ASSESSING THE IMPACT OF BEET WEBWORM MOTHS ON SUNFLOWER FIELDS USING MULTITEMPORAL SENTINEL-2 SATELLITE IMAGERY AND VEGETATION INDICES

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ABSTRACT:

Remote sensing technology plays a crucial role in detecting and monitoring environmental issues, offering the ability to monitor large areas, diagnose problems early, and facilitate accurate interventions. By integrating in-situ data with qualitative measurements obtained from satellite images, comprehensive insights can be obtained, and statistical inferences can be established. This study focuses on analyzing the damages caused by beet webworm moths (*Loxostege sticticalis)* in sunflower fields located in the Ortaca neighborhood of Tekirdağ province in Thrace region, utilizing Sentinel-2 satellite images and in-situ data collected from the sunflower fields in Ortaca. The relationship between different spectral indices, such as the Enhanced Vegetation Index, Chlorophyll Index Green, and spectral transformation techniques like Tasseled Cap Greenness, derived from Sentinel-2 satellite images, and the observed damage rates in various sunflower fields' in-situ data was investigated. The results revealed a negative correlation between the variables, highlighting EVI as the most effective indicator of damage among the plant indices. Leveraging these findings, a damage map was generated using EVI, enabling visual interpretation of the damage status in other sunflower fields within the study area. These findings offer valuable insights into the impact of pests on sunflower crops, despite the accuracy evaluation results falling below the desired level, with an overall accuracy of 75% and a Kappa accuracy of 65%, attributed to the limited availability of in-situ data.

1. INTRODUCTION

Agriculture is a strategically important sector all over the world. Improving productivity in agricultural production and minimizing product losses are essential for strengthening the economy and highlighting the importance of the agricultural sector. Additionally, effective crop monitoring plays a crucial role in examining crop health and growth stages in agricultural areas, enabling early intervention when unexpected problems arise.

Agriculture in Turkey has become one of the leading sectors due to its contribution to employment, exports, and national income. According to statistics from 2019, Turkey was determined as the tenth largest agricultural country with a production capacity of 70 billion dollars (Anadolu Agency, 2020). Sunflower constitutes a certain part of this production capacity, as Turkey produces more than 4% of world sunflower production, according to a study conducted in 2023 (Republic of Türkiye, Ministry of Agriculture and Forestry, 2023). Sunflower crops undergo unique growth stages that require specific conditions for healthy growth, like other crop types. However, several factors, including climate change, limited water resources, and depletion of natural resources, can pose significant challenges to creating and maintaining the optimal conditions necessary for successful sunflower production. Consequently, these challenges can result in detrimental effects. In such circumstances, anomalies may arise during the various growth stages of sunflowers, presenting obstacles and deviations from the expected growth patterns.

Another factor that can disrupt the growth stages of sunflowers is the presence of harmful insects. Examples of these pests include beet webworm moths, green beetles, grasshoppers, and aphids. These insects tend to feed on the leaves, nodules, and flowers of the crops, leading to increased stress levels, reduced biomass, and lower yields. One of the important species that causes damage in this way is *Loxostege sticticalis* (Bahadır et al., 2016). They are commonly referred to as leaf-eating insects since they primarily target young leaves. Additionally, these pests may also feed on bulbs alongside the leaves. The feeding behavior of these insects negatively impacts the growth stages of the crops, causing a slowdown in development (Capinera, 2020). Detecting and addressing pest damage at an early stage is crucial to prevent the spread of infestation to other agricultural fields, which would necessitate chemical interventions like spraying. However, it is important to note that agricultural spraying, particularly when crops are present, can lead to inefficient harvests. Therefore, regular monitoring of agricultural areas and crops, from planting to harvesting, and even after maintaining bare soil, is necessary.

Various technologies have been developed for the control of harmful insects and the sustainability of agriculture. Remote sensing is among these technologies with the images obtained from earth observation satellites and the processing of these images. This advanced satellite technology even enables the assessment of chlorophyll content in crops (Narin et al., 2021). The health/stress conditions of the crops can be analyzed with the spectral reflectance values obtained from the satellite images. Additionally, the biomass can be evaluated by employing diverse analyses, such as various vegetation indices and spectral transformations, to the satellite images. Another approach involves classifying satellite images, resulting in thematic maps based on input data. (Akkartal et al., 2004; Akkartal et al., 2005; Sunar et al., 2017). Numerous spectral indices and transformations described in the literature can be utilized as input data for the classification process subsequent to their application. Through this classification process, agricultural areas affected by pest damage can be easily distinguished from those that are not, highlighting the crucial role of remote sensing in the analysis and management of crop damage.

