How do drought periods boost rural unemployment? Empirical evidence of Iran

Abstract

Drought periods are one of the major challenges in many countries that have affected various economic and social factors. The impact of drought on rural unemployment is one of the most important research issues that have not been well studied. In this study, using time series data and econometric methods, the effect of drought on rural unemployment in Iran was investigated. The results showed that drought periods have affected agricultural and non-agricultural GDP. Between these two variables, non-agricultural GDP growth significantly reduces rural unemployment. Therefore, in addition to the effects of drought on other components affecting rural unemployment, such as the quality of rural living and rural working environments, drought also increases rural unemployment by reducing the growth potential of the Iranian agricultural sector. Rural credits and the ratio of rural incomes to rural expenditures were also identified as other important factors affecting rural unemployment. Finally, targeting rural credits to increase non-agricultural occupations consistent with rural characteristics was presented as the most important policy recommendation of the study.

Keywords: Drought Periods; Rural Unemployment; Econometric Analysis; Iran

JEL Classification: J21; O18; Q54

1. Introduction

The impact of drought and climate change on agricultural activities is somewhat known. With the occurrence of drought caused by climate change, agricultural production is directly affected; in the sense that with the creation of drought, agricultural production yields are affected by stress. As a result, climate stress can potentially cause fluctuations in crop yields and jeopardize farmers' production. This phenomenon has been proven by many experimental studies; Cohen et al. (2020) reported that drought and heat stress combination significantly impacts yield by decreasing harvest index, shortening the life cycle of crops, and altering seed number, size, and composition. Abdelmalek and Nouiri (2020) in another study concluded that drought has influenced significantly main crop productions (cereals, olives, and citrus) in Tunisia. Also, we can refer to the study of Hameed et al. (2020) who showed agricultural production decreased in the Middle East after the 2009 drought. In addition, other studies, including Dutta (2018); Vrieling et al. (2016); Yu et al., (2014), and Yanling and Yanxia (2012) have shown that drought has affected agricultural products. Therefore, it can be inferred that the direct and significant effect of drought on agriculture is related to production reduced. This effect could potentially lead to a decline in agricultural incomes. In support of this claim, Quiroga and Suarez (2016) have shown that drought can worsen the distribution of agricultural incomes. This means that the drought limits the income of some farmers. However, it can be argued that reducing the supply of agricultural products due to drought by increasing prices reduces this effect for some others. Studies by Schaub and Finger (2020) and Quiggin (2007) are among the studies that have reported rising price effects of drought. In addition, Noack et al. (2019) in the case of developing countries showed that drought during the growing season reduces crop incomes but that these negative shocks are partly offset by increased incomes from forest extraction. They consider natural biodiversity to be an effective factor. Therefore, based on previous studies, the hypothesis that drought will definitely reduce agricultural incomes cannot be generally confirmed. On the other, the impact of drought on non-agricultural incomes has not been well studied and there is not well-founded evidence. Accordingly, a greater ambiguous issue is what will be the impact of the drought on rural employment; especially, if the drought is long and turns into drought periods. In other words, given the uncertainty in the conclusion about the impact of drought on rural incomes, can it be said that there is also uncertainty about the impact of drought on rural employment? In fact, our question is how drought affects rural employment in a situation where a definitive analysis of the impact of drought on rural income is unclear. To the best of our knowledge, no definitive and reasoned answer to this question has been provided so far. One possible way to answer this question is to prove that drought affects rural unemployment by affecting rural GDP; GDP whose changes per se can have a positive or negative overflow on rural employment. In fact, the hypothesis is that rural GDP is affected by drought and then will ultimately increase rural unemployment. Therefore, if this hypothesis is correct, the mentioned ambiguities will be largely removed. In this regard, the supplementary hypothesis is that drought can indirectly affect rural occupations, especially agricultural activities. In other words, drought affects rural unemployment by affecting work environments and rural life needs. Adequate and quality agricultural and drinking water is one of the most important requirements for work and life in rural areas, which is seriously dependent on drought periods. Naturally, if the drought is longer, the effects will be deeper. However, the hypothesis must be confirmed. For this purpose, it is first necessary to study the factors that explain rural unemployment. Then, the drought index can be considered as another main factor in explaining rural unemployment status. In the studies conducted, Dutta (2019) introduced agricultural growth as an important factor in improving rural employment in Gujarat and West Bengal and emphasizes agricultural development to reduce rural unemployment. Helmy (2019) identified income as the main cause of unemployment for rural women in Egypt. Dănăcică (2013) proved the existence of an urban-rural gap regarding unemployment spells and exit destinations in Romania. Adanacioglu et al. (2012) investigated the roles of GNP, and rates of growth in the agricultural, industrial, and service sectors as the most factors influencing rural unemployment in Turkey. Blinova (2002) reported that in rural regions the development of non-agricultural employment produces positive effects on the regional labor markets' behavior in Russian regions. So, based on reviewing these studies and other related researches including Du Toit et al. (2018); Nachiappan et al. (2018); Kamran et al. (2014) it can be concluded that economic factors such as the growth rate of agricultural and non-agricultural sectors and the amount of rural income are significant factors in explaining rural unemployment. Therefore, to test the proposed hypothesis, the drought index can be examined simultaneously with economic indicators to interpret rural unemployment. To this end, the coordinates of rural unemployment and drought in Iran have been investigated. Because Iran has the characteristics of rural unemployment and drought; the share of 17% for rural unemployed in the total number of unemployed in the country and the experience of long drought periods are of these characteristics. As an output, it is expected that the results of this study would be able to provide documentary and reasoned evidence on the subject of research and to expand the research literature.

