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Analysis and prediction of annual precipitation values in Cyprus

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ABSTRACT

This present work studies the prediction of water resource quantity in Cyprus by using the mathematical technique called the Markov chains of the fuzzy states (MCFS) prediction method. This region is considered as a poor water country in Europe with a semi-arid climate that also has a frequent occurrence of drought and limited water resources that are mainly dependent on rainfall. Cyprus is suffering from unevenly distributed rainfall and small catchments, where extreme drought events are suspected due to climate change. The water policy in Cyprus is based on two pillars: sustainable development of water resources and water demand management. Around 1970 changes in the rainfall pattern in addition to population growth led to critical situations in many aquifers, which deteriorated due to the intrusion of seawater intrusion into the aquifer. Hence, the estimation of water resource values and water consumption for the following decades is important to implement effective management plants. By collecting and analyzing 100 years of standardized precipitation index data the future expected precipitation probabilities of the island of Cyprus were estimated using Markov chains (MC) and MCFS analysis. For this purpose, the inter-state transition probability matrix of the system has been determined and long-term equilibrium vectors have been calculated to determine the stability of the system. This study shows that the use of the MCFS gives more sensitive results for the prediction of future precipitation than the classical MC model.

Keywords: Annual precipitation; Rainfall; Markov chain of the fuzzy states; Stochastic processes; Water resource management

1. Introduction

Rainfall is one of nature's ways of reviving both biological and non-biological activities. It has fundamental importance for supporting and protecting human, plant and animal life. The amount of large-scale variation of precipitation that is either too low or too high in a given area may contribute to the tendency of drought or floods respectively. These are very two important hydrological environmental disasters affecting various regions of the world. Therefore, it is important to develop a measurement system for estimation. One such important system that provides vital and substantial information that is required for a wide range of applications is the quantitative precipitation estimation/forecasting [1]. This approach can be applied to fields such as reservoir operation, water resources management, agriculture, and flood protection among others [2].

Precipitation can be perceived as an important variable that determines the land surface hydrological process at all

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space-timescales. Since it holds a particularly important position in this determination, it is very crucial to improve our comprehension of how precipitation can be spatially and temporally distributed to basins ranging in size from 100 km^2 to 100,000 km^2. Also, it is important for temporal integration of rainfall inputs that range from hours to days [3]. These are important considerations for water resources management. One of the drawbacks is the observation limitations of ground-based radar or gauge management with regard to remote areas and mountainous regions.

The terms global warming and climatic variations are used to describe the increase in average temperature around the globe, which is causing changes in the quantity and modality of rainfall and has consequently increased the probability of droughts [4]. The increase in greenhouse gasses is one of the factors that is causing global warming. Certainly, the increase in heat-absorbing gases directly leads to higher temperatures being detained in the atmospheric layer of the planet, which causes warming of the Earth's surface. In Cyprus, the combination of the annual lowest precipitation with the highest evaporation caused by hot weather in the summer and also the increasing population has led to a scarcity of water (Fig. 1).

This study will analyze the future status of precipitation for this region, where water resources are rare and the ecological situation needs water abundance. However, around 1970, the precipitation values decreased unusually and there is a concern that it will become worse in the future (Fig. 2).