This study analyzed the damage caused by beet webworm moths in sunflower crop fields in the Trace region of Turkey. Additionally, the extent of the damage spread within the region was examined, with the aim of assessing the health and stress

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status of other sunflower fields in the area. To achieve this, the study investigated the relationship between the damage rate in the fields and several vegetation indices, including the Enhanced Vegetation Index (EVI) and Chlorophyll Index Green (CIG), as well as spectral transformation techniques such as Tasseled Cap Greenness (TCG).

2. STUDY AREA

Tekirdağ is one of the provinces located in the Northwest of Turkey, in the north of the Marmara Sea and in the region of Trakya. The province has an area of 6.313 km² and is between 0–200 m above sea level (Tekirdağ Metropolitan Municipality, 2023). The province's fertile agricultural lands and favorable climatic conditions make it an ideal location for sunflower cultivation, which is an essential component of agriculture in Tekirdağ. Moreover, its proximity to Istanbul makes Tekirdağ an important supplier of agricultural products to both local and international markets.

Süleymanpaşa, the largest district in Tekirdağ province, encompasses numerous neighborhoods within its central district. The selected study area for this research is Ortaca, a neighborhood within Süleymanpaşa district, located approximately 30 km away from the city center. Ortaca is surrounded by agricultural and rural areas, and agriculture plays a crucial role in its economy, alongside other farming activities. The arable lands in Ortaca are primarily used for cultivating crops such as wheat, sunflower, canola, barley, and silage corn (Tekirdağ Governorship, 2023). Figure 1 displays the distribution of sunflower fields within the study area.

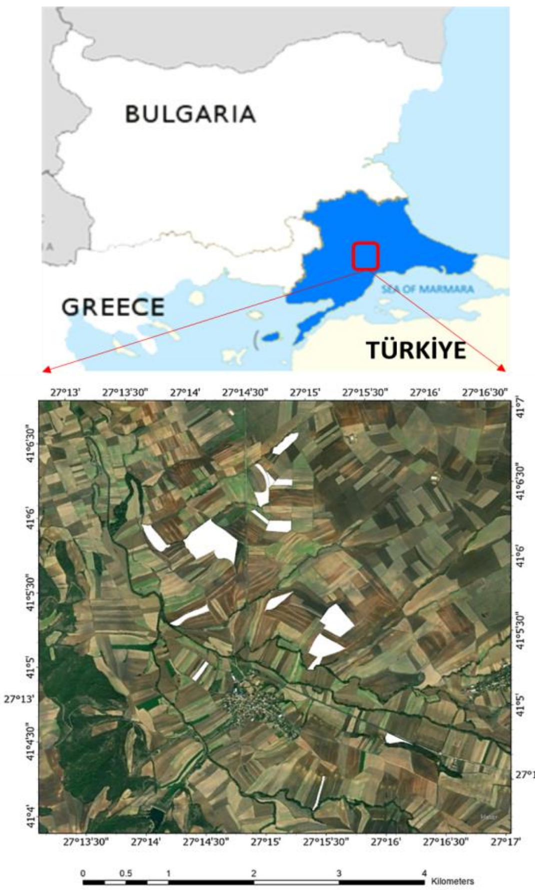

Figure 1. Map of the study area in Ortaca neighborhood, Tekirdağ, depicting the locations of 17 in-situ sunflower fields overlaid on the Sentinel-2 satellite image (© Copernicus).

3. MATERIALS AND METHODOLOGY

3.1 Materials

Sentinel-2 satellite images taken on 21 June, 1 July, 6 July, 16 July, 21 July, and 26 July 2022 were used in the study. However, no cloud-free Sentinel 2 satellite image data for August was found, especially during the sunflower growth phase R8. These satellite images, freely available from the European Space Agency, offer different atmospheric correction levels, including Top Of Atmosphere (TOA) and Bottom Of Atmosphere (BOA). For this study, Bottom Of Atmosphere (BOA) reflectance values was utilized. The main features of the Sentinel-2 satellite, which has different spatial resolutions (10 m, 20 m, and 60 m) at many different wavelengths (Coastal Blue - SWIR) are shown in the below table (Table 1).

Main features	Sentinel – 2 satellite
Spectral resolution	13 bands Coastal Blue:433- 453 Blue: 458–523 Green: 543–578 Red: 650–680 Red-Edge (RE1): 698–713 Red-Edge (RE2): 733–748 Red-Edge (RE3): 773–793 NIR: 785–899 NIR Narrow:855-875 Water Vapour:935-955 SWIR Cirrus:1360-1390 SWIR1: 1565–1655 SWIR2: 2100–2280
Spatial resolution	10-m / 20-m / 60-m
Temporal resolution	10 days with each satellite five days with (S2A & 2B)
Radiometric resolution	12 bytes

Table 1. Main features of Sentinel – 2 satellite.

