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# Forecasting Potential Evapotranspiration Using Seasonal ARIMA Model for Northern Telangana Zone, India

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***Authors' contributions***

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## ABSTRACT

Present study aims to predict the evapotranspiration values over the Northern Telangana Zone through the identification or patterns in correlated data trends and seasonal variation and to assess the accuracy of the forecasting model. Plans for managing crop water consumption include potential evapotranspiration heavily. As a result, in a semi-arid environment, forecasting of the potential evapotranspiration is the foundation of any successful water resources management plans. The Thronthwaite method was used to estimate daily evapotranspiration, and a Seasonal Auto

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Regressive Integrated Moving Average was used to forecast potential evapotranspiration. Time series analysis of evapotranspiration data set showed a seasonality behaviour and thus Seasonal ARIMA model with the least Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) values were selected. The Seasonal Arima model selected for the districts Adilabad, Jagtial, Karimnagar, KumuramBheem, Nirmal, and Peddapalli was $(2,0,2)(2,1,0)_{12}$ and for Nizamabad district $(2,0,2)(1,1,0)_{12}$. Basic statistical properties are used to compare the observed and forecasted data which shown that that there is no significant difference between the mean values of the observed and predicted data at a 5% significance level. Hence the developed model was optimum to forecast the evapotranspiration over the study area and to sustain the forecasting accuracy.

*Keywords: SARIMA; potential evapotranspiration; forecasting; model.*

## 1. INTRODUCTION

"Evapotranspiration (ET) represents the combination of evaporation and transpiration, where evaporation is vaporization from the soil or water surface and transpiration is a plant water absorption from the root zone" [1]. "Both precipitation and the ET represent climate of a given region and are used as a decision support tool for water management in agriculture. While contributing to the surface energy balance, the ET quantifies the water requirement for the efficient water management" [2,3]. "Not only in irrigation assessments but also in the accurate modelling of river basin hydrology, estimation of the local ET is one of the essential tasks" [4]. Krishna [5] highlighted that "the accurate estimation of ET is important because understanding and quantifying the processes governing ET clarifies the uncertainties in the behaviour of the hydrologic cycle with the changing climate". "Since the ET is a critical factor in water balance from the plot scale to a global scale, well-grounded ET estimations are required to regulate the components of the irrigation system: the size of canals and dams, and the capacity of pumps" [6].

One of the most significant agricultural backward links is irrigation. The need to improve water use efficiency and the performance of large irrigation systems is driven in part by the competition for water, high pumping costs, challenges associated with water storage and delivery, and environmental concerns. Agricultural managers have long relied on the evapotranspiration (ET) measurements or estimates for the purpose of timely and effective water application. Therefore, in order to improve water management practices, an accurate assessment of the ET is required.

Knowledge of evapotranspiration is important for watershed management activities in meteorological and hydrological modelling, particularly water management in irrigated agriculture [7]. "Evapotranspiration plays a major role in the crop water requirement (CWR) of any crop. Determining the crop water requirement using evapotranspiration is considered one of the main planning needs for water resources management. In much long-term planning, it is necessary to outline the future state of rainfall and dry and wet periods for the region. For this purpose, the prediction of drought and the estimation of its characteristics are of great importance in water resources management" [8]. "One of the ET forecasting methods is the use of time series analysis, which has been rapidly developed for predictive and analytical issues since the 1970s. Therefore, due to the nature of the hydrological events, if the correct selection of the model and correct calculations are made, time series can be particularly consistent with the hydrologic data" [9]. "In many time series, there is a consistent correlation between the observations, which is a hallmark of the autoregressive integrated moving average model (ARIMA) and seasonal ARIMA (SARIMA) models" [10].

"One definition of a time series is that of a collection of quantitative observations that are evenly spaced in time and measured successively. Time series are analysed in order to better understand the underlying structure, repetitive behaviour and functionality that produce observational data [11]. Understanding the theoretical explanation of a time series analysis allows a mathematical model to be developed to explain the data trend in such a way that monitoring, simulation, prediction, assessment and management can occur" [12-15].

