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Measuring drought agriculture by using ADSI and VHI indices and determining crops irrigation effects (case study: Markazi province)

M.H Davodabadi Farahani[1], Alireza Sharifi[2*]*, Mahdi Arabi[3]

[1,2,3] Department of Surveying Engineering and Geomatics, Faculty of Civil Engineering, Shahid Rajaee Teature Training University, Tehran, Iran

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ABSTRACT

Drought Agricultural is the most repeatedly natural disaster, particularly in arid/semi-arid regions. It causes diversity losses such as crop quality, production, utility rate, and food security as the most important threat. In this study, first, SPEI index is calculated whereby precipitation and temperature data, respectively. The correlation analysis performed between crop yield anomalies and SPEI index to determine critical month/months in which drought severity is severe, and crop reproductive stage is vulnerable. After this step, the best timescale of SPEI is demonstrated and the slope between the best SPEI and crop yield anomalies is calculated to compute ADSI values. Finally, for appreciation of irrigation effects in response to drought stress, analysis of covariance and panel data regression due to SPEI values and crop yield are applied. In addition, the relationship between the SPEI, VHI, and ADSI will be discussed. It is necessary to state that the majority of crops in the region of interest are studied. Also, for obtaining VHI, LST, and NDVI indices as MODIS products have been utilized in the study area. For the most crops, The results indicated that July was a critical month and for the residual crops, August was a critical month with severe drought, whereas some crops had three critical months. Furthermore, significant amount of the crops have been damaged in the flowering stage, plus the corn was more sensitive to drought relative to other crops. The results derived from panel data model regression show that drought sensitivity is incremental in non-irrigation harvest and vice versa. In other words, non-irrigated crops are more sensitive to drought and drought stress increase in an arid and semi-arid acres, significantly. At the end, comparing results of VHI and ADSI imply their strong relationship. ADSI and VHI were able to quantitatively measure the drought intensity. Also, the panel data regression was able to discriminate irrigation and non-irrigation effects.

KEYWORDS

Agricultural drought, ADSI, SPEI, VHI, crop irrigation.

* Corresponding author

E-mail addresses: davodabadi.mohamad@yahoo.com (M.H Davodabadi Farahani); a_sharifi@sru.ac.ir (Alireza Sharifi); mahdi.a@sru.ac.ir (Mahdi Arabi)

1. Introduction

Drought is a devastating disaster that occasionally occurs unpredictably without specific district and encompasses extensive losses such as pasture losses, and forage supply, etc. Drought is categorized into four main types comprising agriculture, meteorology, hydrology, and economic based on diversity science definition (Kogan, 2000). Meteorological Drought is created by rain-fall mitigation and mostly happened in either arid or semi-arid region and depending on climate condition in each zone. For example, if the annual rainfall was 180 mm in Libya, it implies severe drought whereas 25 mm rain-fall in 15 days period time shows severe drought in England. The second type is hydrology drought which takes place when plane and sub-plane water sources decrease that is few time after meteorology drought. Moreover, it affects sub-ground water level and rain-off. The third type of drought is the matter of this study and is named drought agricultural. This merely occurs whereby plant moisture decreasing, not only rain-fall decrement. However, change of humidity relies on rainfall. Based on statistics, 15 percent of the total disaster is relevant to agriculture (NOAA, 2016). This type of drought hurts the yield and is causes willing the plants. The final sort is the economic drought, derived from combination of the former types, it takes place for demand increment in proportion to crop's run-fed supply.

Drought evaluation help to adopt decision as well as effective management for controlling drought effects that influence the quality and amount of crops. Because raw data and descriptive attributes won't able to measure drought, so a drought index is needed for this aim to measure drought in digit format.

In this study, drought assessment has been accomplished whereby SPEI[†], ADSI[‡], and VHI[§] indices. All research show SPI[**] and SPEI are better than other indices because they have flexible scale unlike PDSI[††] and its variables such as PZI[‡‡], PHDI[§§], and PMDI[***]. SPI and SPEI operate in any timescale (e.g. 1 month, 3 months, etc.) (Lu, et al., 2020). SPI is obtained from temperature and precipitation data while SPEI is measured by using potential evapotranspiration and precipitation (McKee , Doeske, & Kleist , 1993.).