2. Methods

2.1 Drought measurement index

To provide a definition of the concept of drought, we can refer to the points of Hisdal and Tallaksen (2000); in the general definition of drought, they point out that a general definition based on precipitation amounts and duration is: "drought is a period of more than some particular number of days with precipitation less than some specified small amount. The chosen thresholds are generally site and/or region-specific, as well as depending on the problem under study. Care must be taken when definitions like this are applied to characterize and compare drought in different regions”. Therefore, if the drought is generally considered as a decrease in rainfall, according to the subject and research method, different indicators can be used to quantify and measure it. It is important to define what is meant by drought indicators. Indicators are variables or parameters used to describe drought conditions. Examples include precipitation, temperature, streamflow, groundwater and reservoir levels, soil moisture, and snowpack (WMO, 2016). According to the research literature, standardized precipitation index (SPI), precipitation variability index (PVI) and De Martonne aridity index (I_{DM}) are of the most important and applied indicators for drought intensity and drought periods in a region. The first two calculate the drought index based on the amount of rainfall and the average and fluctuations of it. The main advantage of the De Martonne aridity index over these indices is that the temperature is also taken into account in calculating the drought index. Also, in a situation where a region has experienced several drought periods, the use of the De Martonne index would show a more accurate condition of that region; because the De Martonne index ideally identifies the climatic class of the region. In addition, since the first two indicators include positive and negative intervals of numbers, they have more limited application in econometric evaluations and data generation (such as logarithmic generation). Therefore, preparing a time series of De Martonne index can indicate changes in drought periods in each region. Therefore, the De Martonne aridity index seems to be a good option to examine the relationship between drought periods and rural unemployment in Iran. I_{DM} was calculated based on the following equation (De Martonne, 1926):

$$I_{DM} = P/(T + 10) \quad (1)$$

where:

P is the annual precipitation (mm) and T is the annual mean air temperature ($°C$). Climate classification according to the De Martonne drought index is shown in Table 1 (Emadodin et al. 2019). It should be notable that drought typically affects various economic and social variables with a time lag. Therefore, rainfall and temperature statistics in this study are considered to be related to water years that have time lags within them[1].

Table 1. Climate classification according to De Martonne drought index (I_{DM})

Climate Class	I_{DM} Values
Arid	$I_{DM} < 10$
Semi-arid	$10 \leq I_{DM} < 20$
Mediterranean	$20 \leq I_{DM} < 24$
Semi-humid	$24 \leq I_{DM} < 28$
Humid	$28 \leq I_{DM} < 35$
Very humid	$35 \leq I_{DM} < 55$
Extremely humid	$I_{DM} \geq 55$

Finally, using the information in Table 1 and the climatic data of the World Bank, the climatic situation of Iran in different time periods has been realized.

2.2 Rural unemployment index

The rural unemployment rate defines rural unemployed people as those who are willing and available to work. To calculate the rural unemployment rate, the number of rural unemployed people is divided by the number of rural people in the labor force, which consists of all rural employed and unemployed people. The rural unemployment rate is calculated as a percentage in the following order (U.S. Bureau of Labor Statistics, 2020):

[1] . The water year in Iran starts in late September every year and continues until the late September of the following year. At the same time, the Iranian calendar year begins in late March each year and ends in late March of the following year. Accordingly, a significant portion of agricultural production in each calendar year depends on the precipitation and temperature of the previous year. In fact, every water year in Iran elapses between two calendar years. Therefore, in this study, the variables of precipitation and temperature of water years with an internal lag are placed next to other variables. It should be noted that the number of A.D. years in this study is equivalent to the sum of the number of solar years plus 621. For example, 2018 is considered the equivalent of the solar year of 1397.

$$U = \frac{Unemployed}{Labor\ Force} \times 100 \qquad (2)$$

The Statistics Center of Iran has used Equation 2 to estimate the rate of rural unemployment in Iran. Therefore, in this study, official Iranian data have been used to investigate rural unemployment.

2.3 Model Specification

The dependent and independent variables used in this study are presented in the form of Equation (3):

$$U = f(AGDP, NAGDP, De, IE, RC) \qquad (3)$$

where U refers to annual rural unemployment in Iran and $AGDP, NAGDP, De, IE$, and AC also refer to the GDP of the agricultural sector, GDP of the non-agricultural sector (industry and services), De Martonne index, the ratio of annual total income to the total expenditure of rural households and rural credits in Iran, respectively. In addition to the De Martonne index, which is a proxy for the drought variable, we can point to the changes in the GDP variables of the agricultural and non-agricultural sectors, which could potentially affect rural unemployment in Iran. This is because, according to economic theories, it is expected that growth in production and incomes of economic sectors that allow rural people to work, will create a derived demand for labor and affect rural unemployment. Also, the ratio of total income to the total annual cost of rural households is another variable that seems to play a significant role in motivating rural employment; because higher rates seem to have less of an impact on villagers' seriousness about doing work. In addition, rural credit is also an important factor that affects the rate of rural unemployment by solving or reducing the problems of villagers. Finally, after investigating the characteristics of appropriate specification and econometric tests, Log-Log (logarithmic-logarithmic) specification was selected as the best functional form for estimating model coefficients (Equation 4).

$$Log(U) = \alpha_0 + \alpha_1 Log(AGDP) + \alpha_2 Log(NAGDP) + \alpha_3 Log(De) + \alpha_4 Log(IE)) + \alpha_5 Log(RC) \qquad (4)$$

2.4 Econometric modeling

This research applies ARDL analysis to estimate the model coefficients and investigate the long and short-run effects of variables. Pesaran et al. (2001) developed ARDL. Other researchers used different cointegration models in literature for different situations: Engle and Granger (1987) cointegration method is the first method that is applicable for two variables in $I(1)$ order. Johansen and Juselius (1990) is the second method of cointegration that is used for large size of data and all series have the same order of integration. These two methods have some limitations that all series should be integrated at the same level. The researcher urged to introduce a novel technique that treats the variables with different series of $I(0)$ and $I(1)$. At last Pesaran et al. (2001) developed Autoregressive Distributed Lag (ARDL), a cointegration model, to solve the issue. ARDL method is applied to deal with the variables having stationary of the series mixture of $I(0)$ and $I(1)$. ARDL model is superior to the other cointegration model and provides reliable results for a small sample size (Khan et al. 2019). Following is the modeling of research variables in ARDL form (Equation 5).

$$\Delta lU_t = \beta_0 + \beta_1 \sum_{i=1}^{P} \Delta lU_{t-1} + \beta_2 \sum_{i=1}^{P} lAGDP_{t-1} + \beta_3 \sum_{i=1}^{P} lNAGDP_{t-1} + \beta_4 \sum_{i=1}^{P} \Delta lDe_{t-1} + \beta_5 \sum_{i=1}^{P} \Delta lIE_{t-1} + \beta_6 \sum_{i=1}^{P} \Delta lRC_{t-1} + \lambda_1 lU_{t-i} + \lambda_2 lAGDP_{t-i} + \lambda_3 lNAGDP_{t-i} + \lambda_4 lDe_{t-i} + \lambda_5 lIE_{t-i} + \lambda_6 lRC_{t-i} + \varepsilon_t \quad (5)$$

