Influence of climatic Parameters on The Two-spotted Spider Mite population based on Remote Sensing in Southeast of the Caspian Sea

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Abstract

Tetranychus urticae Koch (Acari: Tetranychidae) is a serious pest in cotton fields worldwide. Monitoring of *T. urticae* with time-series of vegetation index and climatic factors based satellite data was applied to near real-time assessing. The current study aimed to determine correlations between *T. urticae* population dynamic and effects of Aerosol index of Sentinel-5, Sentinel-2-NDVI (10m), The Land Surface Temperature (LST), MODIS-Evapotranspiration (ET) and CHIRPS-precipitation. Spider mite out-breaking has coincided with the wheat harvesting and where experienced several dusty days with high aerosol index 0.167. Rainfall had a significant negative correlation with *T. urticae* population ($R^2 = 0.378$) and a threshold precipitation level was estimated at least 2 mm to clean up the canopy. We could not find a significant pattern between temperature and *T. urticae* population until August 2020 and then the significant positive relationships were observed during August 2020, $R^2 = 0.3519, 0.1283, 0.1675$ and 0.178 , weekly. Evapotranspiration depicted a statistically synchronous relationship $R^2 = 0.637$ with *T. urticae* dynamism. There was a positive correlation between increasing NDVI and *T. urticae* population until August 2020 and then was shifted to negative pattern $R^2 = 0.273$ and 0.139 . These findings, aerosol index of sentinel-5 and MODIS-evapotranspiration have potential to forecast spider mite population with high temporal resolution.

Introduction

Tetranychus urticae Koch, is a serious economic pest in cotton fields worldwide because of polyphagous behavior with a wide range of plant hosts about 900 plant species (Brown et al. 2017). The main spider mite fauna, *Tetranychus* spp., is consisting of *Tetranychus pacificus*, *Tetranychus turkestanii* and *T. urticae*, and known as a common pest of cotton. *T. urticae* distribution is extended in all territory of Iran (Golestan, Tehran, Azerbaijan, Khorasan, Ardebil, Fars) on cotton fields (Honarparvar et al. 2012). Yield loss due to dusty spider mite infestation of cotton, *Gossypium hirsutum* L., was measured by entomological researchers such as during 2010 and 2011 to determine two-spotted spider mite population and injury ratings (Scott et al. 2013). Among abiotic parameters, climatic parameters play a key role in pest population dynamism especially temperature, relative humidity, rainfall, sunshine hours, etc. The climate factors affected not only mites (Ahmed et al. 2012) but also ticks such as a 14-year population study on Scabies in Taiwan (Liu et al. 2016). Five years of systematic sampling program in Bangladesh was studied the effect of weather parameters on *Oligonychus coffeae* N. (Acarina: Tetranychidae), Red Spider Mite, and showed positive (temperature, relative humidity, and sunshine hours) and negative response (rainfall and cloud coverage) (Ahmed et al. 2012). Demographic parameters of spider mite pests are temperature-dependent such as the intrinsic rate of increase (r_m) of *T. pacificus*, *Eotetranychus willamettei* (McGregor) (Acari: Tetranychidae) (Stavrinides and Mills 2011) as well as development time, sex ratio, and fecundity of *T. urticae* (Margolies and Wrensch 1996). The life-tables of *T. urticae* significantly was influenced by different levels of macronutrient N, P and K (Wermelinger et al. 1991). Population dynamics of *T. urticae* were seasonally investigated under acaricide constraint on eggplant in Bursa Province, Turkey. *T. urticae* population was positively and