"Hydrological processes are complicated; since they are influenced by not only deterministic, but also stochastic factors" (Wang et al. 2007). "Generally speaking, determinism includes the periodicity, tendency and abrupt change. A strict deterministic hydrological process is rare. Stationary time series has been widely used in hydrological data assimilation and prediction to tackle the stochastic factors in hydrological processes. Some researchers have used ARIMA model for the analysis of hydrological processes, while most of the studies neglected stationary test and the influence from the inter-monthly variation within a year" [16-18].

Telangana is the most recent state to join the Indian Union. In terms of both population and area, Telangana is ranked 11th in the nation. The Godavari and Krishna rivers, with catchment areas of 79% and 69% respectively, are the main drains of the region. The monsoons are primarily responsible for the unpredictable and uneven rainfall that characterises Telangana state. A comprehensive irrigation development strategy has been adopted by the Telangana government in order to provide irrigation facilities for about 125 lakh acres of land throughout the state. The government has also launched a number of initiatives and adopted strategies to expeditiously complete ongoing irrigation projects. With the predicted rise in atmospheric temperature that comes with climate change, there will be more energy available for evaporation. Therefore, Accurate estimation of the ET must serve as the foundation for improvements in water use efficiency and sustainable water management in agriculture. In light of these facts, the current study's objective is to forecast the evapotranspiration values for the Northern Telangana Zone by identifying patterns in correlated data trends and seasonal variation and evaluating the forecasting model's precision.

## 2. MATERIALS AND METHODS

The Northern Telangana semi-arid zone lies between 17°42' and 19°84' N Latitude and 77°38' and 81°16' E Longitude. This zone includes the districts of Adilabad, KumuramBheem, Manchiriala, Nirmal, Karimnagar, Jagtial, Peddapalli, Rajanna Siricilla, Nizamabad and Kamareddy with Regional Agricultural Research Station, Jagtial as Regional headquarters. The annual average rainfall is 900 to 1150 mm mostly from the south-west monsoon. The maximum and minimum temperature during south-west monsoon ranges from 32°C to 37°C and 21°C to 25°C respectively. Red soils are predominant in the zone which includes chalkas, red sandy, deep red loamy and very deep black cotton soils, which are also seen in some parts of the zone. This zone has a total geographical area of 35.5 lakh ha. The climate is typically tropical rainy. The net sown area is 2.21 m. ha. of which 0.67 m. ha. is irrigated representing 30.3 per cent of the net sown area. Cropping intensity is 110 per cent. Wells are the main source of irrigation followed by canals. The Important crops grown are rice, maize, soybean, cotton, redgram and turmeric.

### 2.1 ARIMA Models

A hydrological time series $[y_t, t = 1,2,........n]$ could be either stationary or non-stationary. Given that there are essentially no strictly deterministic hydrological processes in nature, the analysis of hydrological data by means of the non-stationary time series is of importance, among which the ARIMA model is one of the available choices. The Autoregressive (AR) models can be considered in conjunction with the moving average (MA) models to create a specific and effective class of time series models called autoregressive integrated moving average (ARMA) models. In the ARMA model, 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. The 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 the analysing of the stochastic characteristics of time series on its own rather than constructing single or simultaneous equation models. The 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 the three parameters (p, d, q) that can have zero or positive integral values" [19].

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

$$\phi(B)\nabla_{Z_t}^{d} = \theta(B)a_t \quad (1)$$

(

where, θ(B) are polynomials of order *p* and *q*, respectively.

