***Original Research Article***

# FORECASTING POTENTIAL EVAPOTRANSPIRATION FOR KALABURAGI DISTRICT USING SEASONAL ARIMA MODEL



**ABSTRACT**

The prediction of potential evapotranspiration (PET) is quite an important task for reliable management of irrigation systems. This article is based on the models which try to mimic the actual occurrence of the potential evapotranspiration in the future days for a Kalaburagi district. In this study, the potential evapotranspiration was estimated with the help of maximum and minimum temperature ($^{o}$C) data using a Thornthwaite method and the prediction was carried out using the Seasonal Autoregressive Moving Average method (SARIMA). The models were developed based upon autocorrelation function (ACF) and partial autocorrelation function (PACF). Furthermore, the model with the least Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) values were selected. The models selected for different stations were 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)$_{12}$ for Kalaburagi, Chincholi, Sedam, Chittapur, Aland, JewargiandAfzalpur respectively. The results showed that, the models developed for JewargiandChincholiwere found to be quite promising compared to the other two stations. All four models were found to be producing better results. The models will provide significant potential in improving the decision making in irrigation planning and command area management practices for better management of water resources.

Keywords: ACF, PACF, SARIMA, PET

## INTRODUCTION

Evapotranspiration (ET) is usually the largest component of the hydrologic cycle, given that most precipitation that falls on land is returned to the atmosphere(Asadi*et al*., 2013). Globally, ET consumes about 60 per cent of the annual precipitation that falls over the earth's surface. The ET quantificationsare used for many purposes including crop production, management of water resources and environmental assessment (Aruna*et al*., 2017). It is a major component for water balance in the field and needs to be quantified accurately. The amount of water supplied to meet the needs of the agricultural crops for evapotranspiration dictates the quality and quantity of production in a field. The ET data for agricultural crops has become increasingly important in irrigation as well as in water resources management. The process of ET is majorly regulated by many hydrological parameters such as temperature, relative humidity, solar radiation, wind speed and other climatological parameters.

The stochastic models are based on the time dependent variation and consider random effects involved in the ET process. The stochastic linear models are fitted to hydrological data are time series such as evapotranspiration series: enabling the integration of an on-farm system with the main system and facilitating the real-time operation of an irrigation system. It is quite important to develop a synthetic or forecast data set in order to design or plan any irrigation systems; in this context, an autoregressive integrated moving average (ARIMA) model is considered as one of the best model in forecasting the time series dataset. In this model, the forecast of a variable is defined as a linear combination of the previous state of variable and previous forecast error.The ARIMA method is a strong time series modeling and forecasting technique which has versatility to include characteristic of time series. In past, ARIMA models have been widely used to model hydrological time series (Popale and Gorantiwar, 2014).Popale and Gorantiwar (2014) used ARIMA model for prediction of rainfall of Rahuri region, India. Gorantiwar and Patil (2009) have carried out analysis of evapotranspirationforRahuri region, India. Hamdi*et al*. (2008) developed seasonal ARIMA model for the Jordan valley. Asadi*et al.* (2014) forecasts evapotranspiration for humid and semi-humid region. Salas *et al*. (1980) discussed in detail about time series modelling.

Knowledge of evapotranspiration is important for watershed management activities in meteorological and hydrological modelling, particularly water management in irrigated agriculture (Dutta*et al.*, 2016). The evapotranspiration plays a major role in crop water requirement(CWR) of any crop. As CWR accounts for more than 95% of the ET, it is quite important to understand its behaviour based on the historical data for better management of water resources, in order to understand and solve the irrigation problems.The objective of this study is to establish a time series model to analyse and forecast potential evapotranspiration for the Kalaburagi district.

## MATERIALS AND METHODOLOGY

Kalaburagi is an administrative district in the Indian state of Karnataka and is the largest city in the region of North Karnataka (Kalyana-Karnataka).This district is situated in north Karnataka between 76°04' and 77°42' east longitude and 17°12' and 17°46' north latitude, covering an area of 10,951 km². This district is bounded on the west by Vijayapura district of Karnataka and Solapur district of Maharashtra state; on the north side by Bidar district and Osmanabad district of Maharashtra state; on the south by Yadgir district and on the east by Sangareddy and Vikarabad districts of Telangana state. The entire district is on the Deccan Plateau and the elevation ranges from 300 to 750 m above MSL. The two main rivers, Krishna and Bhima flow through the district.

