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Research Article

Prediction for Monthly Rainfall of Six Meteorological Regions and TRNC (Case Study: North Cyprus)

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rainfall,
time series models,
TRNC.

Abstract

This paper works with the monthly rainfall of six meteorological regions and TRNC (North Cyprus) as a whole for the hydrologic years from September 1975 to August 2014 period. In order to predict 5 years ahead of the yearly rainfall of each meteorological region and TRNC, three different time series models (Markov, Auto-regressive (AR) and Holt-Winter Multiplicative) were used. For this reason, the rainfall of hydrologic years from 1975-76 to 2003-04 were used for training and from 2004-05 to 2013-14 were used for forecasting (testing) the trained data. The best representative time-series model for each region was selected based on the standardized averages of four statistical error checking measures (MAPE, MAD, MSE and RMSE). The selected model for each region was then used to predict (estimate) the rainfall for five successive hydrologic years ahead from 2014-15 to 2018-19.

1. Introduction

1.1 Study Area

The study area is North Cyprus which is divided to 6 regions (Central Mesaria,East Coast, East Mesaria, Karpaz, North Coast, West Mesaria, and TRNC as general).

1.2 Time series

A collection of organized observations of a quantitative variable taken at successive points in time is called a time series. Time in terms of years, months, days, or hours is a tool that permits one to connect occurrence to a set of common, stable reference points [1].

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Time series forecasting is the use of a model to predict future values based on previously observed values.There are two main goals of time series analysis: (a) identifying the nature of the phenomenon represented by the sequence of observations, and (b) forecasting (predicting future values of the time series variable). Both of these goals require that the pattern of observed time series data is identified and more or less formally described.

1.3 Stationary Time Series

A time series is stationary if it is free of trends, shifts, or periodicity. It means that the statistical parameters of the series such as mean and variance remain constant through 62 time. Otherwise the time series is non-stationary. Generally hydrologic time series defined on an annual time scale are stationary [2]. The stationary test should be done to determine if the mean values and variances of the series vary with time. Other recent suggested methodes can be found in [3-8]. Stationary time series implies that none of the data varies with time. In this study the Augmented Dickey – Fuller (ADF) test is used to check Stationarity of times series:

1.4 Augmented Dickey–Fuller Unit Root Test

Augmented Dickey–Fuller unit root test (ADF) as its name refers is a test for a unit root in any time series. Being augmented implies larger and more complicated set of time series models.

$$\Delta yt = \alpha + \beta t + \gamma yt-1 + \delta 1\Delta yt-1 + \cdots + \delta p-1\Delta yt-p-1 + \varepsilon t \quad (1)$$

where α is a constant, β the coefficient on a time trend and p is the lag order of the autoregressive process.

By including lags of the order p the ADF formulation allows for higher-order autoregressive processes. This means that the lag length p has to be determined when applying the test. The unit root test is then carried out under the null hypothesis $\gamma \geq 0$ against the alternative hypothesis of $\gamma < 0$. In this study Autoregressive order 1 (AR1) is used, therefore:

$$\Delta yt = \alpha + \beta t + \gamma yt-1 + \varepsilon t \quad (2)$$

H0: $\gamma \geq 0$ implies that the data is stationary, H1: $\gamma < 0$ implies that the data is non-stationary.

Result : Central Mesaria rainfall (time series) is stationary. For other regions also this test was applied:

Table1. ADF test result of all regions

Region	γ= Slope of regression	comment
Central Mesaria	0.43>0	Time series is Stationary
East Coast	0.28>0	Time series is Stationary
East Mesaria	0.34>0	Time series is Stationary
Karpaz	0.26>0	Time series is Stationary
North Coast	0.27>0	Time series is Stationary
West Mesaria	0.08>0	Time series is Stationary
TRNC	0.33>0	Time series is Stationary

2. Methodology

Forecasting model involves the selection of an estimation procedure. A forecast after all, is an estimate of a future outcome of a random process. In this study three forecasting models were used:

2.1 Markov Model

The Markov pocess considers that the value of an event at one time is correlated with the value of the event at an earlier period. In a first-order Markov process, this correlation exists in two consecutive values of the proceedings. The first order

Markov model, which comprises the classic method in synthetic hydrology, declares that the value of a variable y in one time period is dependent on the value of 'y' in the preceding time period plus a random component.

$$y_i = d_i + \varepsilon_i \tag{3}$$

where y_i= rainfall at i[th] year, d_i= deterministic part of i[th] year, and ε_i = random part of i[th] year.