The dynamics for error correction in the short run are represented by the terms with summation signs while the long-run relation is shown in the next half of the equation represented by λ. To investigate the long-run and short-run co-integration among the variables, Shin et al. (2014) proposed two operational tests, which include the bounds testing procedure of Pesaran et al. (2001) through a modified F-statistic and the t-statistic proposed by Banerjee et al. (1998). In this study, the approach of Banerjee et al. (1998) was used to prove the long-run relationship between the variables. After selection of the lag length and model estimation, if there exists the cointegration relationship so the short run and the long run ARDL model equations are the following (Khan et al. 2019).

$$\Delta lU_t = \beta_0 + \beta_1 \sum_{i=1}^{P} \Delta lU_{t-i} + \beta_2 \sum_{i=1}^{P} lAGDP_{t-i} + \beta_3 \sum_{i=1}^{P} lNAGDP_{t-i} + \beta_4 \sum_{i=1}^{P} \Delta lDe_{t-i} + \beta_5 \sum_{i=1}^{P} \Delta lIE_{t-i} + \beta_6 \sum_{i=1}^{P} \Delta lRC_{t-i} + \theta_1 ECT_{t-1} + \varepsilon_t \quad (6)$$

In the above equation, the error correction term (ECT_{t-1}) represents the long-run equilibrium speed of adjustment. The data period was from 1986 to 2018. Rural unemployment, cost, and income statistics were obtained through the database of the Statistics Center of Iran. Agricultural and non-agricultural GDP and rural credits were collected through the Central Bank of Iran and rainfall and temperature data were collected through the historical data of the World Bank and

National Center for drought and crisis management of Iran respectively. Finally, Eviews 9 software was used to make estimates.

3. Results and discussion

3.1 Drought situation of Iran

The available statistics on the situation of climate variability in Iran show that the amount of average rainfall has been decreasing over the past forty years. In this regard, Figure 1 is depicted, which clearly shows this issue. According to Figure 1, average rainfall fluctuations in Iran have been numerous during the last four decades. However, the trend of rainfall changes has been decreasing. Therefore, it can be concluded that the passage of time has been associated with a negative impact on rainfall in Iran. This warns of the challenge of climate change in Iran.

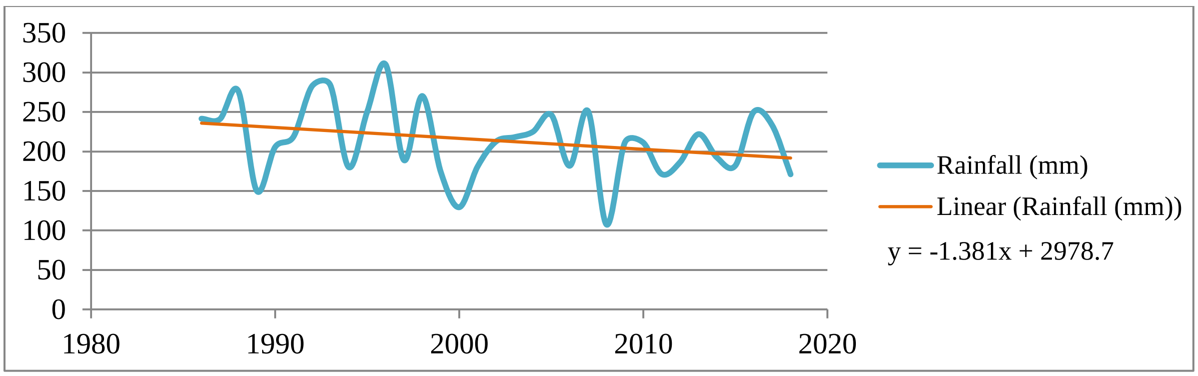

Figure 1. Time trend of average rainfall variability in Iran

(Source: Climate data of the World Bank)

Another component that can explain the temporal trend of Iran's climate is the country's temperature changes. In this regard, Figure 2 shows the long-run trend of Iran's average temperature. Figure 2 shows that average temperature fluctuations in Iran have been numerous during the last four decades. However, the trend of temperature changes has been increasing. Therefore, it seems that despite the rain, the passage of time in Iran has been accompanied by an increase in temperature.

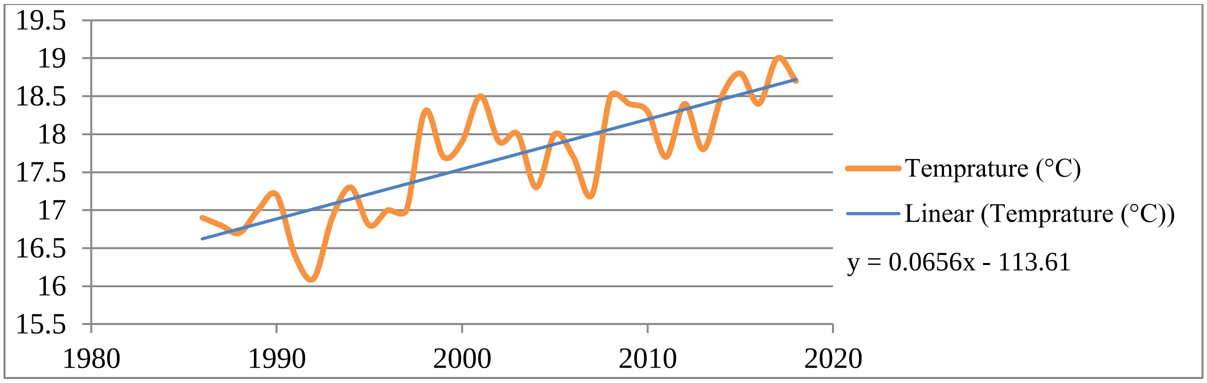

Figure 2. Time trend of average temperature variability in Iran
(Source: National Center for Drought and Crisis Management of Iran)

Considering rainfall and temperature variability, the De Martonne index could depict the drought situation of Iran in Figure 3. As can be seen, Iran has fluctuated in the arid and semi-arid regions in terms of drought in the long run. Given that Iran is an arid and/or semi-arid country, the use of the De Martonne index with more objectivity indicates the drought periods in Iran. In proportion to the increase in temperature and decrease in rainfall, the severity of drought in Iran has gradually increased and has taken a stronger trend. As the figure shows, the Iranian climate has suffered from several drought periods over time. Therefore, it seems that the possible continuation of the drought periods in Iran and its increase in severity can have significant consequences on various sectors, especially for agriculture. Naturally, longer drought periods can have far more consequences for Iran's rural areas. The challenge of rural unemployment is one of these consequences.