### 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 of the Box Ljung Test, $H_0$, is that the model does not show lack of fit (or in simple terms—the model is just fine). The alternate hypothesis, $H_a$, is just that the model does show a lack of fit. A significant p-value in this test rejects the null hypothesis that the time series isn't an auto correlated (Malik *et al*., 2021).

### Stationary test (Dickey fuller test)

A time series is said to be stationary (in the weak sense) if its statistical properties do not vary with time (means and variance). If the computed p values are greater than 0.05, the series is said to be non-stationary. The time series need to be in stationary form in order to fit to stochastic models (Patil *et al*., 2022).

**Description of the stochastic models**

The stochastic models, also referred to as time series models, were used for the study of time series in mathematical, economic and engineering applications. The time series modeling techniques have been shown to provide a systematic analytical tool to simulate and predict the behavior of unpredictable hydrological systems and to measure the predicted accuracy of the forecasts (Mishra and Desai, 2005).

**ARIMA models**

Autoregressive (AR) models can be considered in conjunction with moving average (MA) models to create a specific and effective class of time series models called autoregressive integrated moving average (ARIMA)models.In an ARIMA model, the present value of the time series is explained as a linear aggregate of ‘p’ lagged values and a weighted sum of ‘q’ former deviations plus a random parameter.

An ARIMA models are generally used for a time series which are stationary in nature. However,these models can be used in non-stationary data set by differencing the series. Box and Jenkins (1976) developed a new forecasting tool, known as the ARIMA methodology, that focus on analyzing the stochastic characteristics of time series on its own rather than constructing single or simultaneous equation models.

ARIMA models allow stating each variable by its own lagged values and stochastic error terms.The general non-seasonal ARIMA model is AR to order *p* and MA to order *q* and operates on $d^{th}$ difference of the time series $z_t$; thus a model of the ARIMA family is classified by three parameters (p, d, q) that can have zero or positive integral values (Mishra and Desai, 2005).

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

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

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 features are cyclic. Quite frequently, such characteristics are on an annual period in hydrologic time series mainly due to earth's rotation around the sun. Such types of series are cyclically non-stationary. After removing the determinist cyclic effects from a series, the ARIMA approach may be applied to obtain a linear model for the stochastic part of the series (Gorantiwar*et al*. 2011). Box *et al*. (1994) standardized the ARIMA model to address seasonality and defined a general multiplicative seasonal ARIMA model commonly referred to as SARIMA models. An inherent advantage of the SARIMA family of models is that, the description of time series requires few model parameters, which exhibit non-stationarity both in season and throughout. In general, the SARIMA model described as ARIMA *(p, d, q) (P, D, Q)s*, where *(p, d, q)* is the non-seasonal part of the model and *(P, D, Q)s* is the seasonal part of the model, which is mentioned below :

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

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**

This step is to identify the possible ARIMA model which represents the time series behavior. The series behavior was investigated based upon the behavior of autocorrelation function (ACF) and partial autocorrelation function (PACF) (Mishra and Desai, 2005; Hsin-Fu Yeh and Hsin-Li Hsu, 2019).The ACF and PACF were used to support in determining the order of the model. The information given by ACF and PACF is useful in suggesting the type of models that may be constructed. The final model was then selected using the Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Prasad *et al*., 2019).

These criteria help to rank models (the models with the lowest criterion value being the best). The AIC and SBC take the mathematical form as shown below:

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

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**

The estimation of model parameters was achieved after identification of the appropriate model as an essential step. The model estimate values for the AR and MA parts were calculated using Maximum likelihood. The AR and MA parameters were tested to make sure that, they are statistically significant or not.

**c. Diagnostic checking**

Diagnosis of the ARIMA model is a crucial part of model development and the last step. It involves checking the appropriateness of the model chosen. Several diagnostic statistics and residual plots are examined to see whether or not the residuals are correlated to white noise. In this study, we obtained the residual ACF function (RACF) to determine whether residuals are white noise.

**d. Drought forecasting**

The prediction of potential evapotranspiration was done using the best fit models from historical data. Basic statistical properties of the observed and predicted data were computed and tested whether the predicted data preserve the basic statistical properties of the observed PETseries. The correlation coefficients (R), RMSE and MAE were observed between the observed and predicted data.