Thus, there is a need to develop prediction tools such as probabilistic tools that can support preparation procedures that can be applied at a suitable time. The study of Huffman [7] established a statistical relationship of the root-mean-square random errors associated with the estimation of precipitation. In another study, a framework was designed to identify possible relationships between sampling error in radar rainfall estimates as well as several other factors [8]. A sensitivity analysis was carried out by Hossain and Anagnostou [9] aimed at comprehending the impact of satellite passive microwave (PM) rainfall retrieval and sampling errors on flood prediction uncertainty for medium-sized (100 km^2) watersheds. Their analysis further evaluated PM in conjunction with infrared (IR)-based satellite rainfall retrieval for flood prediction using a probabilistic error model. This was also followed by the exploration of the uncertainty bound of simulated flood events based on various microwave rainfall samples and hourly IR-based rainfall estimates. The findings of these analyses by Hossain et al. [10] indicated the necessity to have improvement measures for communication between precipitation data producers and user communities by quantifying the estimation error and assessing the influence of error propagation on hydrologic processes. After the successful study that employed weather radar, several researchers including Baltas and Mimikou [11], Grecu and Krajewski [12], and Morin et al. [13] embarked on several investigations aimed at enhancing the existing research and providing new insights. They raised issues regarding the level of accuracy when employing radar-based rainfall forecasting. Luís et al. [4] analyzed the spatial and temporal rainfall feature of a specific area and they found a spatial pattern of the rainfall trend for a different region of this selected area. Another researcher Chiang et al. [1], successfully applied the dynamic artificial neural network method for precipitation estimation by utilizing the meteorological radar data. However, another study employed the product-driven uncertainty technique for estimating the probabilistic quantitative precipitation [14].

Among the varying probabilistic methods, it is observed that the chain models provided by Markov also have been used in 1963 for obtaining the probability of precipitation occurrence of different intervals lengths [15] and frequently have been studied in the literature ([16,17]). Since then, modeling has been developed for non-stationary situations, with discrete chains for a certain period of time, for a period of 1 year, as well as for different times of the year for optimizing transition probabilities [18] Different orders of Markov's chains have been studied with the conclusion that for a variety of sites, a variety of chain orders are also required [19]. The tendency throughout the years has been to increase the number of conditions to obtain a Markov model with better results [20]. As an example, in 2008, a model of Swedish precipitation was developed using an n-step transition probability of the Markov chain [21]. It was found

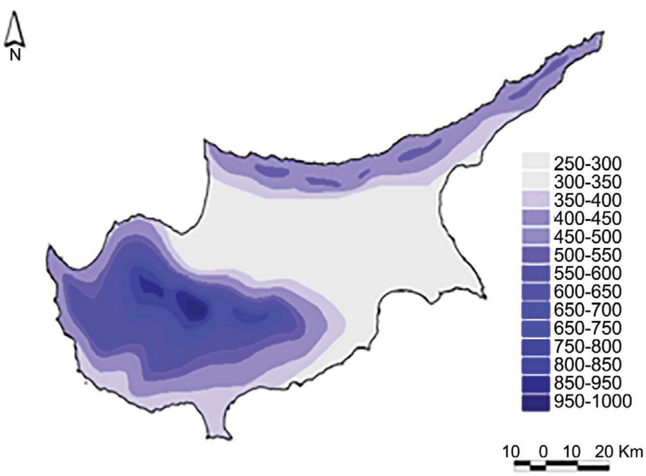

Fig. 1. Precipitation distribution of Cyprus [5].

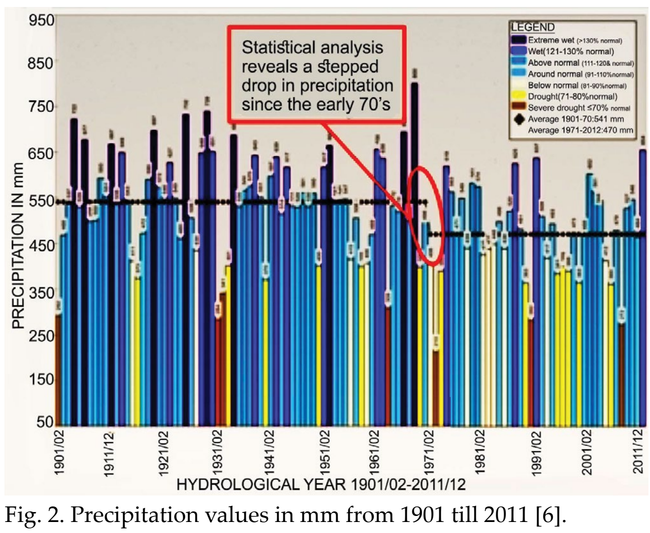

Fig. 2. Precipitation values in mm from 1901 till 2011 [6].