The non-seasonal AR operator of order *p* is written as follows:

$$\phi(\mathrm{B}) = \left(1 - \phi_1 B - \phi_2 B^2 - \cdots\cdots \phi_P B^P\right) \quad (2)$$

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

$$\theta(\mathrm{B}) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots\cdots \theta_q B^q\right) \quad (3)$$

## 2.2 Seasonal ARIMA Models

"A lot of time series features are cyclic in nature. Quite often, such characteristics are on an annual period in hydrologic time series mainly due to the Earth's rotation around the sun. Such a type of series is 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" [20]. 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 a 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) is the seasonal part of the model which is mentioned below:

$$\phi_p(B)\Phi_P\left(B^s\right)\nabla^d\nabla_s^D Z_t = \theta_q(B)\varphi_Q\left(B^s\right)a_t \quad (4)$$

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

## 2.3 Implementation of the ARIMA Model

The procedure of estimating ARIMA model involves the following steps:

1. Stationary identification: The input time series for the ARIMA model needs to be stationary, i.e., the time series should have a constant mean, variance, and auto correlation through time. Therefore, the stationarity of the data series needs to be identified first. If not, the non-stationary time series is then required to be stationarized. Although the stationary test, such as the unit root test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are used to identify whether a time series is stationary, plotting approaches based on scatter diagrams, autocorrelation function diagrams, and partial correlation function diagrams are also often used. The latter approach can usually not only provide information on whether or not the testing time series is stationary, but it can also indicate the order of the differencing which is needed to stationarize the time series.

In this study, we use the autocorrelation function diagram and partial correlation function diagram to determine a time series' stationarity. A time series is typically differentiated to make it stationary if it is found to be non-stationary. The lowest order of differencing that produces a time series in the differencing method that fluctuates around a clearly defined mean value and whose autocorrelation function (ACF) plot decays fairly quickly to zero, either from above or below, is typically considered to be the appropriate amount of differencing. The time series is often transformed for stabilizing its variance through proper transformation, e.g., logarithmic transformation. The reduction in variance of a time series is typically helpful to reduce the order of difference in order to make it stationary, even though logarithmic transformation is frequently used to stabilise the variance of a time series rather than directly stationarize one.

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 (i.e., means and variance). If the compute 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 the stochastic models.

2. The identification of the order of ARIMA model: After a time series has been stationarized, the next step is to determine the order terms of its ARIMA model, i.e., the order of differencing, d for non-stationary time series, the order of auto-regression, p, the order of moving average, q, and the seasonal terms if the data series show seasonality. While one could try some

different combinations of terms and valuate what works best strictly, the more systematic and common way is to tentatively identify the orders of the ARIMA model by looking at the autocorrelation function (ACF) and partial autocorrelation (PACF) plots of the stationarized time series. The ACF plot is merely a bar chart of the coefficients of correlation between a time series and lags of itself, while the PACF plot presents a plot of the partial correlation coefficients between the series and lags of itself. The detailed guidelines for identifying the ARIMA model parameters based on the ACF and PACF, can be found elsewhere in relevant literature, e.g., Pankratz [21] and Shumway and Stoffer [22]. It should be noted that, to be strict, the ARIMA model built in this step is actually an ARMA model with if the time series is stationary, which is in fact a special case of the ARIMA model with d = 0.

3. Estimation of ARIMA model parameters: while least square methods (linear or nonlinear) are often used for the parameter estimation, in this paper we use the maximum likelihood method [23,24] in this paper. A t test is also performed to test the statistical significance. The information given by the 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).

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

$$AIC = -2\log(L) + 2k \quad (5)$$

$$SBC = -2\log(L + k\ln(n)) \quad (6)$$

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.