VHI is a composite index, it is obtained from NDVI[†††] and LST[‡‡‡] and assesses drought based on the temperature and vegetation stress. So VHI is used to monitor vegetation conditions. VHI is not immediately determined through NDVI and LST. NDVI is used to determine Vegetation Condition Index (VCI) whereas LST is used to determine Temperature Condition Index (TCI). VHI can identify the vegetation canopy stress, so it is used as a drought indicator index (Rusydi & Masitoh , 2019).

Badami et al. (2020) established ADSI index whereby the contribution of TCI, VCI, and ETCI[§§§] indices to assess the drought in 14 years distance in Niger. Based on unbiased results. This index was trustworthy for drought assessment. (Gerard, Badamassi , El-Aboudi , & Gerard , 2020). Similarly, Lu et al. (2020) performed the irrigation effects assessment on some crops in entire the U.S. by applying ADSI index and a panel regression model in one century, from 1950 through 2016. They ascertained critical months with rigorous drought based on the maximum SPEI, therefore, they devoted SPEI values to ADSI and panel regression relation and argued about irrigation or non-irrigation effects. Results indicated the irrigated crops had losses less than dry or non-irrigation crops (Lu, et al., 2020). Masitoh and Rusydi.(2019) measured drought agriculture whereby VHI index across Brantas watershed in one decade from 2008-2017. They utilized NDVI and LST for obtaining TCI and VCI indices. With respect to the results of the correlation between LST and NDVI, either LST or NDVI influences VH (Rusydi & Masitoh , 2019) Möllmann et al. (2018) used VHI index derived from TCI and VCI to manage the drought stress in the east-northern of Germany. Consequently, they understood these indices are the best indices associated with drought when weather stations are separate form another (Möllmann , Buchholz , & Musshoff, 2019). Sholihah et al. (2016) attempted to assess the drought stress throughout Sobeng and Karavang from 2000-2015 by using vegetation index and landsat8 imagery for food security purposes. With regard to this aim, they specified the drought zone via VHI index so that VHI had been immediately derived from VCI and TCI. They concluded drought will be severe if LST and NDVI will increase

† . Standard precipitation Evapotranspiration Index
‡ . Agricultural Drought Severity Index
§ . Vegetation Health index
*** . Standard precipitation Index*
†† . Palmer Drought Severity Index
‡‡ . Palmer Z index
§§ . Palmer Hydrological Drought Index
**** . Palmer Modified Drought Index*

††† . Normalized Difference Vegetation Index
‡‡‡ . Land surface Temperature
§§§ . Enhanced Temperature Condition Index