In this study, a dataset consisting of 30 sunflower crop parcels was used as in-situ data. Out of these parcels, 17 were selected for training, while the remaining 13 were reserved for validation. Table 2 provides specific details, including planting area, leaf loss, and total damage values, for the 17 parcels used in the training dataset, while Table 3 presents the corresponding information for the 13 parcels in the validation dataset.

Field#	Plantation Area	Leaf Loss of Plant	Total Damage
1	13.69	5	0
2	8.69	5	0
3	8.87	5	0
4	44.78	5	0
5	10.00	50	16
6	29.58	60	25
7	4.18	60	25
8	36.92	70	37
9	10.00	70	37
10	26.00	70	37
11	29.52	80	49
12	5.95	80	49
13	68.00	80	49
14	16.11	80	49
15	14.20	80	49
16	26.94	80	49
17	7.15	80	67

Table 2. Main features of 17 sunflower parcels used for training.

Field #	Plantation Area	Leaf Loss of Plant	Total Damage
1	17.60	5	0
2	9.47	5	0
3	19.20	5	0
4	38.00	5	0
5	9.00	5	0
6	24.00	80	18
7	42.00	60	25
8	13.09	70	37
9	19.15	70	37
10	19.20	70	37
11	8.50	70	37
12	35.00	70	37
13	50.00	70	37

Table 3. Main features of 13 sunflower parcels used for validation.

3.2 Methodology

The methodology employed in this study consists of three main stages: i) the of spectral vegetation indices and spectral transformation techniques to analyze the biomass and health conditions of sunflower fields affected by beet webworm moths; ii) the application of correlation analysis to statistically interpret the applied indices and transformations by examining the relationship between damage rates in the in-situ data; iii) the implementation of density slicing to generate a final output map that identifies and delineates areas with varying levels of damage within the sunflower fields. Figure 2 illustrates the flowchart depicting the methodology employed in this study.

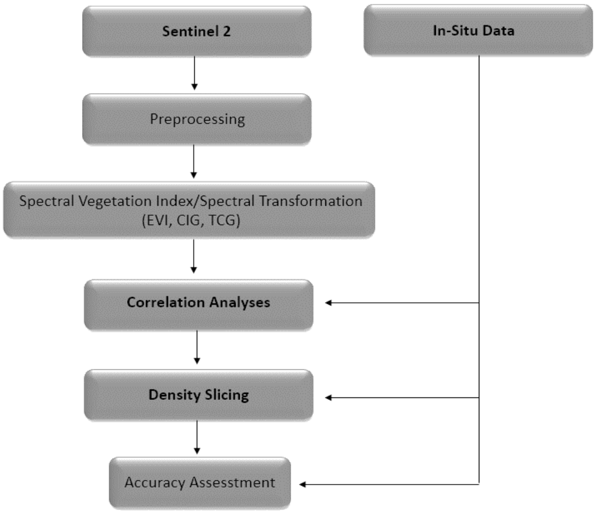

Figure 2. Flowchart of the methodology used.

3.2.1 Spectral Vegetation Index: Various spectral vegetation indices have been developed for agricultural studies. These indices, obtained by calculating reflectance values in two or more spectral bands, provide information about the growth stages of crops (Taşan et al., 2022; Sunar et al., 2011).

In this study, the Enhanced Vegetation Index (EVI) and the Chlorophyll Index Green (CIG) were employed as spectral vegetation indices to detect damage in sunflower fields and analyze the health condition of the crops. The Enhanced Vegetation Index (EVI) incorporates the red, blue, and near-infrared bands to account for variations in canopy background reflectance and atmospheric influences and provides a more accurate estimation of vegetation properties, particularly in areas with dense vegetation or under challenging atmospheric conditions (Huete et al., 2002). The Chlorophyll Index Green (CIG) is a vegetation index specifically designed to estimate chlorophyll content in plants, providing insights into plant vitality, chlorophyll synthesis, and photosynthetic activity (Niu et al., 2022). Long-term or medium-term variations in chlorophyll content within vegetation can provide valuable insights into growth stages and canopy stresses (Gitelson et al., 2005).

3.2.2. Spectral Transformation: Spectral transformation is a widely employed method for extracting valuable and significant information from satellite images by applying mathematical operations or algorithms to spectral data. Numerous spectral transformation techniques are available in the literature, and one of these techniques is Tasseled Cap transformation (TC), which was utilized in this study. TC creates composite bands (i.e., brightness, yellowness, and greenness) representing specific land surface characteristics, which provide valuable information about vegetation health, soil moisture, and other land surface features (Crist and Cicone, 1984).

