



**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<sup>1\*</sup>, J. Behmanesh<sup>1</sup>, J. Bazrafshan<sup>2</sup>, H. Rezaie<sup>1</sup>, C. De Michele<sup>3</sup>

<sup>1</sup> Department of Water Engineering, College of Agriculture, Urmia University, Urmia, Iran.

<sup>2</sup> Department of Irrigation and Reclamation Engineering, University of Tehran, Karaj, Iran.

<sup>3</sup> 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](mailto: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 ( $\pi$ ) 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  
     $[v_1. \ v_2. \ \dots \ v_s]$  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  $\pi$ , where  $\pi$  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

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

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

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

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

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

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  
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

### 2.5.3 Sharpness Score (SS) 207

66 Given two reliable forecast systems, the one producing the sharper forecasts is preferable to use. 208  
67  
68 Analogous to formulation of coefficient of variation, a simple score is introduced here to compare 209  
69  
70  
71  
72  
73  
74  
75  
76  
77  
78  
79  
80  
81  
82  
83  
84  
85  
86  
87  
88  
89  
90  
91  
92  
93  
94  
95  
96  
97  
98  
99  
100  
101  
102  
103  
104  
105  
106  
107  
108  
109  
110  
111  
112  
113  
114  
115  
116  
117  
118  
119  
120  
121  
122  
123  
124  
125  
126  
127  
128  
129  
130  
131  
132  
133  
134  
135  
136  
137  
138  
139  
140  
141  
142  
143  
144  
145  
146  
147  
148  
149  
150  
151  
152  
153  
154  
155  
156  
157  
158  
159  
160  
161  
162  
163  
164  
165  
166  
167  
168  
169  
170  
171  
172  
173  
174  
175  
176  
177  
178  
179  
180  
181  
182  
183  
184  
185  
186  
187  
188  
189  
190  
191  
192  
193  
194  
195  
196  
197  
198  
199  
200  
201  
202  
203  
204  
205  
206  
207  
208  
209  
210  
211  
212  
213  
214  
215  
216  
217  
218  
219  
220  
221  
222  
223  
224  
225  
226  
227  
228  
229  
230  
231  
232  
233  
234  
235  
236  
237  
238  
239  
240  
241  
242  
243  
244  
245  
246  
247  
248  
249  
250  
251  
252  
253  
254  
255  
256  
257  
258  
259  
260  
261  
262  
263  
264  
265  
266  
267  
268  
269  
270  
271  
272  
273  
274  
275  
276  
277  
278  
279  
280  
281  
282  
283  
284  
285  
286  
287  
288  
289  
290  
291  
292  
293  
294  
295  
296  
297  
298  
299  
300  
301  
302  
303  
304  
305  
306  
307  
308  
309  
310  
311  
312  
313  
314  
315  
316  
317  
318  
319  
320  
321  
322  
323  
324  
325  
326  
327  
328  
329  
330  
331  
332  
333  
334  
335  
336  
337  
338  
339  
340  
341  
342  
343  
344  
345  
346  
347  
348  
349  
350  
351  
352  
353  
354  
355  
356  
357  
358  
359  
360  
361  
362  
363  
364  
365  
366  
367  
368  
369  
370  
371  
372  
373  
374  
375  
376  
377  
378  
379  
380  
381  
382  
383  
384  
385  
386  
387  
388  
389  
390  
391  
392  
393  
394  
395  
396  
397  
398  
399  
400  
401  
402  
403  
404  
405  
406  
407  
408  
409  
410  
411  
412  
413  
414  
415  
416  
417  
418  
419  
420  
421  
422  
423  
424  
425  
426  
427  
428  
429  
430  
431  
432  
433  
434  
435  
436  
437  
438  
439  
440  
441  
442  
443  
444  
445  
446  
447  
448  
449  
450  
451  
452  
453  
454  
455  
456  
457  
458  
459  
460  
461  
462  
463  
464  
465  
466  
467  
468  
469  
470  
471  
472  
473  
474  
475  
476  
477  
478  
479  
480  
481  
482  
483  
484  
485  
486  
487  
488  
489  
490  
491  
492  
493  
494  
495  
496  
497  
498  
499  
500  
501  
502  
503  
504  
505  
506  
507  
508  
509  
510  
511  
512  
513  
514  
515  
516  
517  
518  
519  
520  
521  
522  
523  
524  
525  
526  
527  
528  
529  
530  
531  
532  
533  
534  
535  
536  
537  
538  
539  
540  
541  
542  
543  
544  
545  
546  
547  
548  
549  
550  
551  
552  
553  
554  
555  
556  
557  
558  
559  
560  
561  
562  
563  
564  
565  
566  
567  
568  
569  
570  
571  
572  
573  
574  
575  
576  
577  
578  
579  
580  
581  
582  
583  
584  
585  
586  
587  
588  
589  
590  
591  
592  
593  
594  
595  
596  
597  
598  
599  
600  
601  
602  
603  
604  
605  
606  
607  
608  
609  
610  
611  
612  
613  
614  
615  
616  
617  
618  
619  
620  
621  
622  
623  
624  
625  
626  
627  
628  
629  
630  
631  
632  
633  
634  
635  
636  
637  
638  
639  
640  
641  
642  
643  
644  
645  
646  
647  
648  
649  
650  
651  
652  
653  
654  
655  
656  
657  
658  
659  
660  
661  
662  
663  
664  
665  
666  
667  
668  
669  
670  
671  
672  
673  
674  
675  
676  
677  
678  
679  
680  
681  
682  
683  
684  
685  
686  
687  
688  
689  
690  
691  
692  
693  
694  
695  
696  
697  
698  
699  
700  
701  
702  
703  
704  
705  
706  
707  
708  
709  
710  
711  
712  
713  
714  
715  
716  
717  
718  
719  
720  
721  
722  
723  
724  
725  
726  
727  
728  
729  
730  
731  
732  
733  
734  
735  
736  
737  
738  
739  
740  
741  
742  
743  
744  
745  
746  
747  
748  
749  
750  
751  
752  
753  
754  
755  
756  
757  
758  
759  
760  
761  
762  
763  
764  
765  
766  
767  
768  
769  
770  
771  
772  
773  
774  
775  
776  
777  
778  
779  
780  
781  
782  
783  
784  
785  
786  
787  
788  
789  
790  
791  
792  
793  
794  
795  
796  
797  
798  
799  
800  
801  
802  
803  
804  
805  
806  
807  
808  
809  
810  
811  
812  
813  
814  
815  
816  
817  
818  
819  
820  
821  
822  
823  
824  
825  
826  
827  
828  
829  
830  
831  
832  
833  
834  
835  
836  
837  
838  
839  
840  
841  
842  
843  
844  
845  
846  
847  
848  
849  
850  
851  
852  
853  
854  
855  
856  
857  
858  
859  
860  
861  
862  
863  
864  
865  
866  
867  
868  
869  
870  
871  
872  
873  
874  
875  
876  
877  
878  
879  
880  
881  
882  
883  
884  
885  
886  
887  
888  
889  
890  
891  
892  
893  
894  
895  
896  
897  
898  
899  
900  
901  
902  
903  
904  
905  
906  
907  
908  
909  
910  
911  
912  
913  
914  
915  
916  
917  
918  
919  
920  
921  
922  
923  
924  
925  
926  
927  
928  
929  
930  
931  
932  
933  
934  
935  
936  
937  
938  
939  
940  
941  
942  
943  
944  
945  
946  
947  
948  
949  
950  
951  
952  
953  
954  
955  
956  
957  
958  
959  
960  
961  
962  
963  
964  
965  
966  
967  
968  
969  
970  
971  
972  
973  
974  
975  
976  
977  
978  
979  
980  
981  
982  
983  
984  
985  
986  
987  
988  
989  
990  
991  
992  
993  
994  
995  
996  
997  
998  
999  
1000