that for Markov's method, a chain with a higher order than 1 is needed. Generated models are utilized for calculating various weather indicators. The modeled indicators were comparable to the empirical results, which is evidence of the higher stability of the model. The Markov chain process is a memoryless model that can predict the future states of systems by utilizing the existing states of those systems and the probability transition matrix [22]. Thus, Markov's theory is used for the analysis and simulation of dynamic variables. In previous studies, the Markov chains (MC) method has been successfully used to estimate the stochastic behavior of variables in many fields such as the estimation of hydrological parameters [19,23–27]; education [28,29]; information systems [30]; social problem analysis [31]; the estimation of economic parameters [32–35] as well as other studies.

Precipitation is considered a random event, so its undeterminable properties are useful for managing water resources. Early forecasts about the future rainfall can be helpful to avoid undesired results. In this study, MC and Markov chains of the fuzzy states (MCFS) models are used to determine the future precipitation in Cyprus.

The MC model is based on classical sets is not very sensitive to the extreme values of the defined states. For real-world problems, in most cases, defining and classifying the systems with fuzzy states, which depend on the fuzzy logic, will give more realistic and sensitive results than classical sets.

The general objective of the present study is to analyze precipitation in Cyprus, based on the variability of the quantity of data recorded over 100 years using the MCFS technique.

The structure of this paper is as follows: the theoretical framework of the MCFS is presented in Part 2. Part 3 gives the fundamental datasets and methodology behind the use of the model as well as the results. Section 4 of the paper will end with some conclusions.

2. Markov chain process with fuzzy states

The definition of the fuzzy set theory is given as the following:

Definition 1: A fuzzy set $\tilde{A}$ in IR is a set of ordered pairs:

$$\tilde{A} = \left\{ \left(x, \mu_{\tilde{A}}(x) \right) \middle| x \in \mathrm{IR} \right\} \tag{1}$$

where $\mu_{\tilde{A}}$: IR → [0,1] and $\mu_{\tilde{A}}(x)$ is called the membership function of the fuzzy set.

Definition 2: A fuzzy number is a set on the real line that satisfies the conditions of normality and convexity.

Definition 3: A Triangular fuzzy number can be denoted with three points as follows: $\tilde{A} = (a_1, a_2, a_3)$ $(a_1 < a_2 < a_3)$, with the membership function given by:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1}, & \text{if} \quad a_1 \le x \le a_2 \\ \dfrac{a_3 - x}{a_3 - a_2}, & \text{if} \quad a_2 \le x \le a_3 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

2.1. Probabilities of MC

Let X_t be the state of the system at time t. The transition probability matrix of a finite state Markov chain P is;

$$P = \left[p_{ij} \right] \forall i, j = \left\{ 0, 1, ..., N \right\} \tag{3}$$

where p_{ij} denotes the one-step transition probability values from state i to state j where $p_{ij} \ge 0$ and for $\forall i,j$,

$$p_{ij} = P\left\{ X_{t+1} = j \middle| X_t = i \right\} = P\left\{ X_1 = j \middle| X_0 = i \right\} \tag{4}$$

where $\sum_{j=0}^{N} p_{ij} = 1$. And the transition probability from state i to state j in r steps p_{ij}^r is:

$$P^r = \left[p_{ij}^r \right], p_{ij}^r \ge 0, \forall i, j \in \left\{ 0, 1, ..., N \right\}, \tag{5}$$

Therefore,

$$P^r = \left(P \right)^r \tag{6}$$

2.2. Markov chain process with fuzzy states

There are some cases in which systems need modeling with fuzzy states such as when there is insufficient information about the system and when the system has too many states to deal with when attempting to make a decision [36].