negatively responded with mean temperature and mean humidity, respectively (Kumral and Kovanci 2005). According to the targets of the Paris agreement (1.6 °C warming by 2050), until 2050 for tomato, a suitability modeler based on climate change (CC) which was equipped with irrigation facilities (AEI) predicted unsuitable conditions for tomato production and increasing outbreak risk of two-spotted spider mite globally, because of failure in biological control (Litskas et al. 2019). Therefore, climate conditions would also be affected the pest population dynamic, especially in large-scale projections. Using reflectance spectroscopy in two common ways with satellite or unmanned aerial vehicle (UAV) equipped by multispectral imagery. Diffuse reflectance spectroscopy (Visible/Near Infrared Reflectance Spectroscopy) identified infestation regions by *T. urticae* and also quantitatively assessed *T. urticae* damages in Strawberries (Fraulo et al. 2009). Some researches such as, Reisig and Godfrey (2006), reported that, Aerial and satellite images to distinguish infested cotton by aphid (*Aphis gossypii* Glover) and spider mite (*Tetranychus* spp.) from healthy plant. Martin and Latheef, (2017) evaluated a ground-based multispectral optical sensor for detecting spider mite damage in greenhouse condition on cotton production. The supervised classification approaches such as Support Vector Machine (SVM) and a transferred Convolutional Neural Network (CNN) was reported for mite-infestation using UAV multispectral imagery (Huang et al. 2018). Species composition are another GIS and remote sensing approaches applied for modeling ecological niche of Tetranychoid mites (Acari: Tetranychidea) in in different climates of Tehran Province, Iran (Ghasemi Moghadam et al. 2016). The current study aimed to determine the potential effects of five climate and vegetation characters including air pollution (dust), The Normalized Difference Vegetation Index (NDVI), The Land Surface Temperature (LST), Evapotranspiration (ET) and precipitation on Spider mite population.

Material And Method

2-1-Study area

The study area presents unique climatic conditions of northeast of the Caspian Sea including the Hyrcanian forest (southern), desert (northern), fertile lands and vast paddy fields (central areas) where 14 adjacent districts located in the northeast of Iran (Figure 1), with latitude ranging from 36° 30' to 38° 10' N and longitudes from 53° 50' to 56° 20' E. Climatic diversity of study areas distinguishes the role of climatic effects on hotspot formation of spider mite. The area occupies 21400 km² approximately, and the altitude oscillates from -39 to 3780 meters above sea level. Average values of annual temperature and precipitation are 16.88 °C and 454 mm, respectively. In the study area, most of the farmer communities have small landholding and wheat, barley, canola, and broad bean are the most important autumn crops. Soybean, cotton, rice, and sorghum also are the most important summer crops in this province. Golestan province is one of the top three cotton-producing provinces in Iran as it is called the "land of white Gold". Our study has strongly covered all cotton agricultural areas within the Golestan province. The highest area under cotton cultivation belongs to Aqqala (33%), western part of Gonbad-e-Qabous (31%), and Gorgan (10%), while the crop is barely present in Minoodasht and Maravehtapeh at all. To achieve more accurate data, all satellite images were masked by of The Shuttle Radar Topography

Mission (SRTM, 30m) (Farr et al. 2007). The mask areas were high-dense forests (Hyrceanian forests) where is not the ecological niche of *T. urticae*.

2-2-Climate and vegetation datasets (Independent factors):

2-2-1-Precipitation

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) is one of reliable precipitation dataset which provided globally high resolution of precipitation by interpolation approaches (around a 0.05°) for a long period (daily, 1981-present) based on infrared Cold Cloud Duration (CCD), ImageCollection ID on Google Earth Engine (GEE), cloud-based image processing platform, "UCSB-CHG/CHIRPS/DAILY", (Funk et al. 2015).

2-2-2- Land Surface Temperature (LST)

The Terra-MODIS land surface temperature (LST) product (MOD11A1, 1 km, daily) form 09/06/2020 to 17/09/2020 was manipulated by Google Earth Engine (GEE). For all fifteen monitoring windows (Table.1), LST time series provided by mean of LST (day, night) temperature for every window.

