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Drought and food security in the middle east: An analytical framework

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ABSTRACT

Natural disasters may act as harmful causes of food insecurity in the Middle East. Frequent drought events, water scarcity, and unsustainable intensive agricultural practices may impact food security in the region. This paper investigates a causal relationship between drought and food security across the Middle East. Meteorological, agricultural, and hydrological droughts are analyzed at multiple timescales over the region for seven decades during the period of 1948–2017. We simulate food security in the Middle East as a function of drought (representing a water stress factor) as well as several other socio-economic drivers. A Bayesian approach is implemented to integrate these drivers in order to accurately predict food security in the region. Results reveal that hydrological drought is the most intensified drought type over the region, especially in Egypt, during the study period. Moreover, the results demonstrate the significant impacts of livestock, population growth, agricultural products, and drought on food security in the Middle East. Our findings further indicate that the agricultural products decreased in the Middle East following the recent drought event that happened in 2010.

1. Introduction

Frequent drought events with increasing severity can substantially impact agricultural productivity and food security in the regions with semi-arid hot climate. Drought as a recurring natural hazard may impact water resources such as: water supply, water quality, surface and subsurface water availability, and management of water resources (Amin et al., 2016; FAO, 2017; Scanlon et al., 2017; van Loon et al., 2014). In general, four types of drought are identified: (1) Meteorological drought which accounts for precipitation shortage (Ahmadalipour et al., 2016; Beguería et al., 2014; Das et al., 2015; Hameed et al., 2018); (2) Agricultural drought which considers soil moisture deficiency (Gao et al., 2015; Mishra et al., 2015; Nichol and Abbas, 2015; Vicente-Serrano et al., 2015; Yan et al., 2017); (3) Hydrological drought which is a lack of surface and subsurface water (Barker et al., 2016; Lorenzo-Lacruz et al., 2013; Madadgar and Moradkhani, 2013; Mo and Lettenmaier, 2014; Van Loon and Laaha, 2015; Zhang et al., 2015); (4) Socioeconomic drought that accounts for water resources system deficit resulting from other types of drought (Huang et al., 2016; Maia et al., 2015; Rajsekhar et al., 2015; van Loon et al., 2014).

It has been identified that food security is vulnerable to extreme weather events. Extreme weather events may negatively influence food supply and security of vulnerable regions (Silva et al., 2018). Moreover, climate change can negatively impact crop, livestock, and fisheries production; therefore, more attention should be paid to action-oriented research (Wollenberg et al., 2016). Rosegrant and Cline (2003) mentioned that food security will continue to be a global concern in the twenty first century given the crop yield failure in many regions due to lack of research and infrastructure as well as increasing water scarcity. Kang et al. (2009) suggested that climate change may markedly affect the growing period, harvest date, and crop rotation period. The United Nations reported that rain-fed agricultural lands are extremely influenced by drought in the Arab region. It consequently results in decreasing yields and depleting vegetation in pasture lands, which in turn affects livestock in the region. Furthermore, land degradation can be another consequence of drought that may decrease the land area covered by native plants (UN, 2015).

Given that adaptation for agriculture is complicated, crop-climate studies should be applied to improve the understanding of food security other than availability (Beveridge et al., 2018). Climate change may pose major challenges to food security and thus agricultural systems need to incorporate adaptive measures considering the negative impacts of climate change on food security along with growing population and demand worldwide (Kumar, 2016). Changes in population, income, and climate, among other drivers play essential role in achieving and maintaining global food security. Hence, predictive models that account for such factors can be helpful for planning and management of

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food security.

Antonelli and Tamea (2015) found that the food and water security in the Middle East and North Africa (MENA) region substantially depend on water from outside the region, and thus increase the food imports and trade in the region. By 2050, food imports are likely to provide about half of the MENA region's food demand to achieve food security (Qadir et al., 2007). A study by Zaitchik et al. (2007) indicated that climate fluctuations might result in significant change in vegetation across the Middle East, and the authors concluded that the vegetation in the Euphrates Plain is predominantly limited by soil moisture availability. In Syria, rain-fed agriculture is affected by fluctuation in precipitation; therefore, crop production and food availability have been impacted by the prolonged-frequent drought events over the country (Tolba and Saab, 2009).

Expanding aridity associated with environmental stresses such as frequent drought and heat stresses (Ahmadalipour and Moradkhani, 2018a; Hameed et al., 2018; Abbas et al., 2018) can impose serious threat to food security in the Middle East. Saadi et al. (2015) assessed the impact of climate change on winter tomato and wheat yields in the Mediterranean region. Their results indicated that spatial and seasonal variations of air temperature and precipitation are two main factors affecting winter tomato and wheat crops in the region. Lelieveld et al. (2012) suggested that the Eastern Mediterranean and the Middle East (EMME) region is likely to be impacted by frequent and intense droughts associated with hot weather conditions in the 21st century.

This study builds up on previous assessments and aims to quantitatively investigate the relation between drought and food security in the Middle East. The overarching goals of this paper are as follows: 1) Characterizing historical drought conditions across the Middle East using long-term (1948–2017) hydro-climatological variables. Meteorological, agricultural, and hydrological droughts are analyzed across the Middle East at different time scales. 2) Statistical simulation of food security in the Middle East considering drought condition and socio-economic drivers. A Bayesian modeling approach is conducted to determine the appropriate model that can accurately simulate food security in the region.

2. Study area and data

The proposed study area is the Middle East region, defined here as sixteen countries, namely, the Arabian Peninsula (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia (KSA), United Arab Emirates (UAE), and Yemen), Iraq, Iran, Syria, Lebanon, Israel, Palestine, Egypt, and Turkey. The Middle East is located in western Asia and northeastern Africa, and it covers an area of roughly 6928,000 km^2 (2675,000 mi^2) residing about 320 million people. According to the International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization (FAO), the dominant land cover pattern in the region is mostly barren land. Notably, Turkey, northwestern Iran, northeastern Iraq, western parts of Syria, Lebanon, and along the Nile River in Egypt are among the regions dominated with grassland, woodland, and cultivated lands. Forests cover the northern parts of Turkey and Iran (see Fig. 1).

In this study and according to the available data provided by FAO, the crop production index (agricultural production for each year relative to the base period of 2004–2006) and food deficit (kilocalories per person per day) are considered as food security indicators in the Middle East. To quantify food security in the Middle East, the relevant factors that explain food availability in the region are identified, including drought, water stress, energy, and other socio-economic factors. Different data sources are explored to investigate the appropriate factors, including the International Energy Agency (IEA), FAO of the United Nations, and the World Bank. The definition of food security and the associated influential factors are regionally explicit due to the differences in natural and anthropogenic resources. Therefore, expert knowledge about the study domain is essential for the analysis (Hameed et al., 2019).

The Global Land Data Assimilation System (GLDAS-2) and (GLDAS-2.1) (Beaudoing and Rodell, 2016, 2015; Rodell et al., 2004) hydro-climatic variables are utilized for characterizing drought. GLDAS-2 covers the period of 1948–2010 and GLDAS-2.1 extends to the period of 2000–current. Monthly precipitation, soil moisture, and runoff data at a 0.25° spatial resolution are used to drive meteorological, agricultural, and hydrological droughts, respectively, at multiple timescales (i.e. 3, 6, 12, 18, and 24 months) over the Middle East for the period of 1948–2017.

