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Developing Reference Crop Evapotranspiration Time Series Simulation Model Using Class a Pan: A Case Study for the Jordan Valley /Jordan

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Abstract

The greatest environmental challenge that Jordan faces today is the scarcity of water resources. Evapotranspiration (ET) affects water resources and it is considered an important process in aridic hydrologic systems. The estimated long-term average of ET in Jordan is over 90% of the total precipitation; nevertheless, there have been no attempts to model reference crop evapotranspiration using a time series approach in Jordan. In this study, a seasonal time series Autoregressive and Moving Average (ARIMA) mathematical model is described. It is used for forecasting monthly reference crop evapotranspiration (ET_o) without using weather data based on past historical records (1973-2002) of measured pan evaporation at Central Jordan Valley: an arid to semi-arid region. The developed ARIMA (1, 0, 0) (0, 1, 1)$_{12}$ model provides reasonable and acceptable forecasts, comparing its performance with a computed reference evapotranspiration from measured pan evaporation parameter. The forecasting performance capability of three tentative ARIMA models was assessed using Root Mean Squared Forecasting Error, Mean Absolute Forecasting Percentage Error, and Maximum Absolute Forecasting Percentage Error. The developed model allows local farmers and water resource managers to predict up to 60 months with a percentage error less than 11% of the mean absolute forecasting. The potential to make such predictions is crucial in optimizing the needed resources for effective management of water resources. Furthermore, the developed model offers a simple, accurate, and an easy short and long-term forecasting in the valley. This would develop a robust strategy for irrigation water management including successful planning, designing, managing, and operating of water resources systems. It also would increase the positive intended outcomes projects conducted by many governmental and nongovernmental organizations. In addition, it would heighten the efficiency of local and national water resources policies.

Keywords: Seasonal reference evapotranspiration modeling; ARIMA model; pan evaporation; Jordan;

1. Introduction

The Hashemite Kingdom of Jordan (HKJ) is located about 100 km from the south-eastern coast of the Mediterranean between latitudes 29º 11' - 33º 22' N and longitudes 34º 59'- 39º 12' E. The neighboring countries to Jordan are Iraq, Palestine, Syria, and Saudi Arabia (Figure 1). The total land area of HKJ is approximately 89 342 km^2, of which, about 40% is irrigated land. The population of HKJ was estimated to

reach 5, 329, and 000 in 2004, of which 30% reside in rural areas (DOS, 2006). The statistics indicates that the population of HKJ is increasing rapidly, with an estimated annual growth rate of 2.6% (DOS, 2006).

ETo : reference crop Evapotranspiration

Figure 1. Map of Jordan shows Deir-Alla Weather Station

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The irrigation water for agriculture sector represents about 68% of the total water demands in HKJ. Due to natural and non-voluntary migration, demands on the domestic water supply increased and accordingly, the per capita share of freshwater decreased. Although the population growth rates are declining (DOS, 2006), the increasing population continue to place enormous pressure on decision makers to find new water supplies and develop an updated water conservation policy. The main water supplies in HKJ are groundwater and surface water. However, HKJ shares most of its surface water resources with neighboring countries, which makes it one of the world's hot spot in regards to water disputes. The groundwater resources represent about 65% of total available water in HKJ. Because of the shortages of the surface water resources, groundwater has been extensively used in the last twenty years; it is overdrafted and becomes susceptible to salt water intrusion. This immense water consumption leads to a decline in water accessibility over the last few decades and is considered one of the most important environmental problems facing decision-makers in HKJ. The extraction of groundwater and contaminants problems comprises a major deterrent to sustain a progressive economy in the region. It may lead to severe limitations in the agricultural and industrial progress in Jordan

Jordan Valley has long been used for agriculture and is one of the main irrigated agricultural areas in the HKJ. The irrigated area is more than 34,000 ha, and the agricultural sector consumes about 68% of Jordan's water resources. This percentage embodies the largest use of water in Jordan. In agriculture, water requirements are linked to irrigation use (Allen et al., 1998). Due to Jordan's scarcity of water, the efficient utilization of water resources including the use of irrigation water is a major national concern. There are three types of irrigation methods in HKJ. These methods are surface irrigation, sprinkler irrigation, and drip irrigation. Irrigation efficiency is a significant dimension of the water preservation issue that needs to be investigated to reach a better water resources management in HKJ. For example, irrigation efficiencies of the drip irrigation system in the Central Jordan Valley varied from 34% to more than 90% (DAI report, 1995). Furthermore, irrigation water is wasted through runoff, and evaporation; the latter lose about 67% of applied irrigation in the Jordan Valley. In spite of the significance of evaporation as a component in the irrigation efficiency, it was not given a well-deserved attention. Most often, applied irrigation in agricultural is based on farmer experiences. Evaporation can either measured or estimated. Pan A Class can be used for measuring daily evaporation. Evaporation can be predicted by using simulation models. These models ranges from simple to more sophisticated such as ARIAM. The evaporation component should be included in the development of any irrigation water management plan in Jordan Valley. Potential evapotranspiration (ET_p) is defined as the rate at which evapotraspration would occur from a large area completely and uniformly covered with growing vegetation which has access to an unlimited supply of soil water and without advection or heat storage effects (Dingman, 2002).

Modeling and predicting the evapotranspiration rate is required for reliable and effective planning, design, managing, and operation of water-resource projects; managing water quality, determining safe yields from aquifers, planning for flood control and forest fire prevention, proper irrigation scheduling, economics of building water-supply reservoirs, determining the water budget at field scale, assessing soil moisture, predicting climate change and ecosystem responses to climate change, estimation of water available to human use and its management as well as playing an important role in other environmental issues and concerns (Jensen, et al., 1990; Singh and Jaiswal, 2006; Fardous et al., 2001; Mazahrih et al., 2001).

Irrigation scheduling for crops in Jordan Valley is quite empirical and could lead to a great loss of irrigation water and low irrigation efficiencies. Evapotranspiration is the most important variable subsequently to rainfall in the context of irrigation to crops and it is a multivariate phenomenon as it is affected by many hydrological variables (Mohan and Arumugam, 1996). Evapotranspiration includes evaporation from open-water, bare wet soil near the plants, transpiration from within the leaves of plants, the use of water by the vegetation to build new plant tissue, evaporation from the moist membrane surfaces of the vegetation as well as sublimation from ice and snow surfaces (Blaney and Hanson, 1965).