The values of ε_i are connected with the historical data by certifying that they belong to the same frequency distribution and possess similar statistical properties (mean, deviation, skewness) as the historical series [9].A variety of forms and combinations of deterministic and random component are established as different models. Single season (annual) rainfall model of lag 1 is the simplest model which presumes that the amount of the current rainfall is considerably correlated with the previous one value only [9].

If the Markov model's parameters are estimated from data, the standard maximum likelihood estimates consider the first order (single step) transitions only. But for many problems, the first order conditional independence assumptions are not satisfied as a result of the higher order transition probabilities can be poorly approximated by the learned model [14].

Formulation of the Markov model for yearly data [9]:

$$x_i = \bar{x} + r_1(x_{i-1} - \bar{x}) + S\sqrt{(1 - {r_1}^2)}t_i \tag{4}$$

where x_i is the rainfall at i[th] year, $\bar{x}$ is the mean of data, $r_1$is lag one – autocorrelation coefficient , S is standard deviation of data, and t_i is random variate from an appropriate distribution with a mean of zero and variance of unity. For obtaining t_i the random number should be generated, and it did by Microsoft Excel in this study, as well inverse error function $erf^{-1}(z)$should be calculated:

$$erf^{-1}(z) = \frac{1}{2}\sqrt{\pi}\left(z + \frac{\pi}{12}z^3 + \frac{7\pi^2}{12}z^5 + \frac{127\pi^3}{40320}z^7 + \cdots\right) \tag{5}$$

Value of z can be obtained from cumulative distribution function (CDF) of the log normal distribution.

If $\mathrm{erf}(x) = y$, then $erf^{-1}(y) = x.$ Let

$$\frac{lnx-1}{\sqrt{2}} = y \tag{6}$$

The value of $t = lnx$. Therefore

$$lnx = \left(y\sqrt{2}\right) + 1 \tag{7}$$

2.1 East Mesaria region rainfall as a sample for establishing Markov Model

In order to establish the Markov model for East Mesaria rainfall the mean, autocorrelation coefficient (r1), standard deviation, random number, and other relevant parameters were determined automatically with help of Excel software and the results were tabulated below.

Table 2. Markov Model of Central Mesaria rainfall

Year	ppt	mean	r1	standard deviation	rand	z	erf-1	ti,j	xi(F forecasting)
1975-1976	355.4	324.2	0.12	94.8	0.999	0.998	1.327	2.877	556.0
1976-1977	260.2	324.2	0.12	94.8	0.969	0.938	1.170	2.655	601.9
1977-1978	345.8	324.2	0.12	94.8	0.985	0.969	1.249	2.766	617.8
1978-1979	292.3	324.2	0.12	94.8	0.800	0.601	0.595	1.841	532.7
1979-1980	354.0	324.2	0.12	94.8	0.782	0.564	0.550	1.778	516.5
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.

2010-2011	345.0	324.2	0.12	94.8	0.214	-0.571	-0.559	0.209	352.4
2011-2012	466.3	324.2	0.12	94.8	0.116	-0.769	-0.834	-0.180	310.7
2012-2013	366.1	324.2	0.12	94.8	0.365	-0.270	-0.244	0.655	384.2
2013-2014	196.2	324.2	0.12	94.8	0.035	-0.931	-1.153	-0.631	272.0

2.2 Auto-regressive (AR) Model

General expression of Auto-regressive model can be defined by:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \quad (8)$$

where $\varphi_1, \varphi_2, \ldots \varphi_p$ are autoregressive coefficients, and ε_t is white noise (residuals) and p is the order of Auto-regressive model.Autoregressive coefficients ϕ_p can be computed with below matrix form as given in following equation:

$$\begin{bmatrix} 1 & r_1 & r_2 & r_3 & r_4 & \ldots\ldots\ldots\ldots r_{p-1} \\ r_1 & 1 & r_1 & r_2 & r_3 & \ldots\ldots\ldots\ldots r_{p-2} \\ r_2 & r_1 & 1 & r_1 & r_2 & \ldots\ldots\ldots\ldots r_{p-3} \\ & & & \ldots & & \\ r_{p-1} & r_{p-2} & r_{p-3} & r_{p-4} & r_{p-5} & \ldots\ldots\ldots 1 \end{bmatrix} \quad (8a)$$

where r is correlation that is a measure of the relation between two or more variables. Correlation coefficients can range from -1.00 to +1.00. The autocorrelation function can be defined as:

$$r_k = \sum_{i=1}^{n-k} \frac{(X_i-\mu)(X_{i+k}-\mu)}{\sum_{i-1}^{(n}(X_i-\mu)^2} \quad (9)$$