Table.1. monitoring windows for synoptic recorded spider-mite population

monitoring windows	Date range
W1	May 30, 2020 - June 9, 2020
W2	June 9, 2020- June 17, 2020
W3	June 17, 2020- June 24, 2020
W4	June 24, 2020- June 30, 2020
W5	June 30, 2020- July 8, 2020
W6	July 8, 2020- July 15, 2020
W7	July 15, 2020- July 21, 2020
W8	July 21, 2020- July 29, 2020
W9	July 29, 2020- August 3, 2020
W10	August 3, 2020- August 11, 2020
W11	August 11, 2020- August 18, 2020
W12	August 18, 2020- August 29, 2020
W13	August 29, 2020- September 5, 2020
W14	September 5, 2020- September 10, 2020
W15	September 10, 2020- September 17, 2020

2-2-3-Evapotranspiration (ET)

Net Evapotranspiration was provided by The MOD16A2/V6 product, Evapotranspiration/Latent Heat Flux, is an 8-Day Global 500m. The algorithm was embedding the MOD16 data collection is based on Penman-Monteith equation (Allen 1996), which combination of different input sources including daily meteorological reanalysis data, vegetation property, albedo, and MODIS-land cover.

2-2-4-The Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is one of the most applicable vegetation indexes in remote sensing projection (Lamqadem et al. 2018). NDVI is worked on the red and NIR reflectance of soil. The NDVI values are in range from -1 (water resources and snow body) to +1 (full vegetation coverage). In the current research, a 7-10-day multi-temporal Sentinel-2 was provided NDVI index during monitoring windows.

2-2-5- Air pollution (aerosol index)

The "NRTI/L3_AER_AI" dataset from Sentinel-5 provides near real-time high-resolution imagery of the UV Aerosol Index (UVAI or AAL). This index is worked according to wavelength-dependent changes in

Rayleigh scattering in the UV spectral range for a pair of wavelengths (at the 354 nm and 388 nm). The positive AAI indicates the presence of phenomena which can absorb UV like dust and smoke. The pair of selected wavelengths have been absorbed very low by ozone (Soleimany et al. 2021).

2-3- spider-mite sampling and spatial analysis for *T. urticae* distribution map (Dependent Factor)

2-3-1- spider mite sampling as ground truth data

Ground-truth data of spider-mite population was reported by mean percentage of leaf area which were infected with various types of spider mite symptoms (dust-silk webbing, yellow spots, etc.). 100 cotton leaves were randomly observed by experienced experts and estimated infestation scoring of spider-mite according to equation (1) at each field.

See formula 1 in the supplementary files.

where n and p were the number of leaves and their infestation percentage, respectively. i, j, l and etc. indicated same infestation percentage. For the unity of procedure, The estimated percentages of infestation were reported based on specific intervals including 0 for no evidence of spider-mite, 1-5 for 1-10%, 11-20%, 21-30%, 31-50% and $50\% \geq$ infected leaf area, respectively. In this research, collected data from 65 cotton fields were used throughout Golestan Province; 6 (min) * 6 (min) grid cells in the Degrees, Minutes, Seconds (DMS) coordinate system (Figure 2). These fields were measured the percentages of spider-mite involvement during a fixed time (Saturday every monitoring window). After that, distribution maps of spider-mite were spatially analyzed for 15 monitoring windows by Inverse Distance Weighted (IDW) interpolation using ArcMap/ GIS 10.6 software. The deterministic interpolator method by 'Spatial Analyst Tools' in ArcMap software package (version 10.6, ESRI, Redlands, CA) was used to draw spider-mite distribution maps from the collected data. This process was performed and tried in every monitoring field located inside a cell grid.

2-3-2 Correlation analysis:

Various satellite data, such as AAL index of Sentinel-5P, LST-MODIS (Terra), NDVI-Sentinel-2, CHIRPS and ET-MODIS, were assessed as main factors (independent) on spider-mite out breaking. For each window, 200 random points were extracted between an interpolation map of spider-mite (dependent) and five satellite-based parameters (Independent) by '*ee.FeatureCollection.randomPoints*' by Google Earth Engine platform. The relations between five parameters and the distribution map were statistically examined using ANOVA regression analysis in SPSS (version 23).