MCFS is a technique of probabilistic modeling, which is more flexible and sensitive to the extreme values of the defined states of systems than the classical probabilistic approach.

2.3. Probabilities of MCFS

Let $X = \{x_1, x_2, \ldots, x_n\}$ be a given set. A fuzzy partition of X is a family of the fuzzy subset of X, denoted by $A = \left\{ \tilde{A}, \tilde{A}_2, ..., \tilde{A}_N \right\}, \left(\forall i = \left\{ 1, 2, ..., N \right\}, \tilde{A}_i \ne \Phi \text{ and } \tilde{A}_i \ne X \right)$ with the corresponding membership functions $\mu_{\tilde{A}_1}, \mu_{\tilde{A}_2}, \ldots, \mu_{\tilde{A}_N}$ which satisfy the following condition;

$$\sum_{i=1}^{N} \mu_{\tilde{A}_i}\left(x_r \right) = 1 \forall x_r \in X, \text{ For } r = \left\{ 1, ..., n \right\} \tag{7}$$

The notion of fuzzy partition is used to define the fuzzy states for the Markovian decision process.

Let $\{\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_N\}$ be a set of fuzzy states, as each fuzzy subset $\tilde{A}_i$, $i \in \{1, \ldots, n\}$ denotes a fuzzy state in the initial Markov chain.

The probability of fuzzy initial state that $P(\tilde{A}_i) = P(X_0 = \tilde{A}_i)$ and it is defined by using the probability of fuzzy event:

$$P\left(\tilde{A}_i \right) = P\left\{ \tilde{X}_0 = \tilde{A}_i \right\} = \sum_{s=0}^{N} P\left\{ X_0 = s \right\} \mu_{\tilde{A}_i}\left(s \right) \tag{8}$$

The conditional probability of the fuzzy state $\tilde{A}_j$, given the initial state m, with $j \in \{1, \ldots, n\}$ and $m \in \{0, \ldots, N\}$, is:

$$P\left(\tilde{A}_j \middle| m\right) = P\left\{\tilde{X}_1 = \tilde{A}_j \middle| X_0 = m\right\} = \sum_{s=0}^{N} P\left\{\tilde{X}_1 = \tilde{A}_j \middle| X_0 = m\right\} \mu_{\tilde{A}_j}(s) \quad (9)$$

and it represents the one-step transition probability of the fuzzy state [18]. The conditional probability of the fuzzy event $\tilde{A}_j$ given the fuzzy event $\tilde{A}_i$, $i,j \in \{1, \ldots, n\}$, is a function of the linear combination of probabilities $P\left(\tilde{A}_j \mid m\right), m \in \{0,\ldots,N\}$ as shown in the equation below:

$$P\left(\tilde{A}_j \middle| \tilde{A}_i\right) = P\left\{\tilde{X}_1 = \tilde{A}_j \middle| \tilde{X}_0 = \tilde{A}_i\right\} = \sum_{m=0}^{N} P\left(\tilde{A}_j \middle| m\right) \frac{P\{X_0 = m\} \mu_{\tilde{A}_i}(m)}{P\left(\tilde{A}_i\right)} \quad (10)$$

This represents the one-step transition probability from the fuzzy initial state to the fuzzy final state [36].