In this study Minitab16 software was used for finding correlations. Before applying autoregressive model to time series, order of Autoregressive model (P) should be defined. In this study Akaike information Criterion is used to find the best order of Autoregressive between AR(1), AR(2), AR(3) in order to show best Autoregressive model for deriving suitable synthetic series of data. After modelling series the time series is forecasted by the best Autoregressive model based on the AIC number [2][10].

2.3 Akaike Information Criterion

The Akaike information criterion (AIC) is a measure of the relative quality of standard models or a given set of data. AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection [11]. Akaike recommends the following relationship for Autoregressive model:

$$AIC(p) = \min\left(n.\, ln\sigma_\varepsilon^{\ 2} + 2(p)\right) \quad (10)$$

where n is the sample size, $\sigma_\varepsilon^{\ 2}$ is the maximum likelihood estimate of the residual variance, p is the order of autoregressive model.The model, which gives the minimum AIC number, is the one to be selected.

2.4 Steps in Calculating AIC number for Central Mesaria Rainfall

- From the measured and hydrologic yearly averaged rainfall, from 1975-76 to 2003-2004 were used to establish AIC numbers. Note that averaged values from hydrologic years 2004-05 to 2013-14 data will be used to check the prediction.
- Auto-correlation coefficients (rk) is calculated using Minitab 16.
- Auto-regressive coefficients of three different orders (AR(1), AR(2), and AR(3)) are used in this study and their coefficients by solving the matrix given in Equation 8a were determined through Excel software.

- First order autoregressive model (AR1) equation is :

$$y_i = 0.39\, y_{i-1} + \varepsilon_i \tag{11}$$

- Second order autoregressive model (AR2) equation is :

$$y_i = 0.43\, y_{i-1} - 0.1\, y_{i-2} + \varepsilon_i \tag{12}$$

- Third order autoregressive model (AR3) equation is :

$$y_i = 0.4\, y_{i-1} + 0.01\, y_{i-2} - 0.28\, y_{i-3} + \varepsilon_i \tag{13}$$

- for AR1:

$$y_i{}^2 = (0.39\, y_{i-1} + \varepsilon_i)^2 \rightarrow 1^2 = 0.39^2 * y_{i-1}{}^2 + 2 * 0.39 * y_{i-1} * \sigma_\varepsilon + \sigma_\varepsilon{}^2 \tag{14}$$

$\sigma_\varepsilon{}^2 = 0.372$

- For AR2: $\sigma_\varepsilon{}^2 = 0.8$
- For AR3: $\sigma_\varepsilon{}^2 = 0.77$
- AIC numbers are:

  For AR1: *AIC=29*ln(0.372)+2(1) = -26.68*

  For AR2: *AIC=29*ln(0.8)+2(2)= -2.47*

  For AR3: *AIC=29*ln(0.77)+2(3)= -1.58*

Table 3. Autocorrelation Coefficients of Central Mesaria rainfall data

Lag (K)	Autocorrelation Coefficients (r_k)
1	0.39
2	0.05
3	-0.26
4	-0.14
5	-0.03
6	-0.08
7	-0.02
8	0.05
9	0.18
10	-0.12
11	-0.21
12	-0.32
13	-0.07
14	0.10
15	0.06
16	0.11
17	0.03
18	-0.03
19	-0.14
20	-0.21
21	-0.12
22	0.04
23	0.11
24	0.02
25	0.01
26	0.00
27	0.05
28	0.02

- The minimum AIC number which is AR(1) model for this region is selected.