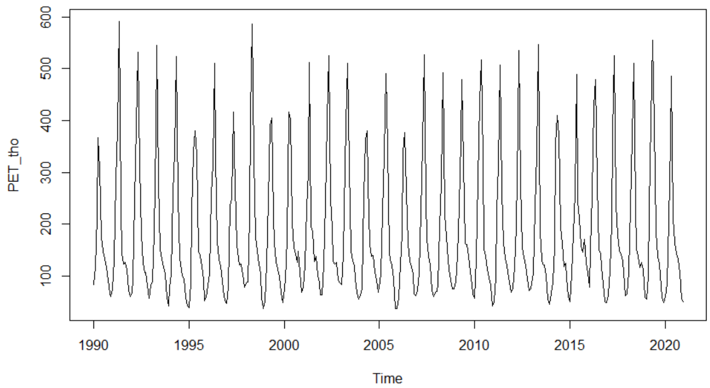


**Fig. 1. Line plot of differenced potential evapotranspiration data of first order (d=1)**

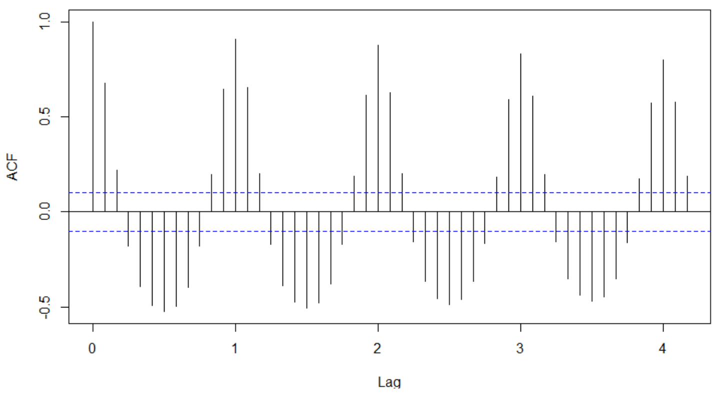


**Fig. 2. Autocorrelation function plot of PET time series for Raichur Station**

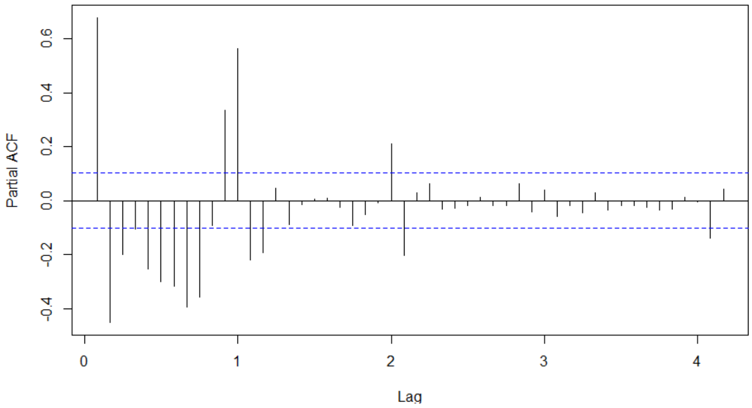


**Fig. 3. Partial autocorrelation function plot of PET time series for Raichur Station**

4. White noise test is used for the residual sequence: It is necessary to evaluate the established ARIMA model with the estimated parameters before using it to make the forecasting. We use white noise test here. If the residual sequence is not a white noise, some useful information has not been extracted and the model needs to be further tuned. The null hypothesis of the Box Ljung Test, $H_0$ is that our 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 auto correlated.
5. ET forecasting: The prediction of the potential evapotranspiration (PET) was done time using the best fit models from the 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 PET series. The correlation coefficients (R), RMSE and MAE were observed between the observed and predicted data.

**Input dataset and software:** The time series of the temperature data set (Max and Min) was taken from the NASA POWER-Prediction of Worldwide Energy Resources and for Jagtial District, data were collected from the meteorological station, Regional Agriculture Research Station (RARS) Jagtial. The data set was from 1990-2020, out of which 1990-2019 was used for the development of the model and the data set for 2019-2020 was used for the validation purpose. The potential evapotranspiration was estimated using the Thornthwaite method and the ARIMA models were developed in the R studio.