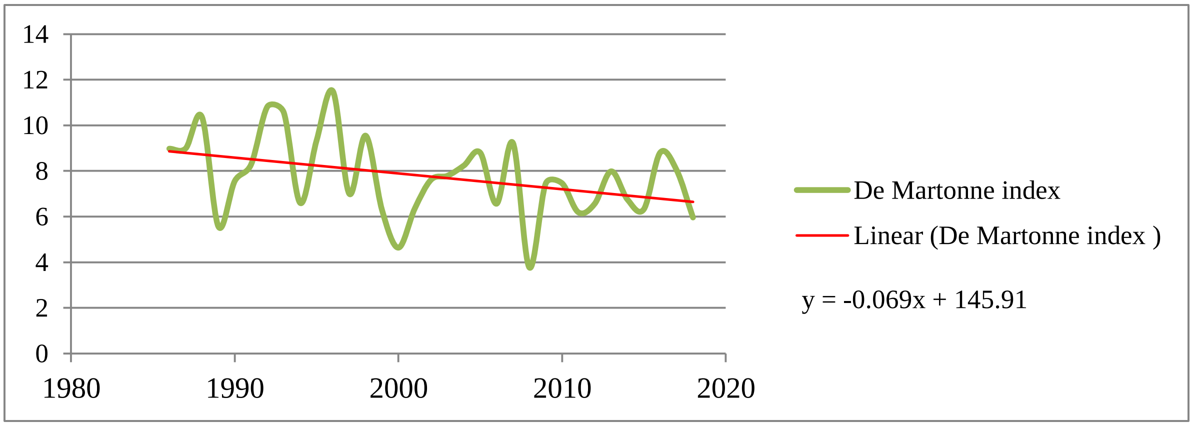

Figure 3. Time trend of drought situation of Iran

3.2 Rural unemployment trend in Iran

Official Iranian statistics on the rural unemployment trend shown in Figure 4 indicate that in the last four decades, the general trend of this variable in the country has been declining. However, rural unemployment has risen sharply for some years. Also, in the last two decades, the trend of rural unemployment in Iran has become relatively rising and stable. Therefore, stabilizing or increasing this trend, in conjunction with or affected by the gradual drought trend, can make the rural and agricultural development process in Iran more challenging. This situation can become more complicated when the impact of other variables that affect unemployment is also considered; variables that can increase rural unemployment in the same direction as drought, or reduce rural unemployment in the opposite sense. Accordingly, the analysis of the effectiveness of the variables in this study is more significant.

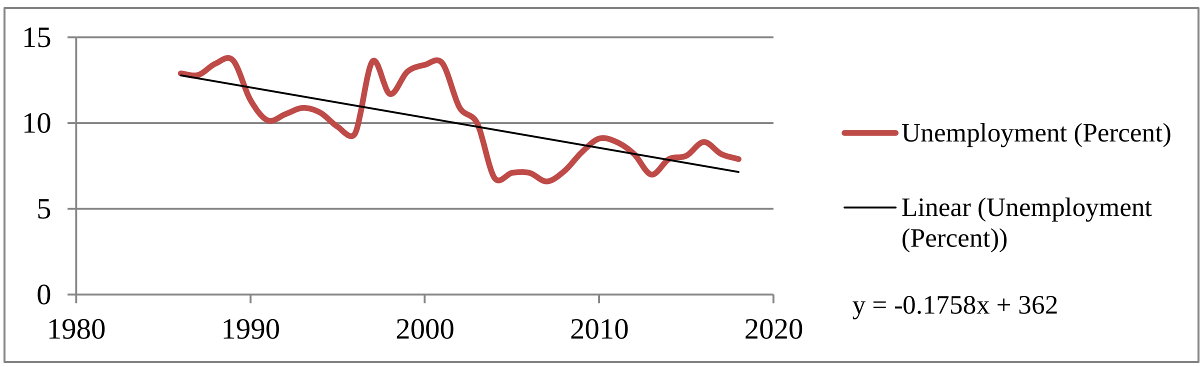

Figure 4. Time trend of rural unemployment variability in Iran
(Source: Statistical Center of Iran)

3.3 Econometric assessments

To check the permissibility of using the ARDL method to estimate the parameters, an Augmented Dickey-Fuller (ADF) unit root test was used. All the time series variables stationarity are checked at the level and at the first difference with the ADF test. The results of the ADF test are reported in Table 2. Results indicate that the De Martonne index is stationary at the level when the equation test includes only intercept. Also, agricultural GDP, non-agricultural GDP, rural credits, and De Martonne index are stationary when the equation includes trend and intercept.

Table 2. ADF Unit Root Test

Variables	Intercept			
	Level		First Difference	
	t-Statistic	Prob.	t-Statistic	Prob.
lU	-1.70	0.41	-5.62	0.0001
$lAGDP$	-1.05	0.72	-6.42	0.0000
$lNAGDP$	-0.40	0.89	-3.66	0.009
lDe	-5.20	0.0002	-6.68	0.0000
lIE	1.43	0.99	-5.39	0.0002
lRC	0.34	0.97	-3.82	0.008
Variables	Trend & Intercept			
	Level		First Difference	
	t-Statistic	Prob.	t-Statistic	Prob.
lU	-2.30	0.41	-5.53	0.0005
$lAGDP$	-2.77	0.21	-6.34	0.0001
$lNAGDP$	-4.80	0.003	-3.62	0.04
lDe	-5.70	0.0003	-6.59	0.0000
lIE	-4.94	0.002	-5.78	0.0005
lRC	-4.44	0.007	-3.77	0.03

Thus, it follows that the order of integration is a mixture of $I(0)$ and $I(1)$, making it valid to use Autoregressive Distributed Lag (ARDL) approach to perform analyzes. The result of the dynamic estimation of the ARDL model is presented in Table 3. The results show that the selected model has sufficient validity. Based on the R-squared statistic, selected variables explain about 91% of the changes in rural unemployment in Iran. Ramsey RESET Test also shows that the functional form chosen to explain the relationship between the variables has acceptable validity. In addition, the statistic of Banerjee, Dolado, and Master Test for long-run relationship (t_B) in comparison to its critical value (-4.19) shows that the model variables have co-integration in the long run. Other reported statistics also confirm the validity of the model from the perspective of econometric tests.

