



HAL
open science

Simple Short-Term Probabilistic Drought Prediction Using Mediterranean Teleconnection Information

Mohammad Mehdi Bateni, Javad Behmanesh, Javad Bazrafshan, Hossein Rezaie, Carlo de Michele

► **To cite this version:**

Mohammad Mehdi Bateni, Javad Behmanesh, Javad Bazrafshan, Hossein Rezaie, Carlo de Michele. Simple Short-Term Probabilistic Drought Prediction Using Mediterranean Teleconnection Information. *Water Resources Management*, 2018, 32 (13), pp.4345-4358. 10.1007/s11269-018-2056-8. hal-03669810

HAL Id: hal-03669810

<https://hal.science/hal-03669810>

Submitted on 17 May 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

[Click here to view linked References](#)

Simple Short-term Probabilistic Drought Prediction using Mediterranean Teleconnection Information

M. M. Bateni^{1*}, J. Behmanesh¹, J. Bazrafshan², H. Rezaie¹, C. De Michele³

¹ Department of Water Engineering, College of Agriculture, Urmia University, Urmia, Iran.

² Department of Irrigation and Reclamation Engineering, University of Tehran, Karaj, Iran.

³ Department of Civil and Environmental Engineering (DICA), Politecnico di Milano, Milano, Italy.

Abstract

Timely forecasts of the onset or possible evolution of droughts is an important contribution to mitigate their manifold negative effects; therefore, in this paper, we propose a mathematically-simple drought forecasting framework gaining Mediterranean Sea temperature information (SST-M) to predict droughts. Agro-metrological drought index addressing seasonality and autocorrelation (AMDI-SA) was used in a Markov model in Urmia lake basin, North West of Iran. Markov chain is adopted to model drought for joint occurrence of different classes of drought severity and sea surface temperature of Mediterranean Sea, which is called 2D Markov chain model. The proposed model, which benefits suitability of Markov chain models for modeling droughts, showed improvement results in prediction scores relative to classic Markov chain model not including SST-M information, additionally.

Keywords Drought Forecasting, Teleconnection, Markov Model, Mediterranean Sea, Model Evaluation, Skill Score

* *Corresponding Author*: E-mail addresses: bateni2000@gmail.com

1. Introduction

Early warning/prediction of droughts is a significant contribution to drought preparedness.

Statistical methods are routinely utilized for drought modeling and forecasting like other problems in hydrology and water resources. This is because most, if not all, hydrological processes such as extreme events have some degree of randomness. Most probabilistic methods used assume that the extreme hydrological values are stationary. However, research has shown that in some areas there are some types of Non-stationarities in hydrologic data (Salas and Obeysekera, 2014).

Non-stationary may be due to normal changes in climate, particularly as a result of the low frequency components of climate change such as El Niño Southern Oscillation (ENSO) and ten years or even decades fluctuating components, such as Pacific Decadal Oscillation (PDO), Atlantic Multidecadal Oscillation (AMO), the Pacific/North American Pattern (PNA) and Sea Surface Temperature (SST) in the Niño region or every other sea. These large-scale tele connections cause oscillations applied synchronously or with a delay in the amplitude of hydrologic events such as storms, floods, droughts and sea level (Biabanaki et al., 2014; Enfield et al., 2001; Jain and Lall, 2000; Jain and Lall, 2001; Meidani and Araghinejad, 2014; Park et al., 2010; Park et al., 2011).

However, these components are used as an auxiliary tool in short term drought prediction in different studies using statistical methods such as linear regression (D'Arrigo and Wilson, 2008; Kumar and Panu, 1997; Wood and Lettenmaier, 2006; Yin, 1994), Artificial Neural Network (Hastenrath and Greischar, 1993; Silverman and Dracup, 2000), adaptive neuro-fuzzy inference system (ANFIS) (Bacanli et al., 2009; Chang and Chang, 2006; Nayak et al., 2004) and Hidden Markov models (Kondrashov et al, 2004; Deloncle et al, 2007). Although some fairly complicated statistical methods were used, evidence of their superiority over a simple method which can gain teleconnection information was not presented.

1
2
3
4 In Iran, Meidani and Araghinejad (2014) used time series of Mediterranean Sea surface 46
5
6 temperature (SST-M) to forecast river flows in south west of Iran. They showed that the use of 47
7
8 Mediterranean's information lead to improved results in comparison with using other common 48
9
10 indices, such as SOI, NAO or AMO (Atlantic Multidecadal Oscillation). However, it is not 49
11
12 surprising, since Mediterranean Sea is the main source of moist air in Iran (Alijani and Harman, 50
13
14 1985). 51
15
16

17
18 Markov model is widely used for drought monitoring and prediction. The non-homogeneous 52
19
20 Markov chain approach was applied to time series of the Palmer Index for early warning aimed at 53
21
22 drought management (Lohani and Loganathan, 1997; Lohani et al., 1998). Cancelliere and Salas 54
23
24 (2004) used a Markov chain approach to study drought length properties. These studies show that 55
25
26 a stochastic approach may be useful for short term prediction and early warning as analyzed in 56
27
28 previous studies (Paulo et al., 2005; Paulo and Pereira, 2007). 57
29
30
31