The natural and socioeconomic factors are explained in Supplementary Table S1, some of which consist of other sub-factors (i.e. agricultural products (8) and drought indices (17)). Agricultural products consist of 12 main products in the region, and drought indices consist of 4 different drought indices which are covered in this study.

3. Methodology

The food security assessment of this study is performed in several steps as follows:

- Data selection, extraction, pre-processing, and reformatting
- Calculating drought indices: the Standardized Precipitation Index (SPI), Standardized Soil Moisture Index (SSI), and Standardized Runoff Index (SRI)
- Normalization to compare different variables
- Multi-collinearity tests to remove redundant variables
- Bayesian analysis to simulate food deficit, crop production index, and model verification

3.1. Drought Analysis

In this study, the monthly precipitation (total precipitation rate), surface soil moisture (0–10 cm), root zone soil moisture, and surface-groundwater runoff are used to derive different types of drought indices: SPI, SSI, SSIrz, and SRI, respectively. The drought indices are calculated and analyzed at different timescales: 3-, 6-, and 9-month for short-term changes and 12-, 18-, and 24-month for long term drought changes over the Middle East. The calculation of SSI, SSIrz, and SRI are similar to that of the SPI (Mckee et al., 1993) as a reference (Hao et al., 2017; Shukla and Wood, 2008; Wu et al., 2016; Zhang et al., 2017).

SPI is a widely used probability-based index detecting precipitation deficiency in a region by quantifying precipitation deviation from historical mean. To avoid dealing with data fitting to a distribution, which is known to have a few issues, a nonparametric approach is implemented to calculate drought indices (i.e. SPI, SSI, SSIrz, and SRI) in this study. Precipitation, soil moisture, and runoff of each grid cell were accumulated to the desired accumulation period, and the empirical Gringorten plotting position (Gringorten, 1963) was utilized as follows:

$$\boldsymbol{p}(\boldsymbol{x_i}) = \frac{\boldsymbol{i} - 0.44}{\boldsymbol{n} + 0.12} \tag{1}$$

Where n is the sample size, i denotes the rank of non-zero variable data from the smallest, and $p(x_i)$ is the corresponding empirical probability. The outputs of Eq. (1) can be transformed into a Standardized Index (SI) as:

$$\boldsymbol{SI} = \varnothing^{-1}(\boldsymbol{p}) \tag{2}$$

Where ϕ is the standard normal distribution function, and p is probability derived from Eq. (1). A negative value of the standardized drought index indicates a dry condition, whereas a positive value indicates a wet condition. A value of zero represents normal climate condition. Table 1 classifies the dry/wet conditions of the standardized drought index as suggested by Mckee et al. (1993).

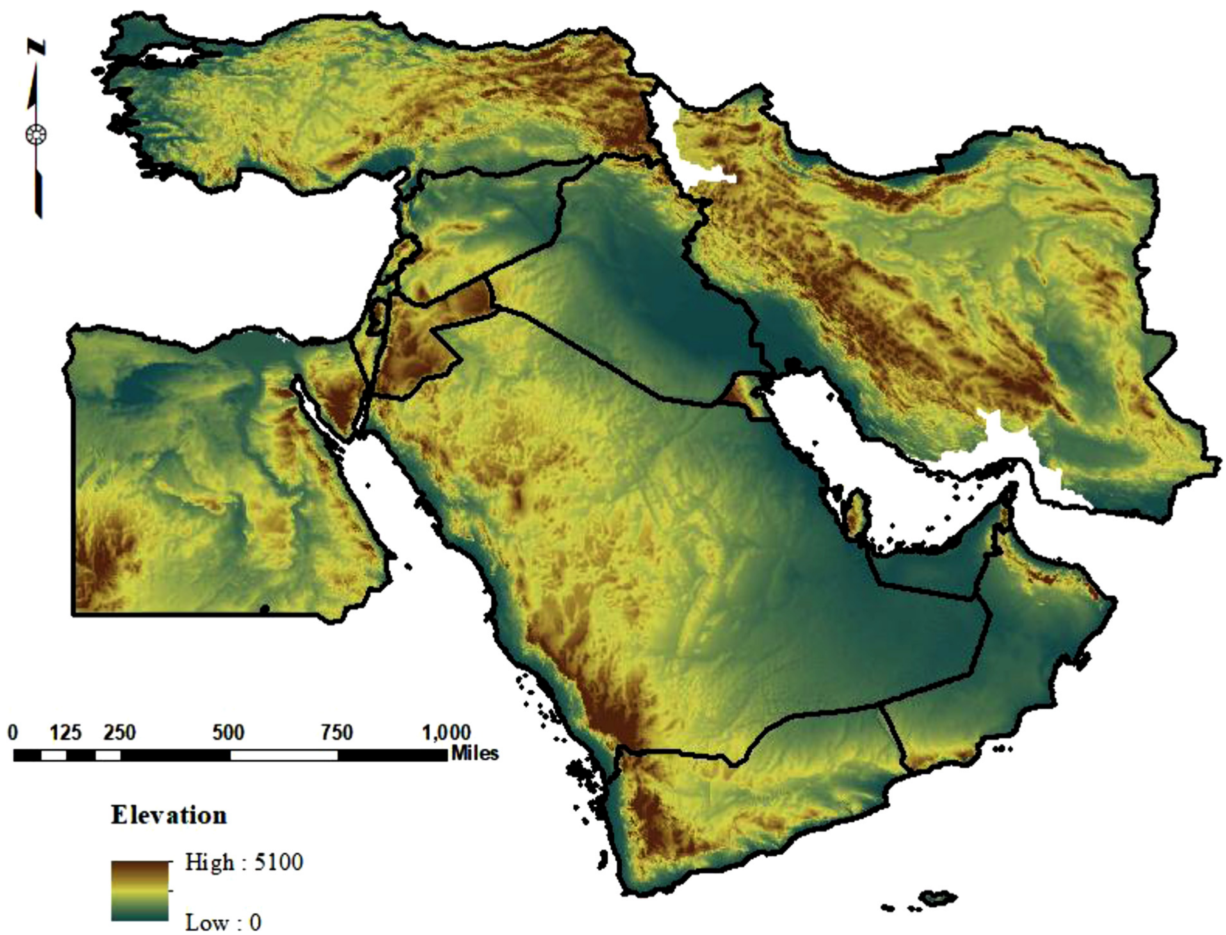

Fig. 1. Elevation map of the Middle East. Data source: http://www.diva-gis.org.

Table 1
Categories of dry/wet classes by drought indices following Mckee et al. (1993).

Category	SI value (min-max)
Extremely dry	Less than −2
Severe dry	−1.99 to −1.5
Moderate dry	−1.49 to −1.0
Near normal	−1.0 to 1.0
Moderate wet	1.0 to 1.49
Severe wet	1.50 to 1.99
Extremely wet	More than 2

3.2. Mann-Kendall test and Sen's slope

A non-parametric monotonic trend test computing Mann-Kendall Tau, Tau-b, and Sen's slope estimator is implemented in this study for analyzing trends of each drought index (Burkey, 2006). The Mann-Kendall test (Kendall, 1955; Mann, 1945) is a well-known statistical test that has been used to verify the significance of temporal trends of variables in long-term behavior of time series (Das et al., 2015; Güner Bacanli, 2017). In this study, the significance of trends are examined based on a significance level of $\alpha = 0.05$. The non-parametric procedure developed by Sen (1968) is used. For more details, readers are referred to Drapela and Drapelova (2011).