## 2.4 Thornthwaite Method (Potential Evapotranspiration Estimation)

The potential evapotranspiration is calculated by the following formula:

$$PET = 16K\left(\frac{10T}{I}\right)^m \tag{7}$$

Where,

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

$$m = 6.75\times10^{-7}\times I^3 - 7.71\times10^{-7}\times I^2 + 1.79\times10^{-2}\times I + 0.492 \tag{8}$$

K is a correction coefficient computed as a function of the latitude and month.

## 3. RESULTS AND DISCUSSION

"For any given time series data set there is at least one assumed systematic pattern embedded in the data. The most common patterns are trends and seasonality; trends are generally either linear or quadratic. To find out trends and/or moving averages, the regression analysis is often used. Seasonality is a trend that repeats itself systematically over time" [12,25].

The development of model was done with the prerequisite tests namely stationary and autocorrelation tests. The autocorrelation test was carried out using the box test and corresponding probability levels that are presented in Table 1. The results revealed that the test statistic for box test with a Chi square 174.24, 171.36, 176.55, 169.84, 173.69, 176.62 and 170.28 and p-values < 0.001 were for Adilabad, Jagtial, Karimnagar, KumuramBheem, Nirmal, Nizamabad and Peddapalli respectively were observed to be significant at 5% level of significance reflecting autocorrelation in data. On the other hand, the adf.test was carried out to check whether the data is stationary or not. The data were observed to have a seasonality there by seasonal differencing was done to the data sets (Table 2).

The principal step in the Box-Jenkins ARIMA model building is identification of the model. Different orders of the Autoregressive (AR) and Moving Average (MA) parameters p and q are considered and a combination of the order which yields maximum log-likelihood and the lowest values of Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) are considered as the best model. The results pertaining to Adilabad, Jagtial, Karimnagar, KumuramBheem, Nirmal, Nizamabad and Peddapalli districts regarding model development are presented in Tables 3 and 4. The ACF and PACF were plotted (Figs. 2 and 3) to determine the model, the data were observed to have a seasonality thereby seasonal ARIMA models were selected with a seasonal differencing as shown in Table 4. The best selected models for the different stations were ARIMA(2,0,2)(2,1,0), ARIMA (2,0,2) (2,1,0), ARIMA (2,0,2) (2,1,0), ARIMA (2,0,2) (2,1,0), ARIMA (2,0,2) (2,1,0), ARIMA (2,0,2) (1,1,0) and ARIMA (2,0,2) (2,1,0) with maximum likelihood values of -1753.77, -1760.99, -1722.34, -1793.98, -1735.35, -1722.63 and -1812.89 respectively for Adilabad, Jagtial, Karimnagar, KumuramBheem, Nirmal, Nizamabad and Peddapalli. The parameters estimated for different districts are presented in Table 4. In addition, the residuals were obtained by differencing original series with the fitted series and residuals were found to be white noise as presented in Table 5.

After the development of models for 7 districts, the forecasting part was carried out seperately and the results (Table 6) reveal that for all stations the forecast was observed to be good with a correlation coefficient of 0.883, 0.838, 0.813, 0.865, 0.847, 0.813 and 0.806 for Adilabad, Jagtial, Karimnagar, KumuramBheem, Nirmal, Nizamabad and Peddapalli districts. The RMSE and MAE were observed to be the least and hence these stochastic models were found to be suitable to forecast up to 1 lead time. The analysis of the Table 6 reveal that seasonal ARIMA models suited well for the forecasting of the potential evapotranspiration under Northern Telangana zone. Basic statistical properties are compared between observed and forecasted data for 1-month lead time, using t-test for the means and F-test for standard deviation [26], as shown in Table 7.