32
33 During recent years, several studies were conducted to identify factors influencing the weather. 58
34
35 In this regard, scientists have devoted much effort to find a mathematical relationship between 59
36
37 climate variability with teleconnection information in order to alleviate some of the socially 60
38
39 undesirable effects of sudden, unexpected occurrences of extremes such as droughts, floods, and 61
40
41 widespread fires. El-Nino Southern Oscillation (ENSO), Southern oscillation index (SOI), Pacific 62
42
43 Decadal Oscillation (PDO), North Atlantic Oscillation (NAO), sea surface temperatures (SST), 63
44
45 and geopotential height (GpH) vastly used to encourage investigation of the possibilities of 64
46
47 forecasting rainfall and other elements of the weather. 65
48
49
50

51
52 Here, values of Agro-Meteorological Drought Index addressing seasonality and autocorrelation 66
53
54 (AMDI-SA), showing drought severity, are categorized in 4 different classes and used in a Markov 67
55
56 framework. Additionally, joint occurrence of drought severity classes and Mediterranean Sea 68
57
58
59
60
61
62

1
2
3
4 surface temperature (SST-M) classes used to monitor and predict droughts in a two-dimensional 69
5
6 Markov chain model (2D-MCM) with 12 different transition classes. Since there is a time lag 70
7
8 between SST-M and correlated drought/wetness condition, prediction is made on the help of 71
9
10 known state of SST-M and previous state of drought. 72
11
12
13
14 This research aims at modeling droughts in Urmia Lake basin, and predicting drought severity for 73
15
16 short lead times. The proposed framework easily exploits temperature information of the 74
17
18 Mediterranean Sea which is the original source of humidity in the region. It also provides 75
19
20 promising probabilistic predictions of droughts, conveying the prediction uncertainty information 76
21
22 which could be useful for operational drought management. 77
23
24
25
26
27

28
29 **2 Material and Methods** 79
30

31
32 **2.1 AMDI-SA** 80
33

34 Having AMDI-SA, monthly soil moisture and precipitation data are used to calculate Standardized 81
35
36 Precipitation Index (SPI) and Standardized Soil-Moisture Index (SSI). SSI, see e.g., AghaKouchak 82
37
38 (2014), can be defined in a similar way to SPI. In order to integrate the indices, copula framework 83
39
40 is used. The Kendall distribution function of the fitted copula are normalized to construct AMDI- 84
41
42 SA. For detailed procedure, see e.g. Bateni et al. (2018). 85
43
44
45 Since AMDI-SA is a standardized index, it can be classified like SPI or other standardized indexes. 86
46
47 In this study, 4 classes for droughts are used based on AMDI-SA values. Classes are described in 87
48
49 table 1. 88
50
51
52

53
54 **Table 1** Classification of wetness/drought condition based on AMDI-SA values (modified from 89
55
56 McKee et al. (1993)) 90
57

Category	Description	Percentiles based on	Index Value
----------	-------------	----------------------	-------------

Normal Distribution			
(1) N	Non Drought	$50 >$	$AMDI-SA \geq 0$
(2) D0	Moderate Drought	16 to 50	$-1 < AMDI-SA < 0$
(3) D1	Severe Drought	7 to 16	$-1.5 < AMDI-SA \leq -1$
(4) D2	Extreme Drought	$7 >$	$-1.5 \geq AMDI-SA$

91

AMDI-SA is a comprehensive agrometeorological drought index, which accounts seasonality and autocorrelation. Since AMDI-SA is seasonally-adjusted, a single Markov model can be adopted to model all its transitions. Moreover, time series of AMDI-SA values doesn't show high autocorrelation, meaning that a first-order Markov model is adequate and the consideration of higher-order models is not needed.

92

93

94

95

96

2.2 Climate Teleconnection Indices

97

Accordingly, here Mediterranean Sea surface temperature is used as a climatic teleconnection index to predict droughts. In order to determine the time lag of influence of the teleconnection which is usually less than a year, eleven covariance matrices of teleconnection data for time lag of one to eleven months and AMDI-SA values are estimated. The covariance matrix which has the greatest (1st) norm, determines the time lag (D) of the influence of the teleconnection on the region.

98

99

100

101

102

Since entire basin follow the same climate regime, the value of D is unique for basin as a whole.

103

When the delay was determined, the teleconnection information for D months before, is used to model and predict current droughts. With the aim of compressing all spatial data covering

104

105

Mediterranean Sea into one single value, Singular Value Decomposition (SVD) technique is used.

106

According to the SVD procedure, a rectangular matrix A can be broken into the product of three

107

matrices, as follows: (1) an orthogonal matrix U, (2) a diagonal matrix D, and (3) the transpose of an orthogonal matrix V. Mathematically, this is represented as (Golub and Van Loan, 1996)

$$A_{mn} = U_{mm} D_{mn} V_{n,n}^T \quad (1)$$

The columns of U are orthonormal eigenvectors of AA^T ; the columns of V are orthonormal eigenvectors of $A^T A$; and S is a diagonal matrix containing the square roots of eigenvalues from U or V in descending order indicating the variance of linearly independent components along each dimension. Firstly, two matrices including values of Mediterranean SSTs grid points and AMDI-SA were developed for 325 months. Then, the cross-covariance matrix for those was computed

$$\text{Covvar} = \frac{1}{n_{month}} \times \begin{pmatrix} \text{SST} - M_{1,1} & \dots & \text{SST} - M_{1,n_{month}} \\ \vdots & \ddots & \vdots \\ \text{SST} - M_{m_g,1} & \dots & \text{SST} - M_{m_g,n_{month}} \end{pmatrix} \times \begin{pmatrix} \text{AMDI} - SA_1 \\ \vdots \\ \text{AMDI} - SA_{n_{month}} \end{pmatrix} \quad (2)$$

