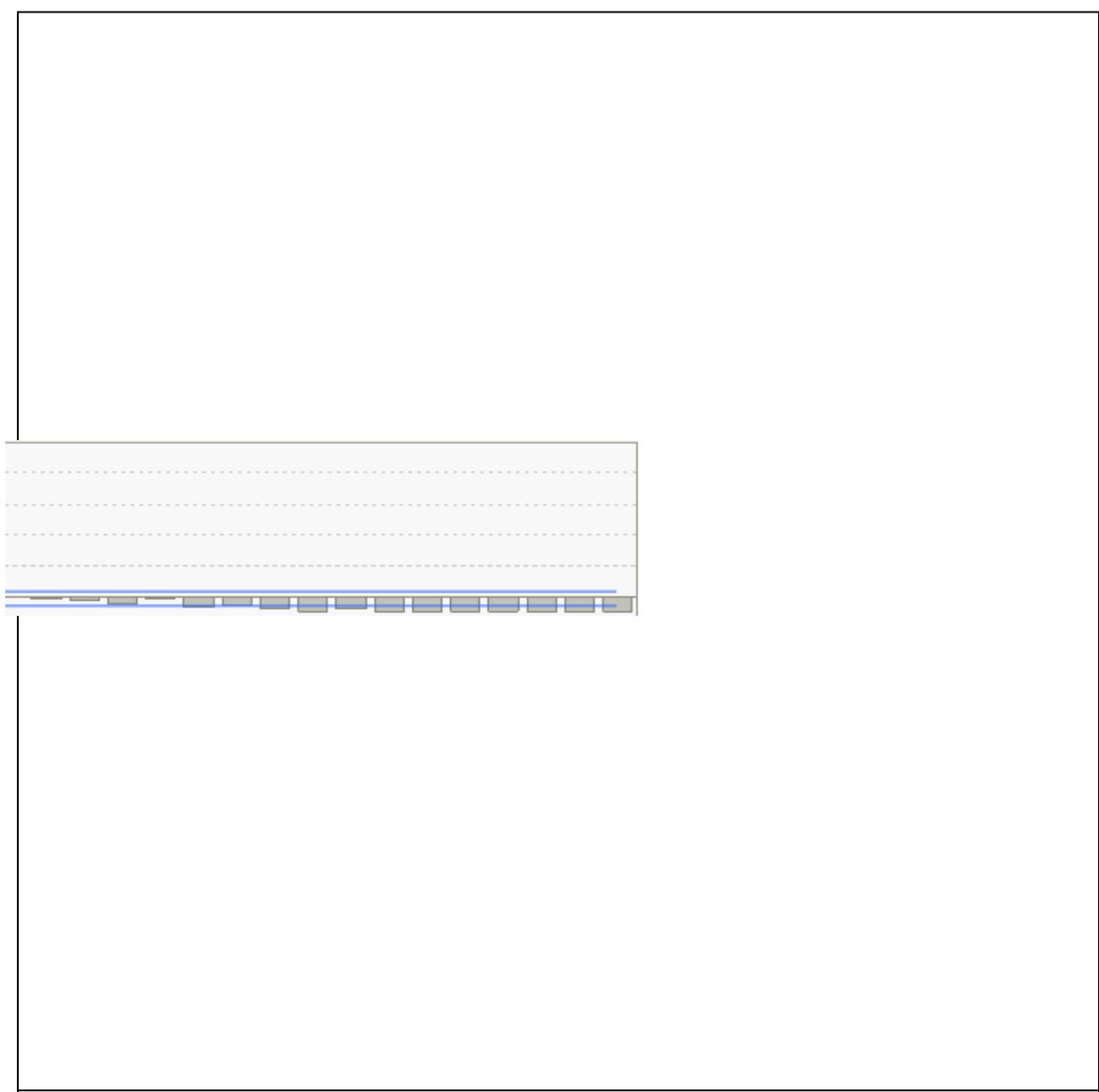
