__Original Research Article__

PREDICTING POTENTIAL EVAPOTRANSPIRATION FOR KALABURAGI DISTRICT USING A SEASONAL ARIMA MODEL.

ABSTRACT

Forecasting potential evapotranspiration (PET) is of great importance in effectively managing irrigation systems. This article centers around models designed to simulate future PET levels for the Kalaburagi district. The study calculates potential evapotranspiration using temperature data in degrees Celsius, employing the Thornthwaite method, and prediction is performed using the Seasonal Autoregressive Moving Average (SARIMA) method. These models are developed based on autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis. Model selection is based on minimizing Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) values. The chosen models for different stations in Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi, and Afzalpur respectively are SARIMA(1,0,1)(2,1,0)12, SARIMA(1,0,1)(2,1,0)12, SARIMA(1,0,0)(2,1,0)12, SARIMA(1,0,1)(2,1,0)12, SARIMA(1,0,1)(2,1,0)12, and SARIMA(1,0,1)(2,1,0)12. The results indicate that the models developed for Jewargi and Chincholi stations show particular promise compared to the other two stations, with all four models performing well. These models have the potential to significantly enhance decision-making in irrigation planning and command area management practices, contributing to improved water resource management.

Keywords: ACF, PACF, SARIMA, PET

INTRODUCTION

Evapotranspiration (ET) represents a vital part of the hydrologic cycle, as it accounts for the majority of precipitation on land returning to the atmosphere (Asadi et al., 2013). Globally, ET consumes approximately 60% of the annual surface precipitation. Precise ET quantification holds significant importance for a variety of applications, including crop production, water resource management, and environmental assessment (Aruna et al., 2017). In agricultural contexts, ET plays a pivotal role in the water balance, directly impacting crop quality and yield. Thus, accurately measuring ET is essential for effective irrigation and water resource management.

ET data for agricultural crops have become increasingly crucial in both irrigation and water resource management. This process is predominantly influenced by various hydrological parameters, such as temperature, relative humidity, solar radiation, wind speed, and other climatic factors.

Stochastic models take into account time-dependent variations and encompass random effects inherent to the ET process. Stochastic linear models, including those applied to ET time series data, facilitate the integration of on-farm systems with the primary irrigation system, enabling real-time operation. One of the most powerful models for forecasting time series datasets is the autoregressive integrated moving average (ARIMA) model. In ARIMA, the forecast of a variable is a linear combination of its previous state and the previous forecast error. ARIMA is renowned for its adaptability to the characteristics of time series data and has seen widespread use in hydrological time series modeling (Popale and Gorantiwar, 2014).

ARIMA models have been applied across various regions and climatic conditions to address different purposes. For example, ARIMA was utilized to predict rainfall in the Rahuri region, India (Popale and Gorantiwar, 2014), and to analyze evapotranspiration in the same region (Gorantiwar and Patil, 2009). Seasonal ARIMA models were crafted for the Jordan Valley (Hamdi et al., 2008), while Asadi et al. (2014) applied ARIMA to forecast evapotranspiration in humid and semi-humid regions. Time series modeling, extensively detailed by Salas et al. (1980), plays a crucial role in comprehending and forecasting various hydrological phenomena.

A comprehensive understanding of evapotranspiration is indispensable for watershed management, meteorological and hydrological modeling, and effective water resource management, especially in irrigated agriculture (Dutta et al., 2016). ET exerts a significant influence on crop water requirements (CWR), constituting over 95% of ET. Analyzing historical ET data is pivotal for addressing irrigation-related challenges and optimizing water resource management.

The primary objective of this study is to establish a time series model for analyzing and forecasting potential evapotranspiration in the Kalaburagi district.

MATERIALS AND METHODOLOGY

Kalaburagi is an administrative district located in the Indian state of Karnataka and serves as the largest city in the North Karnataka region, also known as Kalyana-Karnataka. Geographically, this district spans between 76°04' and 77°42' east longitude and 17°12' and 17°46' north latitude, covering a total area of 10,951 square kilometers.