Table 4. AIC number of regions and TRNC

region	Akaike information criteria(AIC)		
	AR(1)	AR(2)	AR(3)
Central Mesaria	**-26.68***	-2.47	-1.58
East Coast	67.26	**3.12**	5.12
East Mesaria	**-6.34**	2.82	4.21
Karpaz	**-5.21**	2.82	4.82
North coast	**-3.06**	2.82	4.82
West Mesaria	**0.82**	4.00	6.00
TRNC	-5.21	2.82	**-107.45**

* The bold numbers are representing the relevant AR model of that region i.e being the smallest value among each row.

2.5 Derivation of the synthetic sequence

After obtaining the suitable model from Akaike information criteria, the derivation of synthetic sequences were obtained by finding the values of normal and independent residual ε_i [10]. The residual can be defined as if obeys normal distribution by:

$$\varepsilon_i = \mu_\varepsilon + \sigma_\varepsilon Z_i \tag{15}$$

where $\mu\varepsilon$ is the mean of residuals, σ_ε is the standard deviation of residuals, Z_{1i}, Z_{2i} represent the standard normal random numbers that must be calculated by using the uniform random numbers, η_i varying randomly between 0 and 1. The standard normal random numbers are defined by:

$$Z_{1i} = (-2ln\eta_{1i})^{1/2}\cos(2\pi\eta_{2i}) \tag{16}$$

$$Z_{2i} = (-2ln\eta_{1i})^{1/2}\sin(2\pi\eta_{2i}) \tag{17}$$

2.6 Derivation of AR(1) Model for Central Mesaria

Through AR(1) model, applying Eq. (15), (16), and (17) to hydrologic yearly averaged measured rainfall values of Central Mesaria regions, their relevant synthetic values were generated and tabulated for the period of hydrologic years 1975-76 to 2003-04 below.

Table 5. Synthetic data generated by AR(1) model for Central Mesaria

uniform random number		Standard normal random number		Residual for AR(1) model		y_i values for AR(1) model	y_i' Synthetic values for AR(1)	
η_1	0.31	Z_1	-0.38	ε_1	-0.23	0	y_1'	302.95
η_2	0.71	Z_2	-1.48	ε_2	-0.90	-0.90	y_2'	237.16
η_3	0.80	Z_3	-0.60	ε_3	-0.36	-0.71	y_3'	250.87
η_4	0.43	Z_4	0.29	ε_4	0.18	-0.10	y_4'	295.72
η_5	0.83	Z_5	-0.39	ε_5	-0.24	-0.28	y_5'	282.62
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
η_{26}	0.22	Z_{26}	0.37	ε_{26}	0.23	0.24	y_{26}'	320.16
η_{27}	0.29	Z_{27}	-1.58	ε_{27}	-0.96	-0.87	y_{27}'	239.50
η_{28}	0.49	Z_{28}	0.06	ε_{28}	0.04	-0.30	y_{28}'	281.24
η_{29}	0.44	Z_{29}	-1.23	ε_{29}	-0.75	-0.87	y_{29}'	239.71

Figure 1 shows the fluctuations of the synthetically generated AR(1) data from the measured hydrological yearly averaged rainfall values from 1975-75 to 2003-04.

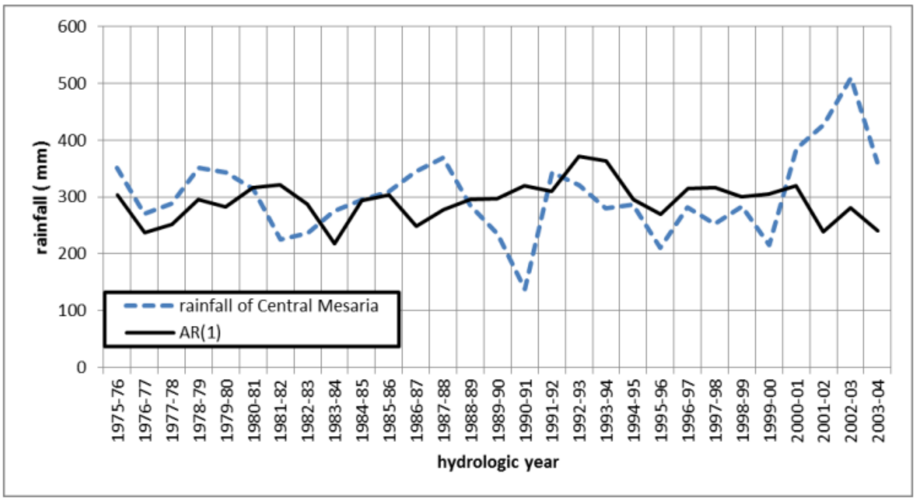

Figure 1. Synthetically generated AR(1) model and the respective measured rainfalls of Central Mesaria for the period of hydrologic years 1975-76 to 2003- 04

2.7 Forecasting hydrologic yearly averaged rainfall of Central Mesaria through AR(1) Model:

Based on the above discussed methodology, AR(1) model was used to generate the forecasted hydrologic yearly average rainfall of Central Mesaria for the period of to 2004-05 to 2013-14 years. Details are given in Table 6.