By applying SVD decomposition for the covariance matrix,

$$\text{SVD}(\text{Covvar}) = \left[U_{m_g, m_g} \cdot \begin{pmatrix} S_{1,1} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & S_{m_g, m_g} \end{pmatrix} \cdot V_{1,1}^T \right] \quad (3)$$

To have a single value for each time step, first Eigen value of the covariance matrix which has the greatest contribution to justify variability is used. Therefore, the time series of SST-M to use as teleconnection index is computed as follows:

$$\begin{pmatrix} \text{SST} - M_1 \\ \vdots \\ \text{SST} - M_{n_{month}} \end{pmatrix} = \begin{pmatrix} \text{SST} - M_{1,1} & \dots & \text{SST} - M_{1,m_g} \\ \vdots & \ddots & \vdots \\ \text{SST} - M_{n_{month},1} & \dots & \text{SST} - M_{n_{month},m_g} \end{pmatrix} \times U(:, 1) \quad (4)$$

As a useful measurement for comparing the relative importance of modes in the decomposition, Bretherton et al. (1992) defines the Squared Covariance Fraction ($\text{SCF} = \text{sv}_i^2 / \sum \text{sv}^2$) where sv represents each of the singular values. SCF is about 88% that shows possibility of the derived SST-

M values from SVD to show great share of variations of original information of SST-M for all grid points. This quantity is an average for the whole basin which is more or less the same all over it. Derived SST-M values are classified in two equiprobable classes to show cold and warm phases of Mediterranean Sea.

2.3 Markovian Modeling

A Markov process is a random process in which the future is independent of the past, given the present. In discrete time, the process (X) is known as a discrete-time Markov chain which its current state space (X_{t+1}) depends only on a few limited number of its previous state ($X_{t-k}, \dots, X_{t-1}, X_t$). Markov chain is defined by a set of finite numbers of classes (S), the probability of transition between the states ($Pr_{ij|\dots|u}$) and order of the chain (l). Hereafter, discussion is limited to first order ($l=1$) Markov chains, used commonly in hydrological sciences. The independence of values that are separated by more than one time period is not required by the first order Markov property. Instead, it implies conditional independence of data values separated by more than one time period, which means that the statistical dependence among elements of the time series decreases as time lags increase (Wilks, 2011).

For a homogeneous Markov model, transition probabilities are independent of time. Elements of Transition matrix (T), which are probability of transitions, can be estimated by empirical relative frequency of class transitions. If the frequency distribution of modeled variable is known in advance, assumptions made to adopt a Markov chain model could be verified by comparing steady-state probability vector of modeled variable (π) with the formerly known frequency distribution. However, in order to achieve a *limiting* steady-state distribution, the Markov chain process has to be regular which needs regularity of the transition matrix. Transition matrix (T) is called regular if, for some integer r , all entries of T^r are strictly positive. Therefore, for a regular transition matrix,

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

(1) T^n approaches T_{ST} as n approaches infinity, where T_{ST} is a matrix of the form 150
[v_1 . v_2 v_s] where each vector (v) has same repeating element. 151

(2) If X_i is any state vector, then as n approaches infinity, $T^n X_i$ approaches π , where π is a fixed 152
probability vector (the sum of its entries is 1). 153

In drought modeling, the state space consists of different drought severity classes which are based 154
on values of an appropriate drought index. 155

Markov chain modeling allows the estimation of the drought class probabilities, which represent 156
the probabilities of occurrence of the various drought classes as an aid to water resources decision 157
makers. Besides, many other features of drought such as the expected residence time in each class 158
of severity and the expected first passage time could be evaluated using a Markov chain 159
framework. 160

2.4 Evaluation of Probabilistic Forecasts 161

In order to address periodicity mainly caused by low-frequency components of climate variability, 162
a 2D Markov chain model (2D-MCM) is proposed. Since AMDI-SA is not seasonal, a time- 163
homogeneous framework is used for the chain. Joint occurrence of classes of SST-M, used as 164
teleconnection information, and classes of drought severity, indicated by AMDI-SA values, consist 165
classes of the Markov chain. Since there are 4 classes for drought severity based on AMDI-SA 166
values and 3 classes for values of SST-M, 12 classes are made showing their joint occurrence 167
conditioned the Markov chain model. It is worthwhile to mention that for example class number 168
nine means that AMDI-SA shows severe drought (D1) while SST-M is in warm phase. As the 169
teleconnection class is available for D months in advance and previous drought [severity] and 170
transition probabilities are given before each time step, probabilistic prediction of AMDI-SA class 171
is possible for the next month. In order to ensure about the adequacy of the model, the regularity 172

of transition probability matrices is assessed for both the classical one dimensional Markov chain model (1D-MCM) using only AMDI-SA and the two dimensional Markov chain model (2D-MCM) gaining SST-M data.

2.5 Evaluation of Probabilistic Forecasts

To evaluate the performance of the multicategory probabilistic forecasts of the models, accuracy of probabilistic forecasts relative to polychotomous observations are measured. Furthermore, sharpness of predictions and discrimination are also important attributes of a forecasting system to be helpful as an aid for making decisions.