To better understand the regional trends of drought intensity, the monthly variations and long-term linear trends are investigated for each drought index.

3.3. Food security analysis

3.3.1. Natural and socioeconomic factors selection

A total of 25 factors were initially considered during the period of 1960 to 2017. Supplementary Table S1 explains each factor and its availability. Based on the data availability and continuity of the data, some of these factors were eliminated. In this study, each factor should be available for at least half of the Middle Eastern countries and for a continuous period of 24 years to be selected for further analysis. Therefore, 12 factors remain to be considered for the period of 1992 to 2015. Each of the chosen factors are normalized separately using the data from all countries to compare different variables.

Given that the principal component analysis (PCA) specifies the relationship among various variables, PCA is performed in this study to eliminate the variables that introduce redundancy and multi-collinearity. The PCA is a popular statistical technique of multivariate analysis (Jolliffe, 2002). The main purpose behind the PCA is dimensionality reduction of data comprising a large number of associated variables, meanwhile preserving data variation as much as possible. This can be attained by transforming the data to a new set of variables (the principal components), which are uncorrelated and ordered in a way that the first few components capture most of the variance in all of the original variables (Jolliffe, 2002). The user can decide the number of PCs based on the acceptable level of variance explained by each PC. PCA has been used by many researchers for various objectives (Kopec et al., 2018; Lecher et al., 2018; Liu et al., 2015; Malik et al., 2018; Meng et al., 2016; Santos et al., 2010; Tan et al., 2016; Thecla et al., 2018; Tielbörger et al., 2014). Generally, the PCA is considered for simplification, data reduction, modeling, outlier detection, variable selection, classification, prediction, and unmixing

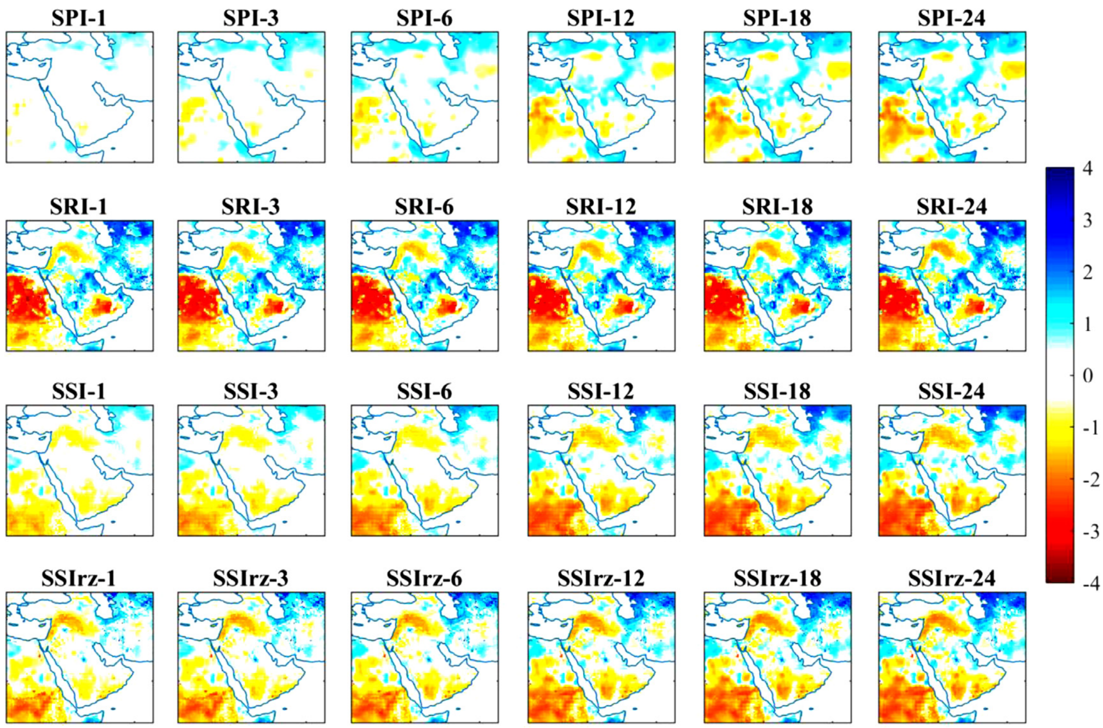

Fig. 2. Drought trends for the period of 1948–2017 according to the SI-1, −3, −6, −12, −18, and −24 months over the Middle East. Please note that the color bar indicates the mean change of SI in seven decades.

(Wold 1987). However, to ensure the independence among the selected variables, the Variance Inflation Factor (VIF) is applied in this study (Ahmadalipour and Moradkhani, 2018b; Kim et al., 2015; O'Brien, 2007). The VIF is a simple technique for measuring the degree of multi-collinearity among variables, defined as:

$$\boldsymbol{VIF_i} = \frac{1}{1 - \boldsymbol{R_i^2}} \tag{3}$$

Note that VIF measures the impact of collinearity of the variable X_i, $i = 1, \ldots, n$, with the rest of the variables on the square of the radius of the confidence interval. R_i is the correlation coefficient of X_i and the other covariates. A value of VIF > 4 indicates the existence of multi-collinearity and that the factors are statistically insignificant (Ahmadalipour and Moradkhani, 2018b). Eventually, the results of the PCA and VIF led to the selection of 7 independent factors for quantifying food security in the Middle East.

3.3.2. Bayesian modeling

Regression analysis is a statistical method that exploits the relationship between two or more quantitative variables, and it can systematically express the variation of the response variable based on the predictors (Neter et al., 1996). To more accurately model the food security in the Middle East, a Bayesian framework is applied in this study. Bayesian methods assist in assimilating an optimal model, dealing with linear and non-linear states, and handling small sample size of data (Vannucci et al., 2012).

Given the aforementioned attributes and approach flexibility, the Bayesian Linear Regression (BLR) method is utilized in this study. In Bayesian analysis, prior distribution assumptions are imposed on model parameters to incorporate knowledge about the model. Moreover, the Bayesian analysis updates the probability distributions of model parameters by acquiring information about the parameters from observing the data. The distribution of the updated parameters is called posterior distribution. These prior-posterior pairs represent the prior model for data likelihood. The data likelihood is defined as:

$$\prod_{t=1}^{T} \varnothing\,(y_t;\ x_t\beta,\ \sigma^2) \tag{4}$$

Where $\varnothing\,(y_t; x_t\,\beta, \sigma^2)$ is the Gaussian probability density evaluated at y_t with x_t, prior mean β, and variance σ^2.

Five of the seven selected factors are the inputs (predictors) to the BLR model, as follows: population growth, energy, agricultural products, drought indices, and livestock. Food deficit and crop production index are the outputs of the BLR model. It should be noted that the mean of 12 agricultural products (number 8 in Supplementary Table S1) are considered as one input to the BLR model. Whereas, each drought index is considered as an input to the BLR model.