(Sholihah , Trisasongko , & Shiddiq, 2015). Dalzious at el.(2014) achieved to assess the drought by using NDVI and AVHRR temperature products to obtain VHI in Greece, from 1981-2001, and they discovered the drought is more severe in summer or heat seasons. Considering drought depends on damaged domain and its influence on economy and agronomy (Dalezios , Blanta , Spyropoulos , & Tarqui, 2014). Ekakun et al. (2015) measured the drought severity by using VHI time series and EVT [****] procedure in Kiev, and they concluded it is possible to denote the high-risk zones (Skakun , Kussul , Shelesto , Kussul , & Geom, 2016).
Temporal and spatial information of drought can help to risk management. Here, we need high-resolution data otherwise that is difficult to estimate drought. For this aim zarei et al. (2013) illustrated the drought extent in Iran's provinces from 1997 to 2005. They estimated VHI, TCI, and SPI indices by using AVHHR images and precipitation data derived from synoptic weather stations. Their results indicated SPI, VHI and TCI were in harmony in all times, either dry or wet seasons (Zarei, Sarajian , & Bazgeer DESERT, 2013). In addition, climate conditions vary drought values thus Essa et al. (2016) detected the drought whereby SPEI as meteorology index and VHI in from 2000-2011. Results show there is a correlation between SPEI and VHI. Moreover, they incorporated their results on GCM [††††] and predicted future weather conditions from 2010 through 2050 (Essa , Khalil , & Abdel-Wahab, 2016). Andujar et al. (2017) like previous investigation, used TCI and VCI for computing VHI and SPEI as meteorology indexes for drought agricultural detection. Results proved SPEI and VHI have the most correlation (13 months), after that VCI and TCI had a correlation in 4 and 2 months, respectively (Andujar, Krakauer , Yi , & Kogan, 2017). Similarly, Bento et al. (2018) identified damaged areas whereby drought by using TCI, VCI, VHI, and SPEI indices. Analysts concluded because of VHI and SPEI correlation also the correlation between TCI, VCI, so VHI, VHI is able to assess drought intensity (Bento , Gouveia , & DaCamara , 2018). In this study, our innovation is the simultaneous usage of ADSI, SPEI, and VHI to analyse their correlation together plus we appear the crop growth rate and benefit of irrigation by using panel data model regression. The correlation between the crop yield and SPEI index is computed to determine critical months and indices performances, rather than using the mean of condition to determine the seasonal pattern. The crop yield trend is determined by using regression models to separate out the climate change effects from the technology effects such as fertilizing for obtaining the crop yield anomalies. Then, ADSI is computed based on SPEI slope to denote the drought districts with different severity. Lastly, ANCOV [‡‡‡‡] and panel data regression is used to appreciate irrigation effects on crops susceptibility to drought and boosting crops. Eventually, VHI is compared with ADSI and SPEI to denote their difference in drought evaluation. The aforementioned section is the framework of the study. In addition, this workflow shows the relationship between different parts of the method.

2. Data and methodology

2.1. Satellite and meteorological data

The MODIS products contain MOD11B1 (LST) and MODI13A1 (NDVI) that they are devoted to computing vegetation indices. In fact, LST is used to obtain BT that used to compute TCI whereas NDVI is applied to compute VCI (Fig. 1). The spectrum channel of 470-670 nm is used to subdue atmospheric effects. Overall, MOD11B1 is MODIS level 3 product with daily temporal resolution, 6 km spatial resolution, and kelvin temperature unit. Conversely, MODI13A1 has 16 days temporal resolution and 500 m spatial resolution, with a 0.0001 scale factor.

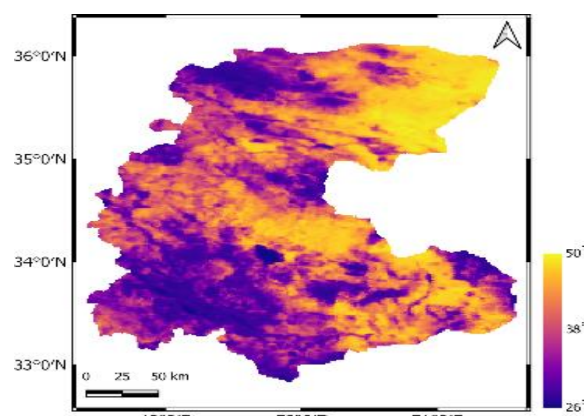


Fig. 1. LST map of study area derived from MODIS satellite imagery in 2009 (in Celsius degree).

In this research, wheat, hay, and corn as major crops in ROI are studied. Thus, we need statistical analysis the dataset derived from crops census in former years. These data exist in agricultural ministry and represent crop yield plus irrigation and non-irrigation crops in any month at the state and county level (Fig. 2).

[****] . Extreme value theory
[††††]. General Circulation Models
[‡‡‡‡] . Analyse of Covariance

Furthermore, SPEI has been calculated by using precipitation and temperature datasets obtained from the synoptic weather station as meteorology data in the study area. It is necessary to mention this tip that MODIS products as satellite data and crop yield as ground data must be concurrent. Therefore, in this text we used ground and satellite data between 2009 through 2018, more accurate in 2009, 2015 and 2018 during growing season.