Here, Brier score, sharpness score and generalized discrimination score are used to evaluate probabilistic forecast models adopted.

2.5.1 Brier Score (BS)

Brier Score proposed by Glenn W. Brier in 1950 (Brier, 1950), determines the magnitude of the probability forecast errors. Brier score is used to evaluate accuracy of predictions, defined as

$$BS = \frac{1}{N} \sum_{i=1}^N \sum_{r=1}^S (p_{ir} - o_{ir})^2 \quad (5)$$

where S is the number of classes, N is the total number of occasions, p_{ir} is the forecast probability of r th class and o_{ir} is the observation probability of r th class (0 or 1), both at i th occasion. The lower Brier score for a set of predictions, the better the predictions are calibrated. BS is Sensitive to observational frequency of the event: the rarer an event, the easier it is to get a good BS without having any real skill.

2.5.2 Generalized Discrimination Score (GDS)

Generalized Discrimination Score shows the degree of correct probabilistic forecast discrimination, even if the forecasts have biases or calibration problems. GDS is generalized to

1
2
3
4 encompass all forecast categories, produces values ranging from 0.5 for a set of probability scores 195
5
6 without skill to 1 as the maximum perfect value (Mason and Weigel, 2009; Barnston et al., 2010). 196
7
8 Let n_k and n_l be the number of observed events for category k and l , respectively. When S is the 197
9
10 number of categories, GDS score is calculated as 198
11
12

$$13 \quad GDS = \frac{\sum_{k=1}^{S-1} \sum_{l=k+1}^S \sum_{i=1}^{n_k} \sum_{j=1}^{n_l} I(\mathbf{P}_{k,i}, \mathbf{P}_{l,j})}{\sum_{k=1}^{S-1} \sum_{l=k+1}^S n_k n_l} \quad (6) \quad 199$$

17 where $\mathbf{P}_{k,i}$ is the vector of forecast probabilities for the i th forecast given category k , and 200
18
19

$$20 \quad I(\mathbf{P}_{k,i}, \mathbf{P}_{l,j}) = \begin{cases} 0 & \text{if } F(\mathbf{P}_{k,i}, \mathbf{P}_{l,j}) < 0.5 \\ 0.5 & \text{if } F(\mathbf{P}_{k,i}, \mathbf{P}_{l,j}) = 0.5 \\ 1 & \text{if } F(\mathbf{P}_{k,i}, \mathbf{P}_{l,j}) > 0.5 \end{cases} \quad (7) \quad 201$$

22 The scoring rule $F(\mathbf{P}_{k,i}, \mathbf{P}_{l,j})$ is defined as 202
23
24
25

$$26 \quad F(\mathbf{P}_{k,i}, \mathbf{P}_{l,j}) = \frac{\sum_{q=1}^{S-1} \sum_{r=q+1}^S p_{k,i}(q) p_{l,j}(r)}{1 - \sum_{q=1}^S p_{k,i}(q) p_{l,j}(q)} \quad (8) \quad 203$$

27 where $p_{k,i}(q)$ is the forecast probability for the q th category, and for the i th observation in category 204
28
29

30 k . The numerator of Eq. 6 sums the $I(\mathbf{P}_{k,i}, \mathbf{P}_{l,j})$ outcomes over all qualifying pairs of forecasts; 205
31
32

33 the denominator contains the number of pairs (Mason and Weigel, 2009). 206
34
35

36 **2.5.3 Sharpness Score (SS)** 207

37 Given two reliable forecast systems, the one producing the sharper forecasts is preferable to use. 208
38
39

40 Analogous to formulation of coefficient of variation, a simple score is introduced here to compare 209
41
42

43 the forecasting models: 210
44
45

$$46 \quad SS = \sqrt{\frac{1}{N-1} \sum_{i=1}^N \sum_{r=1}^S (p_{ir} - \mu_{ir})^2} \quad (9) \quad 211$$

47 where μ_{ir} is historical average probability of r th class at i th occasion. Values approaching 0 212
48
49

50 indicate an increasingly wider forecasts and values approaching ∞ indicates increasingly sharper 213
51
52

53 forecasts. 214
54
55
56
57
58
59
60
61
62
63
64
65

1
2
3
4 For all above scores, since nonzero values of predictions in both 1D and 2D cases are restricted to 215
5 number of drought classes, i.e. 4, S is assumed to be 4. 216
6
7
8

9 **2.6 Study Area** 217

10 Urmia Lake basin is located between $37^{\circ}4'$ to $38^{\circ}17'$ latitude and $45^{\circ}13'$ to 46° longitude in 218
11 northwestern Iran (Fig. 1). The catchment area is shared between the three provinces West 219
12 Azerbaijan (21500 km^2), East Azerbaijan (19000 km^2) and Kurdistan (5000 km^2) (Yekom 220
13 Consulting Engineer, 2005). The lake basin, as a unique socio-ecological region, is facing extreme 221
14 water shortages due to poor water governance and climate change (Alipour, 2006; Zarghami et al., 222
15 2009). Climate in the Urmia Lake basin is harsh and continental, affected mainly by the mountains 223
16 surrounding the lake (Ghaheri et al., 1999). The annual average precipitation is about 500 mm. 224
17
18
19
20
21
22
23
24
25
26
27
28