The district is bordered by Vijayapura district of Karnataka and Solapur district of Maharashtra state to the west, Bidar district and Osmanabad district of Maharashtra state to the north, Yadgir district to the south, and Sangareddy and Vikarabad districts of Telangana state to the east. Kalaburagi district is situated entirely on the Deccan Plateau, with elevations ranging from 300 to 750 meters above mean sea level.

Two major rivers, the Krishna and the Bhima, traverse the district, contributing to its geographical and ecological characteristics.

Thornthwaite method (Potential evapotranspiration)

The potential evapotranspiration is calculated by:

$$PET=16K\left(\frac{10T}{I}\right)^{m}$$

Where T is monthly mean temperature (°C); I is heat index calculated as the sum of 12 month index values; m is the coefficient dependent on I.

$m=6.75 \times 10^{-7} \cdot I^{3} - 7.71 \times 10^{-7} \cdot I^{2} + 1.79 \times 10^{-2} \cdot I + 0.492.$

K is a correction coefficient computed as a function of the latitude and month(Shadab*et al.*, 2020).

Auto correlation test (Box Ljung test)

The null hypothesis, denoted as H0, in the Box-Ljung Test asserts that the model exhibits no lack of fit, essentially meaning the model is an appropriate fit for the data. In simpler terms, it suggests that the model is a good representation of the data. On the other hand, the alternative hypothesis, denoted as Ha, suggests that the model does display a lack of fit, indicating that it may not accurately represent the data.

When the p-value obtained from the Box-Ljung Test is statistically significant, it leads to the rejection of the null hypothesis. In such cases, it suggests that the time series data does exhibit autocorrelation, implying that the model may not be a suitable fit for the data (Malik et al., 2021).

Stationary test (Dickey fuller test)

In the context of time series analysis, a time series is considered to be stationary in the weak sense when its statistical characteristics, such as means and variance, remain constant and do not change over time. Conversely, when the calculated p-values are greater than 0.05, it indicates that the series is non-stationary. Achieving a stationary form for the time series is essential for it to be fitted to stochastic models, as highlighted by Patil et al. (2022).

Description of the stochastic models

Stochastic models, which are also known as time series models, have found extensive application in the analysis of time series data across mathematical, economic, and engineering fields. These modeling techniques offer a systematic and analytical approach to simulate and forecast the behavior of complex and unpredictable hydrological systems. Additionally, they enable the measurement of the accuracy of the forecasts, as demonstrated by Mishra and Desai in 2005.

ARIMA models

Autoregressive (AR) models and moving average (MA) models can be combined to create a specific and effective class of time series models known as autoregressive integrated moving average (ARIMA) models. In ARIMA models, the current value of a time series is described as a linear combination of 'p' lagged values and a weighted sum of 'q' previous deviations, along with a random parameter.(Moghimi et al. 2020)

ARIMA models are typically applied to time series data that exhibit stationarity. However, they can also be used with non-stationary data by differencing the series. Box and Jenkins (1976) introduced a novel forecasting tool, the ARIMA methodology, which focuses on analyzing the stochastic characteristics of time series independently, rather than constructing single or simultaneous equation models.

ARIMA models enable the representation of each variable using its own lagged values and stochastic error terms. The general non-seasonal ARIMA model consists of an AR component of order p and an MA component of order q, operating on the dth difference of the time series, denoted as zt. Therefore, a model in the ARIMA family is defined by three parameters (p, d, q), with each parameter taking zero or positive integral values, as described by Mishra and Desai in 2005.

The general non-seasonal ARIMA model may be written as:

$$\emptyset(\mathrm{B})\nabla^{\mathrm{d}}_{\mathrm{Z_t}} = \theta(\mathrm{B})\mathrm{a_t}$$

Where, θ (B) are polynomials of order p and q respectively. The non-seasonal AR operator of order p can be written as:

$$\emptyset(B) = \left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots \emptyset_p B^p\right)$$

and non-seasonal MA operator of order q is written as:

$$\theta(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q\right)$$

Seasonal ARIMA models

Many time series exhibit cyclic patterns, often following an annual cycle in hydrological time series due to the Earth's rotation around the sun. These cyclic patterns make such series cyclically non-stationary. By removing the deterministic cyclic effects from a series, the ARIMA (AutoRegressive Integrated Moving Average) approach can be applied to model the stochastic component of the series, as described by Gorantiwar et al. in 2011.