2-3-3 Spatial Autocorrelation

Moran's Index has known the more applicable statistic for spatial autocorrelation. Global Moran's I estimate the possibility of spatial correlation at study region. The amplitude of fluctuations of the

Moran's I values is between 1 and -1. Positive autocorrelation (clustered) and negative autocorrelation (dispersed) in the data translates into positive and negative values of Moran's I, respectively. Random distribution of a variable (no autocorrelation) results in a value close to 0 (Overmars et al. 2003). The relationship between a pixel and its surrounding pixel was estimated by weights matrix. Therefore, a distance-based weight matrix (a threshold distance 5000 m) was applied to consider "neighbors" (just non zero value) for all pixels located at a certain distance. The normal approximation for global Moran's I could be standardized to z and t (Legendre and Fortin 1989). The significance level of z was a threshold (1.96) so that the spatial autocorrelation can be consider significant if fluctuates between 1.96 and -1.96 (Zhang and McGrath 2004). The spatial correlogram shows patterns of spatial autocorrelation when increasing the distance between observations. The spatial correlogram is drawn by two common shapes including Moran's I or I^* (standardized Moran's I) (Legendre and Fortin 1989) plotted in ordinate, against distances (in abscissa). Although, the standardized correlogram represented the spatial correlation distance that is the first positive peak (Zhang et al. 1998). Local Moran's I is computed to identify the locations of spatial clusters and outliers (Anselin 2010). In the Local Moran's I analysis, there are five possibilities for local spatial autocorrelation. Two types of them distinguish spatial clusters including high values surrounded by high values (High-high), and low values surrounded by low values (Low-low). Two types of them are known as outliers, including high values surrounded by low values (High-low) and low values surrounded by high values (Low-high). Finally, the last one is non-significant spatial patterns in other words spatial randomness.

2-3-4 Geostatistic Method

In the grid system, the classical Inverse Distance Weighted (IDW) interpolation method had the lowest root mean square error (RMSE) in pre-evolution (Gorgan data) than the rest of the methods used to build the abundance maps which is consistent with the results of Al-Kindi et al., (2017). The IDW method estimated values of an unknown pixel by nearby pixels predicted but restricted in the range of maximum and minimum values of true pixels. Nearest Neighbor Statistical (NNS) analysis was spatially detected statistical moth distribution including absence, random, regular, or aggregation possibility in each area (Vinatier et al. 2011).

Results And Discussion

3.1. Spatial Pattern Analysis of Spider-mite using the Spatial Autocorrelation Analysis

Generally, the higher Moran's I in absolute value presents the greater the spatial correlation and also, more significant spatial autocorrelation shows by the higher standardized form of Moran's I. I^* is able to compare statically spatial patterns of different phenomenon or different calculating parameters of the same phenomenon. At the global autocorrelation, Table 2 depicted the first three windows (there was not data for spider-mite population at first window) did not show the significance correlation (random distribution) for the standardized form of global Moran's I (≥ 1.96), and fourth window was at the

significance level during June 2020. Those periods, the cotton plant did not complete canopy but at fourth window was symmetrical with the wheat harvesting calendar in Golestan province. Wheat harvesting causes huge local dust. After that, a sinusoidal pattern was shown in Global autocorrelation (randomness to aggression, vice versa) (Table 2). By beginning in August 2020 (nine and eleventh windows), study areas had faced with a spider mite out-breaking and the strongest spatial structure (Figure.3 h, i). Descending spatial structure at tenth, thirteen and fourteen windows could be related to pesticide application at cotton fields.

Table 2. Spatial global autocorrelation of spider mite population at monitoring programs, Dispersed [$Z(I)^{**} < -2.58$; $-2.58 \leq Z(I)^* \geq -1.96$; p-value =0.1, $-1.96 \leq Z(I) \geq -1.65$], Random [$-1.96 \leq Z(I)^{ns} \geq -1.65$], Clustered [$Z(I)^{**} > 2.58$, $1.96 \leq Z(I)^* \geq 2.58$; p-value =0.1, $1.65 \leq Z(I) \geq -1.96$]