The Akaike information criteria (AIC; Akaike 1974) and Bayesian information criterion (BIC; Schwarz 1978) are utilized to evaluate the quality of each model, and they are defined as follows:

$$\boldsymbol{AIC}(\boldsymbol{m}) = -2\boldsymbol{L} + 2\boldsymbol{m} \tag{5}$$

$$\boldsymbol{BIC}(\boldsymbol{m}) = -2\boldsymbol{L} + \boldsymbol{m}\boldsymbol{log}(\boldsymbol{n}) \tag{6}$$

Where m denotes the number of fitted parameters, n is the number of observations, and L is the maximized value of likelihood function of a statistical model for a given data. A lower value for AIC and BIC criteria indicates a better model. Moreover, the root mean square error (RMSE) metric, which is the square root of the average of squared differences between prediction and actual observation, is also utilized to evaluate the final model.

4. Results

4.1. Drought characterization

4.1.1. Trends of drought intensity

It is of high importance to assess drought trends in a changing climate (Güner Bacanli, 2017). Therefore, spatial variability of the long-term trends of meteorological, agricultural, and hydrological drought intensity are estimated over the Middle East in this study. Trends are calculated for short timescales (i.e. 1-, 3-, and 6-month) and long timescales (i.e. 12-, 18-, and 24-month). First, a linear trend for each SI is estimated using the least squares method. Fig. 2 shows the linear trend of each SI at each grid cell during the study period (1948–2017). The estimated slope represents the mean change of the drought index during the seven decades. The positive slope value (shown in blue) denotes a decrease in drought intensity, whereas, a negative value (shown in red) indicates a decreasing drought index and therefore, an aggravation in drought intensity. From Fig. 2, the 24-months timescales (SI-24) show the most intensified drought trends in the Middle East compared to other timescales. Results of SPI-1, −3, −6 indicate minor changes in the intensity of meteorological drought in the region. However, results of SPI-12, −18, and −24 show considerable changes of meteorological drought, especially over Egypt and eastern Iran. Hydrological drought (at all timescales) is mostly intensified in Egypt, western Iraq, Saudi Arabia, and northern parts of Oman. The results of agricultural drought at root zone show intensified drought at SSIrz-12, −18, and −24 over Iraq, Syria, Lebanon, Palestine, Israel, northern Jordan, Oman, and Saudi Arabia. Whereas, agricultural drought based on near surface soil moisture (SSI) reveals less intensification of drought in the region.

Fig. 3 shows the results of the Mann-Kendall and Sen slope estimator statistical test at 1-, 3-, 6-, 12-, 18-, 24-months SIs (all of which are aggregated to annual timescale) over the Middle East during the study period (1948–2017). The analysis of Mann–Kendall test of hydrological and agricultural droughts reveal that the negative trends in drought magnitudes (intensified droughts) are significant at 5% level of significance for all timescales. Whereas, both trend tests (i.e. linear trend

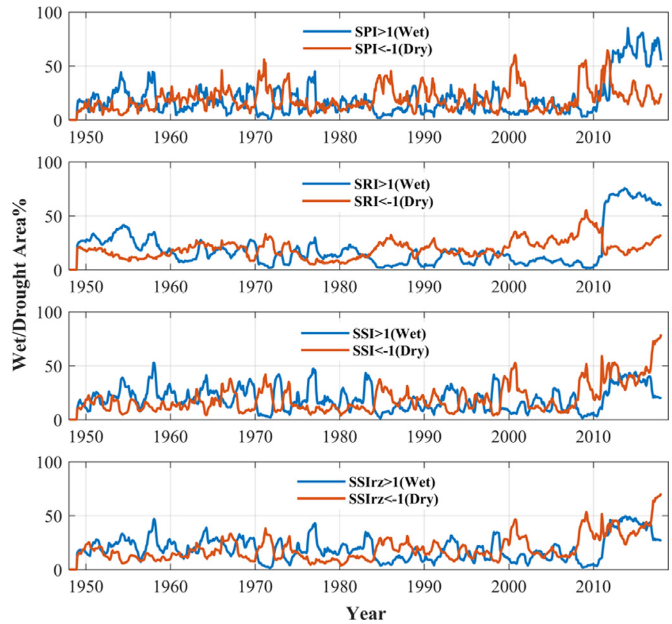

Fig. 4. Temporal variations of monthly dry (SI < −1) and wet (SI > 1) extent over the Middle East. All indices are showing the results of 12-months timescale.

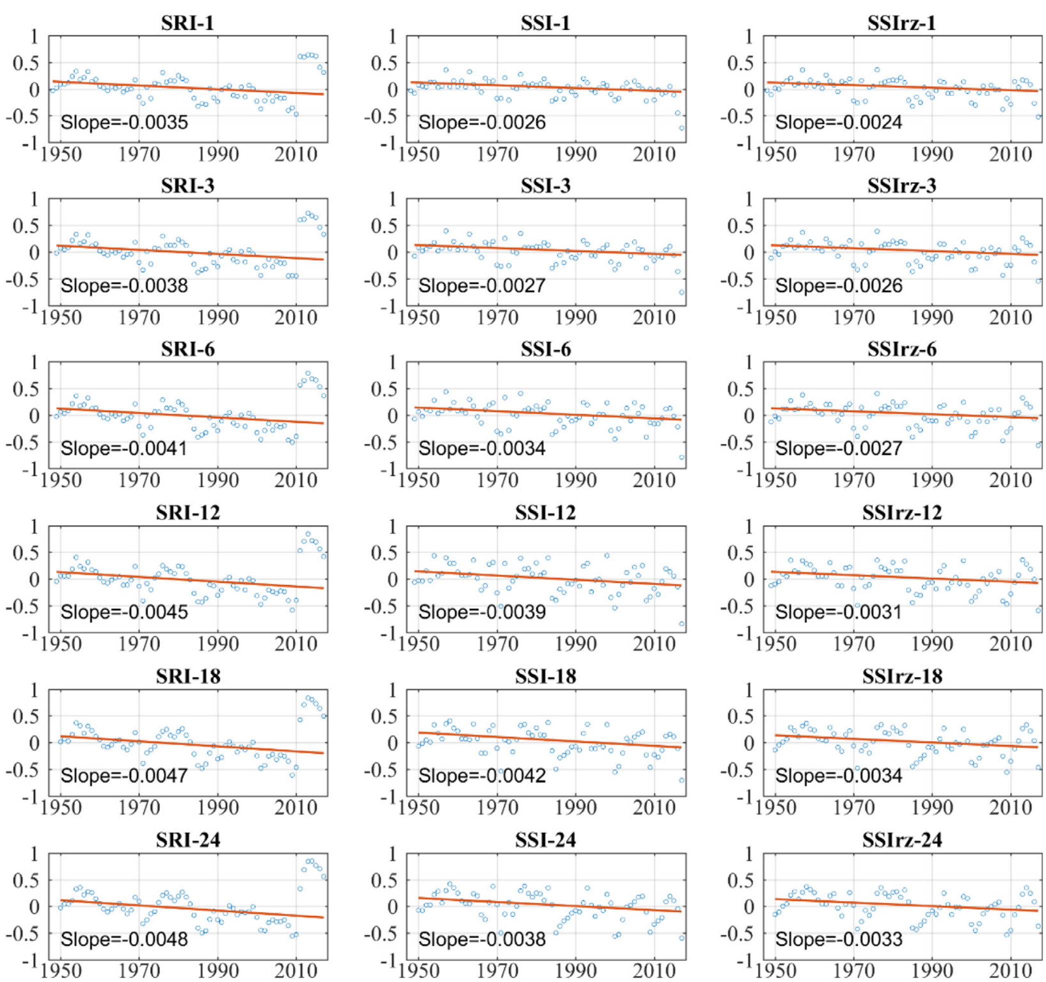

Fig. 3. Trend test including Sen's slope method using Mann-Kendall Tau-b technique. The results for 1-, 3-, 6-, 12-, 18-, 24-months SRI, SSI, and SSIrz during the study period (1948–2017). All the trends are significant at 0.05 significance level, and the slope in each case is included for each plot.