Since $t_{cal}$ values related to means were between $t_{critical}$ and table values (±1.71 for two tailed at a 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 a 5% significance level. Hence, we can conclude that the selected ARIMA (2,0,2) (2,1,0) and ARIMA (2,0,2) (1,1,0) seem to provide an adequate predictive model for evaluation of the evapotranspiration. Combining the use of the remote sensing data to estimate the evapotranspiration and the use of Seasonal ARIMA model provides the keystone of the advanced and rational water resources management in arid ecosystems, which agreed with similar results conducted by Landeras et al. [27] and Patil et al. [28].

**Table 1. Auto correlation test for different districts of NTZ**

| Station | Chi-square | Lag order | p-value |
|---|---|---|---|
| Adilabad | 174.24 | 1 | <0.001 |
| Jagtial | 171.36 | 1 | <0.001 |
| Karimnagar | 176.55 | 1 | <0.001 |

| Station | Chi-square | Lag order | p-value |
|---|---|---|---|
| KumuramBheem | 169.84 | 1 | <0.001 |
| Nirmal | 173.69 | 1 | <0.001 |
| Nizamabad | 176.62 | 1 | <0.001 |
| Peddapalli | 170.28 | 1 | <0.001 |

**Table 2. Stationery test for different districts of NTZ**

| Station | Dickey fuller | Lag order | p-value |
|---|---|---|---|
| Adilabad | -19.367 | 7 | 0.01 |
| Jagtial | -19.132 | 7 | 0.01 |
| Karimnagar | -18.725 | 7 | 0.01 |
| KumuramBheem | -19.256 | 7 | 0.01 |
| Nirmal | -18.965 | 7 | 0.01 |
| Nizamabad | -18.73 | 7 | 0.01 |
| Peddapalli | -18.758 | 7 | 0.01 |

**Table 3. Log likelihood AIC and BIC values of ARIMA model for different station**

| Station | Model | Log-Likelihood | AIC | BIC |
|---|---|---|---|---|
| Adilabad | ARIMA(2,0,2)(2,1,0)$_{[12]}$ | -1753.77 | 3523.54 | 3554.36 |
| Jagtial | ARIMA(2,0,2)(2,1,0)$_{[12]}$ | -1760.99 | 3537.97 | 3568.79 |
| Karimnagar | ARIMA(2,0,2)(2,1,0)$_{[12]}$ | -1722.34 | 3458.68 | 3485.64 |
| KumuramBheem | ARIMA(2,0,2)(2,1,0)$_{[12]}$ | -1793.98 | 3603.96 | 3634.77 |
| Nirmal | ARIMA(2,0,2)(2,1,0)$_{[12]}$ | -1735.35 | 3486.69 | 3517.51 |
| Nizamabad | ARIMA(2,0,2)(1,1,0)$_{[12]}$ | -1722.63 | 3459.27 | 3486.23 |
| Peddapalli | ARIMA(2,0,2)(2,1,0)$_{[12]}$ | -1812.89 | 3639.79 | 3666.75 |