3. Methodology

3.1. Study area

Cyprus is a medium-sized island in the Eastern Mediterranean. With an area of 9,251 km^2, it is marked by noticeable variations in the northern and southern areas. It has diverse precipitation among the different regions. The rainfall largely varies based on the location from the sea line. The yearly precipitation rises from 450 up to 1,100 mm at the highest points. On the other hand, levels of between 300 and 350 mm are recorded in the central plain. The Kyrenia region, located along the northern coast of the island, has a rainfall of 550 at 1,000 m, which is relatively low compared with other regions. Rainfall recorded in the warmer months is not sufficient to cover the water needs. These minimal amounts of rainfall are deleted by absorption into the dry soil of the island. The seasons that are rich in rainfall are a reliable source for different water needs. The total annual precipitation is around 480 mm, although it decreased to a level of 182 mm in the early 70's and increased to a level of 759 mm in the late 60's. Statistics recorded on Cyprus's precipitation show a decline in the last three decades. Snow falls rarely on the island except for altitudes exceeding 1,000 m and generally only from December until April. Although snow cover is minimal during winter and spring, there may be considerable snow levels during certain weeks, particularly on the high "Troodos Mountains". The average precipitation rate in Cyprus throughout the 20th century and in the first decade of the 21st century decreased by approximately 1 mm on an annual basis. The decline in precipitation primarily occurred in the second half of the 20th century, thus reducing the annual precipitation levels below the normal amounts.

Table 1
Annual precipitation in the last 20 years (1991–2011) [37]

Hydro meteorological year	Annual precipitation (mm))
1991–1992	637
1992–1993	509
1993–1994	417
1994–1995	493
1995–1996	383
1996–1997	399
1997–1998	388
1998–1999	473
1999–2000	363
2000–2001	468
2001–2002	604
2002–2003	561
2003–2004	545
2004–2005	412
2005–2006	360
2006–2007	479
2007–2008	272
2008–2009	527
2009–2010	546
2010–2011	465
Average for the last 20 years	465

Comparative conclusions can be drawn by checking the average precipitation levels for different 30-year time spans: 1901–1930 was 559 mm, and 1931–1960 was 524 mm, 1961–1990 was 503 mm, and 1971–2000 was 462 mm. The normal precipitation level over the most recent 30-year time span was 17% lower than the period 1901–1930. The average precipitation in the 1990s represented the lowest levels recorded in the entire period.

This study includes the annual precipitation data for the island of Cyprus from 1901 to 2010. To obtain the transition probability matrix of the precipitation states of Cyprus, the standardized precipitation index (SPI) was calculated for the given period. The yearly classification of SPI data with regard to the range is shown in Table 2.

The average precipitation value of this island is 513.37 mm, which is corresponds to the nearly normal state (NN), where the standard deviation is 113.36 mm for the given period.

3.2. Markov chain application and results

The frequencies of passing between the states for the selected period are shown in Table 3.

The obtained one-step probability transition matrix of the precipitation states of Cyprus is seen below in matrix *P*.

P =

	ED	SD	MD	NN	MW	VW	EW
ED	0.00	0.25	0.25	0.25	0.25	0.00	0.00
SD	0.00	0.00	0.33	0.67	0.00	0.00	0.00
MD	0.08	0.00	0.15	0.69	0.00	0.08	0.00
NN	0.03	0.00	0.12	0.65	0.13	0.06	0.01
MW	0.08	0.08	0.00	0.67	0.08	0.00	0.08
VW	0.00	0.00	0.00	1.00	0.00	0.00	0.00
EW	0.00	0.00	0.50	0.00	0.50	0.00	0.00

This one-step probability matrix shows that the probability of passing from the state of moderately dry (MD) (–1.49 ≤ SPI ≤ –1) to the NN state (–0.99 ≤ SPI ≤ 0.99) is

Table 2
SPI values [38]

2.0+	Extremely wet (EW)
1.5 to 1.99	Very wet (VW)
1.0 to 1.49	Moderately wet (MW)
–99 to 99	Nearly normal (NN)
–1.0 to –1.49	Moderately dry (MD)
–1.5 to –1.99	Severely dry (SD)
–2 and less	Extremely dry (ED)

Table 3
Transition frequencies of precipitations states of Cyprus

	ED	SD	MD	NN	MW	VW	EW
ED	0	1	1	1	1	0	0
SD	0	0	1	2	0	0	0
MD	1	0	2	9	0	1	0
NN	2	0	8	46	9	4	1
MW	1	1	0	8	1	0	1
VW	0	0	0	5	0	0	0
EW	0	0	1	0	1	0	0

P(NN|MD) = 69%. While the present year SPI value is in the very wet (VW) condition range (SPI ≥ 2), the next year is expected to be in the NN state with P(NN|VW) = 100% probability.