To address seasonality and cyclic patterns in time series, Box et al. (1994) introduced a standardized version of the ARIMA model, known as the Seasonal ARIMA (SARIMA) model. SARIMA models are designed to handle time series data with both non-seasonal and seasonal non-stationarity. A significant advantage of the SARIMA family of models is their ability to describe time series with only a few model parameters, accounting for non-stationarity both within seasons and throughout the data. In general, a SARIMA model is denoted as ARIMA (p, d, q) (P, D, Q)s, where (p, d, q) represents the non-seasonal component of the model, and (P, D, Q)s represents the seasonal component of the model.

$$\emptyset_p(B)\Phi_p(B^s)\nabla^d \nabla_s^D Z_t = \theta_p(B)\varphi_Q(B^s)a_t$$

where p is the order of non-seasonal auto-regression, d the number of regular differencing, q the order of non-seasonal MA, P the order of seasonal auto-regression, D the number of seasonal differencing, Q the order of seasonal MA, s is the length of season, seasonal AR parameter of order P, seasonal MA parameter of order Q.

a. Model identification

The initial step in the analysis involves identifying a suitable ARIMA model that can effectively capture the behavior of the time series data. To accomplish this, the behavior of the time series is examined, with a focus on the autocorrelation function (ACF) and the partial autocorrelation function (PACF), as suggested by Mishra and Desai in 2005 and Hsin-Fu Yeh and Hsin-Li Hsu in 2019. The ACF and PACF provide valuable information for determining the appropriate order of the ARIMA model. They assist in suggesting the types of models that might be appropriate for modeling the data. (Liu et al. 2021)

Following the ACF and PACF analysis, the final ARIMA model is selected using statistical criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as recommended by Prasad et al. in 2019. These criteria serve to rank the candidate models, with the models having the lowest AIC and BIC values considered the best-fitting models. The mathematical forms of AIC and BIC are as follows: [Further content related to AIC and BIC may be included here].

$$AIC= -2 \log (L) + 2k \text{ and } SBC= -2 \log (L) + k \ln(n).$$

Where k is number of parameters in the model; L is the likelihood function of the ARIMA model; and n is the number of observations.

b. Parameter estimation

Once the appropriate ARIMA model has been identified, the next crucial step is to estimate the model parameters. The estimation process involves determining the values for the autoregressive (AR) and moving average (MA) components of the model. These parameter values are calculated using the Maximum Likelihood method.

After estimating the AR and MA parameters, it is important to conduct statistical tests to ascertain their significance. This step ensures that the AR and MA parameters are statistically meaningful and contribute significantly to the model's ability to explain the underlying patterns in the time series data.

c. Diagnostic checking

Diagnosing the ARIMA model is a critical and final step in the model development process. It involves assessing the suitability of the chosen model. Various diagnostic statistics and residual plots are examined to determine if the residuals exhibit any correlation or follow a white noise pattern.

In this study, one of the diagnostic tools used is the residual autocorrelation function (RACF). The RACF is employed to evaluate whether the residuals behave like white noise. If the residuals exhibit a pattern or correlation in the RACF, it suggests that the model might need further refinement or that there is additional information in the data that the model has not captured. (Abedi-Koupai et al. 2022)

d. Drought forecasting

To predict potential evapotranspiration (PET), the study employed the best-fit models identified from historical data. After generating these predictions, fundamental statistical properties were computed and tested to determine whether the predicted data maintained the basic statistical characteristics of the observed PET series.

This assessment included examining various statistical measures, such as correlation coefficients (R), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), which were used to quantify the relationship and accuracy of the observed and predicted data. These metrics provide insights into how well the predictions align with the observed PET series, helping to assess the model's performance.(Pino-Vargas et al. 2022)

Input Dataset and software

The time series temperature data (both maximum and minimum) were collected from the Zonal Agricultural Research Station (ZARS) in Kalaburagi. The dataset covers the years from 1990 to 2021. For the purpose of model development, data from 1990 to 2019 were utilized, while data from 2020 to 2021 were reserved for validation.