The objective of this study is to develop a time series model to simulate the Reference Crop Evapotranpiriation for the Jordan Valley. Specifically, the objectives are to use historical information of ET_o to calibrate the developed model, and generate a simulation projections for ET_o for the next five years. If the calibrated model will, approximately duplicates measured ET_o, then, the local farmer communities and other water authorities will use it to predict evapotranspiration, which will improve water resources management in the Jordan Valley. This can be done by means of the Box-Jenkins parametric modeling to identify seasonality effects and conduct trend analysis and forecasting as well as to develop a seasonal forecast for future events in the time series. Furthermore, using autoregressive integrated moving average (ARIMA) model (Box and Jenkins, 1976), this study meant to develop the ARIMA model for forecasting the monthly values of ET_o and to analyze the predictability and the performance of these models.

In Jordan, there have been no attempts to model reference crop ET data using a time series technique. This is the first study of its kind conducted in Jordan, thus the scarcity of available data was a challenge. The focal point of this paper is restricted to improving the long-term predictions using past E_{pan} data that was converted to ET_o. With this objective, the Jordan Valley was selected for the study as it contributes the largest proportion of irrigated area; irrigated area being 32.4% of the total cultivated area in Jordan (DOS, 2006).

1.1. Climate and Topographic Features of the Study Area

Jordan is located at the eastern margins of the Mediterranean climatic zone with highly variable and irregular rainfall. This climate is characterized by hot, dry summers and cool, wet winters. The estimated long-term average of ETmight reaches 93% of the total precipitation (Taha, 2006; MWI, 2004). During 2004, it was estimated that 7334 MCM were returned to the atmosphere by evaporation and transpiration from the surface of Jordan (MWI, 2004). However, the estimated long term average potential ET in the Jordan Valley ranges between 1289 mm/yearn in the north at Baqoura and increases in the south at Ghor Al-Safi to reach 1545 mm/y (DOS, 2006)(Figure 1).

Jordan valley lies between 200-400 m below sea level, extending from Lake Tiberia in the North to the Dead Sea, with a length of 104 km and a width of between 4-to16 km; it is surrounded in the east and west by high mountains. The Jordan Valley consists of the Northern Ghor (11 586 ha), Middle Ghor (7875 ha) and the Southern Jordan Valley (11 500 ha). Jordan Valley produces 80% of the national agricultural production and is considered the most important agricultural area, as there is a permanent source of water from the Yarmuk River and side dams for the Jordan River.

In the Jordan Valley, rainfall decreases from approximately 300 mm in the north to 102 mm in the south. The climate of the valley is characterized by very dry, hot summers with average temperature of 31.5 ^{o}C and cool, wet winters with average temperature of 14 ^{o}C. The relative humidity ranges between 64% in the winter to 27% during the summer. Due to its position below sea level and high temperatures (microclimate), Jordan Valley is considered the most important winter vegetable producing area (85%), with citrus and banana production (10%), because of its tropical climate and the limitation of irrigation water. Forage crops (5%) are grown on a very limited scale (Abu-Zanat, 1995). These crops and vegetables are exported abroad to Europe and other countries. Therefore, the valley is considered a food basket for all riparian countries due to its unique climate and agricultural environment. Most cultivable lands in Jordan Valley are irrigated where 73% of the total irrigation sector exists. The majority of holdings are between (3-4 ha). Farmers use modern agricultural techniques in irrigation, production, and marketing.

2. Methodology and Assumptions

It is essential for a successful water resources management in HKJ to evaluate crop water requirements on monthly bases because it is included in any long-term water management operation of water supply and storage systems. The crop water requirement is related to crop evapotranspiration, ET_c, of the crop being grown. Therefore, it is realistic to provide one forecast of a reference crop evapotranspiration rate, ET_o, for a region. Subsequently the ET rate for each crop growing in the region can be forecasted. A time series is a set of measurements of a variable taken over time at equally spaced time intervals. Additional valuable information could be offered during time series analysis. Analysis of time series involves analysis of the statistical manners of a series of data over time, giving that the record is complete, and continuous along with assumption of negligible variability of physical conditions over the period of analysis. If changes of these conditions occur over a long time, one should consider it prior to the analysis.

Reference crop evapotranspiration is the rate of evapotranspiration from an extended surface of 8 to 15 cm tall, with green cover of uniform height, actively growing, completely shading the ground under, and no deficiency of water. Although the estimation of ET_o can be done easily, but the objective of the study is to forecast the ET_o, i.e., to predict future values to be able to improve planning and managing of the water resources and to test the predictability of the developed model. To forecast the ET_o rate, one can use either relationships that rely on forecasts of physical weather parameters or one can consider a mathematical method that seeks to predict future ET_o rates based on the past history of the ET_o rates in a certain region. In this manuscript, we will focus on the latter case.

Pruitt developed different methods and Doorenbos (1977) for estimating ET_o in a region using relationships relating physical parameters incorporated in the ET process. Of these relations are the Blany-Criddle equations; the Penman equation, the Radiation equation; or the Pan Evaporation method. Pans provide a measurement of the integrated effect of radiation, wind, temperature, and humidity on the evaporation from an open water surface. They concluded that mistaken forecasts of the mean wind speed are the main source of difference between the predicted and measured reference crop ET. Moreover, the physically based relationships for forecasting evapotranspiration have some limitations. However, in 1990, the International Commission adopted the Penman-Monteith combination method as a standard for Reference crop Evapotranspiration for Irrigation, Drainage, and World Meteorological Organization. A direct measurement of Evapotranspiration is costly and is not easy; therefore, using historical information of ET_o, time series can be an alternative method for forecasting $ET_{o.}$

Pan Evaporation (E_p) data was recorded at Deir-Alla Weather Station and obtained from Applied Meteorological (Division Jordan Department of Meteorology, 2006). The Station is located in the Central Jordan Valley, at latitude of 32^{o} 13’ N, 35^{o} 37’ East-longitude with an elevation of 224 meters below the sea level. ET_o was predicted using 30 years of past records of weather values of pan evaporation from the Station. The values of ET_o for this period were produced by pan evaporation method (E_p). In spite of the difference between pan evaporation and the evapotranspiration of cropped surfaces, the use of pan evaporation may be warranted to predict ETo for periods of 10 days or longer (Allen et al., 1998; Abdo, F., 2007. Personal communication. Senior Agronomist, Jordan Department of Meteorology, Amman, Jordan). Using pan evaporation to predict ET_o for periods of 10 days is an international convention that has been reliably put into practice due to the fact that a 10 days is a reasonable time to put any agricultural activity or problem that might occur into operation to be benefited or corrected by the farmers easily and satisfactorily.