Before assessing the impact of the De Martonne on rural unemployment, it is necessary to analyze the impact of other variables. The dynamic model shows that the rural unemployment variable with a lag has a positive effect on rural unemployment. In economic terms, the dynamic pattern suggests that the occurrence of rural unemployment in one year strengthens rural unemployment in the following year. In fact, the occurrence of unemployment in one period in the Iranian rural areas will intensify unemployment in the next year. In this regard, it seems that the occurrence of unemployment in each period reduces the motivation of job seekers in the following year to find rural jobs and increases unemployment in the next period. Therefore, it can be concluded that the increase in rural unemployment each year has negative propaganda effects on job finding in other years. In other words, reducing rural unemployment at any given time and in any way strengthens the possibility of work found in other years. An important variable whose impact on rural unemployment has been assessed is agricultural GDP. Because at first glance, it seems that the growth of agricultural GDP creates a derived demand for the employment of rural labor for agricultural activities. In fact, economic theories support this hypothesis. But what can be seen in Table 3 is that however, the growth of agricultural GDP is in line with the decline in rural unemployment, the impact of increasing agricultural GDP on rural unemployment is not statistically significant. According to available statistics, in the period 1986 to 2018, the average annual growth of agricultural GDP at fixed prices was about 3%. Therefore, it is concluded that this annual growth of agricultural GDP has not been sufficient to meet the derived demand of annual rural employment. However, according to the results in Table 3, the increase in GDP of the non-agricultural sector has a significant effect on reducing rural unemployment. According to available statistics, in the mentioned period, the average annual GDP growth of the non-agricultural sector at fixed prices was about 4%. Thus, although the annual GDP growth of the non-agricultural sector was only one percent higher than the GDP growth of agriculture, but in comparison has caused a significant reduction in rural unemployment. Given that non-agricultural GDP is almost 10 times higher than agricultural GDP, this difference seems to be justified.

The non-agricultural sector includes various occupations in industry and services. But naturally, sectors that do not involve complex job activities will be able to employ rural laborers. Because the majority of the rural unemployed do not have sophisticated industrial skills, it seems more likely that they will be employed in agricultural-related industrial jobs. Among the industries that are dependent on agriculture in the areas close to the villages in Iran, we can mention the processing industries of agricultural products. These industries cover a wide range of occupations from sorting and packaging of agricultural raw materials to the production of industrial foods. Also, various jobs in the field of handicrafts and traditional carpet weaving are other jobs in the non-agricultural sector that stimulate the demand for rural labor in Iran. In relation to the aims of rural employment in Iran, one of the supportive policies includes the payment of rural credits to the villagers. As can be seen in Table 3, the increase in rural credits in

Iran during the mentioned period has significantly reduced rural unemployment. These credits generally include the payment of facilities for various agricultural and non-agricultural activities in rural areas. Among the agricultural activities targeted by this policy are crop production, horticulture, animal husbandry, and fisheries. Non-agricultural occupations also included agricultural-related industries, handicrafts, and carpet weaving. According to the latest disaggregated statistics, the share of rural credits for agricultural occupations has decreased from about 70% in 2001 to about 46% in 2018. On the contrary, the share of rural credits for non-agricultural occupations in this period has increased from about 11% to about 41%. Therefore, it seems that one of the major factors in the difference between the impact of increasing agricultural and non-agricultural GDP is related to the impact of credit policies to support rural employment. In fact, it can be accepted that the most impact of rural credits on rural unemployment has occurred through the increase of agricultural and non-agricultural GDP. However, part of the credits (average of 12% per year) is spent on other items such as providing and equipping rural homes. The next variable that describes the changes in rural unemployment is the ratio of rural incomes to rural expenditures. The results in Table 3 show that increasing this ratio and the ability to cover rural expenditures by rural incomes reduces the rate of rural unemployment in subsequent years.

Table 3. Dynamic estimation of ARDL model

Variables	Coefficient	Std. Error	t-Statistic	Prob.
$lU\ (-1)$	0.39	0.12	3.33	0.003
$lAGDP$	-0.01	0.26	-0.03	0.98
$lNAGDP$	-1.44	0.35	-4.07	0.001
lRC	-0.66	0.24	-2.79	0.01
$lRC\ (-1)$	-0.58	0.26	-2.23	0.04
lIE	0.90	0.39	2.31	0.03
$lIE\ (-1)$	-1.08	0.40	-2.68	0.01
$lIE\ (-2)$	-1.17	0.39	-3.01	0.01
lDe	-0.24	0.08	-3.04	0.01
$Intercept$	12.77	2.51	5.10	0.0001
$Trend$	0.13	0.03	4.38	0.0003
R-squared: 0.91	F-statistic: 19.99	D-W stat: 2.58	Sch Criterion: - 2.96	
Ramsey RESET Test	*Heteroskedasticity Test*	*Serial Correlation Test*	*Lon- run Co-Integration Test*	
F-statistic: 0.02 Prob: 0.89	F-statistic: 0.64 Prob: 0.77	F-statistic: 1.72 Prob: 0.21	t_B: -5.06	