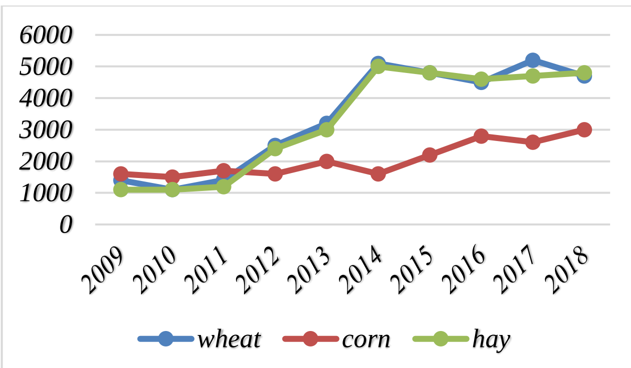


Fig. 3. Crop yield of study area from 2009 to 2018.

2.2. Crop yield anomalies

For rendering of drought impact on agriculture, one requirement is to separate out climate and technology effects that are caused in high-frequency fluctuation and non-linear trend, respectively. In other words, we should transform non-linear trend of the crop yield into linear trend. For this goal, the long-term crop yield is simulated to the linear and stationary trend by using several regression models. Because of the advantage of locally weighted regression, this model has been used. This manner based on surrounding point election around the main point. In other words, weigh function assign weight to the nearest points of the main point more than other points farther away. This model uses statistical method for detrending. The locally weighted regression model is obtained from the weight function as follows:

$$Yt_i = \hat{\beta}_0(t_i) + \hat{\beta}_1(t_i)\, t_i + \hat{\beta}_2(t_i)\, t_i \qquad [1]$$

Where $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$ are model coefficients and Yt_i is the fitted value in time t_i. Now to separate out climate and advanced technology effects the multiplicative decomposition model is used. The decomposition model obtain detrended data from ratio of original data and trend data. Then, this output indicate percent of anomalies in various times. In other statement, this model delete variance of the trend (Junyu , Gregory , Carbone , & GaoDepartment, 2017).

2.3. SPEI computation

SPI only uses precipitation data unlike SPEI in which is used precipitation and potential evapotranspiration together. In SPEI calculation process, first potential evapotranspiration is computed by using the bellow method. Then PPT[§§§§] *and PET*[*****] *is converted to Gaussian distribution. Finally, SPEI is calculated by Gaussian distribution inversion and is classified to mid through worse intensity (0 to -2). Primary stair for SPEI calculation procedure is PET computation, therefore, it's measured as follow (SERRANO & SERGIO , 2009).*

$$PET = 16K\left(\frac{10T}{I}\right)^{m} \qquad [2]$$

Where K is corresponding to the correction coefficient based on latitude and month. T is temperature and I is heat index that relies on it. Also, m is constant-coefficient equal to 6.75×10^{-7} I^3 -7.71×10-5 *I^2 +1.79×10^{-2}*I +0.492. Next precipitation and PET difference is computed as following formula (SERRANO & SERGIO , 2009).*

$$D_i = P_i - PET_i \qquad [3]$$

For modelling Di, suitable distribution is required, so log-logistic distribution is used. The probability density function of a three-parameter log-logistic distributed variable is expressed as:

$$F(X) = \sum_{i=1}^{n} \left(1 + \left(\frac{\alpha}{X - Y}\right)^{\beta}\right)^{-1} \qquad [4]$$

Where a, b, and g are scale, shape, and origin parameters, respectively. The parameters can be obtained from L-moment. Initially, crop yield were detrended by using LOWESS coupled with multiple decomposition models from 2009-2019. Pearson correlation model performed between SPEI and crop yield and represented the best index and critical month/months with severe drought (SERRANO & SERGIO , 2009).