Table 6. Forecasted rainfall by AR(1) for central mesaria for the period of hydrologic years 2004-05 to 2013-14.

uniform random number		Standard normal random number		Residual for AR(1) model		y_i values for AR(1) model	Forecasted synthetic data y_i'	
η_{30}	0.11	Z_{30}	0.76	ε_{30}	0.69	0.87	y'_{30}	366.1
η_{31}	0.30	Z_{31}	-1.27	ε_{31}	-1.16	-0.82	y'_{31}	243.0
η_{32}	0.60	Z_{32}	-0.87	ε_{32}	-0.79	-1.11	y'_{32}	221.8
η_{33}	0.04	Z_{33}	-0.46	ε_{33}	-0.42	-0.85	y'_{33}	241.2
η_{34}	0.28	Z_{34}	2.47	ε_{34}	2.24	1.92	y'_{34}	442.8
η_{35}	0.10	Z_{35}	2.16	ε_{35}	1.97	2.71	y'_{35}	500.5
η_{36}	0.01	Z_{36}	0.14	ε_{36}	0.13	1.18	y'_{36}	388.7
η_{37}	0.83	Z_{37}	0.03	ε_{37}	0.02	0.48	y'_{37}	337.9
η_{38}	0.76	Z_{38}	-0.60	ε_{38}	-0.55	-0.36	y'_{38}	276.4
η_{39}	0.30	Z_{39}	1.55	ε_{39}	1.41	1.27	y'_{39}	395.4

The graphical representation of this forecasted data set are shown in Figure 2.

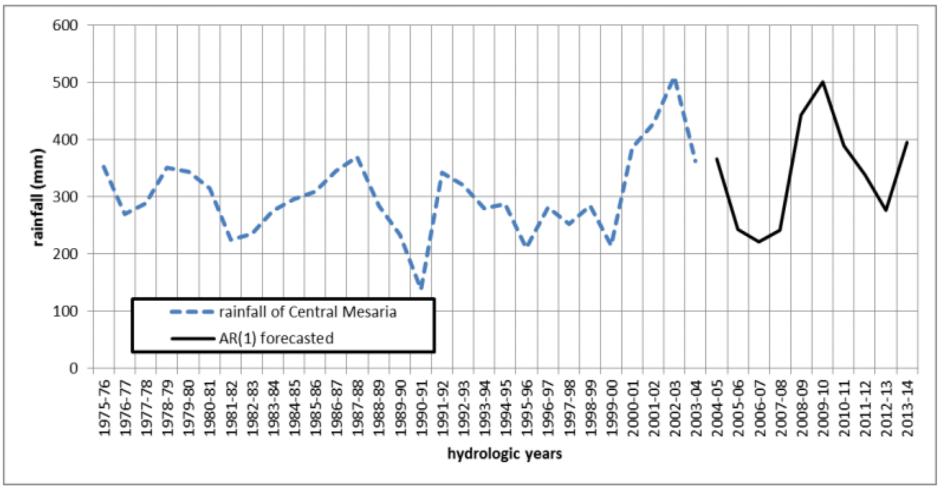

Figure 2. Forecasted synthetic data by AR(1) for central mesaria for the period of hydrologic years 2003-04 to 2013-14.

2.8 Holt-Winter method

The Holt-Winters seasonal method includes the forecast equation and three smoothing equations , one for the level l_t, one for trend b_t, and one for the seasonal component denoted by S_t, with smoothing parameters α, β and γ. There are two variations to this method that differ in the nature of the seasonal component. The additive method is preferred when the seasonal variations are roughly constant through the series, while the multiplicative method is preferred [12-14]. In this study Holt-Winter Multiplicative Model is adopted using Minitab 16software.