Finally, according to the interpretation of the results obtained on the impact of other variables on rural unemployment, it is more possible to interpret the impact of drought periods on rural unemployment. According to Table 3, it can be seen that increasing the De Martonne index reduces rural unemployment. This means that reducing drought periods (leaving the arid and semi-arid climate) will reduce rural unemployment. To analyze how drought affects rural unemployment, it is necessary to mention the channel of the impact of this variable. As Todaro and Smith (2009) pointed out, one of the common characteristics of many developing countries, including Iran is that they are located near the equator region and, consequently, some agricultural products and laborers of these countries are exposed to warm weather. According to them, high air temperatures reduce production levels and affect the health and productivity of labor in these countries. Therefore, to get an idea of this theory, in this study, the hypothesis that drought periods affect the variables of agricultural GDP, as well as non-agricultural GDP and the share of rural income to rural expenditures, has been investigated using the Granger causality test. In fact, if, according to economic theories, the GDP of agricultural and non-agricultural sectors (economic sectors) is generally a function of capital and labor, then the drought component can affect both of these factors. The Granger causality test can be an effective tool in this regard. The results of this test are reported in Table (4). According to Table 4, the point that can be deduced is that between the three variables of agricultural GDP, non-agricultural GDP, and the ratio of rural incomes to rural expenditures, drought periods have a causal relationship with agricultural GDP and non-agricultural GDP. Considering that the effect of time lags has been considered in calculating the drought index, the null hypothesis of the Granger causality test for agricultural GDP with one lag has been investigated. In comparison, the null hypothesis of the Granger causality test for non-agricultural GDP is evaluated up to three lags. This is because, first of all, water consumption in the non-agricultural sector is much lower than in agriculture. In addition, the existence of water recycling systems in the non-agricultural sector has increased the resilience of this sector in the face of drought periods compared to the agricultural sector. Therefore, the impact of drought periods on the GDP of the non-agricultural sector occurs with more time lags. Several lags were also evaluated in the case of the rate of rural incomes to rural expenditures, but no significant difference was observed. It should be noted that the negative impact of the drought periods is not limited to these cases and includes other important issues such as the quality of rural life. One of the most important issues in this regard is the quality of drinking water, which is a vital consumable for the villagers to maintain their permanence in the village and their rural employment; because drought periods can limit and affect the quantity and quality of rural drinking water. Under this situation, the significant increase in the cost of rural drinking water supply in Iran is one of the most important problems reported by various researchers, including Barghi and Memar Emameih (2016).

Table 4. Pairwise Granger Causality Tests

Null Hypothesis:	F-Statistic	Prob.
lDe does not Granger Cause $lAGDP$	4.68	0.03
lDe does not Granger Cause $lNAGDP$	2.75	0.06
lDe does not Granger Cause lIE	0.01	0.89

Accordingly, drought periods do not seem to have a causal relationship with changes in the ratio of rural incomes to rural expenditures. Therefore, it can be concluded that drought periods potentially play a wider role in the issue of rural unemployment by affecting agricultural and non-agricultural GDP. It seems that the continuation of drought periods has not been ineffective in the insignificant impact of agricultural GDP growth on rural unemployment. In other words, it seems that the impact of drought periods on agricultural GDP has caused the growth of agricultural GDP to have no significant effect on reducing rural unemployment. Several studies including Ghaffari Esmaeili et al. (2018) and Panahi and Esmaeel Darjani (2020) have already proven the negative impact of drought on the growth of Iran's agricultural sector. On the other hand, it seems that annual increases in non-agricultural GDP in Iran have had the potential to overcome the harmful effects of drought periods in reducing rural unemployment. Therefore, by comparing the effects of agricultural and non-agricultural sectors in reducing rural unemployment and the impact of drought periods on them, it seems that to neutralize the effects of drought periods on rural unemployment, stronger agricultural GDP growth is needed. However, there is more capacity in the non-agricultural sector for this purpose, especially in rural and agricultural-dependent industries. Two other important aspects need to be considered regarding the impact of agricultural GDP on rural unemployment; the first point is related to the productivity of agricultural labor, which according to the statistics of the Central Bank of Iran has had an increasing trend during the period under review. According to the latest available statistics, the agricultural labor productivity index in Iran has grown by an average of about 5% per year from 2004 to 2018. Therefore, it can be inferred that part of the relative growth of agricultural GDP during this period has been achieved by increasing production per labor. The second point is related to the agricultural mechanization trend in Iran. The latest statistics from the Iranian Ministry of Agriculture show that the mechanization index has grown by an average of about 8% per year in the period from 2002 to 2017. Therefore, the conclusion which should be strongly stated is that raw production activities in the agricultural sector, which generally includes crop production, horticulture, animal husbandry, and fisheries, do not have a significant potential to reduce rural unemployment in Iran by employing more labor. However, if the drought periods intensify, it will make the process more difficult by having a greater impact on agricultural GDP factors. Despite this, for the reasons stated, there is significant potential in the non-agricultural sector to reduce rural unemployment, which is less affected by drought periods. In other words, according to the results, the impact of the drought periods on the GDP of the non-agricultural sector in Iran occurs with a delay of several years. On the other hand, the impact of drought periods on non-agricultural GDP is not so great as to be a serious obstacle to reducing rural unemployment. It should be added that drought periods can also strengthen rural unemployment through social issues that may not be adequately quantified while their effects are undeniable. In the case of Iran, studies have shown that factors such as reduced emotional bonds of rural people, weakening of rural social organizations, endangering the mental health of rural people, and reducing the desire of rural people to carry out rural activities are among the most important drought-dependent social issues (Kiani Salmi and Amini Faskhoodi, 2018). In addition to known variables, it should be noted that naturally other unknown factors affect rural unemployment which their effect can be seen in the intercept. Furthermore, time-lapse with the emergence of new phenomena such as the growth of labor-saving technologies also intensify rural unemployment (Intended with trend variable). In the following, based on the results of Table 5, the short-run effects of variables on rural unemployment in Iran are analyzed.

According to Table 5, it can be seen that the negative impact of agricultural GDP on rural unemployment in the short run is not statistically significant. At the same time, the negative effect of non-agricultural GDP on rural unemployment in the short run is quite significant. Also, increasing rural credits in the short run reduce rural unemployment. Therefore, these results are consistent with the dynamic pattern. However, it is observed that in the short run, increasing the ratio of rural incomes to rural expenditures increases rural unemployment. In this regard, it can be seen that the time lag of this variable has also had a positive effect on rural unemployment. Therefore, it seems that in the short-run in Iran, the priority of rural households to find a job is to provide an initial livelihood (covering expenses). In other words, it seems that the more the annual expenses of rural households are covered by their income, the more their desire for employment decreases. Therefore, it seems that in the short run, the motivation to work more and earn higher incomes other than providing a livelihood for the villagers is not significant. It may be inferred that the lack of sufficient incentive to save part of the income is an important reason in this regard. This is because there are not many options for making savings profitable in rural areas of Iran compared to urban areas. However, cultural reasons also seem to play a role; naturally, there is less desire for progress and development in rural areas than in cities. So, lack of motivation to work harder is also of this kind. Finally, what should be noted about Table 5 is the impact of drought periods on rural unemployment in the short run. As can be seen, the De Martonne variable coefficient is negative in the short run. Accordingly, increasing this coefficient, which means decreasing drought periods, reduces rural unemployment in the short run. Therefore, interpreting how drought periods boost rural unemployment in the short run is like interpreting its effects on the dynamic pattern. But what matters is comparing the impact of drought periods on the short and long-run periods. In this regard, the amount and sign of the error correction variable are important.