Past ET_o data is used to get the long-term ET_o estimates by modeling the time series using suitable ARIMA techniques known as Box–Jenkins model which is very popular type of time series models used in hydrological forecasting. The longest available data set was used to avoid misleading results when using ARIMA procedure (Box and Jenkins, 1976). The data set was divided into two sections: the first section, composed of twenty-five years (1973-1997) (300 months) of data that was used for calibration to identify and develop a univariant seasonal ARIMA model, the second, composed of five years (1998-2002) (60 months) was used to validate and test the model performance and its predictability. Various time series models were developed and tested using monthly averaged ET_o for the study area for the period1973 to 2002.

The pan has proved its practical value and has been used successfully to estimate reference evapotranspiration by observing the evaporation loss from a water surface and applying the pan coefficient to relate pan evaporation to ET_o (Allen et al., 1998). Mazahrih et. al (2001) shows a good relationship (R^2=0.72) between evaporation from class-A pan and the measured crop evapotranspiration of pepper inside a plastic house. In this manuscript, the variable K_p method to derive the 30-year reference evapotranspiration from E_p data was used. The pan coefficient (K_p) was calculated from class-A pan located at Deir-Alla using tabulated values (table 5 in FAO Irrigation and Drainage Paper 56) or table 7 (regression equation) of the method described by Allen et al. (1998) in chapter 4. Then the ET_o was calculated using the following relation (Allen et al., 1998)

$$ET_o = K_p\, E_p \qquad (1)$$

Where ET_o is reference crop evapotranspiration (grass) [mm/day], K_p is pan coefficient [-], and E_p is pan evaporation [mm/day].

2.1. Models and ARIMA Development

The most common approaches to forecasting evapotranspiration is extrapolation or the prediction method which is based on an inferred study of past data behavior over time. In time series analysis, the observations taken at a constant interval of time are considered random variables. Any particular observed series is supported to be the only realization of all possible series that could be generated under the same set of conditions. ARIMA models in time series analysis can satisfactorily explain such processes according to Box and Jenkins (1976). The Box–Jenkins model authorizes us not only to expose the hidden patterns in the data but also to generate forecasts of the future based exclusively on historical values of the dependent variable. Moreover, the accuracy of forecast of time series models are good, convenient to use when seasonal or monthly patterns must be taken into account, supple enough to be modified when strategy changes occur, the least data-intensive compared to many other models, and easily developed by means of various standard software packages. In addition, seasonal ARIMA models allow for randomness in the seasonal pattern, unlike the classical method approach based on linear regression. However, they are inaccurate when considerable changes in determining variables occur in the future and can be susceptible to their starting values, when carrying the greatest weight in the forecast.

A general ARIMA model contains autoregressive (AR) and moving average (MA) parts. The AR part describes the relationship between present and past observations, whereas the MA part characterizes the autocorrelation structure of the error or disturbance series. In this paper, time series analyze; reference crop evapotranspiration (ET_o) or $\{Y_t\}$ for forecasting and modeling as a function of time. A time series is usually represented by $\{Y_t\}$ where the dependent series $\{Y_t\} = Y_1, Y_2, Y_3 \ldots Y_t$. When t=1 the observation is Y_1 and so on. Then the ARIMA model of Y_t can be represented by ARIMA (p,d,q), where p is the order of non-seasonal autoregressive operators; d is the order of the non-seasonal difference passing operators and typically have a value of 0 or 1, and seldom greater than that; q is the order of non-seasonal moving average operators applied in non-seasonal modeling process.

If we can express the variable Y at time t as the sum of residuals at previous times, then the moving average model can be written as:

$$Yt = C + \theta q\ (B)\ \varepsilon t \qquad (2)$$

Where C is a constant term; θ_q (B) = 1-θ_1(B) - θ_2(B^2)-…..- θ_q (B^q) is the moving average operator of order q; B is backward shift operator ($By_t = y_{t-1}$ and $B^s y_t = y_{t-s}$, y_t is the current value of the time series examined). q is the order of moving average operator which considered the number of lagged periods correlated to present value of the time series. The value of q can be determined from the characteristic of the series of Autocorrelation Function (ACF). The ACF values should be reduced gradually and disappeared after a time lag of q. If the variable Y at time t can be written as the sum of the weighted variables of previous time, then the auto regression model can be expressed as:

$$\phi p\ (B)Yt = C + \varepsilon t \qquad (3)$$

Where ϕ_p (B) = 1-ϕ_1(B) - ϕ_2(B^2)-…..- ϕ_p (B^p) is the autoregressive operator of order p (the number of lag periods where the error term is correlated to the time series). Gradually reducing ACF values and disappearing of the PACF after a time lag of p.

The combined models can be written as:

$$\phi p(B)Yt = C + \theta q(B)\varepsilon t \qquad (4)$$

For a seasonal time series to be modeled, the relationships at the seasonal lag must be incorporated. The lag in this study is 12 for the monthly data collected monthly. These relations can be represented by including of AR and MA parts at that lag. The same procedure is applied to determine the tentative values of P, D, and Q, where P is the order of seasonal autoregressive operators; D is the order seasonal difference passing operators and typically have a value of 0 or 1, and seldom greater than that; Q is the seasonal moving average operators applied in seasonal modeling process. In this case, the time series regarded as non-stationary. Differencing techniques (the integration component of ARIMA) are often used to transform a non-stationary time series into a stationary time series. Visual inspection of the plot of ET_o time series point out a periodic trend (Figure 2).

Now considering that y_1, y_2... y_t are the differenced values of ET_o of time series data, using the backshift operator “B" shifting the subscript of a time series observation backward in time by one period gives:

$$By_t = y_{t-1} \qquad (5)$$

Then the seasonal operator will be:

$$\nabla_s = 1\text{-}B^s \quad (6)$$

Where "s" is the periodicity or seasonality of the series (12 in this study), Using the general stationary transformation, the transformed time series explained as:

$$Z_t = \nabla^D{}_s\, y_t \quad (7)$$

Where $\nabla^{(D)} y_t$ is the lag-12 difference operator

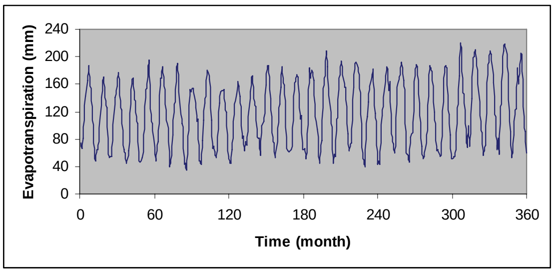

Figure 2. Time series of reference crop evapotranspiration of the studied area between 1973 and 2002