**Table 4. Parameter estimation of SARIMA by maximum likelihood method for different station**

| Station | Model | Parameters | Estimate | S.E. | Z value | P-value |
|---|---|---|---|---|---|---|
| Adilabad | ARIMA (2,0,2)(2,1,0)$_{[12]}$ | AR1 | -0.079653 | 0.464948 | -0.1713 | 0.864 |
| | | AR2 | 0.24941 | 0.349428 | 0.7138 | 0.475 |
| | | MA1 | 0.256002 | 0.47104 | 0.5435 | 0.587 |
| | | MA2 | -0.07307 | 0.302982 | -0.2412 | 0.809 |
| | | SAR1 | -0.697556 | 0.056636 | -2.3164 | < 0.001 |
| | | SMA1 | -0.272944 | 0.056214 | -4.8555 | < 0.001 |
| | | SMA2 | 0.050321 | 0.122127 | 0.412 | 0.680 |
| Jagtial | ARIMA (2,0,2)(2,1,0)$_{[12]}$ | AR1 | -0.0791 | 0.3581 | -0.2209 | 0.825 |
| | | AR2 | 0.2732 | 0.2852 | 0.9579 | 0.338 |
| | | MA1 | 0.2537 | 0.3651 | 0.6947 | 0.487 |
| | | MA2 | -0.0806 | 0.26 | -0.3101 | 0.757 |
| | | SAR1 | -0.6878 | 0.0568 | -2.1141 | < 0.001 |
| | | SMA1 | -0.2394 | 0.0565 | -4.2392 | < 0.001 |
| | | SMA2 | 0.0527 | 0.1301 | 0.4048 | 0.686 |
| Karimnagar | ARIMA (2,0,2)(2,1,0)$_{[12]}$ | AR1 | -0.072463 | 0.278068 | -0.2606 | 0.794 |
| | | AR2 | 0.188861 | 0.237323 | 0.7958 | 0.426 |
| | | MA1 | 0.329784 | 0.27958 | 1.1796 | 0.238 |
| | | MA2 | 0.070375 | 0.204407 | 0.3443 | 0.731 |
| | | SAR1 | -0.563659 | 0.047201 | -1.9416 | < 0.001 |
| | | SMA2 | 0.073067 | 0.155137 | 0.471 | 0.638 |
| Kumuramb heem | ARIMA (2,0,2)(2,1,0)$_{[12]}$ | AR1 | -0.127469 | 0.367393 | -0.347 | 0.729 |
| | | AR2 | 0.247821 | 0.307589 | 0.8057 | 0.420 |
| | | MA1 | 0.263579 | 0.374477 | 0.7039 | 0.482 |
| | | MA2 | -0.073922 | 0.293495 | -0.2519 | 0.801 |
| | | SAR1 | -0.67717 | 0.05713 | -1.8531 | < 0.001 |
| | | SMA1 | -0.247445 | 0.056703 | -4.3639 | < 0.001 |
| | | SMA2 | 0.045271 | 0.133255 | 0.3397 | 0.734 |

| Station | Model | Parameters | Estimate | S.E. | Z value | P-value |
|---|---|---|---|---|---|---|
| Nirmal | ARIMA(2,0,2) | AR1 | -.0102837 | 0.4648525 | -0.0221 | 0.982 |
| | $(2,1,0)_{[12]}$ | AR2 | 0.1916833 | 0.3503454 | 0.5471 | 0.584 |
| | | MA1 | 0.2279929 | 0.467351 | 0.4878 | 0.626 |
| | | MA2 | -.0027449 | 0.2841486 | -0.0097 | 0.992 |
| | | SAR1 | -.7142443 | 0.0562602 | -2.6954 | < 0.001 |
| | | SMA1 | -.2738084 | 0.055936 | -4.895 | < 0.001 |
| | | SMA2 | 0.0674401 | 0.1205473 | 0.5594 | 0.576 |
| Nizamabad | ARIMA(2,0,2) | AR1 | -0.072633 | 0.278162 | -0.2611 | 0.794 |
| | $(1,1,0)_{[12]}$ | AR2 | 0.188288 | 0.237448 | 0.793 | 0.428 |
| | | MA1 | 0.329702 | 0.279661 | 1.1789 | 0.238 |
| | | MA2 | 0.070771 | 0.20454 | 0.346 | 0.729 |
| | | SAR1 | -0.563714 | 0.047203 | -1.9424 | < 0.001 |
| | | SMA2 | 0.073186 | 0.155168 | 0.4717 | 0.637 |
| Peddapalli | ARIMA(2,0,2) | AR1 | -0.058909 | 0.301447 | -0.1954 | 0.845 |
| | $(2,1,0)_{[12]}$ | AR2 | 0.376635 | 0.24794 | 1.5191 | 0.129 |
| | | MA1 | 0.214592 | 0.31331 | 0.6849 | 0.493 |
| | | MA2 | -0.191379 | 0.241965 | -0.7909 | 0.429 |
| | | SAR1 | -0.66275 | 0.056576 | -1.7142 | < 0.001 |
| | | SAR2 | -0.216286 | 0.056216 | -3.8474 | < 0.001 |