**Input Dataset and software**

The time series of temperature data set (Max and Min) were taken from the Zonal Agricultural Research Station (ZARS)Kalaburagi. The data set were from 1990-2021, out of which 1990-2019 was used for the development of the model and the 2020-2021 was used for the validation purpose. The estimation of potential evapotranspiration was estimated using MS Excel and SARIMA models were developed in the R studio software.

## RESULTS AND DISCUSSION

Development of model was done with prerequisite tests namely stationary and autocorrelation tests. The autocorrelation test was carried out using box test and corresponding probability levels are presented in Table 1. The results revealed that, the test statistic for box.test with a Chi square and P values were187.17(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 Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi and Afzalpur respectively, were observed to be significant at 5 % level of significance reflecting autocorrelation in data. On the other hand, adf.test was carried out to check whether the data is stationary or not. The datawasobserved to have seasonality thereby seasonal differencing was done (Table 2) to the data sets.

**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 principal step in Box-Jenkins ARIMA model building is identification of the model. Different orders of Autoregressive (AR) and Moving Average (MA) parameters *p* and *q*were considered and combination of the order which yields maximum log-likelihood and lowest values of Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) wereconsidered as best model. The results pertaining to Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi and Afzalpur stations regarding model development are presented in Table 3& 4. The ACF and PACF were plotted (Fig. 1 and 2) to determine the model. The data have seasonality;therebyseasonal ARIMA models were selected with a seasonal differencing as shown in Table 4. The best selected models for different stations were: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 an maximum likelihood values of -1532.32, -1542.42, -1732.01, -1552.32, -1512.62, -1542.24 and -1544.46respectively for Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi and Afzalpur. The parameters estimated for different stations are presented in Table 4. In addition, the residuals were obtained by differencing original series with the fitted series and residuals were found (Table 5) to be as white noise.