The estimation of potential evapotranspiration was carried out using Microsoft Excel, and SARIMA models were developed using R Studio software. This approach allowed for the development and validation of models to predict potential evapotranspiration based on the temperature data collected from 1990 to 2019.

RESULTS AND DISCUSSION

The model development process included essential prerequisite tests, which encompassed checks for stationary and autocorrelation. Autocorrelation tests were conducted using the Box test, and the corresponding probability levels are presented in Table 1. The results indicated that the test statistics for the Box test, along with the associated Chi-square values and P-values, were as follows: 187.17 (0.01), 185.64 (0.01), 172.77 (0.01), 182.4 (0.01), 187.26 (0.01), 99.88 (0.01), and 189.64 (0.01) for the locations Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi, and Afzalpur, respectively. These values were deemed significant at a 5% level of significance, indicating the presence of autocorrelation in the data.

Conversely, the Augmented Dickey-Fuller (adf.test) was employed to assess whether the data exhibited stationarity or not. The results indicated the presence of seasonality in the data. Consequently, seasonal differencing was performed on the datasets, as shown in Table 2. This step aimed to address the seasonality observed in the data and make it more amenable for modeling.

Table 1: Auto correlation test for different stations of Kalaburgi district

Station	Chi-Square	Lag order	P-value
Kalaburagi	187.17	1	<0.001
Chincholi	185.64	1	<0.001
Sedam	172.77	1	<0.001
Chittapur	182.4	1	<0.001
Aland	187.26	1	<0.001
Jewargi	99.883	1	<0.001
Afzalpur	189.64	1	<0.001

Table 2: Stationarity test for different stations of Kalaburgi district

Station	Dickey fuller	Lag order	P-value
Kalaburagi	-18.022	7	0.01
Chincholi	-17.777	7	0.01

Sedam	-17.193	7	0.01
Chittapur	-17.491	7	0.01
Aland	-18.028	7	0.01
Jewargi	-4.8282	7	0.01
Afzalpur	-18.195	7	0.01

The primary step in constructing the Box-Jenkins ARIMA model involves identifying the appropriate model. Various combinations of autoregressive (AR) and moving average (MA) parameters, denoted as p and q, were considered. The model selection process aimed to find the combination of orders that yielded the maximum log-likelihood and the lowest values of the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). The results for model development at the Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi, and Afzalpur stations are presented in Tables 3 and 4.

To identify the model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) were plotted, as shown in Figures 1 and 2. These plots were instrumental in recognizing the presence of seasonality in the data. Consequently, seasonal ARIMA models were selected, incorporating seasonal differencing, as detailed in Table 4.

The best-selected models for different stations included SARIMA (1,0,1)(2,1,0)12, SARIMA(1,0,1)(2,1,0)12, SARIMA(1,0,0)(2,1,0)12, SARIMA(1,0,1)(2,1,0)12, SARIMA(1,0,1)(2,1,0)12, SARIMA(1,0,1)(2,1,0)12, and SARIMA(1,0,1)(2,1,0)12, with maximum likelihood values of -1532.32, -1542.42, -1732.01, -1552.32, -1512.62, -1542.24, and -1544.46, respectively, for Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi, and Afzalpur. The estimated parameters for these models at different stations are presented in Table 4.

Furthermore, the residuals were obtained by differencing the original series with the fitted series. The results showed (Table 5) that the residuals exhibited characteristics of white noise, indicating the adequacy of the model in capturing the underlying patterns in the data.