2.4. Agriculture drought sensitivity index

The linear regression slope between the best SPEI and the crop yield anomalies is used to compute ADSI. In clear, the Steeper slope indicates lower crop yield means severe drought. The higher ADSI value, the higher the drought sensitivity and vice versa. ADSI formula is expressed as follows:

[§§§§] *. Potential precipitation Temperature*

[*****] ***. Potential Evapotranspiration Temperature***

$$ADSI = \frac{\sum_{c=1}^{10} \sum_{i=1}^{n} SLP_{c,i} A_{c,i}}{\sum_{c=1}^{10} A_{c,i}} \quad [5]$$

Where C shows crop, A represents the harvested area in which i is state or county, SLP depicts the described linear regression slope in the previous section. Note that, SLP is based on dominant plant and ADSI is divided into the lowest, low, moderate, high, and the highest sensitivity (Lu, et al., 2020).

2.5. Panel data regression

Panel data regression model provides an appropriate appreciation about irrigation/non- irrigation role in response to drought sensitivity for each crop. In this approach, the best SPEI considering its performance and raw data is used instead of SPI and crop yield. Here, log-transformed yield is utilized with respect to its normal distribution. This model is estimated as below, involving sum of the county fixed model (panel data model).

$$Log(Y_{i,g,t}) = \alpha_{i,g} + \beta_{i,g}T + \delta_g SPEI_{i,t} + \theta_g SPEI_{i,t}^2 + \varepsilon_{i,t,g} \quad [6]$$

Where i exhibits Specific County, t depicts time or months and g appears irrigation and non-irrigation, Y is raw crop yield data. Additionally, α demonstrates county fixed effect in which irrigation vs non-irrigation discrepancy and time-in variation difference is shown. Β is a linear time trend that shows technology differences in irrigation and non-irrigation crops. Ө and ծ are parameters by ability to identify crop irrigation effects. SPEI term is quadratic because the hypothesis is irrigation effects may be not linear (Lu, et al., 2020).

2.6. Vegetation health index

VHI is abbreviation of vegetation health index that is constituted from VCI and TCI. These indices are organized from NDVI and LST, respectively. Hence, MODIS satellite imagery is acquired to measure NDVI and LST (BT). Consequently, BT and NDVI computation give us TCI and VCI that are used in VHI calculation process. Thereby, for obtaining VHI, first VCI and TCI are calculated, then VHI is measured by these indices. Hence, VCI relation is expressed as follow:

$$VCI = \frac{NDVI' - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad [7]$$

Where NDVI' is the average of NDVIs while $NDVI_{max}$ and $NDVI_{min}$ are the min and max of NDVI value, respectively. It is necessary to mention how NDVI is derived, which is beyond the scope of this text. VCI is an efficient index for drought evaluation among variety of drought indices with great accuracy. TCI is the next indices for VHI measurement as follows:

$$TCI = \frac{BT_{min} - BT'}{BT_{max} - BT_{min}} \quad [8]$$

Where BT' is average brightness temperature values throughout the study area. BT_{max} and BT_{min} are max and min brightness temperature values. With regard to previous section, BT is determined by LST. At the end, VHI calculation through VCI and TCI is expressed bellow:

$$VHI = \alpha * VCI + (1-\alpha) * TCI \quad [9]$$

Where α is a constant equal to 0.5. And VHI values were defined as 4 classes: Extreme drought (<10), Severe Drought (10-20), Moderate Drought (20-30), mid drought (30 – 40), and No Drought (>40) (Rusydi & Masitoh , 2019). The flowchart of the proposed methodology is shown in Fig. 3.