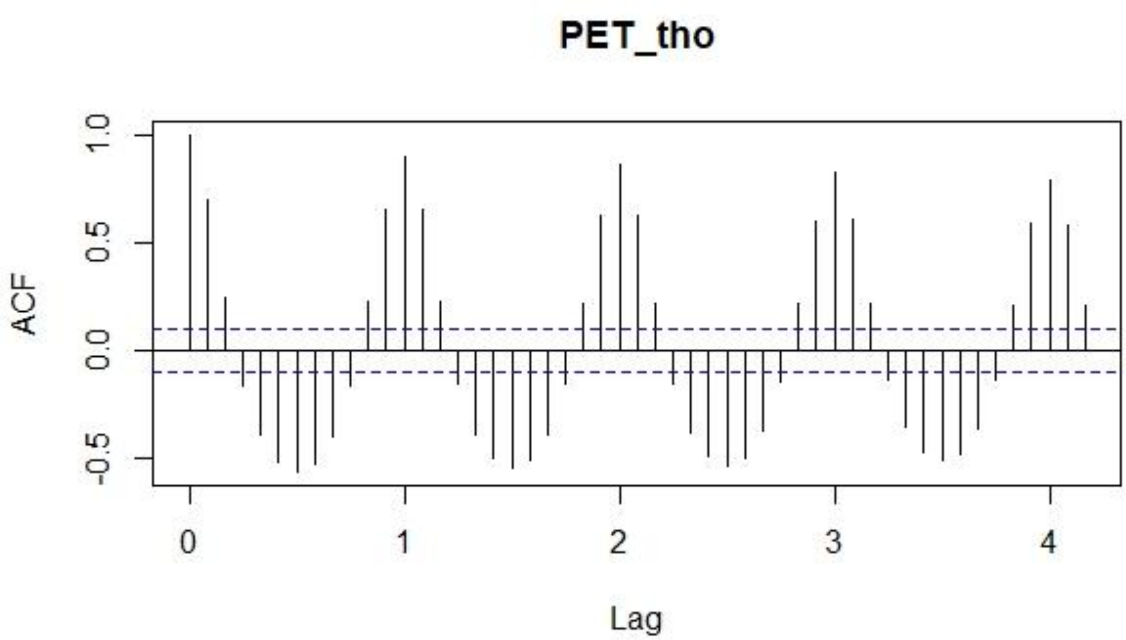


**Fig. 1: Autocorrelation function plot of PET time series for Kalaburagi Station**

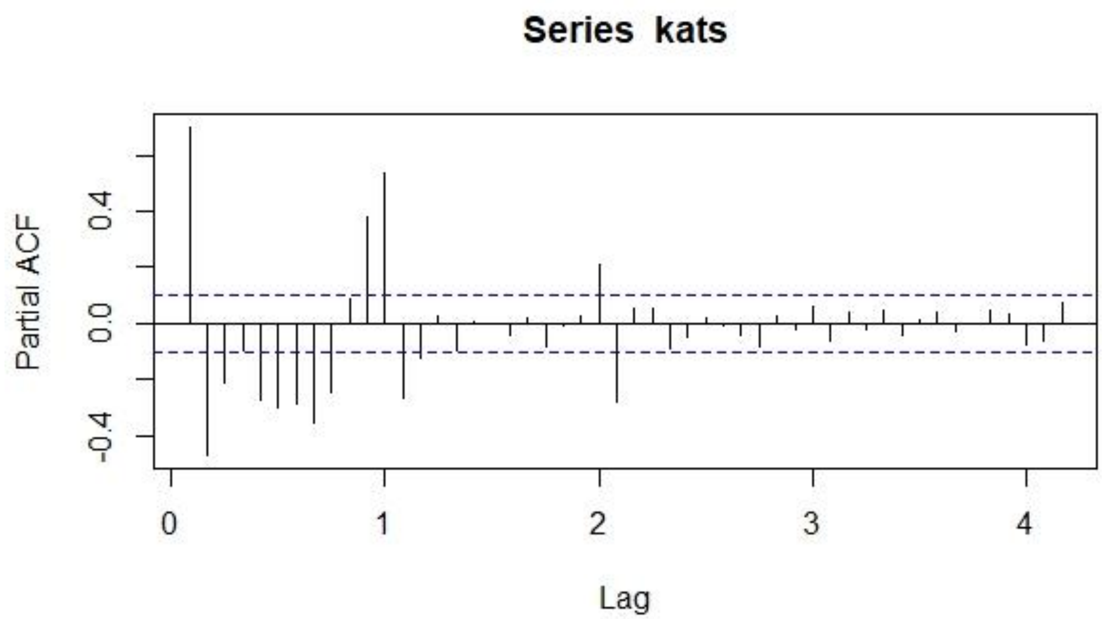


**Fig. 2: Partial autocorrelation function plot of PET time series for Kalaburagi Station**

**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 |

After the development of models for all the seven taluks (selected stations) of Kalaburgi district, the forecasting part was carried out and the resultsarepresented in Table 6. The results reveal that, initially for all stations the forecast was observed to be good with a correlation coefficientof 0.96, 0.95, 0.90, 0.88, 0.89, 0.92 and 0.86 for Kalaburagi, Chincholi, Sedam, Chittapur, Aland, Jewargi and Afzalpurrespectively. Basic statistical properties were compared between observed and forecasted data using t-test for the means and F-test for standard deviation (Haan,1977) and are shown in Table 7. Since $t_{cal}$ values related to means were between t-critical table values (±1.71) for two tailed at 5% significance level), the data shows that, there is no significant difference between the mean values of observed and predicted data. Similarly, the $F_{cal}$ values of standard deviation were smaller than the F-critical values at 5% significance level. Thus, the results show that, the predicted data preserves the basic statistical properties of the observedseries.

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

| Station | Model | Performance measures | |
|---|---|---|---|
| Kalaburagi | SARIMA $(2,0,2)(1,1,2)_{12}$ | RMSE | 22.61 |
| | | 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 Seasonal ARIMA models revealed that, the models have an ability to forecast up to 12 month lead time with a higher accuracy over all the stations. Out of all the stations, Seasonal ARIMA model provided excellent results at Jewargi station with an R, RMSE and MAPE values of 0.92, 20.15 and 14.96respectively. The seasonal ARIMA models for different stations were found to forecast potential evapotranspiration accurately up to one ahead with the least error. Similarly, for the basic statistical analysis, the difference between the observed and forecasted mean were found to be non-significant, which in turn reveal that, the models are found to be quite promising in forecasting the potential evapotranspiration over the study area. The prediction of evapotranspiration guarantees reliable project planning, design and operation of irrigation systems.

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