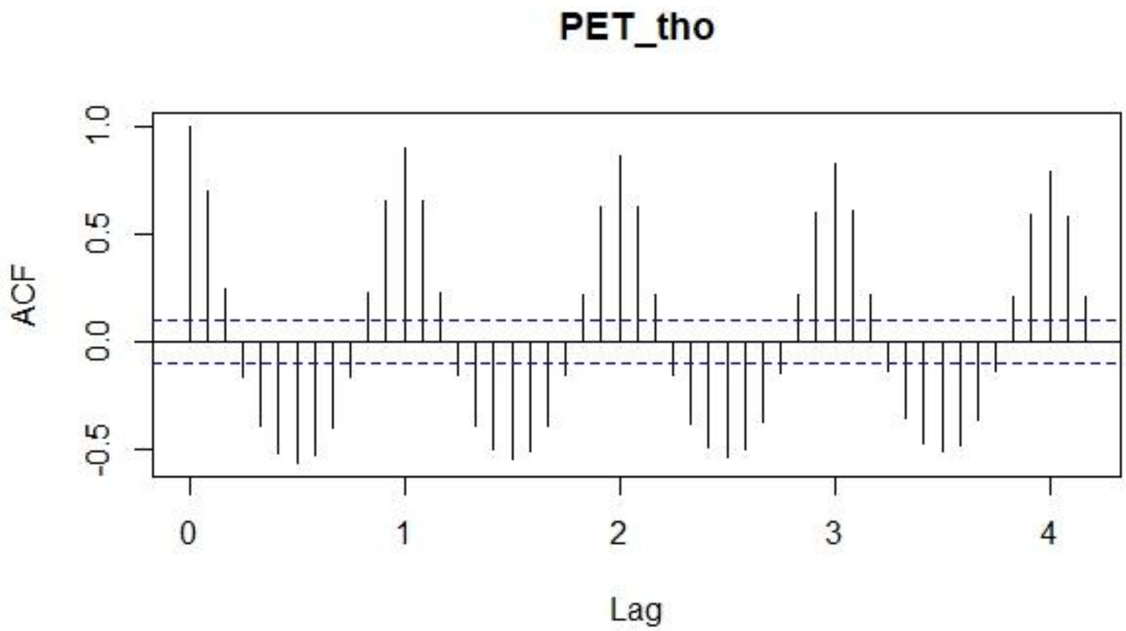

Fig. 1: Autocorrelation function plot of PET time series for Kalaburagi Station

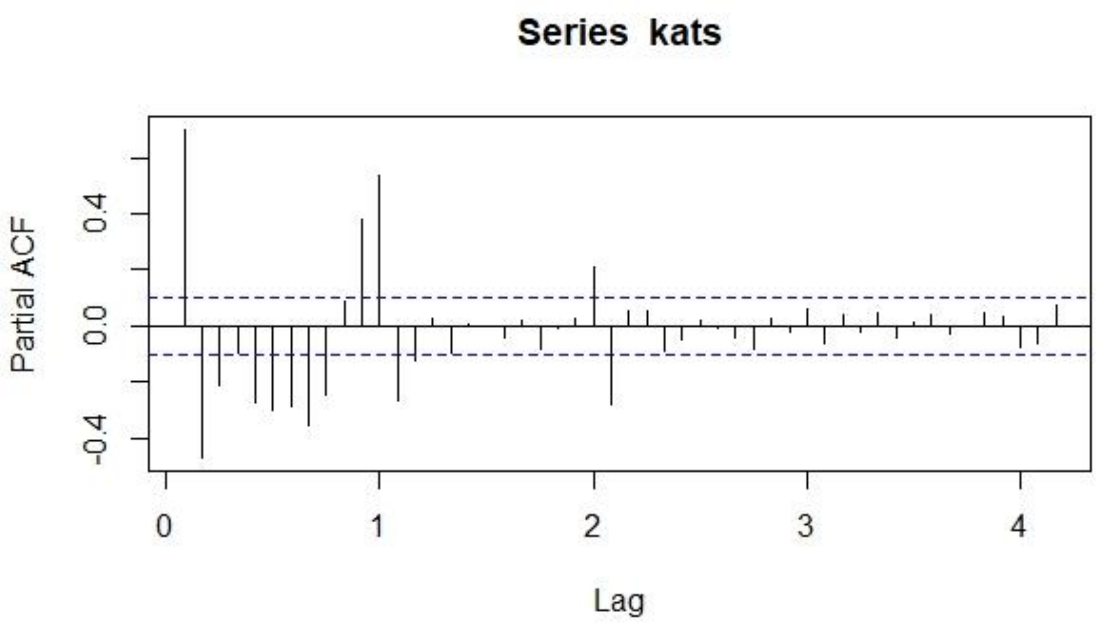

Fig. 2: Partial autocorrelation function plot of PET time series for Kalaburagi Station