and Mann–Kendall) indicate that SPI trends at all timescales are not significant at the 0.05 significance level, and therefore, the SPI results are not included in Fig. 3.

From Fig. 3, SRI indicates wet condition after 2010 over the Middle East. Whereas, SSI and SSIrz indicate both wet and dry conditions after 2010 across the region. In general, slopes of all drought indices indicate larger decreasing trends (more drought intensification) at longer timescales. Moreover, SRI shows more intensifying drought (sharper slopes) than SSI and SSIrz at all time scales.

4.1.2. Spatial extent of drought

Temporal variations of monthly drought condition ($SI < -1$) and wet condition ($SI > 1$) are investigated in this section. This is obtained by calculating the ratio of the number of grids with dry or wet condition to the total number of grids covering the Middle East during the study period of 1948–2017 (Fig. 4). Here, the 12-months timescale is selected for each drought index as it captures a relatively long-term drought analysis. From Fig. 4, it can be seen that the temporal patterns vary towards greater drought extent in the late 1990s and the period between 2007–2013. Whereas, lower drought extent is observed in the previous decades (1950s, 1960s, 1970s, and 1980s). In general, drought indices indicate coherence for most of the study period. Meteorological drought extent (SPI, top panel) reached its peak in early 1970s, early 2000s, and the period of 2008–2012 with about 60% drought extent. Whereas, hydrological drought (SRI, second panel) governs the period of 1999–2012 over the Middle East and reaches its maximum in 2009 with more than 50% drought extent. Moreover, agricultural drought (SSI, bottom two panels) affected the region in late 1990s-early 2000s, the period of 2007–2012, and reached its maximum in 2017 with almost 80% drought extent over the region.

To better understand the seasonal changes in the spatial extent of drought, seasonal drought patterns are invistigated for each drought type during the growing season (April-September) for the two main drought periods invistigated in the study: (1998–2002) and (2007–2013) (Figs. 5 and 6). From Fig. 5, meteorological, hydrological, and agricultural droughts occured over most of the northern, eastern, and central parts of the Middle East during 1999 to 2001. The most intensified droughts occured in 2000 over the eastern parts of the Middle East (i.e. Tigris-Euphrates basin and Gulf region). Most parts of Turkey and eastern Iran were under the three types of drought (meteorological, hydrological, and agricultural) in 2001 (Fig. 5). From Fig. 6, all types of drought occurred in 2008 and 2009 over the Middle East, espetially the Tigris-Euphrates basin and the Gulf region. The most intensified meteorological and agricultural droughts occurred in Iran in 2011. Whereas, Egypt and Saudi Arabia were under intensified drought condition in 2012 (Fig. 6). The results indicate that if drought happens in winter, it generally persists in summer months, as the majority of the study area receives precipitation mainly in fall and winter, and due to high temperature in summer, drought usually persists during growing season and intensifies in summer. Early-season drought can delay crop planting activities, subsequently reducing agricultural area and production. Remarkably, mid-season drought can impact crop growth, whereas the late-season drought may affect the harvest (Das et al., 2015). Additional seasonal drought patterns are available in the supplementary file.

4.2. Principal component analysis (PCA)

Fig. 7 shows the results of PCA considering the 12 selected factors. PC1 explains about 68% of the total variance, whereas PC2 accounts for 12% of the total variability. The length of each vector with respect to each PC indicates the relative contribution of that factor to that PC. In other words, the longer vectors contribute more than the shorter vectors with respect to the given component. Vectors of similar length and extending in the same direction represent correlated factors. For instance, crop production and food production are negatively correlated with PC1 and positively correlated with each other, showing that as one of the two factors increase, so does the other factor. Conversely, food deficit is positively correlated with PC1. This means as crop production and food production increase, the food deficit decreases. Population growth and agricultural land are correlated more strongly with PC2. Knowing that the inputs to the BLR model have to be uncorrelated, PCA results assist identifying the correlated factors.

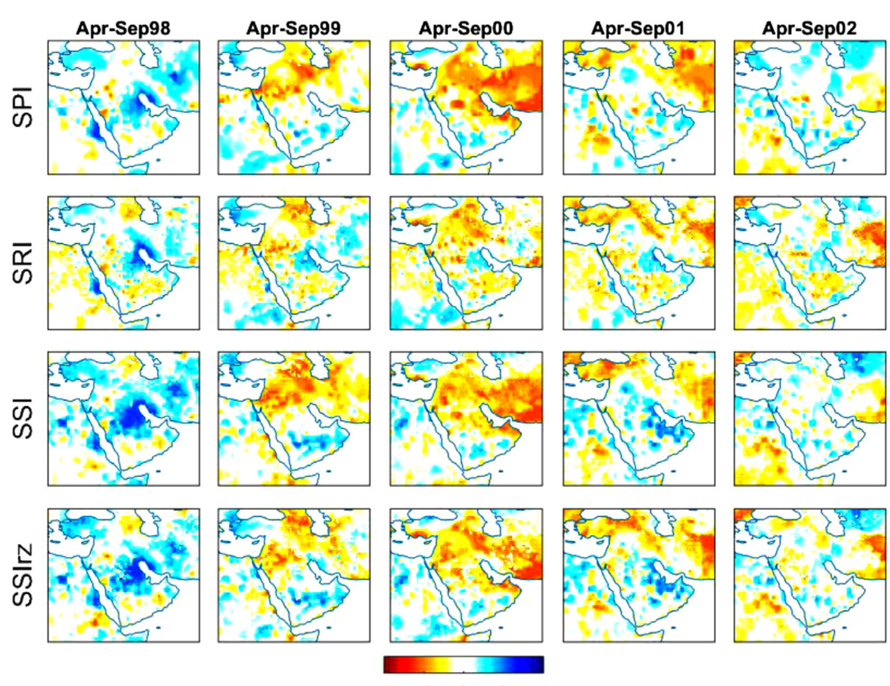

Fig. 5. Seasonal drought patterns over the Middle East for the growing season during the period of 1998–2002.