3.2.3 Correlation Analysis: Correlation analysis is a statistical method used to determine the strength and direction of the relationship between two or more variables. It measures the degree to which changes in one variable are associated with changes in another variable. In the context crop damage analysis, correlation analysis helps in understanding the level of dependency or association between the calculated index values and the extent of leaf damage, providing insights into the potential impact of damage on the vegetation indices (Udovičić et al., 2007). The correlation can be categorized as negative correlation, positive correlation, or zero correlation, depending on the values it takes, which range between -1 and +1.

3.2.4 Density Slicing: Density slicing is a data analysis technique that involves dividing a continuous data range into discrete intervals or slices to classify and segment the data based on their values, enabling the identification and visualization of distinct regions or clusters within the data. In this study, density slicing was applied to highlight and delineate the varying levels of damage within the sunflower fields.

4. APPLICATION AND RESULTS

The total duration of sunflower plant development and the intervals between different stages depend on the genetic characteristics of the plant and the environmental conditions during the growing season (Blamey et al, 1997). However, the growth of sunflower can be categorized into two distinct stages: vegetative (V) and reproductive (R). The reproductive classification, developed by Schneiter and Miller (1981), is depicted in Table 4 and serves as a common basis for discussions on plant development among producers, scientists, and the industry. The vegetative stages (Vn) of sunflower are determined by counting the number of leaves on the stem that are at least 4 cm long or longer, such as V-1, V-2, V-3, V-4, V-12, and so on. On the other hand, sunflowers progress through a series of numbered reproductive stages, ranging from R1 to R9. These stages encompass the development of a miniature flower head (R1), elongation of the immature bud up to 0.5 - 2.0 cm above the nearest leaf attached to the stem (R2), further elongation of the immature bud beyond 2.0 cm above the nearest leaf (R3), unfolding of the inflorescence (R4), initiation of anthesis (R5), completion of anthesis and subsequent wilting of the ray flowers (R6), transition to a pale-yellow color on the back of the head (R7), transformation to a yellow color on the back of the head while the bracts remain green (R8), and final maturity (R9) (Blamey et al., 1997; NDSU Sunflower Production Guide, 2023).

In this study, sunflower plants exhibited damage characterized by wilting and rot, resulting in noticeable changes in their physical appearance during the R5 reproductive stage. Figure 3 shows a sunflower leaf affected by damage caused by beet webworm moths.

Reproductive Stages		Sentinel 2 Images
	R1	June 16
	R2	June 21
	R3	Jul 1
	R4	Jul 6
	R5	Jul 16
	R6	Jul 21
	R7	Jul 26
	R8	
	R9	Sep 9

Table 4. Growth stages of sunflower, corresponding field photos, and dates of Sentinel-2 image acqusition.

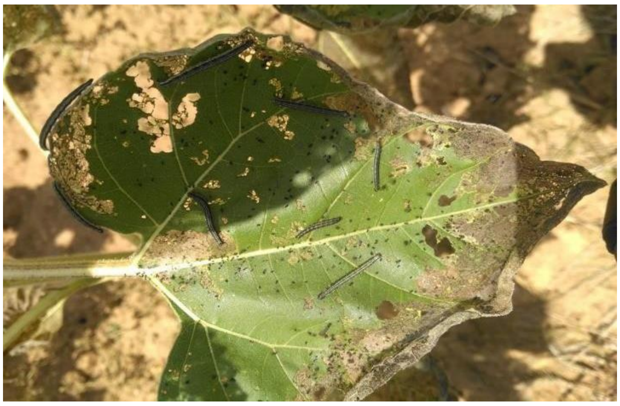

Figure 3. Damage caused by beet webworm moths during the R5 reproductive stage.

As a first step, the necessary scripts were prepared for performing spectral transformation and spectral index calculations on the Google Earth Engine platform. Subsequently, the Enhanced Vegetation Index (EVI), Chlorophyll Index Green (CIG), and Tasseled Cap Greenness Index (TCG) were applied to satellite images of 17 sunflower parcels selected from in situ data.

To visually represent the results obtained from the application of the Enhanced Vegetation Index (EVI), two sunflower parcels were chosen, one with 50% damage and the other healthy (i.e., 0%, undamaged). Figure 4 illustrates the comparison of EVI values plotted on a graph, highlighting the impact of damage on vegetation health for the two parcels. To verify the results, multitemporal spectral reflectance plots were examined to analyze the spectral reflectance characteristics of healthy and highly damaged sunflower parcels throughout their growth cycles. Figure 5 illustrates the spectral reflectance values of six satellite images captured between 21st June and 26th July, providing insights into temporal variations and the impact of damage on sunflower fields at different growth stages.