Table 5. Short-run estimation results

Variables	Coefficient	Std. Error	t-Statistic	Prob.
$D(lAGDP)$	-0.01	0.26	-0.03	0.98
$D(lNAGDP)$	-1.44	0.35	-4.07	0.001
$D(lRC)$	-0.66	0.24	-2.79	0.01
$D(lIE)$	0.90	0.39	2.31	0.03
$D(lIE(-1))$	1.17	0.39	3.01	0.01
$D(lDe)$	-0.24	0.08	-3.04	0.01
$D(Trend)$	0.13	0.03	4.38	0.0003
$CointEq(-1)$	-0.60	0.12	-5.03	0.0001

According to Table 5, the sign of this coefficient is negative and its value is between 0 and -1, which is justified in terms of econometric theories. The value of this coefficient indicates that the process of adjustment from a short-run imbalance to a long-run equilibrium, known as the error correction process, takes about 1.7 years. Therefore, there is a significant process of adjusting the effect of variables including drought from short-run to long-run. For example, if an unexpected and deep drought occurs in a year, the impact on rural unemployment will be profound. In a way, after this incident, it takes about 1.7 years for rural unemployment to move in its long-run trend.

In order to compare the short-run and long-run results, the estimated coefficients of the variables for the long-run are reported in Table 6.

Table 6. Long-run estimation results

Variables	Coefficient	Std. Error	t-Statistic	Prob.
$lAGDP$	-0.01	0.43	-0.03	0.98
$lNAGDP$	-2.39	0.50	-4.74	0.0001
lRC	-2.06	0.60	-3.44	0.003
lIE	-2.23	1.01	-2.20	0.04
lDe	-0.41	0.15	-2.73	0.01
$Intercept$	21.22	4.02	5.27	0.000
$Trend$	0.21	0.05	3.95	0.001

According to Table 6, the agricultural GDP variable has no significant effect on rural unemployment in the long run. In other words, in addition to the short-run, the increase in agricultural GDP, in the long run, is not enough to significantly reduce rural unemployment. Despite this, increasing non-agricultural GDP in addition to the short-run reduces rural unemployment in the long run, and the impact of this increase is greater in the long run. Therefore, it seems that the positive effects of non-agricultural GDP on reducing rural unemployment, in the long run, are the result of aggregating its short-run effects. Therefore, it can be assumed more seriously that barriers to non-agricultural GDP growth, including drought periods, cannot prevent the potential for rural employment by the non-agricultural sector. Thus, increasing non-agricultural GDP through any channel can have stable effects on reducing rural unemployment. This rule also applies to the rural credits variable when it is observed that the intensity of its impact is greater in the long run. Therefore, the key conclusion that can be obtained by comparing the effects of the last two variables on rural unemployment is that increasing rural credits for rural-friendly industries (Effective non-agricultural sector for employing rural labor), can reduce rural unemployment more drastically. Under these circumstances, it can be hoped that many of the current problems caused by rural unemployment in Iran, including the unprincipled migration of rural unemployed to cities, will be reduced. This issue is in line with the results of the study of Alipour and Mosavi (2019); their study showed that the growth of the non-agricultural sector in Iran increases migration from rural areas. So, this policy recommendation is more important from this perspective. The elasticity of the De Martonne variable is also greater in the long run. Therefore, it is concluded that the long-run effects of this variable are greater than the short-run ones and are the result of the aggregation.

Given the above, it seems that freezing rural unemployment in the way of increasing targeted rural credits will be much more successful. Contrary to these results, the negative coefficient of the ratio of incomes to rural expenditures in the long run compared to its short-run effects suggests that in the long run, rural incomes are more important to cover expenses for villagers and motivate them to increase their working. Therefore, it seems that the accumulation of short-run costs will increase the efforts of rural people, in the long run, to increase their income through more work.

4. Conclusion

What the results of this study show are that the increase in drought periods in Iran has strengthened rural unemployment. Conversely, the reduction of drought periods in Iran has led to an increase in rural employment. The indirect impact of drought on rural unemployment can be related to its impact on rural living and the working environment. However, based on the results of this study, drought was identified as effective on agricultural and non-agricultural GDP. On the other hand, the increase of the last two variables on rural unemployment was known as negative. Therefore, it can be concluded that drought can not only indirectly increase rural unemployment, but also increase rural unemployment by affecting agricultural and non-agricultural GDP. In further explanation, it should be noted that the effect of increasing agricultural GDP on reducing rural unemployment or in other words, the effect of increasing agricultural GDP on increasing rural employment is not statistically significant. Therefore, it seems that the impact of drought periods on agricultural GDP has been effective in the inability of the agricultural sector to significantly employ rural laborers. On the other hand, it seems that the impact of drought on non-agricultural GDP has not been able to significantly reduce the ability of the non-agricultural sector to employ rural laborers. Considering the positive effect of paying rural credits on reducing unemployment in rural areas in Iran, it seems that targeting these credits to non-agricultural jobs that are compatible with rural environments such as agricultural conversion industries, handicrafts, and carpet weaving can effectively reduce rural unemployment and its related issues. At the same time, more credit support for livelihoods and rural living facilities can be also useful and effective in keeping rural people in villages and reducing rural unemployment. In addition, trying to raise the level of rural culture to strengthen the work ethic, further effort, and financial progress is another policy recommendation that based on the results of this study to reduce rural unemployment, especially in the short-run can be mentioned.