The steady condition of this MC has been obtained in 6 steps, as seen with vector π:

π =

ED	SD	MD	NN	MW	VW	EW
0.04	0.02	0.12	0.64	0.11	0.05	0.02

3.3. Markov chain with fuzzy states application and results

Yearly SPI values of Cyprus are classified to seven fuzzy states from an extremely dry state to an extremely wet state (ED-EW) using the triangular fuzzy set with the formula below:

$$\mathrm{ED}=\begin{cases}1, & \mathrm{SPI}\le -2.24\\ \left(-\mathrm{SPI}-1.74\right)/0.50, & -2.24<\mathrm{SPI}<-1.74\\ 0, & \text{otherwise}\end{cases} \tag{11}$$

$$\mathrm{SD}=\begin{cases}\left(-1.24-\mathrm{SPI}\right)/0.50, & -1.74\le \mathrm{SPI}<-1.24\\ \left(\mathrm{SPI}+2.24\right)/0.50, & -2.24<\mathrm{SPI}<-1.74\\ 0, & \text{otherwise}\end{cases} \tag{12}$$

$$\mathrm{MD}=\begin{cases}-\mathrm{SPI}/1.24, & -1.24\le \mathrm{SPI}<0\\ \mathrm{SPI}+1.74/0.50, & -1.74<\mathrm{SPI}<-1.24\\ 0, & \text{otherwise}\end{cases} \tag{13}$$

$$\mathrm{NN}=\begin{cases}\left(1.24-\mathrm{SPI}\right)/1.24, & 0\le \mathrm{SPI}<1.24\\ \left(\mathrm{SPI}+1.24\right)/1.24, & -1.24<\mathrm{SPI}<0\\ 0, & \text{otherwise}\end{cases} \tag{14}$$

$$\mathrm{MW}=\begin{cases}\left(1.74-\mathrm{SPI}\right)/0.50, & 1.24\le \mathrm{SPI}<1.74\\ \mathrm{SPI}/1.24, & 0<\mathrm{SPI}<1.24\\ 0, & \text{otherwise}\end{cases} \tag{15}$$

$$\mathrm{VW}=\begin{cases}\left(2.24-\mathrm{SPI}\right)/0.50, & 1.74\le \mathrm{SPI}<2.24\\ \left(\mathrm{SPI}-1.24\right)/0.50, & 1.24<\mathrm{SPI}<1.74\\ 0, & \text{otherwise}\end{cases} \tag{16}$$

$$\mathrm{EW}=\begin{cases}1, & \mathrm{SPI}\ge 2.24\\ \left(\mathrm{SPI}-1.74\right)/0.50, & 1.74\le \mathrm{SPI}<2.24\\ 0, & \text{otherwise}\end{cases} \tag{17}$$

Then, SPI values of each data are converted to their fuzzy states as shown in Table 4.

Table 5 shows the fuzzy transition frequencies of data from 1901–2010.

Lastly, the fuzzy transition probability was utilized by using the conditional probability of the fuzzy state $\tilde{S}_j$, given the fuzzy state $\tilde{S}_i$ to obtain the one-step transitions probabilities of the precipitation of Cyprus ($\tilde{P}$).