Table 3: Log likelihood AIC and BIC values of ARIMA model for different stations

Stations	Model	Log-Likelihood	AIC	BIC
Kalaburagi	SARIMA (1,0,1)(2,1,0)$_{12}$	-1532.32	3074.64	3093.9
Chincholi	SARIMA(1,0,1)(2,1,0)$_{12}$	-1542.42	3024.82	3019.5
Sedam	SARIMA(1,0,0)(2,1,0)$_{12}$	-1732.01	3474.02	3488.45
Chittapur	SARIMA(1,0,1)(2,1,0)$_{12}$	-1552.32	3064.64	3083.9
Aland	SARIMA (1,0,1)(2,1,0)$_{12}$	-1512.62	3094.64	3098.9
Jewargi	SARIMA (1,0,1)(2,1,0)$_{12}$	-1542.24	3054.64	3053.9
Afzalpur	SARIMA (1,0,1)(2,1,0)$_{12}$	-1544.46	3094.64	3148.6

Table 4: Parameter estimation of SARIMA by maximum likelihood method for different stations

Station	Model	Parameters	Estimate	S.E.	Z value	P-value
Kalaburagi	SARIMA (2,0,2)(1,1,2)$_{12}$	Ar_1	0.73	0.080	9.207	<0.001
		Ma_1	-0.401	0.110	-3.630	<0.001
		Sar_1	-0.84	0.049	-16.919	<0.001
		Sar_2	-0.40	0.050	-8.133	<0.001
Chincholi	SARIMA (1,0,1)(2,1,0)$_{12}$	Ar_1	0.74	0.082	8.263	<0.001
		Ma_1	-0.412	0.116	-5.654	<0.001
		Sar_1	-0.88	0.045	-18.324	<0.001
		Sar_2	-0.49	0.052	-9.124	<0.001
Sedam	SARIMA (1,0,1)(1,1,2)$_{12}$	Ar_1	0.314	0.050	6.245	<0.001
		Sar_1	-0.752	0.052	-14.289	<0.001
		Sar_2	-0.306	0.052	-5.789	<0.001
Chittapur	SARIMA (1,0,1)(2,1,0)$_{12}$	Ar_1	0.728	0.088	9.408	<0.001
		Ma_1	-0.409	0.114	-3.840	<0.001
		Sar_1	-0.862	0.042	-16.918	<0.001
		Sar_2	-0.400	0.062	-8.152	<0.001
Aland	SARIMA (2,0,2)(1,1,2)$_{12}$	Ar_1	0.732	0.084	9.407	<0.001
		Ma_1	-0.410	0.118	-3.830	<0.001
		Sar_1	-0.842	0.042	-16.812	<0.001
		Sar_2	-0.406	0.054	-8.203	<0.001
Jewargi	SARIMA (1,0,1)(2,1,0)$_{12}$	Ar_1	0.74	0.081	9.203	<0.001
		Ma_1	-0.420	0.122	-3.633	<0.001
		Sar_1	-0.862	0.044	-16.84	<0.001
		Sar_2	-0.410	0.051	-8.234	<0.001
Afzalpur	SARIMA (2,0,2)(1,1,2)$_{12}$	Ar_1	0.82	0.086	9.308	<0.001
		Ma_1	-0.54	0.212	-3.744	<0.001
		Sar_1	-0.842	0.056	-16.984	<0.001
		Sar_2	-0.48	0.058	-8.458	<0.001

Table 5: Auto correlation check for residuals of Seasonal **ARIMA model at different station**