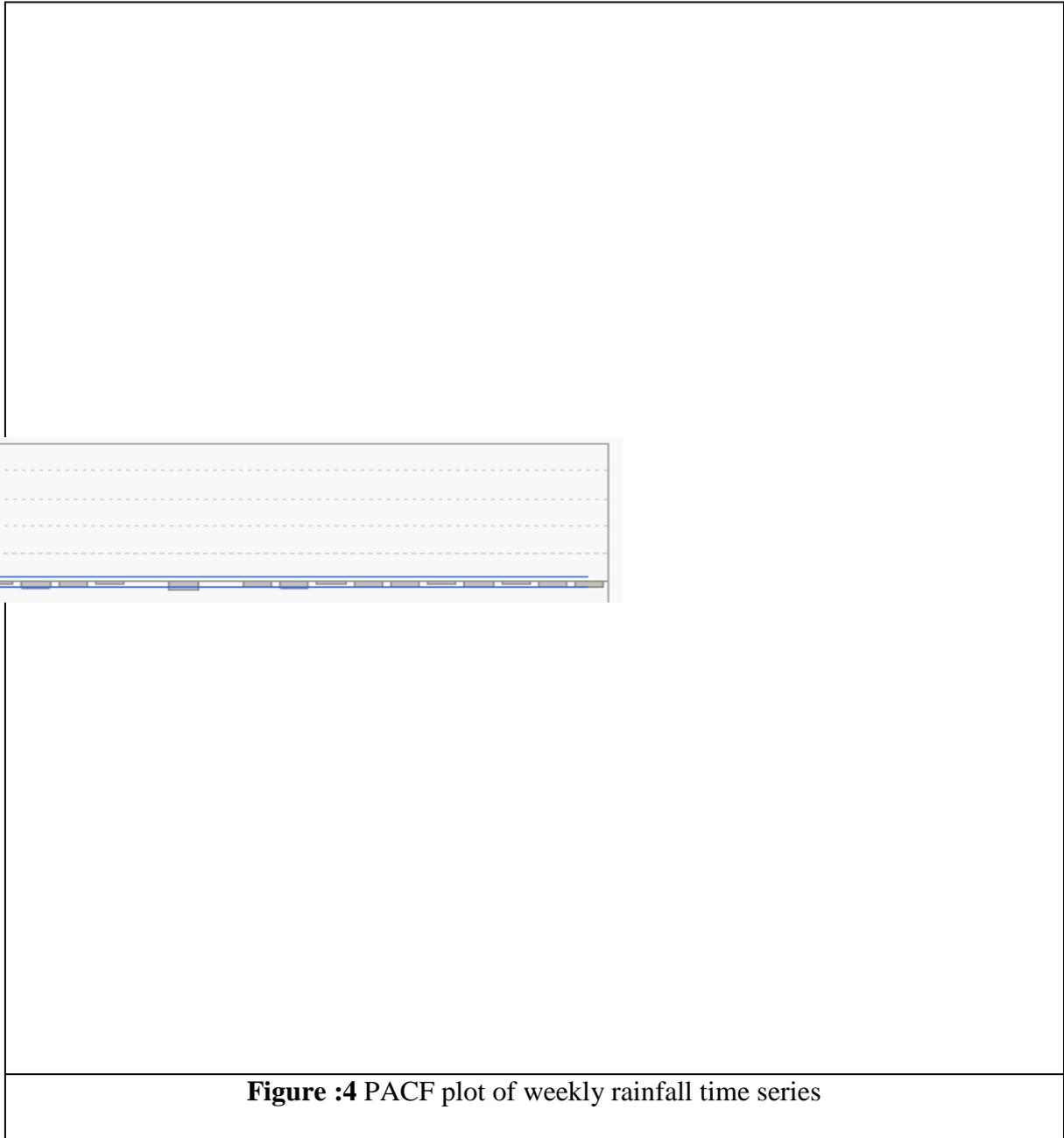