Therefore, the general full general multiplicative seasonal and non-seasonal ARIMA Box-Jenkins model using backshift operator is (Pankratz, 1983):

$$\varphi_P(B)\varphi_P(B^s)(1-B)^d(1-B^s)^D Z_t = C + \theta_q(B)\theta_Q(B^s)\varepsilon_t \qquad t = 1, 2, n \quad (8)$$

This can be summarized as ARIMA (p, d, q) (P, D, Q) $_{12}$, where p, d, q, P, D, and Q as defined earlier. It is worth noting that the polynomials Φ (B^s) and Θ (B^s) capture the seasonal behavior of the series (P- and Q-order seasonal AR and MA operators, respectively) and C is constant with no specific meaning. Besides, the stationary and invertibility (stationary condition for the MA part of the ARIMA model) conditions demand that all the roots of the characteristics equation Φ (B^s) =0, φ (B) = 0, Θ (B^s) =0, θ (B) =0, lie outside the unit circle in the complex plane (Box and Jenkins, 1976).

The following operators can be used to describe Box-Jenkins models as non-seasonal and seasonal autoregressive operator of order *P* and moving average operator of order *Q* respectively.

$$\phi_P(B) = (1-\phi_1 B-\phi_2 B^s-\ldots-\phi_p B^P) \quad (9)$$

$$\phi_P(B^s) = (1-\phi_{1,s}B^s-\phi_{2,s}B^{2s}-\ldots-\phi_{P,s}B^{Ps}) \quad (10)$$

$$\theta_q(B) = (1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q) \quad (11)$$

$$\theta_Q(B^s) = (1-\theta_{1,s}B^s-\theta_{2,s}B^{2s}-\ldots-\theta_{Q,s}B^{Qs}) \quad (12)$$

Where Φ and θ are unknown parameters, which represent the autoregressive and moving average coefficients at different lags of t time. In this study, ET_o is considered a seasonal time series. The seasonal time series have relationships at a definite lag s (12 for the data collected monthly).

To develop a suitable model for forecasting ET_o, an iterative procedure involving a four-step modeling procedure is conducted. These steps are identification of a tentative model, estimation of model parameters by Maximum Likelihood (ML) Technique, diagnostic checking, and testing the adequacy of this model and providing necessary modification of the model if the tentative model is poor. The final model is then used for forecasting purposes at the fourth stage. This iterative procedure necessitates visual assessment of intermediate statistical results, and the model is ultimately developed based on the expert judgment of the authors.

2.2. Preparing Data for Analysis and Model Identification

The Model identification step in the Box-Jenkins iterative modeling proves to be the most complicated and hard task, particularly if the time series is seasonal or periodic. Seasonal time series might be caused by the nature of the annual weather cycle as in the case of the ET_o time series data of this study (Figure 2). Since Box-Jenkins assumes a stationary time series, therefore stationary nature of the process that generated the time-series is one of the most considerable conditions that have to be imposed on the development of an ARIMA model in order to improve the forecasts.

The first part of this step consists of checking whether the variation in the time series is unstable with time. Transformation must be done on unstable series. If the data fluctuates with increasing variation, a pre-differencing treatment (e.g., logarithmic or square root transformations) is required to stabilize the variance of the time series. Moreover, a trend existing in time series data requires differencing. A time series may be considered stationary if the mean, variance, and its covariance of the time series are constant through time (Box and Jenkins, 1976). Box-Jenkins time series analysis was applied to the monthly ET data sets. The plot of autocorrelation function (ACF) for the overall data sets is presented in Figure 3. The continuous lines in the graphs represent the confidence limits. Values of the ACF within these limits are not significantly different from zero.

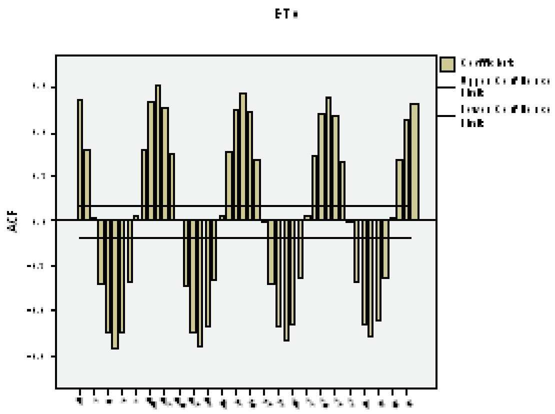

Figure 3. Autocorrelation function of the monthly averaged reference crop evapotranspiration between 1973-2002

By visual inspection of the sample ACF of the original ET_o time series plot, an evidence of periodicity or seasonality exists indicating strong seasonal serial dependencies and some correlation at lags up to 12. In order to remove the serial dependency and to model/forecast the $ET_o(Y)$, time series analysis begins by transforming Y to ensure it being stationary. Examining the characteristics and statistics of both ACF and PACF (PACF not shown to reduce the size of the manuscript) of the transformed series is the second part of step one. The purpose of this part is to determine if the series need additional differencing to remove the trend or seasonality to make the series stationary by eliminating seasonal and non-stationary behaviors of the ET time series. The ACF of a stationary time series shows a quick decay for moderate and large lags. A distinctive feature of the data that suggests the convenience of differencing the original time series is a slowly decaying positive ACF.

The plot above illustrates this behavior, which clearly indicates seasonal periodicity in the studied data. To eliminate this periodicity trend, the time series must be differenced until a rapidly decaying ACF (Brockwell and Davis, 1996). The ACF plot of the overall time series shows that the data are seasonal due to the peaks of the ACF at lags that are multiples of 12. The peaks presented in the plot show a correlation in the data every 12 lags. This means that the order of the seasonal differencing is one (D=1). Removing this seasonal component of period 12 from the series Y_t, the transformed series $Z_t = Y_t - Y_{t-12} = (1-B^{12})\, Y_t$ was generated where B is the backward shift operator as indicated earlier (Box and Jenkins, 1976). In this study, various types of differenced series for both non-seasonal and seasonal patterns are plotted and examined until most of serial dependencies have disappeared.

Differencing creates a new data series, $\{Z_t\}$, which becomes input for the Box-Jenkins analysis; the ARIMA (Figure 4 and 5). Then, the transformed time series is fitted with an ARIMA model where the current value of the time series, $\{Y_t\}$, is expressed as a linear combination of *p* earlier values and a weighted sum of *q* earlier deviations (original value minus fitted value of previous data) plus a stochastic random process or error, ε_t that are independently and identically distributed with a normal distribution $N(0, \sigma_a^2)$.