Station	Chi-Square	Lag order	P-value
Kalaburagi	0.01	1	0.919
Chincholi	0.04	1	0.82
Sedam	0.330	1	0.565
Chittapur	2.27	1	0.13
Aland	0.0103	1	0.919
Jewargi	0.06	1	0.921
Afzalpur	0.08	1	0.924

Following the development of models for all seven taluks (selected stations) in the Kalaburagi district, the forecasting phase was executed, and the results are summarized in Table 6. The results indicate that, initially, the forecasts were found to be highly accurate, with correlation coefficients of 0.96, 0.95, 0.90, 0.88, 0.89, 0.92, and 0.86 for Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi, and Afzalpur, respectively.

To further evaluate the forecasting results, basic statistical properties were compared between the observed and forecasted data. This comparison involved employing a t-test for means and an F-test for standard deviation, following the methodology outlined by Haan in 1977. The outcomes are presented in Table 7.

The results of these statistical tests indicate that the t-calculated values associated with means fell within the range of t-critical table values (±1.71) for a two-tailed test at a 5% significance level. This implies that there is no significant difference between the mean values of the observed and predicted data.

Similarly, the F-calculated values for standard deviation were smaller than the F-critical values at a 5% significance level. This indicates that the forecasted data effectively preserves the basic statistical properties of the observed time series data.

Table 6: Performance measure of Seasonal ARIMA models at different stations

Station	**Model**	**Performance measures**	
	SARIMA $(2,0,2)(1,1,2)_{12}$		
		RMSE	22.61

Kalaburagi		MAPE	13.72
		R	0.96
Chincholi	SARIMA $(1,0,1)(2,1,0)_{12}$	RMSE	21.61
		MAPE	15.52
		R	0.95
Sedam	SARIMA $(1,0,1)(1,1,2)_{12}$	RMSE	23.45
		MAPE	11.25
		R	0.90
Chittapur	SARIMA $(1,0,1)(2,1,0)_{12}$	RMSE	28.54
		MAPE	19.45
		R	0.88
Aland	SARIMA $(2,0,2)(1,1,2)_{12}$	RMSE	29.52
		MAPE	9.85
		R	0.89
Jewargi	SARIMA $(1,0,1)(2,1,0)_{12}$	RMSE	20.15
		MAPE	14.96
		R	0.92
Afzalpur	SARIMA $(2,0,2)(1,1,2)_{12}$	RMSE	30.12
		MAPE	18.92
		R	0.86

Table 7: Comparison of statistical properties of the observed and predicted data

Stations	**Mean observed**	**Mean forecasted**	**Decision (t<1.79)**	**Observed variance**	**Forecast variance**	**Decision (f < 0.74)**
Kalaburagi	151.59	142.86	0.19	4580.23	6143.2	0.31
Chincholi	142.36	112.24	0.17	3245.26	3878.69	0.25
Sedam	136.74	122.25	0.006	3008.58	3152.63	0.29
Chittapur	136.54	152.36	-0.045	2254.69	2296.69	0.21
Aland	161.23	112.02	0.17	2985.63	3001.98	0.31
Jewargi	159.85	98.85	-0.017	4012.96	4112.65	0.30
Afzalpur	165.66	107.25	0.15	2160.52	2560.32	0.24

CONCLUSION

The results from the Seasonal ARIMA models indicate that these models are highly effective in forecasting potential evapotranspiration with a lead time of up to 12 months across all the stations. Among all the stations, the Seasonal ARIMA model performed exceptionally well at the Jewargi station, yielding an impressive set of results with an R value of 0.92, an RMSE value of 20.15, and a MAPE value of 14.96.

The Seasonal ARIMA models for different stations consistently demonstrated the ability to forecast potential evapotranspiration accurately up to one year in advance with minimal error. Moreover, the statistical analysis revealed that the difference between the observed and forecasted means was found to be non-significant, further affirming the promising performance of these models in forecasting potential evapotranspiration across the study area.

The successful prediction of evapotranspiration is crucial for ensuring the reliability of project planning, design, and the operation of irrigation systems, making these models valuable tools in water resource management and agriculture.

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