Figure:3 ACF plot of weekly rainfall time series



183 **3.2 Model Development and Parameter Estimation**

184 Figures 3 and 4 provide a detailed depiction of the Autocorrelation Function (ACF)
 185 and Partial Autocorrelation Function (PACF), offering profound insights into the periodic
 186 nature of the variables associated with weekly rainfall. These graphical representations
 187 consistently reveal patterns indicative of seasonal variations within the time series. Building
 188 upon these findings, we assume a yearly period of 52 weeks for the given rainfall time series.

189 Figures 5 and 6 provide a concise overview of the SARIMA (0,0,4)(0,1,1) model's
190 performance in predicting weekly rainfall. Figure 5 illustrates the model's predictions,
191 showcasing its ability to capture both non-seasonal and seasonal components. The parameters
192 (0,0,4) indicate the absence of non-seasonal autoregressive and moving average effects, while
193 (0,1,1) signifies first-order differencing in the seasonal part for stationarity. This visualization
194 offers a clear representation of how well the SARIMA model aligns with observed weekly
195 rainfall trends. In Figure 6, the Residual Plot for SARIMA (0,0,4)(0,1,1) allows for a quick
196 assessment of model residuals. A well-behaved residual plot indicates a well-fitted model,
197 and analysing it provides insights into the accuracy and reliability of the SARIMA model in
198 predicting weekly rainfall.
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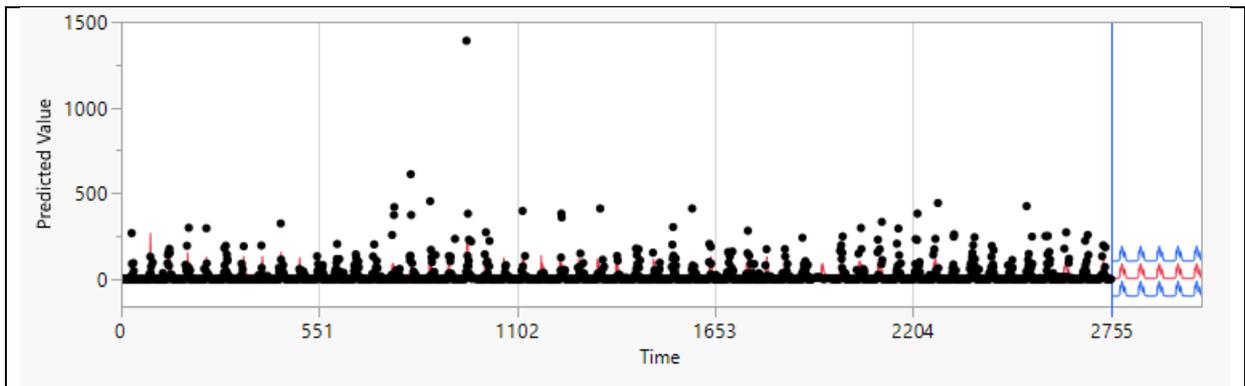


Fig:5 Prediction of weekly rainfall using SARIMA (0,0,4) (0,1,1)

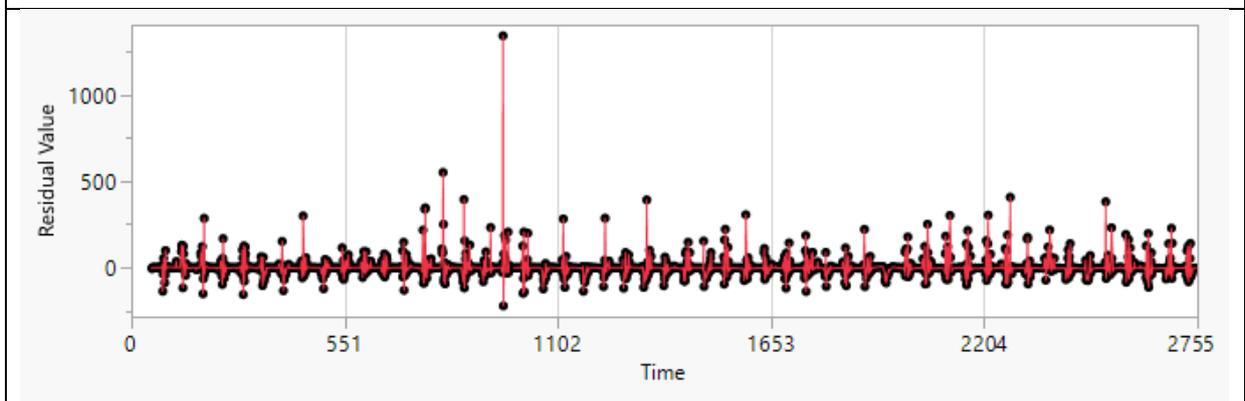


Fig:6 Residual Plot for SARIMA (0,0,4) (0,1,1)

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Following the essential stationarities steps, we systematically explored various orders of Seasonal ARIMA models tailored to the weekly rainfall series. The model selection process involved a thorough assessment, considering not only the ACF and PACF charts but also key metrics such as the Akaike Information Criterion (AIC), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). Following a meticulous evaluation, the Seasonal ARIMA model (0,0,4)(0,1,1)⁵² emerged as the optimal choice for accurately forecasting weekly rainfall in the Junagadh region. Subsequently, a comprehensive five-year forecast spanning 2018 to 2022 was executed. Visual representations of the selected model dynamics are thoughtfully presented in Figures 7 and 8, while a detailed breakdown of parameters and statistical insights is thoroughly documented in Table 2 and Table 3.