2.9 Holt-Winter Multiplicative method

$$\hat{y}_t = (l_t + hb_t)S_{t-m+h} \tag{20}$$

$$l_t = \alpha\left(\frac{y_t}{S_{t-m}}\right) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{20a}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{20b}$$

$$S_t = \gamma(\frac{y_t}{l_{t-1}+b_{t-1}} + (1-\gamma)S_{t-m} \tag{20c}$$

and the error correction form of the smoothing equations is:

$$l_t = l_{t-1} + b_{t-1} + \alpha\frac{e_t}{S_{t-m}} \tag{21}$$

$$b_t = b_{t-1} + \alpha\beta\frac{e_t}{S_{t-m}} \tag{21a}$$

$$S_t = S_t + \gamma\frac{e_t}{(l_{t-1}+b_{t-1})} \tag{21b}$$

where:

$$e_t = y_t - (l_{t-1} + b_{t-1})S_{t-m} = y_t - \hat{y}_t \tag{21c}$$

2.10 Accuracy Measures of the Forecasted Models

when selecting a forecasting model, or when evaluating an existing model, one has to use measures that summarise the overall accuracy provided by that model [15-19]. Beside the visual comparison, the suggested models performances are also evaluated using the below mentioned statistical accuracy measures:

- The mean absolute deviation (MAD),

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{22a}$$

- The mean square error (MSE),

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \tag{22b}$$

- The root mean square error (RMSE), and

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{22c}$$

- The mean absolute percentage error (MAPE) .

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| * 100 \tag{22d}$$

3. Results and Discussions

The time series models with forecasting values was used to understand the occurrence of the random mechanism so as to predict future series based on the past data. For time series model studies, the gathered rainfall values were initially divided into two time series parts,

1. from September 1975 to August 2003, and
2. from September 2004 to August 2014.

The data within the first part was used to train the model and the data set of the second part was used for comparing the error accuracy of the suggested models based on the previously trained data [20][21]. Once the best fitted model was obtained within the acceptable confidence limits, since the sample size is comparably small (n=39), only 5 years ahead values were predicted based on the most representative model, i.e., up to 2018- 19.

3.1. Forecasted values by time series models of Central Mesaria rainfall for the hydrologic years period 2003-04 to 2013-14

3.1.1. Markov Model

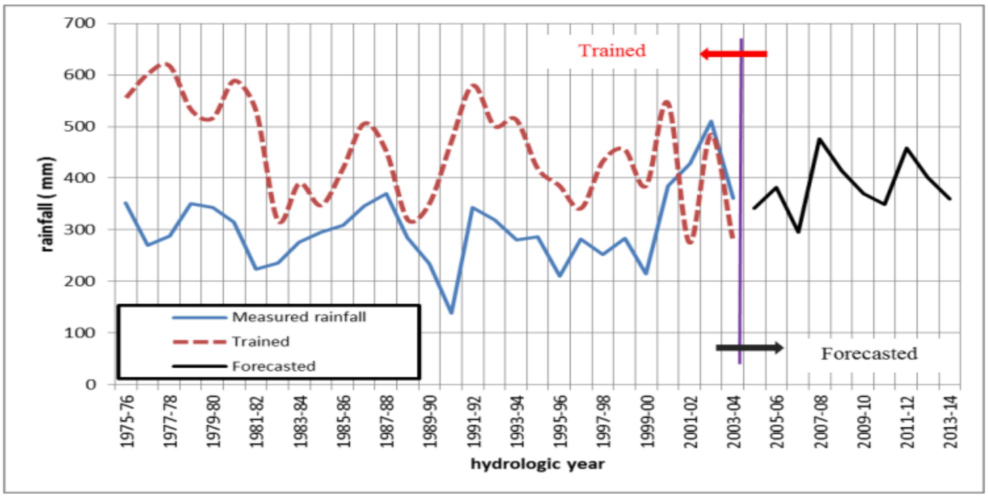

Figure 3. Graphical comparison of Markov model (trained and forecasted) and the hydrologic yearly averaged rainfall (measured) of Central Mesaria