112 where  $\mu_{ir}$  is historical average probability of  $r$ th class at  $i$ th occasion. Values approaching 0 212  
113  
114  
115  
116  
117  
118  
119  
120  
121  
122  
123  
124  
125  
126  
127  
128  
129  
130  
131  
132  
133  
134  
135  
136  
137  
138  
139  
140  
141  
142  
143  
144  
145  
146  
147  
148  
149  
150  
151  
152  
153  
154  
155  
156  
157  
158  
159  
160  
161  
162  
163  
164  
165  
166  
167  
168  
169  
170  
171  
172  
173  
174  
175  
176  
177  
178  
179  
180  
181  
182  
183  
184  
185  
186  
187  
188  
189  
190  
191  
192  
193  
194  
195  
196  
197  
198  
199  
200  
201  
202  
203  
204  
205  
206  
207  
208  
209  
210  
211  
212  
213  
214  
215  
216  
217  
218  
219  
220  
221  
222  
223  
224  
225  
226  
227  
228  
229  
230  
231  
232  
233  
234  
235  
236  
237  
238  
239  
240  
241  
242  
243  
244  
245  
246  
247  
248  
249  
250  
251  
252  
253  
254  
255  
256  
257  
258  
259  
260  
261  
262  
263  
264  
265  
266  
267  
268  
269  
270  
271  
272  
273  
274  
275  
276  
277  
278  
279  
280  
281  
282  
283  
284  
285  
286  
287  
288  
289  
290  
291  
292  
293  
294  
295  
296  
297  
298  
299  
300  
301  
302  
303  
304  
305  
306  
307  
308  
309  
310  
311  
312  
313  
314  
315  
316  
317  
318  
319  
320  
321  
322  
323  
324  
325  
326  
327  
328  
329  
330  
331  
332  
333  
334  
335  
336  
337  
338  
339  
340  
341  
342  
343  
344  
345  
346  
347  
348  
349  
350  
351  
352  
353  
354  
355  
356  
357  
358  
359  
360  
361  
362  
363  
364  
365  
366  
367  
368  
369  
370  
371  
372  
373  
374  
375  
376  
377  
378  
379  
380  
381  
382  
383  
384  
385  
386  
387  
388  
389  
390  
391  
392  
393  
394  
395  
396  
397  
398  
399  
400  
401  
402  
403  
404  
405  
406  
407  
408  
409  
410  
411  
412  
413  
414  
415  
416  
417  
418  
419  
420  
421  
422  
423  
424  
425  
426  
427  
428  
429  
430  
431  
432  
433  
434  
435  
436  
437  
438  
439  
440  
441  
442  
443  
444  
445  
446  
447  
448  
449  
450  
451  
452  
453  
454  
455  
456  
457  
458  
459  
460  
461  
462  
463  
464  
465  
466  
467  
468  
469  
470  
471  
472  
473  
474  
475  
476  
477  
478  
479  
480  
481  
482  
483  
484  
485  
486  
487  
488  
489  
490  
491  
492  
493  
494  
495  
496  
497  
498  
499  
500  
501  
502  
503  
504  
505  
506  
507  
508  
509  
510  
511  
512  
513  
514  
515  
516  
517  
518  
519  
520  
521  
522  
523  
524  
525  
526  
527  
528  
529  
530  
531  
532  
533  
534  
535  
536  
537  
538  
539  
540  
541  
542  
543  
544  
545  
546  
547  
548  
549  
550  
551  
552  
553  
554  
555  
556  
557  
558  
559  
560  
561  
562  
563  
564  
565  
566  
567  
568  
569  
570  
571  
572  
573  
574  
575  
576  
577  
578  
579  
580  
581  
582  
583  
584  
585  
586  
587  
588  
589  
590  
591  
592  
593  
594  
595  
596  
597  
598  
599  
600  
601  
602  
603  
604  
605  
606  
607  
608  
609  
610  
611  
612  
613  
614  
615  
616  
617  
618  
619  
620  
621  
622  
623  
624  
625  
626  
627  
628  
629  
630  
631  
632  
633  
634  
635  
636  
637  
638  
639  
640  
641  
642  
643  
644  
645  
646  
647  
648  
649  
650  
651  
652  
653  
654  
655  
656  
657  
658  
659  
660  
661  
662  
663  
664  
665  
666  
667  
668  
669  
670  
671  
672  
673  
674  
675  
676  
677  
678  
679  
680  
681  
682  
683  
684  
685  
686  
687  
688  
689  
690  
691  
692  
693  
694  
695  
696  
697  
698  
699  
700  
701  
702  
703  
704  
705  
706  
707  
708  
709  
710  
711  
712  
713  
714  
715  
716  
717  
718  
719  
720  
721  
722  
723  
724  
725  
726  
727  
728  
729  
730  
731  
732  
733  
734  
735  
736  
737  
738  
739  
740  
741  
742  
743  
744  
745  
746  
747  
748  
749  
750  
751  
752  
753  
754  
755  
756  
757  
758  
759  
760  
761  
762  
763  
764  
765  
766  
767  
768  
769  
770  
771  
772  
773  
774  
775  
776  
777  
778  
779  
780  
781  
782  
783  
784  
785  
786  
787  
788  
789  
790  
791  
792  
793  
794  
795  
796  
797  
798  
799  
800  
801  
802  
803  
804  
805  
806  
807  
808  
809  
810  
811  
812  
813  
814  
815  
816  
817  
818  
819  
820  
821  
822  
823  
824  
825  
826  
827  
828  
829  
830  
831  
832  
833  
834  
835  
836  
837  
838  
839  
840  
841  
842  
843  
844  
845  
846  
847  
848  
849  
850  
851  
852  
853  
854  
855  
856  
857  
858  
859  
860  
861  
862  
863  
864  
865  
866  
867  
868  
869  
870  
871  
872  
873  
874  
875  
876  
877  
878  
879  
880  
881  
882  
883  
884  
885  
886  
887  
888  
889  
890  
891  
892  
893  
894  
895  
896  
897  
898  
899  
900  
901  
902  
903  
904  
905  
906  
907  
908  
909  
910  
911  
912  
913  
914  
915  
916  
917  
918  
919  
920  
921  
922  
923  
924  
925  
926  
927  
928  
929  
930  
931  
932  
933  
934  
935  
936  
937  
938  
939  
940  
941  
942  
943  
944  
945  
946  
947  
948  
949  
950  
951  
952  
953  
954  
955  
956  
957  
958  
959  
960  
961  
962  
963  
964  
965  
966  
967  
968  
969  
970  
971  
972  
973  
974  
975  
976  
977  
978  
979  
980  
981  
982  
983  
984  
985  
986  
987  
988  
989  
990  
991  
992  
993  
994  
995  
996  
997  
998  
999  
1000