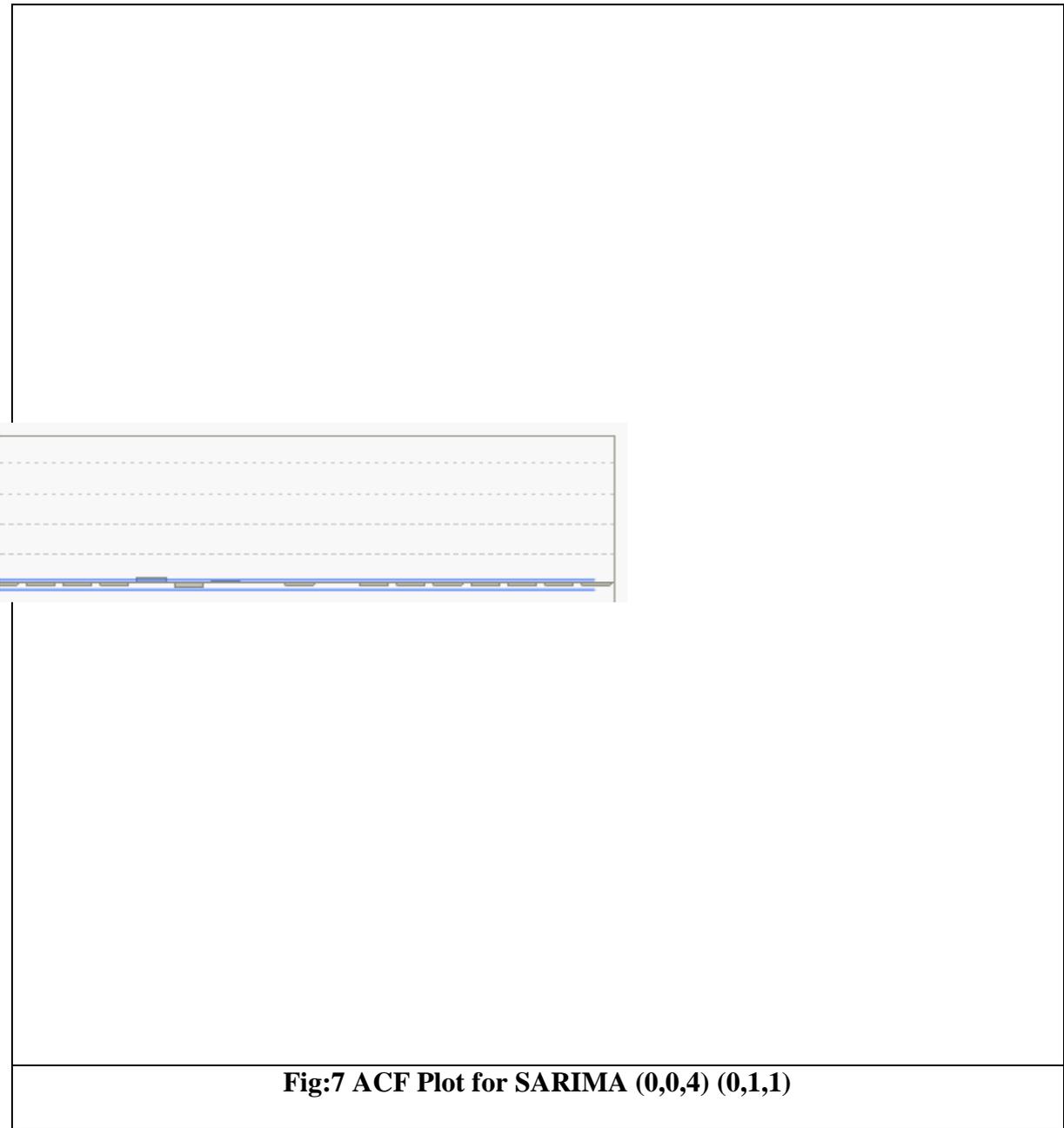
Table:2SARIMA (0,0,4) (0,1,1)Model Summary