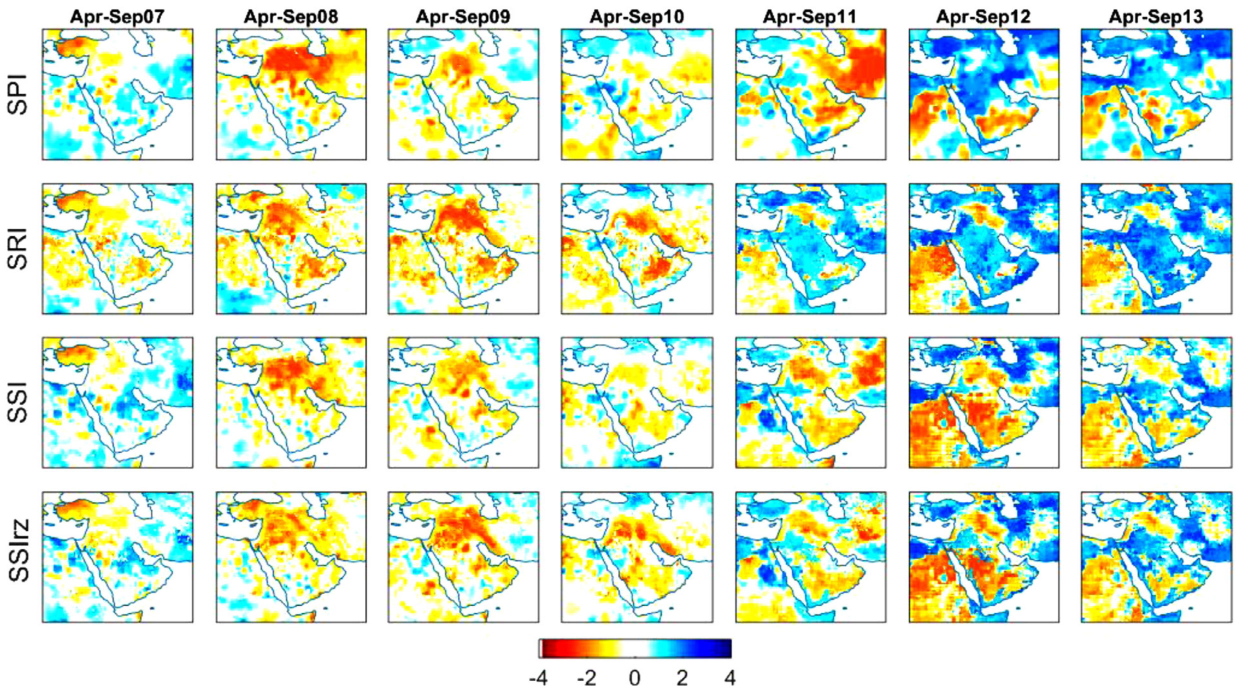

Fig. 6. Seasonal drought patterns over the Middle East for the growing season during the period of 2007–2013.

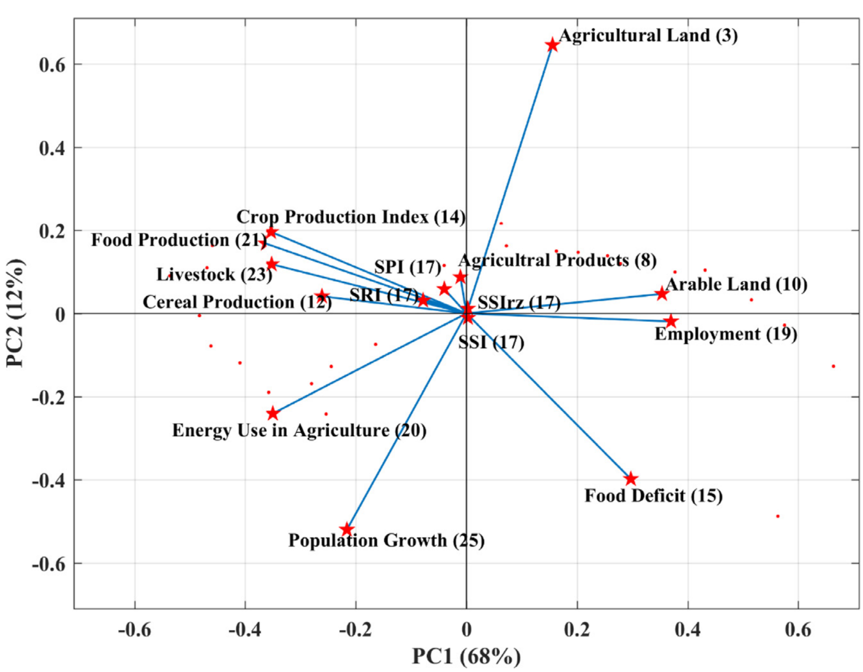

Fig. 7. Results of the Principal Component Analysis (PCA). Components 1 and 2 accounted for 68% and 12% of the total variability, respectively. Coefficient vectors represent how much each factor contributed to the component, with the longer vectors contributing more than the shorter ones. The numbers next to each factor indicate the factor order provided in Supplementary Table S1.

4.3. Bayesian linear regression analysis

Food security in the Middle East is investigated in this study using two measures: food deficit and crop production index. A total of six models are presented here to predict food security in the region. To overcome multi-collinearity existence among the selected factors in each model, PCA and VIF tests are used as explained in Section 3.3. Population growth, agricultural products, livestock, energy, and drought indices are selected as inputs to the BLR models. Crop production index and food deficit are selected as models targets/outputs.

The following section will present the models that predict food security in Middle East according to the chosen inputs in this study.

4.3.1. Food deficit and crop production index models

Agricultural products, population growth, energy used in agriculture, livestock, meteorological drought, agricultural drought, and hydrological drought are the final selected factors utilized to simulate food deficit and crop production index (using BLR models) during the period of 1992–2015. The analysis is conducted on the spatially averaged data for the entire Middle East region at annual scale. Table 2 presents the food deficit and crop production index models as indicators of food security in the Middle East. The table also provides the performance measures for model verification purposes.

Fig. 8 shows the linear fit of each model with 95% confidence interval. In Fig. 8, the x-axis shows BLR model outputs and y-axis shows the observations. The results indicate that the 2nd model was the most

Table 2
Food deficit and crop production models as indicators of food security in the Middle East. The VIF results and statistical metrics are provided in this table too.