$\tilde{P}$ =

	ED	SD	MD	NN	MW	VW	EW
ED	0.00	0.10	0.35	0.37	0.18	0.00	0.00
SD	0.03	0.08	0.26	0.49	0.14	0.00	0.00
MD	0.06	0.03	0.29	0.40	0.17	0.03	0.01
NN	0.02	0.01	0.23	0.40	0.24	0.06	0.03
MW	0.03	0.05	0.08	0.52	0.24	0.05	0.02
VW	0.00	0.00	0.03	0.75	0.22	0.00	0.00
EW	0.00	0.00	0.39	0.36	0.25	0.00	0.00

In Table 4, the SPI values are considered as a stochastic process with 7 fuzzy states space {ED, …, EW} with Markov

Table 4
Transformed fuzzy states of the SPI values of Cyprus between 1901–1905

Year	SPI	ED	SD	MD	NN	MW	VW	EW
1901	–1.97	0.46	0.54	0	0	0	0	0
1902	–0.40	0	0	0.33	0.67	0	0	0
1903	0.21	0	0	0	0.83	0.17	0	0
1904	1.86	0	0	0	0	0	0.76	0.24
1905	0.14	0	0	0	0.89	0.11	0	0

Table 5
Fuzzy transition frequencies of the precipitation of Cyprus

	ED	SD	MD	NN	MW	VW	EW
ED	0.00	0.35	1.29	1.36	0.67	0.00	0.00
SD	0.13	0.30	0.94	1.78	0.49	0.00	0.00
MD	1.47	0.63	6.67	9.09	3.85	0.74	0.26
NN	0.88	0.66	11.13	19.29	11.60	2.85	1.36
MW	0.73	1.15	2.02	12.48	5.85	1.31	0.56
VW	0.00	0.00	0.15	3.66	1.08	0.00	0.00
EW	0.00	0.00	0.85	0.78	0.56	0.00	0.00

chain structure. The conditional transition degree of passing from state EW to MD is $\tilde{P}(\text{MD}|\text{EW})$ = 39%, while passing from EW to moderately wet (MW) is $\tilde{P}(\text{MD}|\text{EW})$ = 25%.

The steady condition of the MCFS ($\tilde{\pi}$) is obtained and it has been compared with the steady conditions of the MC model, as seen in Fig. 3.

$\tilde{\pi} =$

ED	SD	MD	NN	MW	VW	EW
0.03	0.03	0.21	0.44	0.22	0.05	0.02

This result shows us the long-term probability distribution of the expected precipitation level for Cyprus. Regardless of the precipitation that occurs in a year, the NN state has the highest probability in the long term for the island, with a value of 64% according to the MC model and 44% according to the MCFS model. However, the EW and severely dry (SD) states have the lowest probabilities with 2% according to the MC model and 3% according to the MCFS model.

Classification of the precipitation data to the states with regard to the SPI values of Cyprus and its transition probability matrixes have been modeled and calculated via the Excel IF function.

The estimated probability distribution of randomly selected years' SPI values is shown in Tables 6–9 with the mean squared error (MSE) values of the MC and MCFS models.

The MSE results show that the MCFS technique estimates the yearly precipitation status of Cyprus with a lower error.

4. Conclusions

In this study, the annual rainfall of Cyprus for the past century was analyzed using the MC and MCFS model. These models were used to predict rainfall values related to past observations for the previous century. Within this framework, the MCFS technique, which depends on the fuzzy set theory, provides more realistic and sensitive results for predicting precipitation than the MC technique. However, the MSE values also show that the MCFS model gives more valuable predictions than the MC model for the precipitation.

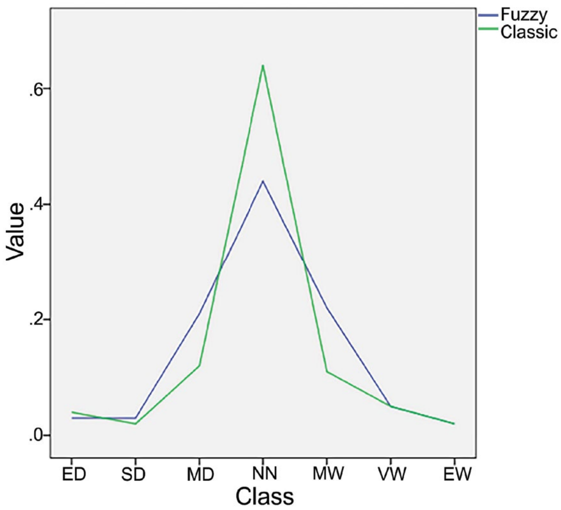

Fig. 3. Steady conditions of the MC and MCFS techniques.