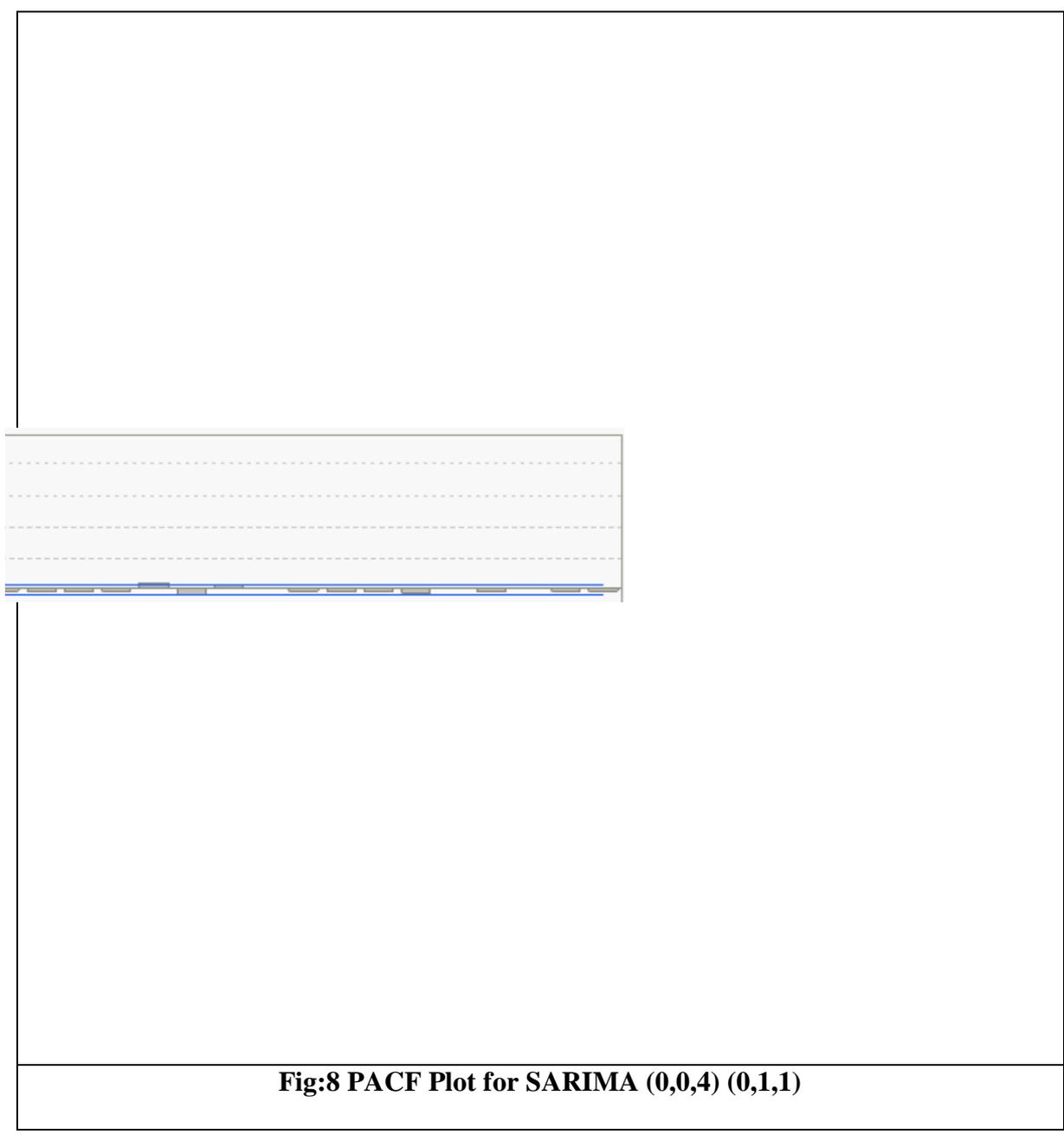
DF	2672
Sum of Squared Innovations	7060778.92
Sum of Squared Residuals	7258474.63
Variance Estimate	2642.50708
Standard Deviation	51.4053215
Akaike's 'A' Information Criterion	28827.5382
Schwarz's Bayesian Criterion	28862.8951
RSquare	0.16994209
RSquare Adj	0.16839635
MAPE	09.5698
MAE	19.5382271
-2LogLikelihood	28815.5382

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Table-3SARIMA (0,0,4) (0,1,1)Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob> t
MA1,1	1	1	-0.1159690	0.0193688	-5.99	<.0001*
MA1,2	1	2	0.0346565	0.0188537	1.84	0.0661
MA1,3	1	3	0.0436783	0.0193018	2.26	0.0237*
MA1,4	1	4	-0.0665500	0.0196808	-3.38	0.0007*
MA2,52	2	52	0.9500147	0.0106861	88.90	<.0001*
Intercept	1	0	0.1583824	0.0904021	1.75	0.0799





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215 **3.3 Comparison of Actual and Predicted weekly rainfall value**