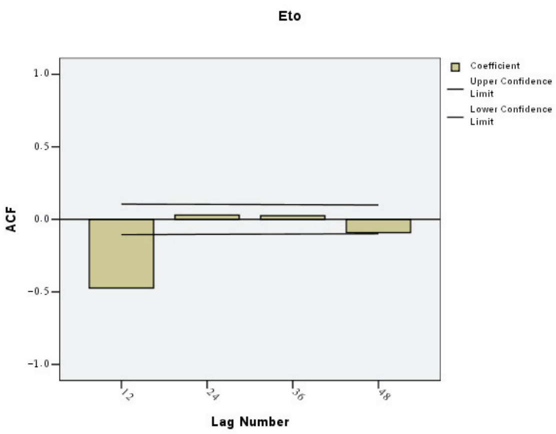

Figure 4. Sample autocorrelation function of transformed reference crop evapotranspiration time series (D=1).

A verification of seasonal removal, is conducting by re-plotting the ACF to see the elimination of the peak. After the elimination of seasonal and/or cyclical components, the resulting time series $\{Y_t\}$ could be non-stationary. Thus, the time series can be transformed into a stationary one, $\{Z_t\}$, differencing recursively D times until the ACF reduced significantly (Brockwell and Davis, 1996). The sample time series ACF, Figure 3 already shows decay for moderate lags, being no necessary more differencing is required. We now have a stationary and seasonal time series, $\{Z_t\}$, and the identification of the ARIMA (p, d, q)*(P, D, Q)$_{12}$ model orders should be undertaken.

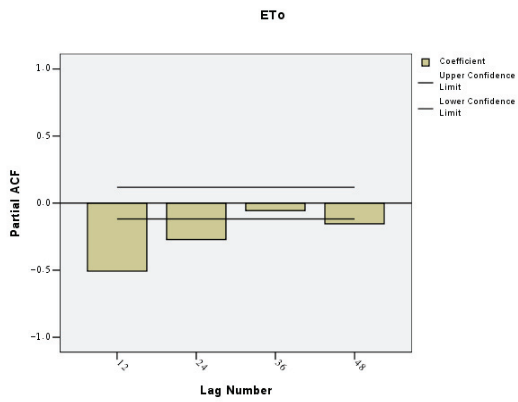

Figure 5. Sample partial autocorrelation function of transformed reference crop evapotranspiration time series (D=1)

3. Results

3.1. Parameter Estimation of the Model

Before we can specify the parameters to be estimated, the formulation of ARIMA model has to be identified based on the transformed ET_o time series data. Here we determine the values of the parameters (θ and ϕ) of the proposed model of both seasonal and non-seasonal time series after determining the type of a tentative ARIMA model, i.e. p, d, q; P, D, and Q using statistics interpretation and plot of ACF and PACF. The parameters are estimated using maximum likelihood approaches. These methods are frequently used and would yield efficient parameter estimates compared to other approaches. Furthermore, ML can tolerate missing data in the series in spite of no missing values in our ET_o data (Shumway and Stoffer, 2000). In this manuscript, the computations were done using SPSS computer software (SPSS, 2005).

In general, sample autocorrelation function and the sample partial autocorrelation function are used for the detection of various types of autocorrelation. This was done by using the behavior of both functions at the non-seasonal level to tentatively identify non-seasonal and seasonal models describing the time series values (Brockwell and Davis, 1996). Then, the parameters of the proposed tentatively identified models are estimated followed by estimating t values for diagnostic and adequacy checking of those models and, if required, to suggest an improved model. The judgment of model selection entails not only knowledge but also a good deal of experimentation with alternative models as well as the technical parameters of ARIMA (Bowerman and

O'Connell, 1993). In the parameter estimation step using the iterative ML method, the optimization criterion is based on the minimizing of residual sum of the squared between the observed data and the estimated one. Besides, the estimation was conducted using 0.001 as a minimal iteration value and 0.0001 as a minimal change between iterations for the sum of the squared residuals. Many models were identified for detailed assessment. Three candidate models were selected for diagnosis; ARIMA (2,0,0) (0,1,1), ARIMA (1,0,0) (2,1,1) and ARIMA (1,0,0) (01,1).

3.2. Diagnostic Checking of the Model

Two objectives should be fulfilled in this step. The first is to test hypothesis process by checking the significant of the parameters for each proposed model. Checking the normality of the residual distribution is the second task. In addition to the visual inspection of the residuals, various diagnostics (i.e., t-ratios, Q stat, Akaike Information Criteria"AIC," etc) are used to check the adequacy of the tentatively identified models and, if necessary, to propose an enhanced model.

Between competing models, the model that produces residuals with ACF that are not significantly different from zero at all lags and have smaller standard error will be selected. The model (1,0,0)(0,1,1) has the smallest error magnitudes, and the autocorrelation coefficients of the prediction errors were not statistically significant, i.e., all values of residual correlations were close to 0 and inside the confidence limit to 95%; there was no serial dependency between residuals.

Moreover, correlation analysis of the residual in the plot of the ACF and the goodness of fit using chi square test is conducted. If the model does not show a correlation in the residuals, then the residuals are white noise indicating the adequacy to represent the time series. ACF of Residuals of the three selected tentative models is shown in Figures 6, 7 and 8. The time series of errors associated with the initial model forecasts was analyzed using the ACF analysis tool. This procedure was repeated until the errors of the forecasting model were reduced to white noise with no significant correlations. Figures 6, 7, and 8 indicate that no significant sample autocorrelations of the residual series are found based on the values of ACF residuals. Based on Box-Pierce chi-square statistics, all the values can be considered negligible and residuals are not correlated. Therefore, the selected two candidate ARIMA models are adequate and the ET_o time series is the white noise.

The results for detailed evaluation and verification of these three models are presented in Table 1. Based on Box and Jenkins (1976), a good model should require the smallest possible number of estimated parameters of an adequate representation of the patterns in the available data. The overall time a seasonal model that includes one non-seasonal autoregressive and one seasonal moving average terms of order1 describes series.

Table 1 also presents the results of parameter values of the tentative models, Box-Pierce and, Box-Pierce chi-square and standard errors. The Box-Pierce is based on the computation of ACF residuals. All ACF lie within the limits indicated by the upper and lower horizontal lines shown in Figure 6, 7 and 8 which reveal that the residuals are not correlated and all the ACF values can be neglected.