Table 6
Estimated precipitation of Cyprus for 1961

(SPI_{1960} = –0.39, NN state)	ED	SD	MD	NN	MW	VW	EW	MSE
$P(MCFS)_{1961}$	0.03	0.02	0.25	0.40	0.22	0.05	0.02	0.106
P(actual SPI V.(1.26))$_{1961}$	0.00	0.00	0.00	0.00	0.94	0.06	0.00	
$P(MC)_{1961}$	0.03	0.00	0.12	0.65	0.13	0.06	0.01	0.171
P(actual SPI V.(1.26))$_{1961}$	0.00	0.00	0.00	0.00	1.00	0.00	0.00	

Table 7
Estimated precipitation of Cyprus for 1999

(SPI_{1998} = –0.36, NN state)	ED	SD	MD	NN	MW	VW	EW	MSE
$P(MCFS)_{1999}$	0.03	0.02	0.25	0.40	0.22	0.05	0.02	0.078
P(actual SPI V.(–1.34))$_{1999}$	0.00	0.20	0.80	0.00	0.00	0.00	0.00	
$P(MC)_{1999}$	0.03	0.00	0.11	0.66	0.13	0.06	0.01	0.178
P(actual SPI V.(–1.34))$_{1999}$	0.00	0.00	1.00	0.00	0.00	0.00	0.00	

Table 8
Estimated precipitation of Cyprus for 2004

(SPI_{2003} = 0.28, NN state)	ED	SD	MD	NN	MW	VW	EW	MSE
$P(MCFS)_{2004}$	0.02	0.02	0.20	0.43	0.24	0.06	0.03	0.053
$P(\text{actual SPI V.}(-0.902))_{2004}$	0.00	0.00	0.73	0.27	0.00	0.00	0.00	
$P(MC)_{2004}$	0.03	0.00	0.11	0.66	0.13	0.06	0.01	0.178
$P(\text{actual SPI V.}(-0.902))_{2004}$	0.00	0.00	1.00	0.00	0.00	0.00	0.00	

Table 9
Estimated precipitation of Cyprus for 2008

(SPI_{2007} = –2.14, ED state)	ED	SD	MD	NN	MW	VW	EW	MSE
$P(MCFS)_{2008}$	0.01	0.09	0.33	0.39	0.17	0.00	0.00	0.054
$P(\text{actual SPI V.}(0.12))_{2008}$	0.00	0.00	0.00	0.90	0.10	0.00	0.00	
$P(MC)_{2008}$	0.00	0.25	0.25	0.25	0.25	0.00	0.00	0.107
$P(\text{actual SPI V.}(0.12))_{2008}$	0.00	0.00	0.00	1.00	0.00	0.00	0.00	

It has been observed that when a very dry year occurs, the following year tends to have increased rainfall. It is also seen that the trend of transition from the states of MD, NN, MW, and VW to the state of NN is high.

Thus, as the results show, the NN state has the highest probability in the long term for Cyprus, while the EW and SD states have the lowest probability.

Recommendation

By using the MCFS model more valuable information about the future annual rainfall of Cyprus can be determined. This method can provide more information about future rainfall using a different classification. In particular, the prediction of the future level of rainfall for each region will be significantly beneficial to the decision-makers to enable them to plan and manage water resources accordingly. Furthermore, using weekly rainfall data could give more efficient and sensitive results about the nature of the precipitation status. Thus, due to the stochastic property of the MCFS phenomenon and also the nature of the stochastic of precipitation, a model for the prediction of precipitation in the short and long term is well calibrated. Hence, by designing a stochastic model that can predict the precipitation at any given time, it will be possible to manage water resources, including sustainable water in the future.

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