216 Figure 9 serves as a visual guide for comparing the actual and predicted values of
 217 weekly rainfall over the five-year span from 2018 to 2022. The graph offers a detailed
 218 examination of how well the SARIMA model performs in forecasting weekly rainfall. A
 219 closer inspection reveals a remarkable proximity between the predicted time series and the
 220 actual data series. This visual coherence signifies the SARIMA model's exceptional

221 capability to provide accurate and reliable forecasts of rainfall patterns. The model adeptly
222 captures the nuances and fluctuations present in the observed data, emphasizing its
223 effectiveness as a valuable forecasting tool. The visual representation in Figure 9 serves as a
224 compelling endorsement of the SARIMA model's robust performance in predicting weekly
225 rainfall values.

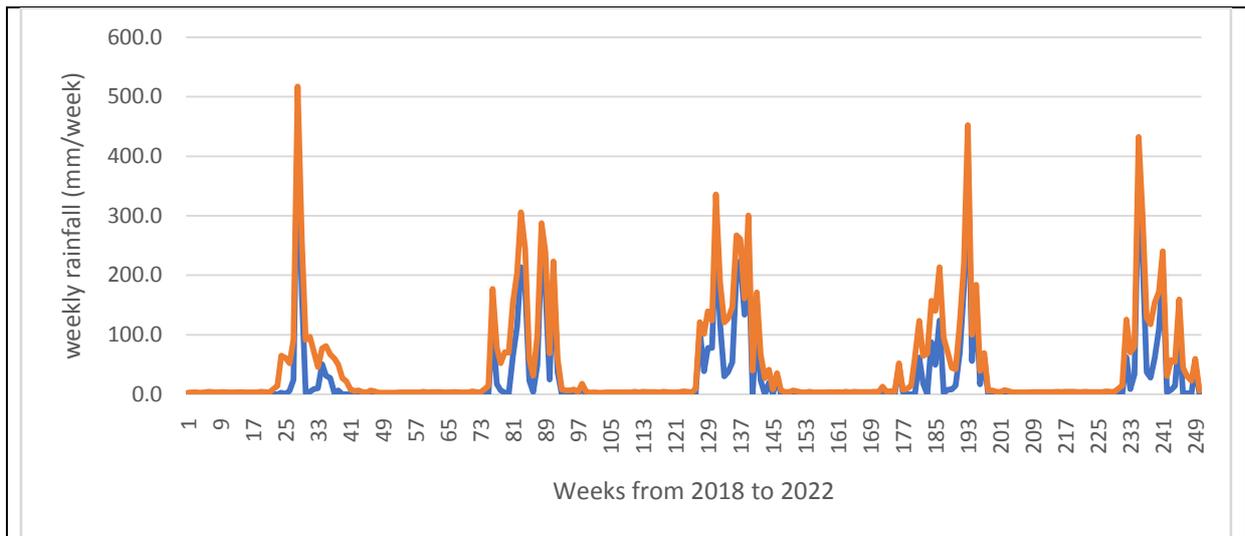


Fig:9 Comparison of Actual and Predicted weekly rainfall value of five years (2018-2022)

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227 4. Conclusion

228 The study conclusively asserts the efficacy of the Seasonal Autoregressive Integrated
229 Moving Average (SARIMA) model as an indispensable tool for forecasting weekly rainfall in
230 the Junagadh region. Boasting commendable accuracy, as evidenced by robust statistical
231 measures, the SARIMA model emerges as a reliable asset for predicting the intricate patterns
232 of weekly rainfall. This finding underscores the pivotal role of the Box-Jenkins methodology,
233 which, through SARIMA, equips decision-makers with valuable insights. Decision-makers
234 are empowered to forge better strategies and prioritize actions to fortify themselves against
235 impending weather changes. Such strategic planning is particularly crucial given the potential
236 enduring impacts of weather fluctuations on the water resources in Junagadh.

237 The SARIMA model's predictive prowess not only enhances forecasting precision but
238 also facilitates proactive decision-making to navigate the dynamic nature of climatic
239 conditions. By embracing SARIMA within the Box-Jenkins framework, decision-makers can
240 not only anticipate and plan for upcoming weather variations but also establish resilient
241 strategies for long-term water resource management. This holistic approach aids in setting
242 priorities and allocating resources efficiently. In essence, the SARIMA model, bolstered by
243 the Box-Jenkins methodology, emerges as a key ally for decision-makers, offering a strategic
244 advantage in mitigating the effects of weather changes and fortifying the water resources of
245 the Junagadh region against the uncertainties of the future.

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