29 **2.7 Data** 225

30 Because of the consistency and availability of the record for long-term, needed monthly 226
31 precipitation data for the basin is acquired from daily $0.25^{\circ} \times 0.25^{\circ}$ high resolution PERSIANN- 227
32 CDR (Ashouri et al., 2015) for the period 1983–2010. The accuracy of PERSIANN precipitation 228
33 data set family for Iran and Urmia Lake basin is demonstrated in some previous publications 229
34 (Moazami et al., 2013; Bodagh-Jamli, 2015; Ghajarnia et al., 2015; Katiraie-Boroujerdy et al., 230
35 2013). 231
36
37
38
39
40
41
42
43
44
45

46 In this paper, soil moisture is derived using ERA-Interim-Land surface fluxes and near-surface 232
47 meteorology to force the land surface model uses HTESSEL (Balsamo et al., 2015) for the period 233
48 of 1983–2010. It is considered that most of the roots vegetation distribution is in the first 3 layers 234
49 of soil in HTESSEL model (0-7cm, 7-28cm and 28-100cm). The 3 upper layers water content data 235
50 weighting averaged to have single value for each $0.25^{\circ} \times 0.25^{\circ}$ pixel. Both mentioned data sets are 236
51 global; however, the data of Urmia Lake basin are extracted and handled further, only. To consider 237
52
53
54
55
56
57
58
59
60
61
62
63
64
65

1		
2		
3		
4	spatial distribution of drought, 79 pixels covering the basin (not lake) are treated as data stations	238
5		
6	and series for each are processed.	239
7		
8		
9	Monthly Mediterranean Sea surface temperature data which is used as a teleconnection	240
10		
11	information is obtained from NOAA Optimum Interpolation (OI) Sea Surface Temperature (SST)	241
12		
13	V2 for the period of 1983-2010 (NOAA_OI_SST_V2) with resolution of $1^\circ \times 1^\circ$. Extracting the	242
14		
15	data of Mediterranean Sea and removing grids which are near coast to exclude ramifications of	243
16		
17	land disturbances, time series for 129 grid point are obtained.	244
18		
19	Performance evaluation of the forecasting system is done for the period of 2004-2010, which lake	245
20		
21	has been affected by prolonged droughts during that.	246
22		
23		
24		
25		
26		247
27		
28		
29	3 Results	248
30		
31	The value of covariance is maximized when the teleconnection information corresponding to one	249
32		
33	month ago are considered in conjunction with the index of the current moment, i.e. the time lag D	250
34		
35	= 1 month.	251
36		
37		
38		
39	To measure the ability of the forecasting system to detect droughts and discriminate between	252
40		
41	different classes of droughts, Brier Score (BS) and Generalized Discrimination Score (GDS) are	253
42		
43	evaluated for all data points in Urmia Lake basin. Furthermore, Sharpness Score (SS) adopted to	254
44		
45	assess the uncertainty of the model predictions are reported. To show the improvement contributed	255
46		
47	by the proposed model, average values of these scores for both case of all grid points for both 2D	256
48		
49	(including SST-M data) and 1D model (only AMDI-SA) are reported in Table 2. The spatial	257
50		
51	integration has the advantage of increasing the sample size used to build the scores.	258
52		
53		
54		
55		
56	In case of BS and GDS, which score values are close, Fig. 2 and 3 shows spatial distributions of	259
57		
58	BS and GDS values for both 2D-MCM and 1D-MCM for all location points within the basin,	260
59		
60		
61		
62		
63		
64		
65		

1
2
3
4 respectively. Using Mediterranean-SST information, caused both BS and GDS to improve for 261
5
6 entire basin. As shown in Fig. 3, 2D-MCM leads to GDS values more than score of 0.5 (without 262
7
8 skill) for almost all points. 263

11 **Table 2** Score values of the drought forecasting method for both 2D-MCM and 1D-MCM. 264

	BS	GDS	SS
1D-MCM	0.675	0.531	0.056
2D-MCM	0.653	0.574	0.072

22
23
24 The accordance of predicted state classes to observations is the main goal of any prediction 266
25
26 framework. In order to evaluate the accordance, frequency distribution of observed and predicted 267
27
28 class through performance evaluation period (2004-2010) for whole basin is showed in Fig. 4 and 268
29
30 5. Since, predictions are probabilistic vectors, probability values for each class are calculated by 269
31
32 element-wise averaging the vectors while empirical probability values are reported for 270
33
34 observations. 271
35
36
37
38

39 Transition probability matrix of both 1D and 2D Markov chain models are reported in Table 3 and 272
40
41 4. It can be shown all elements of 2nd power of both transition probability matrices are strictly 273
42
43 positive (regular matrix). Like previous studies using standardized drought indices (Paulo et al., 274
44
45 2005), there is a strong diagonal tendency in Markov transition probability matrix. For 2D model, 275
46
47 since each 2 consecutive classes have the same drought severity, there is a 2-diagonal tendency. 276
48
49
50

277

Table 3 Transition probability matrix of the 1D model (only AMDI-SA).

278

State <i>i</i>	State <i>j</i>			
	1	2	3	4
1	0.810	0.155	0.021	0.014
2	0.221	0.681	0.080	0.018
3	0.125	0.293	0.432	0.151
4	0.095	0.149	0.231	0.525

279

Table 4 Transition probability matrix of the 2D model (including SST-M data).