period	Global Moran's Index	Z-score	p-value	pattern
Window_1	No Data			
Window_2	0.029207	0.731330	0.464578	Random
Window_3	-0.003930	0.107097	0.914712	Random
Window_4	0.247838	3.871930	0.000108	Clustered
Window_5	0.053822	1.018388	0.308494	Random
Window_6	0.043046	0.961567	0.336267	Random
Window_7	0.096227	1.789161	0.073589	Clustered
Window_8	0.076148	1.641488	0.100696	Random
Window_9	0.337405	6.283151	0.000000	Clustered
Window_10	-0.009247	-0.016164	0.987104	Random
Window_11	0.262986	6.777026	0.000000	Clustered
Window_12	0.217330	4.373817	0.000012	Clustered
Window_13	0.039474	0.991156	0.321610	Random
Window_14	0.042141	1.339547	0.180393	Random
Window_15	0.264988	5.138441	0.000000	Clustered

Figure.S1 represent the standardized spatial correlograms of spider-mite distribution at all monitoring windows (15 windows) and the threshold distance of weight matrix where the Moran's I and the standardized Moran's I, $Z(I)$ reached a maximum value. At first windows (May 30, 2020 - June 9, 2020), spider-mite was not observed in pilot farms. Therefore, any data was reported by local experts. In generally, the optimal distance was 10 km to reach maximum Moran's I for detecting local spatial pattern. Positive value of standardized Moran's I values at a distance from 5 km to 15 km indicated spatial

clusters of similar spider-mite population at these distance ranges. The interpolation maps of spider-mite population were performed using the Inverse Distance Weighted (IDW) method by the cross-validation of parameters. Evaluation indices from cross-validation of IDW maps for all monitoring windows are given in Table 3 and Figure S2. Cross-Validation of spatial interpolation was estimated model accuracy. Common parameters which could measure errors are Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). RMSE which sensitive to outliers is known as an optimal model evaluator by measuring error size (Willmott 1982; Hernandez-Stefanoni and Ponce-Hernandez 2006). The smaller RMSE showed that semivariogram parameters calculated by fitting of experimental values are suitable and geostatistical prediction works more accurate. According to interpolation maps of spider mite distribution, some regions struggled with high population density of *T. urticae* (Figure 3). The pattern of infestation of *T. urticae* was the temporal hot spots in central and eastern areas of Golestan province where grains were mechanized harvested with dust pollution (Figure 3 b-f). In late July, by establishing spring and summer crops (such as cotton), the pattern of *T. urticae* was changed to other regions of study areas. From the eighth window (July 21, 2020- July 29, 2020), Aqqala was showed the main area of *T. urticae* (Figure 3 g). This finding was confirmed by the Agriculture Administration which named Aqqala is the niche of *T. urticae* at Golestan province. On fifteenth window, *T. urticae* population has declined sharply because of completion of the growing season of cotton and the arrival of the harvest dates (Figure 3 n). Spatial analysis of *T. urticae* during growing season of cotton showed ups and downs in *T. urticae* populations but the climatic aspects which influencing this pattern was remained hidden. Based on empirical observations, climatic variables have a significant impact on *T. urticae* population, especially Aerosol and dust in air.

Table 3. Evaluation indices of the interpolation maps (IDW) of spider-mite distribution during monitoring program

period	equations	RMSE
Window_1	No data	
Window_2	$0.029 * x + 0.023$	0.3556
Window_3	$0.018 * x + 0.1086$	0.5555
Window_4	$0.035 * x + 0.116$	0.4650
Window_5	$0.063 * x + 0.284$	0.62478
Window_6	$0.035 * x + 0.201$	0.7948
Window_7	$0.0557 * x + 0.209$	0.6404
Window_8	$0.091 * x + 0.161$	0.6792
Window_9	$0.255 * x + 0.102$	0.534
Window_10	$0.0279 * x + 0.239$	1.009
Window_11	$0.066 * x + 0.257$	0.891
Window_12	$0.137 * x + 0.259$	0.893
Window_13	$0.032 * x + 0.239$	1.054
Window_14	$0.012 * x + 0.25$	0.919
Window_15	$-0.008 * x + 0.071$	0.6030