5. References

1. Abdelmalek, M., and Nouiri, I. (2020). Study of trends and mapping of drought events in Tunisia and their impacts on agricultural production. Science of the Total Environment. 739: 1-17.
2. Adanacioglu, H. Gumus, S. G., and Olgun, F. A. (2012). Rural Unemployment, the Problems which it generates and Strategies to reduce it: A Case-Study from Rural Turkey. New Medit. 11(2): 50-57.
3. Alipour, A., and Mosavi, S. H. (2019). Analysis of the effects of non-agricultural sector growth on labor migration from the agricultural sector in Iran. Journal of Space Economy & Rural Development. 4(26): 189-210. (In Persian)
4. Banerjee, A. Dolado, J., and Mestre, R. (1998). Error-correction mechanism test for co-integration in a single-equation framework. Journal of Time Series Analysis. 19: 267-283.
5. Barghi, H., and Memar Emameih, M. (2016). Study of Drought Effects on Constant of Economy Development in Golab County with Using AHP and FA (Case study: Golab County, Kashan Township. Geographical Researches. 31(2): 128-136. (In Persian)
6. Blinova, T. V. (2002). Rural Development and Unemployment Reduction. 2002 International Congress, August 28-31, 2002, Zaragoza, Spain 24821, European Association of Agricultural Economists.
7. Cohen, I. Zandalinas, S. Huck, C. Fritschi, F., and Mittler, R. (2020). Meta-analysis of drought and heat stress combination impact on crop yield and yield components. Physiologia Plantarum. 171(1): 66-76.
8. Dănăcică, D. (2013). Cercetări privind impactul factorilor ce influenĠează durata úomajului úi probabilitatea (re)angajării în România Editura Academiei Române, Bucureúti. (In Romanian)
9. De Martonne E. (1926). Une nouvelle fonction climatologique: L'indice d'aridité. La Meteorologie. 449-458. (In French)
10. Du Toit, M. De Witte, H. Rothmann, S., and Van den Broeck, A. (2018). Contextual factors and the experience of unemployment: A review of qualitative studies. South African Journal of Economic and Management Sciences. 21(1): 1-11.

11. Dutta, R. (2018). Drought Monitoring in the Dry Zone of Myanmar using MODIS Derived NDVI and Satellite Derived CHIRPS Precipitation Data. Sustainable Agriculture Research. 7(2): 46-55.
12. Dutta, S. (2019). Rural Unemployment in Gujarat and West Bengal. South Asia Research. 39(1): 1-22.
13. Engle, R. F. Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. Econometrica, Journal of the Econometric Society. 55(2): 251-276.
14. Ghaffari Esmaeili, S. M. Akbari, A., and Kashiri Kolaei, F. (2018). The Impact of Climate Change on Economic Growth of Agricultural Sector in Iran (Dynamic Computable General Equilibrium Model Approach). Journal of Agricultural Economics & Development. 32(4): 333-342. (In Persian)
15. Hameed, M. Ahmadalipour, A., and Moradkhani, H. (2020). Drought and food security in the Middle East: An analytical framework. Agricultural and Forest Meteorology. 281: 1-12.
16. Helmy, H. E. (2019). Thirty Years of Urban Bias: An Estimation of the Rising Disparities in Female Rural and Female Urban Unemployment and Income in Egypt. Agrarian South. 8(3): 349-390.
17. Hisdal, H., and Tallaksen, L. M. (2000). Drought Event Definition. Assessment of the Regional Impact of Droughts in Europe (ARIDE). Technical Report No. 6.
18. Johansen, S., and Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. Oxford Bulletin of Economics and Statistics. 52(2):169–210.
19. Kamran, A. Shujaat, S. Syed, N.A., and Ali, S.N. (2014). A Study on Determinants of Unemployment in Pakistan. In: Xu J., Fry J., Lev B., Hajiyev A. (eds) Proceedings of the Seventh International Conference on Management Science and Engineering Management. Lecture Notes in Electrical Engineering, vol 242. Springer, Berlin, Heidelberg.
20. Khan, M. K. Teng, J. Z. H., and Khan, M.I. (2019). Cointegration between macroeconomic factors and the exchange rate USD/CNY. Financial Innovation. 5(5): 1-15.
21. Kiani Salmi, S., and Amini Faskhoodi, A. (2018). Identifying the Social factors of drought and uncovering its effects. Journal of Spatial Planning. 7(4): 1-18. (In Persian)

22. Nachiappan, S. Hock, K. E. Zabit, M. N. M. Sukri, N. A. Suffian, S., and Sehgar, S. C. (2018). International Journal of Academic Research in Progressive Education and Development. 7(3): 14-25.
23. Noack, F. Riekhof, M. C., and Di Falco, S. (2019). Droughts, Biodiversity, and Rural Incomes in the Tropics. Journal of the Association of Environmental and Resource Economists. 6(4): 2333-5955.
24. Quiggin, J. (2007). Drought, climate change and food prices in Australia. Melbourne: Australian Conservation Foundation.
25. Quiroga, S., and Suárez, C. (2016). Climate change and drought effects on rural income distribution in the Mediterranean: a case study for Spain. Natural Hazards and Earth System Sciences. 16: 1369-1385.
26. Panahi, H., and Esmaeel Darjani, N. (2020). Effects of Global Warming and Climate Changes on Economic Growth (Case Study: Iran provinces during 2002-2012). Journal of Environmental Science and Technology. 22(1): 79-88. (In Persian)
27. Pesaran, M. H. Shin, Y., and Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Economics. 16(3): 289–326.
28. Schaub, S., and Finger, R. (2020). Effects of drought on hay and feed grain prices. Environmental Research Letters. 15: 1-9.
29. Shin, Y. Yu, B., and Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In Festschrift in Honor of Peter Schmidt (pp. 281-314). Springer, New York, NY.
30. Todaro, M. P., and Smith, S. C. (2009). Economic Development, 10th Edition. Publisher: Pearson. Hardcover: 896 pages.
31. U.S. Bureau of Labor Statistics. (2020). Data and Statistics | U.S. Department of Labor. Available at: https://www.bls.gov.
32. Vrieling, A. Meroni, M. Mude, A.G. Chantarat, S. Ummenhofer, C.C., and de Bie, K. (2016). Early assessment of seasonal forage availability for mitigating the impact of drought on East African pastoralist. Remote Sensing of Environment. 174: 44-55.
33. WMO (World Meteorological Organizatio). (2016). Integrated Drought Management Programme. No. 1173.

34. Yanling, S., and Yanxia, ZH. (2012). Effects of Drought on Winter Wheat Yield in North China during 2012–2100. ACTA METEOROLOGICA SINICA. 26: 516-528.
35. Yu, Ch. Li, Ch. Xin, Q. Chen, H. Zhang, J. Zhang, F. Li, X. Clinton, N. Huang, X. Yue, Y., and Gong, P. (2014). Dynamic assessment of the impact of drought on agricultural yield and scale-dependent return periods over large geographic regions. Environmental Modeling & Software. 62: 454-464.