280

State <i>i</i>	State <i>j</i>							
	1	2	3	4	5	6	7	8
1	0.594	0.228	0.097	0.040	0.015	0.008	0.012	0.007
2	0.264	0.531	0.054	0.123	0.006	0.014	0.001	0.008
3	0.196	0.077	0.423	0.212	0.043	0.029	0.012	0.008
4	0.052	0.125	0.210	0.508	0.033	0.056	0.007	0.009
5	0.099	0.035	0.275	0.111	0.191	0.152	0.070	0.068
6	0.043	0.073	0.073	0.158	0.126	0.360	0.055	0.111
7	0.087	0.024	0.151	0.069	0.172	0.059	0.262	0.177
8	0.039	0.044	0.041	0.062	0.079	0.148	0.152	0.438

281

4. Discussion

282

According to Table 2 and Fig. 2 and Fig. 3, the accuracy of prediction evaluated by Brier score is

283

significantly improved using teleconnection information of Mediterranean Sea surface

284

1
2
3
4 temperature. The improvement is substantial for all location points within the Urmia basin. This 285
5
6 highlights the fact that the main source of humidity in the basin is Mediterranean Sea. Both 1D 286
7
8 and 2D Markov chain model do not show strong ability to discriminate between different classes 287
9
10 of droughts ($GDS < 0.7$) for most parts of the basin. However, 2D Markov chain model is more 288
11
12 promising to discriminate. For a small share of location points within the basin, classical 1D model 289
13
14 doesn't show any desirable skill to discriminate between drought classes, exceptionally. 290
15
16 Comparison of Sharpness score for the proposed 1D and 2D Markov chain models indicate that 291
17
18 2D model produces sharper predictions. However, this attribute only matters when comparing two 292
19
20 models of same accuracy. 293
21
22 As indicated in Fig. 4 and Fig. 5, since empirical probability of observed class number one (or one 294
23
24 up to three in Fig. 5) is more than 0.5, the period of performance evaluation (2004-2010) is a wetter 295
25
26 than normal period. Nevertheless, probability distributions of predictions produced by 1D and 2D 296
27
28 models generally follow empirical distribution of observations. 297
29
30
31
32
33
34
35
36 Diagonal tendency in transition probability matrices for both 1D and 2D models reflects the 298
37
38 persistence of recent drought categories, more highlighted for classes with extreme drought 299
39
40 severity: when the actual state is D2 the more probable state for a month ahead is the present state, 300
41
42 i.e. no changes of state are predictable. 301
43
44
45
46
47

48 **5. Conclusions** 303

49
50
51 This study was conducted to predict droughts, one of the world's natural hazards and controversial 304
52
53 issue. For this purpose, time series of an agro-meteorological drought index, namely AMDI-SA, 305
54
55 were used. The proposed Markov framework exploits the temperature information of the 306
56
57
58
59
60
61
62
63
64
65

1		
2		
3		
4	Mediterranean sea - as the original source of humidity in the region - in order to perform the task	307
5		
6	of prediction.	308
7		
8		
9	Application of Markov method provides a probabilistic qualitative model of droughts. On the other	309
10		
11	hand, the nature of drought is qualitative. Therefore, probabilistic frameworks like Markov models	310
12		
13	seem to be the most reasonable approach to model droughts.	311
14		
15	Moreover, the probabilities of transition can be used in planning or operational mode for designing	312
16		
17	mitigation measures as the drought evolves.	313
18		
19	The prediction capability of the Markov models concerning short-term forecasts are limited by the	314
20		
21	characteristics of the climate, which tends to be reproduced in these short-term forecasts. However,	315
22		
23	taking advantage of teleconnection information improves performance of the drought early	316
24		
25	warning system as well as enhancing the understanding of the evolution of drought events.	317
26		
27	The proposed 2D Markov chain model, using teleconnection information, has promising values of	318
28		
29	prediction evaluation scores. Since it doesn't have much mathematical burden, it is recommended	319
30		
31	to use this model in all regions which its over-year variations certainly correlated to some climatic	320
32		
33	teleconnections.	321
34		
35	Acknowledgments Thanks to NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, for freely available	322
36		
37	NOAA_OI_SST_V2 data provided at their web site (NOAA, 2017).	323
38		
39		
40		
41	Conflict of Interest	324
42		
43	The authors declare that they have no conflict of interest.	325
44		
45		
46		
47		
48		
49		
50		
51		
52		
53	References	327
54		
55		
56		
57		
58		
59		
60		
61		
62		
63		
64		
65		

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

AghaKouchak A (2014) A baseline probabilistic drought forecasting framework using standardized soil moisture index: application to the 2012 United States drought. *Hydrol Earth Syst Sci* 18:2485-2492 328 329 330

Alijani B, Harman JR (1985) Synoptic climatology of precipitation in Iran. *Ann Assoc Am Geogr* 75:404-416 331 332

Alipour S (2006) Hydrogeochemistry of seasonal variation of Urmia salt lake, Iran. *Saline Syst* 2:1-19 333 334

Ashouri H, Hsu KL, Sorooshian S, Braithwaite DK, Knapp KR, Cecil LD, Nelson BR, Prat OP (2015) PERSIANN-CDR: Daily precipitation climate data record from multi-satellite observations for hydrological and climate studies. *B Am Meteorol Soc* 96:69-83 335 336 337

Bacanli UG, Firat M, Dikbas F (2009) Adaptive neuro-fuzzy inference system for drought forecasting. *Stoch Environ Res Risk Assess* 23:1143-1154. doi:10.1007/s00477-008-0288-5 338 339