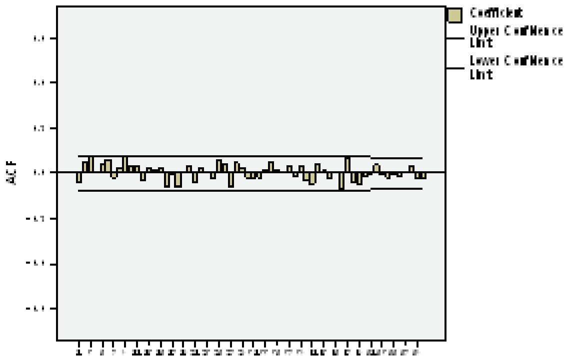

Figure 6. Autocorrelation function of residuals of ARIMA (1, 0, 0) (2, 1, 1)12

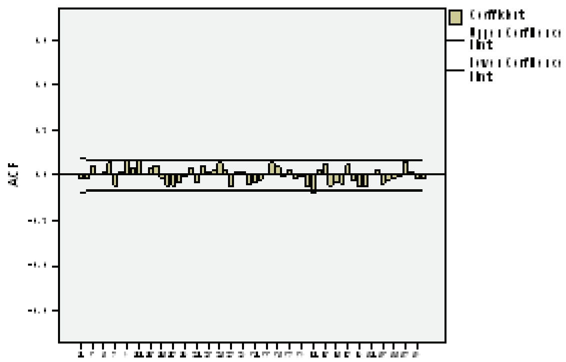

Figure 7. Autocorrelation function of residuals of ARIMA (2, 0, 0) (0, 1, 1)12

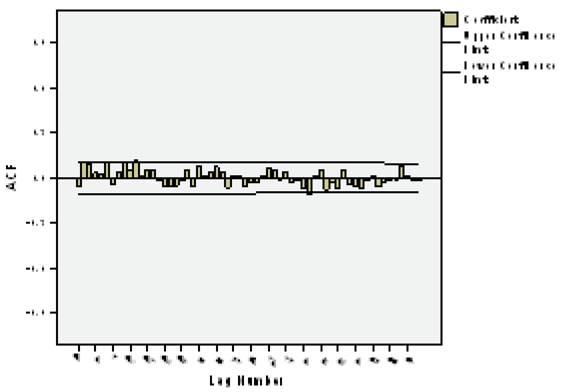

Figure 8. Autocorrelation function of residuals of ARIMA (1, 0, 0) (0, 1, 1)12

A high standard error corresponds to a higher uncertainty in parameter estimation, which queries the stability of the model. If the result of the ratio between the parameter values to the standard error is larger than two, then the model is adequate. The Akaike Criteria (AIC) and the residual variance are additional helpful parameters in selecting the best models.

Table 1. Results of Model Estimation and Verification

Tentative Models	ARIMA Model I (200)(011)12			ARIMA Model II (100)(211)12				ARIMA Model III (100)(011)12	
	Parameter			Parameter				Parameter	
Tests	AR(1)	AR(2)	SMA(1)	AR(1)	SAR(1)	SAR(2)	SMA(1)	AR(1)	SMA(1)
Parameter value	0.30	0.148	0.91	0.34	0.065	0.088	0.96	0.35	0.914
Standard error	0.052	0.052	0.041	0.05	0.067	0.064	0.081	0.05	0.041
t-ratio	5.708	2.833	22.366	6.761	0.983	1.371	11.877	7.027	22.363
Q-value	24.732			34.921				24.726	

Although the models 1, 2, and 3 have no major differences in terms of the parameters shown in table 1, model No 3 is preferable. Based on the lower values of Q, lower number of parameters, t value and other verification results, model 3 is recommended and is therefore more suitable than model 1 and 2 in forecasting. Furthermore, model 2 does not meet the t-stat condition, unlike model 1 and 3. Table 2 shows simple statistics for both the original time series of the evapotranspiration and the predicted time series using the best-diagnosed models. The values of Model III are closest to those statistics that we selected: mean variance and skew ness.

Table 2. Simple statistics of the best-diagnosed model

Model	Mean	Variance	Skewness
Original ETo Time Series	118	2310	0.08
Predicted ETo Time Series, Model I (2,0,0)(0,1,1)	117	1932	-0.002
Predicted ETo Time Series, Model II (1,0,0)(2,1,1)	117	1936	0.000
Predicted ETo Time Series, Model II (1,0,0)(0,1,1)	115	2016	0.031

3.3. Model Forecasting

We fitted on the first 300 data points, using the Q-stat, t ratio, AIC criterion, and standard error. The best obtained model is for p = ۱, d=0, q = 0, P = ٠, D=1, Q = 1. The final model can be written in the following form:

$$ET_{o,t} = 0.35ET_{o,t-1} + ET_{o,t-12} - 0.35ET_{o,t-13} - 0.914\varepsilon_{t-12} + \varepsilon_t \quad (13)$$

This model is used to forecast future values of the transformed time series. Lastly, the previous transformations are undone, in order to obtain the future values of the original time series, $\{Y_t\}$. All the steps were done in an iterative fashion. The process of forecasting usually requires a great deal of experience and testing alternative models. The resulted forecasts are shown in Figure 9.

Once a final satisfactory ARIMA model was selected, the tentative models were used to forecast monthly values of ET_o. The forecasting period was 1 month ahead for 60 months that covers the period 1998 to 2002 based on the previous 300 months. The forecasting performance capability for the post sample period of the tentative ARIMA models was assessed using Root Mean Squared Forecasting Error (RMSFE), Mean Absolute Forecasting Percentage Error (MAFPE), and Maximum Absolute Forecasting Percentage Error (MXAFPE). By examining the mean and maximum across all models, we can get an indication of the uncertainty in the predictions.

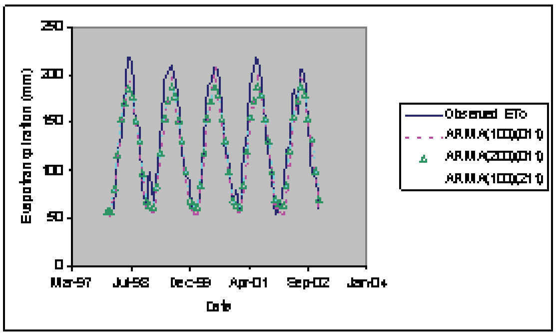

Figure 9. Comparison of predicted to actual reference crop evapotranspiration of the two tentative ARIMA models

Typically, the RMSFE is defined as the error accumulated in the forecasted observations.

$$RMSFE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Y_t - \hat{Y}_t)^2} \quad (14)$$

The mean percentage absolute forecasting error is the absolute error in the desired prediction length, which considered a measure of how much a dependent series varies from its model-predicted level. The mathematical representation of this measure is:

$$MPAFE = \frac{1}{N}\sqrt{\sum_{t=1}^{N}\frac{|e_t|}{Y_t}} * 100 \quad (15)$$

Where e_t is the absolute error between observed and estimated ETo, Yt based on an estimated model at time i and *N* is the number of forecasts used for this purpose.