3.2. Effect of climatic factors on Spider-mite population

As mentioned before, until the fifth windows (Figure 3d), there was not enough canopy to establish *T. urticae* on cotton fields, after that, spider mite out-breaking was coincided with the wheat harvest and high aerosol index 0.167 on 21 June 2020. In the first three windows, study area where experienced several dusty days, faced with first *T. urticae* population peak (Figure 3d and Figure 4). Statically tight relationship between dusty days and spider mite was repeated in transition mode from the ninth and thirteenth to their next windows (w9 to w10 and w13 to w14) (Figure 4). The effect of dust or different environmental conditions on spider mites was reported by several studies (Hodek 1987; Thomas 2001; Guerena and Sullivan 2003). Results of previous studies conducted by Flint (1998) and Guerena and Sullivan (2003) supported current results. For mentioned studies also represented that the dusty conditions almost cause to increase *T. urticae* population on farms. According to Demirel and Cabuk (2008) finding, spider mite densities were 1.72, 1.75, 4.39 and 2.65 times higher on cotton farms in the vicinity of dirt roads than asphalt roads. Therefore removal of dust population is considering one of applicable approach in organic cotton production (Guerena and Sullivan 2003) to control *T. urticae* including insecticidal soaps and water washing by complete coverage. Precipitation effect which has the ability to remove dust on cotton canopies on *T. urticae* population presented in (Figure 5). In first windows, it could be observed a hidden aspect of rainfall on low population of *T. urticae*, because of not

only low density canopy but also about 2.5 mm/day precipitation at this period. This negative relationship was repeated in the ninth and twelfth windows (approximately 2 mm). Based on current result, even if rain did not fall about 2 mm on July 6 and 16, 2020 you would experience severe out-breaking during July 2020. The threshold precipitation level was estimated at least 2 mm to clean up canopy. Rao et al., (2018) evaluated the effect of environmental factors on the population dynamics of *T. urticae* in Brinjal, India ecosystem and reported a gradual increase in *T. urticae* population from 4.34 to 32.64 (number of mites present in 2 cm² leaf area) in agreement with current research by increasing from 0.05 to 0.45 spider-mite scoring. According finding Rao et al., (2018) rainfall ($Y=19.358 - 1.055X$; $R^2=0.378$) had significant negative correlation with *T. urticae* population which confirmed negative correlation in the second ($y=-1.494x+0.3184$; $R^2=0.2201$), ninth ($y = -0.4616x + 0.6478$; $R^2=0.1329$) and twelfth ($y = -0.1428x + 0.1103$; $R^2=0.1213$) windows of the current study. The absence of precipitation when coupled with suitable temperature was introduced a main contributing environmental factor for the rise in *T. urticae* population by Rao et al., (2018). Evaluating the relationship between spider-mite population and the means of temperature was another part of the climate studies. The main source of temperature measurement was MODIS-LST imagery twice a day (Figure 6). We could not find a significant pattern between temperature and *T. urticae* population until August 2020. The significantly tight relationships were observed in the ninth ($y = 8.4748x + 38.298$; $R^2=0.3519$; P-value= 0.000), tenth ($y = 7.5261x + 38.43$; $R^2=0.1283$; p-value= 0.008), eleventh ($y = 3.7942x + 33.272$; $R^2=0.0859$; P-value= 0.041), twelfth ($y = 6.6459x + 35.306$; $R^2=0.1675$; P-value= 0.004), thirteenth ($y = 6.322x + 36.522$; $R^2=0.178$, P-value= 0.002) windows. In many studies, negative correlated with temperature and spider mite population were reported (Majeed et al. 2016; Fahim and El-Saiedy 2021). The current result is compatible by Fahim and El-Saiedy (2021) who reported a non-significant relationship with respect to mean temperature and *T. urticae* on the beginning of the season. However, there many findings from previous literatures supporting the positive relationship between the *T. urticae* population and temperature (Meena et al. 2013; Chauhan and Shukla 2016). Seasonal abundance of *T. urticae* is influenced by biotic and abiotic factors. Parasitoid and predators are known as biological factor which are suppressed by temperature and drought (Romo and Tylanakis 2013). Another climate parameter, evapotranspiration was predicted that it affects the abundance, distribution and activity of pests. Increasing evapotranspiration has potential to simulate drought conditions (Mullan et al. 2005). Correlation between spider mite population and evapotranspiration depicted a strong relationship statistically (Mean Square= 0.349; F= 21.038, $R^2=0.637$; p-value= 0.001) in Figure 7. The current result had similarity with finding of Litskas et al., (2019) who reported relationship between evapotranspiration and the *T. urticae* and its natural enemy, *P. persimilis*, with R^2 0.46 and 0.60 , respectively. Since that, all climate factors induced their effects to the plant, NDVI is could support a correlation with spider mite population. During monitoring windows, we observed a negative and positive relationship between NDVI and spider mite scoring. There was positive correlation between increasing NDVI and *T. urticae* population until the tenth window (August 2020) (Figure 8 a-g). The fifth and sixth windows (middle of July 2020) showed significant relation $R^2=0.107$ (p-value= 0.016) and $R^2=0.110$ (p-value= 0.015), respectively. Beginning in August, 2020, the type of relationship was shifted to negative especially ninth and thirteenth windows