3.1.2. Auto-Regressive (AR) Model

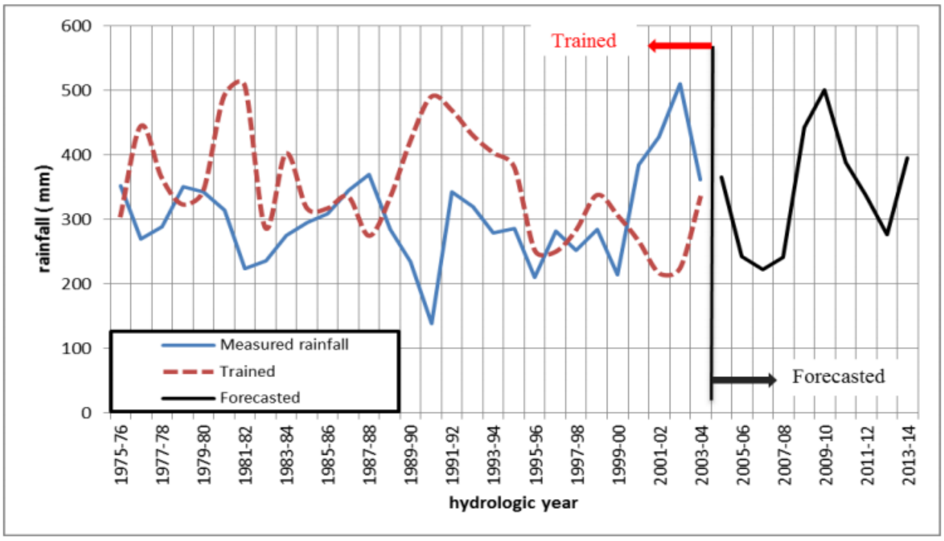

Figure 4. Graphical comparison of AR(1) model (trained and forecasted) and the hydrologic yearly averaged rainfall (measured) of Central Mesaria

3.1.3. Holt-Winter Multiplicative Model

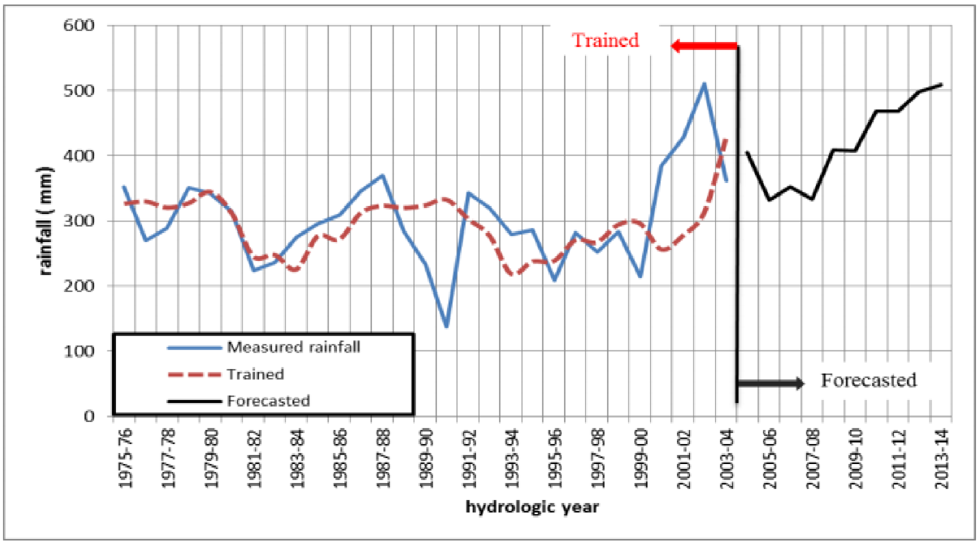

Figure 5. Graphical comparison of Holt-Winter Multipilicative method model (trained and forecasted) and the hydrologic yearly averaged rainfall (measured) of Central Mesaria

Result : AR(1)model is the best model among the others, having the lowest overall error ratio based on the given 4 standardized error measures. Hence, for Central Mesaria Region, AR(1) model is used to generate (predict) the rainfall for the hydrologic years 2014-15 to 2018-19 which are tabulated below.