Model	VIF	Metrics
1) Food Deficit = 0.0167 + 0.6495 × Population Growth - 1.0115 × Energy - 2.0535 × Agricultural Products - 0.4482 × SPI + 2.2160 × SSIrz	Population Growth: 3.26 Energy: 3.44 Agricultural Products:1.26 SPI: 3.98 SSIrz: 3.25	RMSE: 0.62 R^2: 0.70 Adjusted R^2: 0.62 *p*-value: 0.00027 AIC: −1.64e+03 AICc: −1.64e+03 BIC: −1.64e+03
2) Food Deficit = −0.0691 −1.3153 × Livestock + 0.3746 × Population Growth - 1.3116 × Agricultural Products + 0.7845 × SPI - 0.3554 × SSI + 1.0319 × SRI	Livestock: 3.09 Population Growth: 1.72 Agricultural Products:1.25 SPI: 1.89 SSI: 1.27 SRI: 3.28	RMSE: 0.45 R^2: 0.84 Adjusted R^2: 0.78 *p*-value: 7.07e-06 AIC: −1.62e+03 AICc: −1.61e+03 BIC: −1.61e+03
3) Food Deficit = 0.0074 - 0.7884 × Livestock + 0.0738 × Population Growth - 1.2181 × Agricultural Products	Livestock: 1.12 Population Growth: 1.14 Agricultural Products:1.03	RMSE: 0.61 R^2: 0.68 Adjusted R^2: 0.63 *p*-value: 3.37e-05 AIC: −1.68e+03 AICc: −1.67e+03 BIC: −1.67e+03
4) Crop Production Index = - 0.0066 - 0.4393 × Population Growth + 1.1492 × Energy + 1.5841 × Agricultural Products + 0.1221 × SPI - 1.0784 × SSIrz	Population Growth: 3.26 Energy: 3.44 Agricultural Products:1.26 SPI: 3.98 SSIrz: 3.25	RMSE: 0.41 R^2: 0.87 Adjusted R^2: 0.83 *p*-value: 2.26e-07 AIC: −1.64e+03 AICc: −1.64e+03 BIC: −1.64e+03
5) Crop Production Index = 0.0188 + + 1.1019 × Livestock + 0.0070 × Population Growth + 1.0704 × Agricultural Products - 0.5705 × SPI - 0.3479 × SSI - 0.4101 × SRI	Livestock: 3.09 Population Growth: 1.72 Agricultural Products:1.25 SPI: 1.89 SSI: 1.27 SRI: 3.28	RMSE: 0.28 R^2: 0.94 Adjusted R^2: 0.92 *p*-value: 1.51e-09 AIC: −1.65e+03 AICc: −1.65e+03 BIC: −1.65e+03
6) Crop Production Index = 0.0035 + + 0.8296 × Livestock + 0.1870 × Population Growth + 0.8463 × Agricultural Products	Livestock: 1.12 Population Growth: 1.14 Agricultural Products:1.03	RMSE: 0.39 R^2: 0.87 Adjusted R^2: 0.85 *p*-value: 4.29e-09 AIC: −1.66e+03 AICc: −1.65e+03 BIC: −1.65e+03

accurate model for food deficit (RMSE = 0.45, Adjusted R^2 = 0.78), and the 5th model was the most accurate one for crop production index (RMSE = 0.28, Adjusted R^2 = 0.92). In general, the crop production index models indicate more accuracy and higher precision than the food deficit models in all cases. The 3rd and 6th models in Table 2 are the same as the 2nd and 5th models, respectively, except that the drought factors are excluded in them. The reason for removing drought indices is to investigate how much drought indices contribute information to food deficit and crop production index models. The results suggest that including drought indices enhances the accuracy of food deficit model and crop production index model by more than 15% and 10%, respectively (Table 2).

To better understand how drought may impact food security in the Middle East, a temporal comparison is conducted between the most severe recent droughts over the Middle East and the major agricultural products in the region. Fig. 9 shows the temporal variations of agricultural products and agricultural drought index (SSI-12) during the period of 1992–2016. The 12 agricultural products, food deficit, and crop production index are individually de-trended and normalized around their mean. From Fig. 9, the red area shows the SSI-12, and if it falls below zero, it indicates agricultural drought. The yellow line represents food deficit, the blue line represents crop production index, and the green line represents the mean of the 12 agricultural products (number 8 in Supplementary Table S1). Two major drought periods are detected in this study: 1998–2002 and 2007–2013. The mean agricultural products and crop production index are decreased in both drought periods, and they indicate lower than average values. Whereas food deficit is increased in the second drought period (i.e. 2007–2013). Our analysis suggest that the mean agricultural products are positively correlated with SSI-12 (R = 0.40), meaning that decreasing SSI (dry condition) will decrease agricultural products. It is to be noted that food deficit is a function of many factors such as food imports and exports, population, trades, political stability, and planning and management; some of which are not necessarily impacted by regional drought conditions or agricultural yield (Hameed et al., 2019; Hillman and Baydoun, 2017).

5. Discussion

Food insecurity may arise due to deficiency of food production as a result of extreme weather events (e.g. drought or flood), population growth exceeding the food supply production, and increasing food prices as a consequence of poor economic growth and market fluctuations (Silva et al., 2018). In east Africa, 13 million people were impacted by food crisis as a consequence of the 2011 drought in the region, which resulted in death of 250,000 people due to starvation in Somalia (Vicente-Serrano et al., 2012). Many studies investigated food security in different regions around the world. However, each study

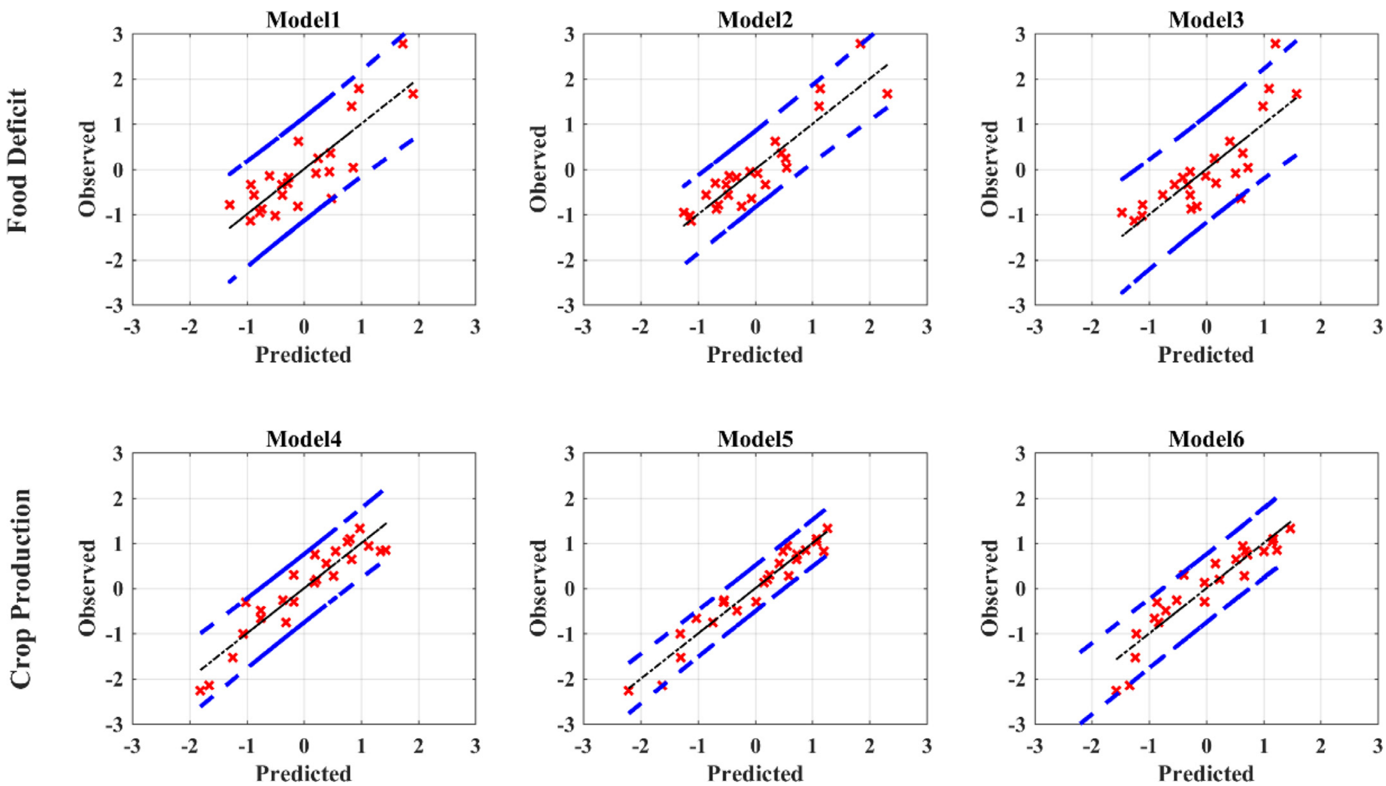

Fig. 8. A linear fit of data with 95% confidence interval of food security models in the Middle East. The x-axis shows BLR model outputs and y-axis is observations. The details for each model is provided in Table 2.