1  
2  
3  
4 For all above scores, since nonzero values of predictions in both 1D and 2D cases are restricted to 215  
5  
6 number of drought classes, i.e. 4,  $S$  is assumed to be 4. 216  
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  $46^{\circ}$  longitude in 218  
11  
12 northwestern Iran (Fig. 1). The catchment area is shared between the three provinces West 219  
13  
14 Azerbaijan ( $21500 \text{ km}^2$ ), East Azerbaijan ( $19000 \text{ km}^2$ ) and Kurdistan ( $5000 \text{ km}^2$ ) (Yekom 220  
15  
16 Consulting Engineer, 2005). The lake basin, as a unique socio-ecological region, is facing extreme 221  
17  
18 water shortages due to poor water governance and climate change (Alipour, 2006; Zarghami et al., 222  
19  
20 2009). Climate in the Urmia Lake basin is harsh and continental, affected mainly by the mountains 223  
21  
22 surrounding the lake (Ghaheri et al., 1999). The annual average precipitation is about 500 mm. 224  
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  
32 precipitation data for the basin is acquired from daily  $0.25^{\circ} \times 0.25^{\circ}$  high resolution PERSIANN- 227  
33  
34 CDR (Ashouri et al., 2015) for the period 1983–2010. The accuracy of PERSIANN precipitation 228  
35  
36 data set family for Iran and Urmia Lake basin is demonstrated in some previous publications 229  
37  
38 (Moazami et al., 2013; Bodagh-Jamli, 2015; Ghajarnia et al., 2015; Katiraie-Boroujerdy et al., 230  
39  
40 2013). 231  
41  
42  
43  
44  
45