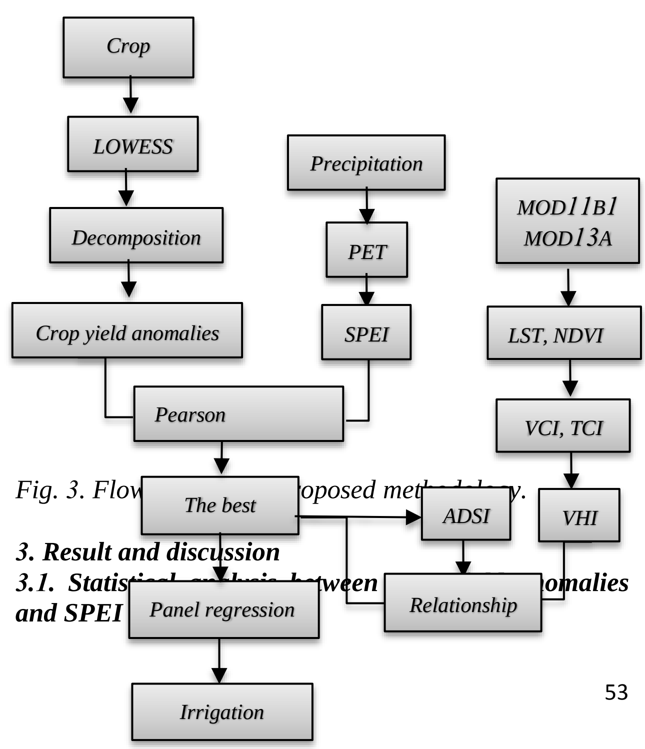


Fig. 3. Flowchart of the proposed methodology.

3. Result and discussion

3.1. Statistical analysis between crop yield anomalies and SPEI

Pearson correlation between SPEI and crop yield anomalies represents the best SPEI timescale and critical month in national-wide nor locally. The average of the Pearson correlation has been portrayed in Fig. 4 The results show the drought severity is more severe in July during the growing season plus hay, and wheat are more sensitive across the study area. Moreover, corn and wheat considering Fig. 4 had the highest correlation with 1-month SPEI coincide with tasseling, silking, and pollination stages in July. Also, hay had the highest correlation with 3-month SPEI comprising May, June, and July. In other expression, three months was critical instead of one month.

3.2. Agricultural drought severity index

ADSI is defined by the best SPEI and crop yield derived from row data. Considering the crop yield anomalies and ADSI results, ADSI has the highest correlation with crop yield anomalies. Also, ADSI values are conforms to irrigation and non-irrigation results. Therefore, drought stress increases with high ADSI value individually in arid region in the east of ROI. Furthermore, ADSI values are consistence with irrigated zones. Based on results, ADSI values is more in irrigated crops than non-irrigated crops. Comparing this results with other performed research in US (Lu, et al., 2020) since1950s is illustrated, results of ADSI in these researches are in harmony together. Both researches show ADSI values increase in non-irrigated crops and arid acres in contrast to irrigated crops.

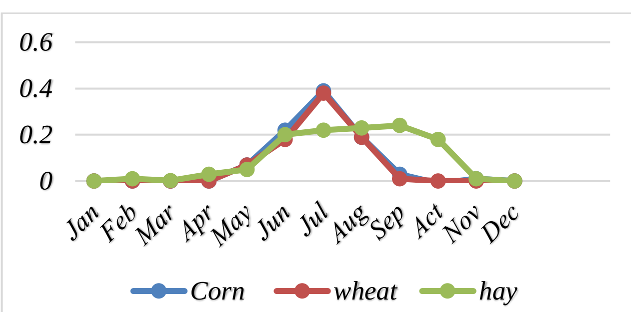


Fig. 4. Pearson correlation coefficients between crop yield anomalies and 1-month SPEI in different months during the growing seasons.

3.3. Irrigation effects on crop yield

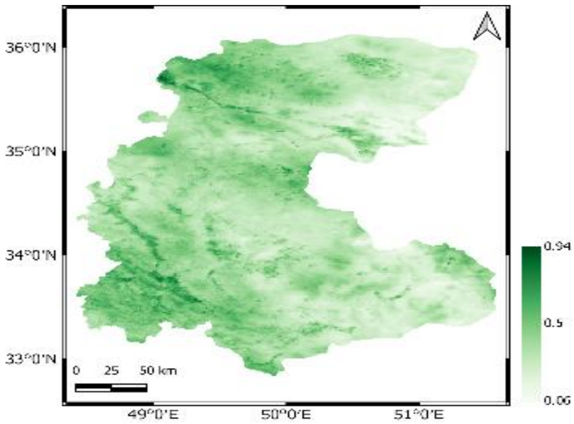
Suppose crop irrigation affects crop yield. Hence, integrating a regression and covariance analysis is performed to estimate the effects of irrigation on crops. For this purpose, SPEI values is adjusted to 0 and the mean of long-term crop yield to discern the irrigation and non-irrigation effects with high confidence. Thereby, with regard to evidences, irrigation has an important role in crop yield whereby boosting the crop. For example, the mean of irrigated corn yield is at least 68% and at most 76%. From fitting the panel data, regression results in crop yield increase/decrease through irrigation/non-irrigation. Therefore, irrigation mitigates crop losses also the responses of the non-irrigation crop to drought show the non-irrigation crop is more sensitive to drought. In this text, row data derived from agriculture census is used containing irrigated crop and non-irrigated-crop, so it also contains mechanized irrigation. With respect to irrigation effect assessment in US (Lu, et al., 2020) they verify the results of this text. This research was accomplished from 1950 to 2010 throughout the U.S. and exhibited drought intensity is more effective in non-irrigated crop.