Balsamo G, Albergel C, Beljaars A, Boussetta S, Brun E, Cloke H, Dee D, Dutra E, Muñoz-Sabater J, Pappenberger F, Rosnay P, Stockdale T, Vitart F (2015) ERA-Interim/Land: a global land surface reanalysis data set. *Hydrol Earth Syst Sci* 19:389-407. doi:10.5194/hess-19-389-2015 340 341 342 343

Bateni, MM, Behmanesh J, De Michele C, Bazrafshan J, Rezaie H (2018) Composite agrometeorological drought index accounting for seasonality and autocorrelation. *J Hydrol Eng* 23:04018020. doi:10.1061/(ASCE)HE.1943-5584.0001654 344 345 346

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Bazrafshan J, Hejabi S, Rahimi J (2014) Drought monitoring using the multivariate standardized precipitation index (MSPI). *Water Resour Manage* 28:1045-1060. doi:10.1007/s11269-014-0533-2 347
348
349

Biabanaki M, Eslamian SS, Koupai JA, Cañón J, Boni G, Gheysari M (2014) A principal components/singular spectrum analysis approach to ENSO and PDO influences on rainfall in western Iran. *Hydrol Res* 45:250-262. doi:10.2166/nh.2013.166 350
351
352

Bodagh-Jamli J (2015) Validation of satellite-based PERSIANN rainfall estimates using surface-based APHRODITE data over Iran. *Earth Sci* 4:11. doi:10.11648/j.earth.20150405.11 353
354

Barnston AG, Li S, Mason SJ, DeWitt DG, Goddard L, Gong X (2010) Verification of the first 11 years of IRI's seasonal climate forecasts. *J Appl Meteorol Climatol* 49:493-520. doi:10.1175/2009JAMC2325.1 355
356
357

Bretherton CS, Smith C, Wallace JM (1992) An intercomparison of methods for finding coupled patterns in climate data. *J Clim* 5:541-560. doi:10.1175/1520-0442(1992)005<0541:AIOMFF>2.0.CO;2 358
359
360

Brier GW (1950) Verification of forecasts expressed in terms of probability. *Mon Weather Rev* 78:1-3. doi:10.1175/1520-0493(1950)078<0001:VOFEIT>2.0.CO;2 361
362

Cancelliere A, Salas JD (2004) Drought length properties for periodic-stochastic hydrologic data. *Water Resour Res* 40. doi:10.1029/2002WR001750 363
364

Chang F-J, Chang Y-T (2006) Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. *Adv Water Resour* 29:1-10. doi:10.1016/j.advwatres.2005.04.015 365
366

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

D'Arrigo R, Wilson R (2008) El Niño and Indian Ocean influences on Indonesian drought: 367
implications for forecasting rainfall and crop productivity. *Int J of Climatol* 28:611-616. 368
doi:10.1002/joc.1654 369

Deloncle A, Berk R, D'Andrea F, Ghil M (2007) Weather regime prediction using statistical 370
learning. *J Atmos Sci* 64:1619-1635. doi:10.1175/JAS3918.1 371

Enfield DB, Mestas-Nuñez AM, Trimble PJ (2001) The Atlantic Multidecadal Oscillation and its 372
relation to rainfall and river flows in the continental U.S. *Geophys Res Lett* 28:2077-2080. 373
doi:10.1029/2000GL012745 374

Ghaheri M, Baghal-Vayjooee M, Naziri J (1999) Lake Urmia, Iran: a summary review. *Int J Salt* 375
Lake Res 8:19-22. doi: 10.1007/BF02442134 376

Ghajarnia N, Liaghat A, Daneshkar Arasteh P (2015) Comparison and evaluation of high 377
resolution precipitation estimation products in Urmia Basin-Iran. *Atmos Res* 158–159:50- 378
65. doi:10.1016/j.atmosres.2015.02.010 379

Golub GH, Van Loan CF (1996) *Matrix computations*. Johns Hopkins University Press, 380
Baltimore, MD 381

Hastenrath S, Greischar L (1993) Further work on the prediction of northeast Brazil rainfall 382
anomalies. *J Clim* 6:743-758. doi:10.1175/1520-0442(1993)006<0743:FWOTPO>2.0.CO;2 383

Jain S, Lall U (2000) Magnitude and timing of annual maximum floods: Trends and large- scale 384
climatic associations for the Blacksmith fork river, Utah. *Water Resour Res* 36:3641-3651. 385
doi:10.1029/2000WR900183 386

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Jain S, Lall U (2001) Floods in a changing climate: Does the past represent the future? *Water Resour Res* 37:3193-3205. doi:10.1029/2001WR000495 387
388

Kao S-C, Govindaraju RS (2010) A copula-based joint deficit index for droughts. *J Hydrol* 380:121-134. doi:10.1016/j.jhydrol.2009.10.029 389
390

Katiraei-Boroujerdy P-S, Nasrollahi N, Hsu K-l, Sorooshian S (2013) Evaluation of satellite-based precipitation estimation over Iran. *J Arid Environ* 97:205-219. doi:10.1016/j.jaridenv.2013.05.013 391
392
393

Kondrashov D, Ide K, Ghil M (2004) Weather regimes and preferred transition paths in a three-level quasigeostrophic model. *J Atmos Sci* 61:568-587. doi:10.1175/1520-0469(2004)061<0568:WRAPTP>2.0.CO;2 394
395
396