defines food security distinctly according to the environment of the region of interest. For instance, food security in Burkina Faso was defined in terms of crop–livestock farming systems (Rigolot et al., 2017). Rigolot et al. (2017) investigated the effect of different climate change scenarios and recommended studying the effect of combining climate related practices with social dimensions on food security. Bakker et al. (2018) developed the Food Distributed Extendable COmplementarity (Food-DECO) model to integrate agricultural, transportation, and economic sectors in order to evaluate food security in Ethiopia. The authors were able to investigate the effects of regional crop failure on food security.

Food demand of a region may highly rely on population size and per capita food consumption (Yang and Zehnder, 2002). Yang and Zehnder (2002) projected the cereal demand in the southern Mediterranean countries based on consumption rate and population growth. They concluded that water scarcity is a major limitation of food production in the region. Their results are in coherence with our findings that food security is impacted by drought (as a water stress factor) and population growth. Alary et al. (2014) studied the adaptation strategies of the recent drought (1995–2010) in the north coastal zone of Egypt, and found that drought drastically impacted agricultural activities and livestock in the region. Our study also confirms that agricultural

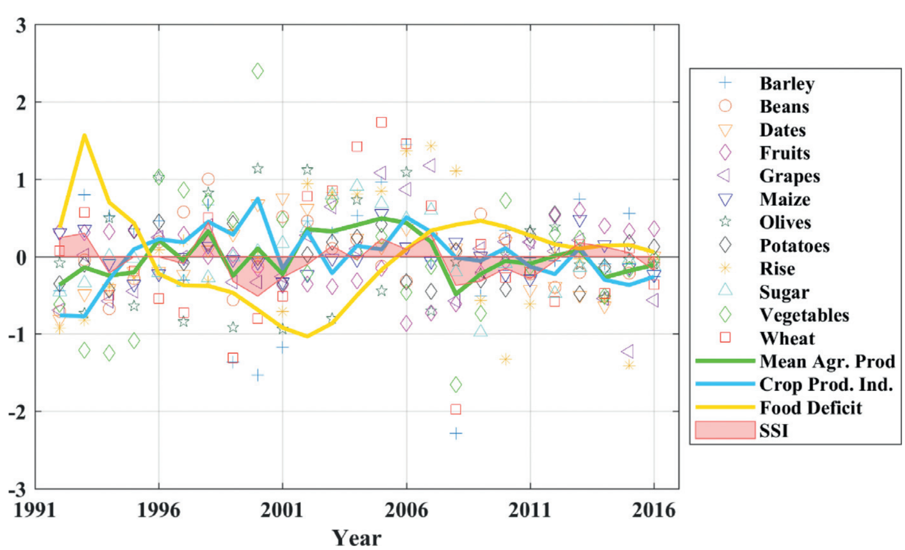

Fig. 9. Annual time series of mean agricultural products, crop production index, food deficit, as well as agricultural drought index (SSI-12) during the period of 1992–2016.

products were impacted by the two major recent droughts during the period of 1998–2002 and 2007–2013 across the Middle East (see Fig. 9).

Eklund and Thompson (2017) investigated the 2007–2009 drought and vegetation productivity over the border region of Iraq, Iran, and Turkey. The authors concluded that resource management may play important role in reducing drought vulnerability. Kelley et al. (2015) mentioned that before the 2007–2010 drought in Syria, agriculture accounted for 25% of Syrian gross domestic products (GDP). Whereas, wheat production considerably reduced and agriculture production GDP dropped to 17% in 2008 drought year. These results are consistent with our findings for the 2007–2013 drought period over the Middle East. Crop production index and agricultural products indicted a decreasing trend during the 2007–2013 drought period, and food deficit indicated an increasing trend during the same drought period (see Fig. 9).

Joint evaluation of biophysical and socioeconomic drivers may enhance our understanding of climate impacts and responses (Islam et al., 2016). The need to integrate climate and socioeconomic drivers to assess food security in a region is one motivation of this study. In addition, our recent findings in Hameed et al. (2019) suggested that natural hazards like drought, precipitation extremes, and heat waves may escalate water stress in the region, which can be exacerbated with increasing population, subsequently impacting food production in Middle East.

One limitation of this study was data availability, especially freshwater withdrawals for agriculture (Supplementary Table S1). More accurate results may have been achieved with the same approach if monthly data were available for the socioeconomic factors that were considered in this study. Water withdrawals data was not available for most of the study period. Therefore, drought was used as an indicator of water stress in Middle East.

This study provided a quantitative assessment of food security as a function of drought and socio-economic factors in the Middle East. The approach of this study can be applied in any region but expert knowledge about the study domain is essential for choosing the relevant drivers of food security in that region. The factors considered in this study are place-based and they are not supposed to be explicitly included in another study regions.

6. Summary and conclusion

This study assessed drought and food security across the Middle East. At first, drought conditions were characterized over the region using short and long timescales of hydro-meteorological data during the period of 1948–2017. Then, food security was modeled in the Middle East based on drought and socio-economic factors. The Global Land Data Assimilation System (GLDAS) monthly precipitation, soil moisture, and runoff data at a 0.25° spatial resolution were utilized to derive meteorological, agricultural, and hydrological droughts at multiple timescales during the past seven decades. Moreover, data from different sources including the IEA, FAO, and the World Bank were employed to investigate the socio-economic factors related to food security in the Middle East. The temporal variations and long-term trends of meteorological, agricultural, and hydrological droughts over the region were investigated, and the main findings of the study are as follows:

- Hydrological drought is the most intensified drought type over the region, especially in Egypt.
- Meteorological drought reached its peak in early 1970s, early 2000s, and during 2008–2012 with about 60% drought extent across the Middle East. Whereas, hydrological drought extent reached its maximum in 2009 with over 50% drought extent. Agricultural drought extent was at its maximum in 2017 with about 80% drought extent over the region.
- The Bayesian linear regression model was capable of predicting food security in the Middle East considering livestock, population growth, agricultural products, and drought condition as inputs.
- Agricultural production decreased in the Middle East following a drought episode, especially for the recent drought event of 2010.

Declaration of Competing Interest

None.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2019.107816.

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