Table 7. Expected yearly rainfall of Central Mesaria region based on AR(1) model for hydrologic years 2014-15 to 2018- 19

Hydrologic Years	Expected yearly rainfall (mm)
2014-15	269.4
2015-16	244.6
2016-17	238.0
2017-18	217.5
2018-19	219.6

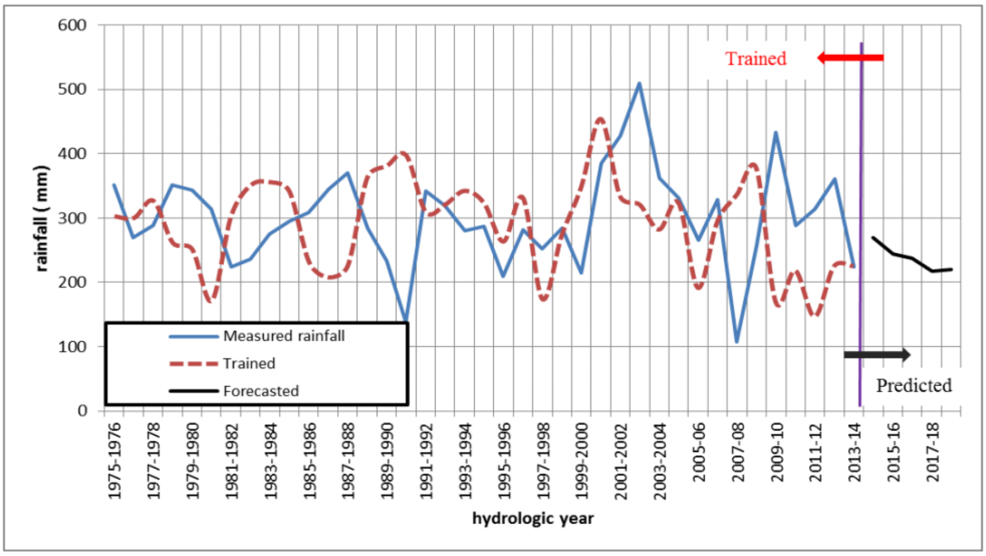

Figure 6. Expected (predicted) yearly rainfall of Central Mesaria region based on AR(1) model for hydrologic years 2014-15 to 2018-19

The mentioned model were applied on other 5 regions and TRNC(general) regions . The synopsis of the time series models of each meteorological region and TRNC as a whole are tabulated below.

Table 8. Synopsis of the rainfall data parameters and time series models of each meteorological region and TRNC as a whole

Region	Long years	Representive time series model (best model)	Expected yearly rainfall / Bellow () or above () long years rainfall means				
			2014-15	2015-16	2016-17	2017-18	2018-19
Central Mesaria	299.9	AR(1)	269.4 ↓	244.6 ↓	238.0 ↓	217.5 ↓	219.6 ↓
East Coast	334.7	Holt-Winter Mult.	304.5 ↓	441.5 ↑	353.1 ↑	258.8 ↓	274.6 ↓
East Mesaria	334.2	AR(1)	318.4 ↓	338.4 ↑	420.3 ↑	304.9 ↓	330.5 ↓
Karpaz	449.7	Holt-Winter Mult.	413.9 ↓	601.2 ↑	478.8 ↑	372.7 ↓	356.9 ↓
North Coast	461.8	AR(1)	553.0 ↑	325.8 ↓	371.3 ↓	569.6 ↑	469.8 ↑
West Mesaria	310.8	Holt-Winter Mult.	383.0 ↑	390.3 ↑	400.1 ↑	322.0 ↑	387.2 ↑
TRNC (general)	378.8	AR(3)	281.2 ↓	355.7 ↓	402.4 ↑	357.5 ↓	323.6 ↓

4. Conclusion

Rainfall of the 6 meteorological regions of North Cyprus and TRNC as a whole were analyzed by three widely used time series models (Markov, Auto-Regressive, and Holt-Winter Multiplicative) and five successive years of predicting data sets (from hydrologic years 2014-15 to 2018-19) were generated. For this purpose, to determine the best time series model for each regions and for TRNC, the standardized MSE, MAPE, RMSE, and MAD were used.

Based on the best representative time series predictions of the five successive years, except North Coast and West Mesaria for hydrologic year 2014-15 will experience lower than the long yearly average rainfall value implying dryness whereas, TRNC will experience higher than its long yearly average during the hydrologic year 2016-17 implying wet period. The other relevant details are given in the following table. It is worth to express that for the coming five hydrologic years (2014-15 to 2018-19) West Mesaria will experience total rainfall more than its long years average for all those years whereas Central Mesaria will experience total rainfall less than its long years average for all those years.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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