3.4. Vegetation health index

In this investigation, VHI has been evaluated from 2009-2019. Comparing VHI with SPEI and ADSI indicate VHI changes is conformed to ADSI and SPEI. The response of VHI to drought is the same as the response of ADSI across the study area considering. Thereby, VHI decreases/increase arid acres and non-irrigated/irrigated crop by decreasing/increasing SPEI and ADSI. According to Fig. 5 VHI values in east of Markazi province are less than west of the province exactly ADSI results that is VHI and ADSI are in harmony together. Also, because of relationship between ADSI and SPEI, SPEI and VHI have the strong correlation. Results of one research for evaluating drought intensity since 2000 indicate agreement among this text results and it about relationship between SPEI and VHI (Essa , Khalil , & Abdel-Wahab, 2016).

4. Conclusion

In this study, the correlation between the SPEI and crop yield anomalies to specify the critical month with severe drought was executed successfully. Among all months, July was the critical month. Also, we obtained SPEI whereby MODIS products and ADSI via SPEI and crop yield anomalies, respectively. In addition, fitting the panel data regression and ANCOV to determine the irrigation effects on crop yield was accomplished. Regarding the results, ADSI is consistent with VHI, and they conform to irrigation or non-irrigation crop yield. Overall, the higher ADSI the higher VHI the higher the drought intensity. Also, corn and corn wheat were more sensitive to drought, unlike hay.



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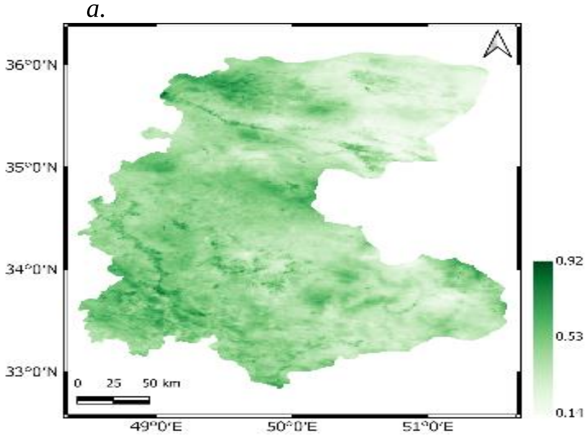

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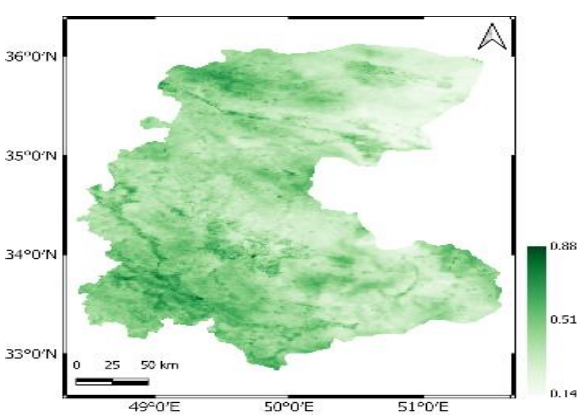

c.

Fig. 5. VHI indices from 2009 to 2019 in the study area: (a) 2009. (b) 2015. c) 2019.

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