**Table 5. Auto correlation check for residuals of seasonal ARIMA model at different stations**

| Station | Chi-square | Lag order | p-value |
|---|---|---|---|
| Adilabad | 1.66E-06 | 1 | 0.999 |
| Jagtial | 3.57E-05 | 1 | 0.9952 |
| Karimnagar | 2.55E-06 | 1 | 0.9987 |
| KumuramBheem | 3.60E-06 | 1 | 0.9985 |
| Nirmal | 1.16E-05 | 1 | 0.9973 |
| Nizamabad | 2.45E-06 | 1 | 0.9967 |
| Peddapalli | 0.0016663 | 1 | 0.9674 |

**Table 6. Performance measure of seasonal ARIMA models at different stations**

| Station | Performance measures | 1-Lead time |
|---|---|---|
| Adilabad | RMSE | 36.40649 |
| | MAPE | 14.89317 |
| | MAE | 23.38337 |
| | R | 0.8827 |
| Jagtial | RMSE | 37.18512 |
| | MAPE | 14.50108 |
| | MAE | 23.79058 |
| | R | 0.8379 |
| Karimnagar | RMSE | 33.333 |
| | MAPE | 13.7328 |
| | MAE | 21.34267 |
| | R | 0.8127 |
| Kumurambheem | RMSE | 40.89183 |
| | MAPE | 15.19015 |
| | MAE | 25.578 |
| | R | 0.8654 |
| Nirmal | RMSE | 34.51507 |
| | MAPE | 13.96106 |
| | MAE | 22.29738 |
| | R | 0.8472 |
| Nizamabad | RMSE | 33.36109 |
| | MAPE | 13.7337 |
| | MAE | 21.35144 |

| Station | Performance measures | 1-Lead time |
|---|---|---|
| | R | 0.8131 |
| Peddapalli | RMSE | 43.19527 |
| | MAPE | 15.1979 |
| | MAE | 26.82257 |
| | R | 0.8061 |

**Table 7. Comparison of the statistical properties of the observed and predicted data**

| Stations | Mean observed | Mean forecasted | Decision (t<1.71) | Observed variance | Forecast variance | Decision (f < 4.05) |
|---|---|---|---|---|---|---|
| Adilabad | 157.62 | 189.46 | 0.457 | 10142.03 | 22187.32 | 0.105 |
| Jagtial | 156.29 | 189.10 | 0.453 | 9219.09 | 20328.94 | 0.103 |
| Karimnagar | 145.53 | 180.87 | 0.474 | 6860.23 | 14470.09 | 0.116 |
| KumuramBheem | 165.54 | 196.11 | 0.457 | 11616.63 | 25411.04 | 0.105 |
| Nirmal | 151.03 | 189.25 | 0.462 | 8415.17 | 18218.94 | 0.108 |
| Nizamabad | 145.58 | 180.96 | 0.474 | 6881.91 | 14522.76 | 0.116 |
| Peddapalli | 169.74 | 198.51 | 0.504 | 11211.69 | 22223.83 | 0.136 |

## 4. CONCLUSION

From the trend shown in both estimation and forecasting of the potential evapotranspiration values, the Seasonal ARIMA models have an ability to forecast potential evapotranspirationwith anoptimum accuracy over all the districts of NTZ. From basic statistical analysis conducted in the presented study, it is revealed that the difference between the observed and forecasted mean are non-significant. Since the trends in the potential evapotranspiration estimation Swere replicated trends in the forecasted potential evapotranspiration, hence forecasting of the evapotranspiration is a powerful tool for related studies. The prediction of the potential evapotranspiration using SARIMA model hence guarantees reliable project planning, design and operating of the irrigation systems.

## DISCLAIMER

The contents and views expressed in this research article are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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