46 In this paper, soil moisture is derived using ERA-Interim-Land surface fluxes and near-surface 232  
47  
48 meteorology to force the land surface model uses HTESSEL (Balsamo et al., 2015) for the period 233  
49  
50 of 1983–2010. It is considered that most of the roots vegetation distribution is in the first 3 layers 234  
51  
52 of soil in HTESSEL model (0-7cm, 7-28cm and 28-100cm). The 3 upper layers water content data 235  
53  
54 weighting averaged to have single value for each  $0.25^{\circ} \times 0.25^{\circ}$  pixel. Both mentioned data sets are 236  
55  
56 global; however, the data of Urmia Lake basin are extracted and handled further, only. To consider 237  
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	<b>3 Results</b>	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	To measure the ability of the forecasting system to detect droughts and discriminate between	252
39		
40	different classes of droughts, Brier Score (BS) and Generalized Discrimination Score (GDS) are	253
41		
42	evaluated for all data points in Urmia Lake basin. Furthermore, Sharpness Score (SS) adopted to	254
43		
44	assess the uncertainty of the model predictions are reported. To show the improvement contributed	255
45		
46	by the proposed model, average values of these scores for both case of all grid points for both 2D	256
47		
48	(including SST-M data) and 1D model (only AMDI-SA) are reported in Table 2. The spatial	257
49		
50	integration has the advantage of increasing the sample size used to build the scores.	258
51		
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

10  
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  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65  
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 Diagonal tendency in transition probability matrices for both 1D and 2D models reflects the 298  
32  
33 persistence of recent drought categories, more highlighted for classes with extreme drought 299  
34  
35 severity: when the actual state is D2 the more probable state for a month ahead is the present state, 300  
36  
37 i.e. no changes of state are predictable. 301  
38  
39  
40  
41  
42  
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	<b>Acknowledgments</b> 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	<b>Conflict of Interest</b>	324
42		
43	The authors declare that they have no conflict of interest.	325
44		
45		
46		
47		
48		
49		
50		
51		
52		
53	<b>References</b>	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

Batani, 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/s11269-014-0533-2 347-349

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.2013.166 350-352

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:10.1175/2009JAMC2325.1 355-357

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;2 358-360

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

Katirae-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)