with $R^2=0.273$ (p-value= 0.000) and $R^2=0.139$ (p-value= 0.006), respectively. This phenomenon was interpreted that by enhancing of cotton canopy, *T. urticae* had opportunity to establish their communities. After that, negative correlations were due to harmful effect of *T. urticae* population on severity NDVI decreasing (Figure 8). The NDVI decreasing created by *T. urticae* was confirmed by numerous studies which assess *T. urticae* population or their damages (Lan et al. 2013; Martin et al. 2015; Martin and Latheef 2017). During multi-temporal NDVI series was observed severe reduction on the eleventh window (3-11 August, 2020) because of high density of aerosol index and low rainfall (Figure 8 j).

Conclusion

We found that *T. urticae* had diverse responses to the climatic factors. In a pre-judgment at the beginning of study, among of climatic factors, aerosol index or dusty days was predicted severity affect to increase the spider mite density on monitoring fields. But evapotranspiration was exactly synched with *T. urticae* dynamic population. Indeed, our findings aerosol index sentinel-5 and MODIS-evapotranspiration have suitable potential to predict spider mite population with high temporal resolution. Studying these drivers offers a realistic view of what exports design accurate model under a regime of climate change.

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Figures

Figure 1

Location of the study area on the world (the Golestan province, Iran).

Figure 2

Distribution of spider-mite throughout Golestan Province; 6 (min)* 6 (min) grid cells in the DMS coordinate system (yellow points are monitoring field)

Figure 3

Distribution maps of spider mite based on IDW model during monitoring windows, a-n are the sequence windows form June 9, 2020 to September 17, 2020. (First window, May 30 to June 9 was not spider mite population data)

Figure 4

The relationship between UV Aerosol Index extracted from Sentinel-5 imagery and spider mite population (mean score of each window) from June 9, 2020 to September 17, 2020. (First window, May 30 to June 9 was not spider mite distribution data)

Figure 5

The relationship between daily CHIRPS-precipitation and spider mite population (mean score of each window) from June 9, 2020 to September 17, 2020. (First window, May 30 to June 9 was not spider mite distribution data)

Figure 6

The relationship between daily Land Surface Temperature and spider mite population (mean score of each window) from June 9, 2020 to September 17, 2020. (First window, May 30 to June 9 was not spider mite distribution data), ... and – are Day and night LST, respectively.

Figure 7

The relationship between MODIS-Evapotranspiration and spider mite population (mean score of each window) from June 9, 2020 to September 17, 2020. (First window, May 30 to June 9 was not spider mite distribution data).

Figure 8

The relationship between NDVI (10 m) provided from Sentinel-2 and density of spider mite during monitoring windows based on ANOVA for linear regression. The alphabetical letters indicate the sequence windows from June 9, 2020 to September 17, 2020. (First window, May 30 to June 9 was not spider mite distribution data).

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