The Maximum Absolute Forecasting Percentage Error is the largest forecasted error, which is considered a measure useful in imagining a worst-case scenario for the forecasts. Assuming that the estimated model is representative of the forecasting period, the post-sample RMSFE should be consistent with the residual standard error of the estimated model. As a result, comparisons of forecast performance based on the RMSFE, MAFPE, and MAXAFP are made.

It is worth mentioning that for evaluation intentions, the post-sample period is employed to provide reasonable cross-validation and to shun the potential misleading idea that the fit is better than it really is due to over-fitting the training series. The out-of-sample error indicators for both candidate ARIMA models are presented in table 3. In general, the best forecasting for the overall time series came from the ARIMA model 3. Overall, the ARIMA approach in forecasting reference evapotranspiration gave very good results for monthly data (Mariño et al. 1993: Hameed et al., 1995; and Trajkovic, 1999) which can be easily implemented following the aforementioned steps.

Table 3. Sample error indicators for the three candidate ARIMA Models

#	ARIMA	RMSFE	MXAFPE	MAFPE
I	Model (200)(011)	12.88	64.68	10.89
II	Model (100)(211)	12.98	68.52	10.99
III	Model (100)(011)	12.75	61.20	10.75

4. Discussion

After a complete evaluation of model identification, estimation, diagnostic checking, and forecasting, time series analysis is eventually established for reference crop evapotranspiration. ACF and PACF, as elements in time series analysis play an important role in this matter. Both functions were tested to calculate the significant autocorrelation existing in the reference crop evapotranspiration data and to identify the components of the ARIMA models. The application of ARIMA model on a time series should obey stationary criterion. A periodic ET_o time series as shown in Figure 2, mandates transforming the data to be stationary by differencing once, reducing ACF of the time series significantly. Throughout the discussion of this data set, 5/6 of the total data is used to established and identify the model, and the remaining 1/6 of the total is used to validate the models.

Twelve different types of ARIMA models are sequentially tested for the ET_o time series data. Based on the exploration of the nature of the time series data (i.e., the identification phase of ARIMA), a seasonal ARIMA and non-seasonal ARIMA with lag 12 are run on the data and both autoregressive and moving average ARIMA parameters are estimated. Table 3 lists three final models prepared for the studied area. To select the best-developed model for forecasting of the crop evapotranspiration, an assessment of the performance of these models was conducted as measurement of how closely two independent data sets match. This evaluation was done using Root Mean Square Forecasting Error as a deterministic approach in addition to the Mean Absolute Forecasting Percentage Error and the Maximum Absolute Forecasting Percentage Error.

The results of this evaluation are shown in Table 3. The three candidate models demonstrated good performance. The seasonal ARIMA model $(1,0,0)(0,1,1)_{12}$ fits slightly better and gives a smaller confidence interval than the models $(1,0,0)(2,1,1)_{12}$ and (2,0,0)(0,1,1). The model diagnostic shows that the residuals do pass the test for normality (not shown). The finest ARIMA model was identified calculating the t statistic and other statistical tools. The RMSFE, MAXAFP, and MAFPE were minimum for the case of the model $(1, 0, 0)\ (0, 1, 1)_{12}$. The selected ARIMA model with two parameters seems to forecast the time series data very well (Figure 9). This result is supported by the work done by Mariño et al., 1993; Hameed et al., 1995; and Trajkovic, 1999. These investigators have obtained good results when ARIMA model was compared with different time series and conventional methods of evapotranspiration estimation.

Figure 9, however, shows that predicted ET_o gave reasonable agreement for the ARIMA $(1, 0, 0)\ (0, 1, 1)_{12}$ up to rates of 200 mm month^{-1} but insignificant underestimation at higher rates. Yet, the ARIMA (1, 0, 0) (0, 1, 1) model forecasts ET_o better than model I and II. To reflect the uncertainty in the forecasts, this analysis therefore follows that an approximate 95% prediction interval for the historical and forecasting values may be made in the same manner as in general least-square regression issues. Furthermore, the model produces similar ACF when predicts the ET_o during the period 1998 to 2002 as indicated in Figure 10. For the same period, by visual inspection, Figure 11 showed an excellent correlation between the observed and the forecasted (calculated) values of ET_o which supports our results.

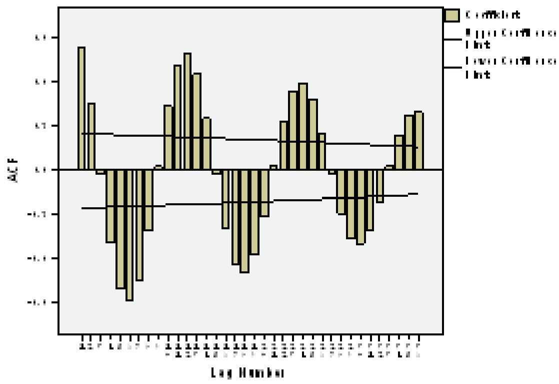

Figure 10. Autocorrelation function of the predicted reference crop evapotranspiration using ARIMA (1, 0, 0) (0, 1, 1)

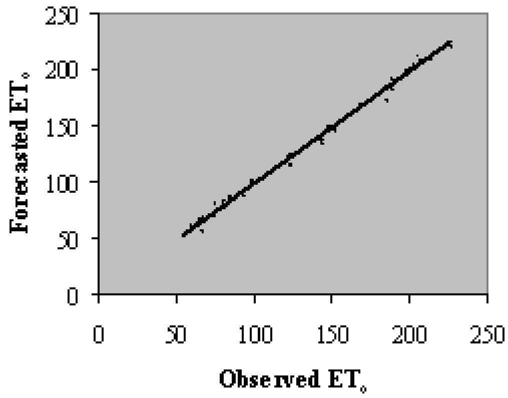

Figure 11. Observed versus forecasted reference evapotranspiration between 1998 and 2002

It must be pointed out that the predicted time series values of reference crop evapotranspiration are relatively lower than the observed values obtained from the Deir-Alla weather station on the year 1998. This might be due to a drought period. Drought periods might lower the performance of the forecasting techniques. To examine the drought periods, ET_o estimation for the 1998 drought year was at relatively higher variance with the reported ET. This variation contributed significantly to increasing the RMSFE and, in turn, lowering the forecasting performance. Moreover, the reference crop ET relating to the severe drought year acts as an outlier and influences the characteristics (e.g. being stationary) of the series. Therefore, we expect a longer series would lead to improved forecasts. This is due to enduring the negative effect of drought periods on the performance of a forecasting technique.