Kumar V, Panu U (1997) Predictive assessment of severity of agricultural droughts based on agro-climatic factors. *J Am Water Res Assoc* 33:1255-1264. doi:10.1111/j.1752-1688.1997.tb03550.x 397
398
399

Lohani VK, Loganathan GV (1997) An early warning system for drought management using the palmer drought index *J Am Water Res Assoc* 33:1375-1386. doi:10.1111/j.1752-1688.1997.tb03560.x 400
401
402

Lohani VK, Loganathan GV, Mostaghimi S (1998) Long-term analysis and short-term forecasting of dry spells by Palmer drought severity index. *Hydrol Res* 29:21-40, doi:10.2166/nh.1998.0002 403
404
405

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Mason SJ, Weigel AP (2009) A generic forecast verification framework for administrative purposes. *Mon Weather Rev* 137:331-349. doi:10.1175/2008MWR2553.1 406
407

McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology, 17-22 January, Anaheim, CA, Amer. Meteorol Soc, Boston, MA, 179–184.* 408
409
410

Meidani E, Araghinejad S (2014) Long-lead streamflow forecasting in the southwest of Iran by sea surface temperature of the Mediterranean sea. *J Hydrol Eng* 19:05014005. 411
412
doi:10.1061/(ASCE)HE.1943-5584.0000965 413

Moazami S, Golian S, Kavianpour MR, Hong Y (2013) Comparison of PERSIANN and V7 TRMM multi-satellite precipitation analysis (TMPA) products with rain gauge data over Iran. *Int J Remote Sens* 34:8156-8171. doi:10.1080/01431161.2013.833360 414
415
416

Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS (2004) A neuro-fuzzy computing technique for modeling hydrological time series. *J Hydrol* 291:52-66. 417
418
doi:10.1016/j.jhydrol.2003.12.010 419

NOAA ESRL (2017) ESRL:PSD:NOAA Optimum Interpolation (OI) Sea Surface Temperature (SST) V2. <https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.html> 420
421

Park J, Obeysekera J, Irizarry M, Barnes J, Trimble P, Park-Said W (2011) Storm surge projections and implications for water management in south Florida. *Clim Change* 107:109-128. doi:10.1007/s10584-011-0079-8 422
423
424

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Park J, Obeysekera J, Irizarry-Ortiz M, Barnes J, Park-Said W (2010) Climate links and 425
variability of extreme sea-level events at Key West, Pensacola, and Mayport, Florida. J 426
Waterway Port Coast Ocean Eng 136:350-356. doi:10.1061/(ASCE)WW.1943- 427
5460.0000052 428

Paulo A, Ferreira E, Coelho C, Pereira L (2005) Drought class transition analysis through 429
Markov and Loglinear models, an approach to early warning. Agric Water Manage 77:59- 430
81. doi:10.1016/j.agwat.2004.09.039 431

Paulo AA, Pereira LS (2007) Prediction of SPI drought class transitions using Markov chains. 432
Water Resour Manage 21:1813-1827. doi:10.1007/s11269-006-9129-9 433

Rajagopalan B, Lall U, Tarboton DG (1996) Nonhomogeneous Markov model for daily 434
precipitation. J Hydrol Eng 1:33-40. doi:10.1061/(ASCE)1084-0699(1996)1:1(33) 435

Salas JD, Obeysekera J (2014) Revisiting the concepts of return period and risk for nonstationary 436
hydrologic extreme events. J Hydrol Eng 19:554-568. doi:10.1061/(ASCE)HE.1943- 437
5584.0000820 438

Silverman D, Dracup JA (2000) Artificial neural networks and long-range precipitation 439
prediction in California. J Appl Meteorol 39:57-66. doi:10.1175/1520- 440
0450(2000)039<0057:ANNALR>2.0.CO;2 441

Wilks DS (2011) Statistical methods in the atmospheric sciences, 3rd edn. Academic Press, 442
Waltham, MA 443

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Wood AW, Lettenmaier DP (2006) A test bed for new seasonal hydrologic forecasting 444
approaches in the western United States. Bull Am Meteorol Soc 87:1699-1712. 445
doi:10.1175/BAMS-87-12-1699 446

Yekom CC (2005) Environmental impacts (qualitative and quantitative) of water resources 447
development projects in Urmia lake basin (in Persian). 448

Yin Z-Y (1994) Reconstruction of the winter Pacific-North American teleconnection pattern 449
during 1895–1947 and its application in climatological studies. Clim Res 4:79-94. 450
doi:10.3354/cr004079 451

Zarghami M, Hassanzadeh Y, Babaeian I, Kanani R (2009) Climate change and water resources 452
vulnerability. Case study of Tabriz City. In: SENSE symposium on climate proofing cities, 453
1 Dec., Amsterdam/Volendam 454

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Fig. 1 Urmia Lake Basin in Iran

Fig. 2 Spatial Distribution of BS for Both 1D-MCM (left) and 2D-MCM (right) in Urmia Lake Basin

Fig. 3 Spatial Distribution of GDS for Both 1D-MCM (left) and 2D-MCM (right) in Urmia Lake Basin

Fig. 4 Frequency Distribution of the Observed and the Model Predicted Classes for 1D Case (only AMDI-SA)

Fig. 5 Frequency Distribution of the Observed and the Model Predicted Classes for 2D Case (including SST-M data)