The lack of water in arid and semi-arid regions constitutes a major deterrent to sustainable development of these areas. To meet demands for water for a multitude of uses, there is a continuing struggle. Insufficient water at the right place, at the right time, and with the right quality requires more than ever before improved management, efficient utilization, and increased conservation of limited freshwater resources. This manuscript aims at providing a time series forecasting approach presentation, which can identify the needs for future developments associated with water resources development, utilization, management, and conservation in arid and semi-arid regions. This would reflect into the real world application where time series modeling may serve as a convenient tool for the prediction of ET_o when water resources are of a paramount importance as in the case of Jordan.

Successful forecasting of evapotranspiration would play a vital role in the irrigated agriculture sector. This will help in water resources management, which will contribute in strengthening Jordan's economy. Therefore, adequate estimations and forecasting of evapotranspiration are required especially in irrigated agriculture. Evapotranspiration is one of the most significant hydrologic processes affected by human activities that alter the type and extent of vegetative cover. Moreover, knowledge of ET on not only a local but also a regional scale enables hydrologists to perform water balance calculations and understand hydrological cycles. ET forecasting shall be useful in irrigated agriculture, i.e., for water and agricultural planners: it will allow agronomists and farmers to assess crop water requirements in Deir-Alla

Irrigated agriculture is a trade of Jordanian lineage practiced in the Jordan Valley, which contributes to the production of food and job opportunities in direct and indirect agricultural employment and supporting services. It also augments the environment and helps apprehend desertification indirectly. This enhances and helps in increasing on-farm irrigation efficiency and maximizing the agricultural output of a unit of land area per unit flow of irrigation water. In addition, in order to determine the volume of replenishment water that is needed for irrigation, evapotranspiration rates need to be forecasted to wet root zone and to sustain a low drainage rate.

ET information is needed for drainage design and drains networking to be help in installing drainage system in the valley where natural drainage is not sufficient to serve this purpose. This encourages community farmers who usually need additional water for soil leaching from salts in the studied area to set up a drainage system in their farms. Forecasting ET would help in that prospective and through minimizing the reuse of treated water as supplement water in irrigation. Therefore, the water surplus that can be saved by knowing ET priori can be used to either irrigate extra arable land to maximize productivity and increasing cropping intensities or use it wherever shortages occur in any of the other water-consumed sectors: municipality and industry.

It is worth mentioning that irrigation water consumes about three-fourths of the available fresh water resources in Jordan. Managing the irrigation water use under geographic, socio-economic, and demographic constraints is of a vital importance to Jordan. This case study shows that forecasting ET can be incorporated in irrigation water management by proper choice of crops and farming patterns. Furthermore, managers who manipulate soil-plant systems in the Jordan Valley should have a good fundamental understanding of the process of ET and the factors that influence its magnitude.

Controlling the fate of water and achieving a proper management of the scarce water resources in Jordan would diminish the exploitation of water resources, which is considered a real threat to peace and future development process in the region. Possible conflict over water in the region might retard any integrated and sustainable development plans. Moreover, improved and efficient water resources management could help in sustaining the tourism since the Jordan Valley contains many tourism attractions and places like the Dead Sea, Jordan River and many others. It has been demonstrated by many studies in the world that the tourism water use produces higher net revenue compared to irrigation use (The PRIDE Report, 1992).

Potential evaporation is extremely high in the studied area. Evapotranspiration is considered on of the most important factor in managing water resources in the Jordan Valley. Poor water management can result in disease-causing pollution, loss of topsoil from erosion, damage to animal habitats and to forests and others. Worst of all is the damage to irrigated agriculture that now provides Jordan's food supply and must be relied upon to provide more since rainfed agriculture has reached a ceiling and can produce little more than it already is producing.

5. Conclusions

On a per capita basis, Jordan is one of the lowest ranked countries in water resources with the per capita share of water being less than 175 for all uses. This places Jordan at only 20 percent of the water poverty level, which reflects the doughtiness level. Evapotranspiration is one of the most important indices in the drought equation, which exceeds 90% in Jordan. Therefore, time series forecasting of evapotranspiration was conducted to help the decision makers and water system mangers establish appropriate strategies to sustain and manage water resources. Time series assume that "history repeats itself," so that by studying the past, better decisions, or forecasts, can be made for the future.

In this paper, an endeavor is made to obtain a long-term forecast of monthly averaged reference crop ET without using weather data. Thirty years of ET data was used in this study to ensure a satisfactory estimate of monthly values. Nevertheless, the change of inherent characteristics in the ET_o may occur very slowly and time-series models may be useful for long-term planning of water resource management.

Modeling was done using deterministic measures such as RMSFE for evaluating the performance of a forecasting technique. ARIMA model has demonstrated good results for monthly data in terms of accumulative error and performing 5-year predictions within an established reasonable accuracy level. This could be put into practice without difficulty following the previously mentioned procedure.

Moreover, the forecasting techniques presented in this paper allow water resource managers to predict up to 60 months within a mean absolute forecasting percentage error less than 11%, making these predictions very useful to optimize the resources needed for effective water resources management. Predictions can also be made for longer periods. These findings guarantee a dependable planning, design and operating of irrigation projects. On the long term, these findings can help enhance both local (Deir-Alla) and national water resources policies and strategies for irrigation water management in addition to assisting in planning a more effective management of these vital resources. This could reflect on the water quality, which has worsened in the last two decades because of the increasing consumption of the groundwater and the usage of treated wastewater. Moreover, it is likely that forecasting models based on arid and semi-arid conditions would be suitable for other similar regions.

Finally, although these conclusions are strengthened by analyzing a longer reference crop ET series, the long-term forecasts with relatively less reliability may still be needed in system planning and analysis. The findings of this study could lay the grounds for further investigations and studies that could lead to the establishment of a complete and reliable weather database and proper ET prediction in the Jordan Valley region using a dynamic programming approach. Future research should be addressed to extend the validation data set and to check the validity of our results on other regions. It should also explore how to improve forecasting as well as exploring intervention models to estimate various types of environmental impacts for a long time.

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