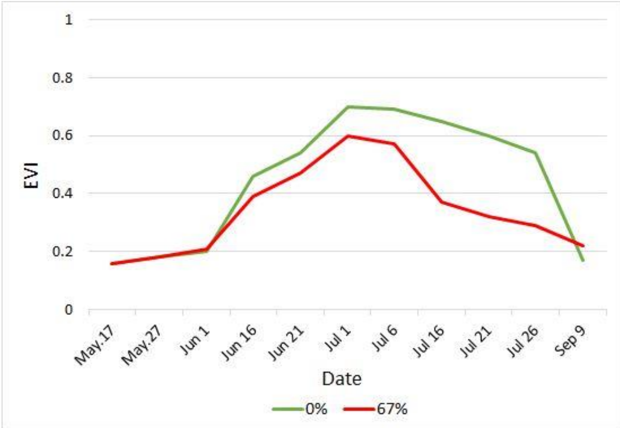

Figure 4. Comparison of multitemporal EVI profiles for healthy and highly damaged sunflower parcels.

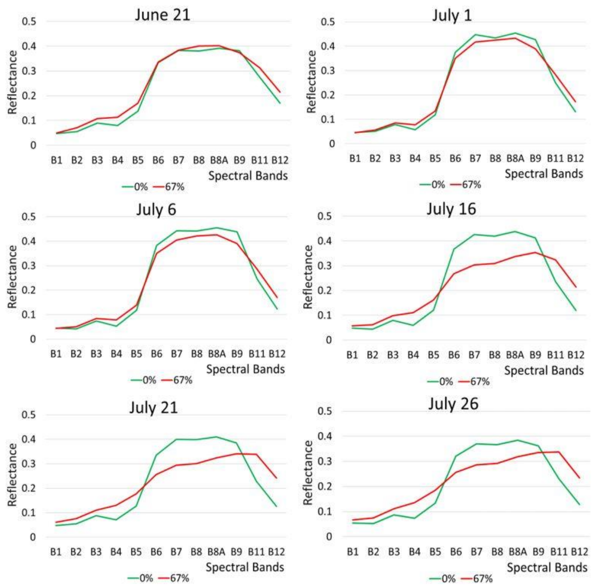

Figure 5. Multitemporal reflectance spectra of healthy and highly damaged sunflower parcels aligned with growth cycles from June 21 to July 26.

In line with existing literature, it is widely recognized that healthy plants generally have higher chlorophyll content compared to stressed plants (Carter and Knapp, 2001). In this study, the Chlorophyll Index-Green (CIG) was used to assess changes in chlorophyll content during the sunflower growth cycle and identify stressed areas in the field. The CIG is calculated by subtracting 1 from the ratio of the Near-Infrared (NIR) band to the Green band (Kumar et al., 2020). Figure 6 illustrates the CIG results, showing noticeable variations in leaf greenness between stressed and healthy sunflower plants in the multitemporal Sentinel-2 dataset. During the R2-R7 reproductive cycle from June 21st to July 26th, highly damaged sunflower field exhibited

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lower CIG values compared to healthy field, with a gradual decrease over this period indicating reduced chlorophyll content due to pest-induced damage (Figure 6).

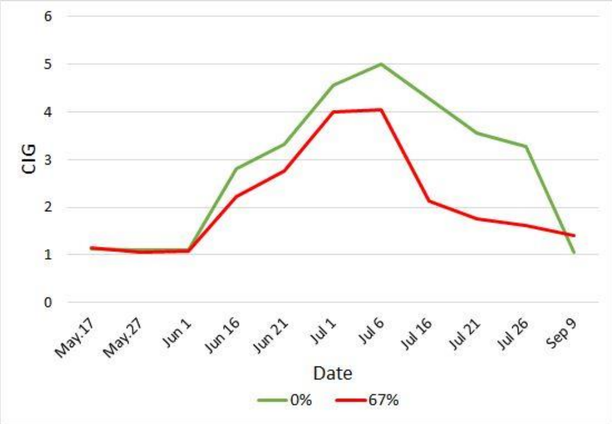


Figure 6. Comparison of multitemporal CIG profiles for healthy and highly damaged sunflower parcels.

Following the application of spectral indices, Tasseled Cap transformation was utilized. The Greenness (TCG) component was employed to examine variations in biomass levels caused by stress, disease, and drought, which significantly affect the health and growth potential of sunflower plants. Figure 7 presents the TCG values of both healthy and highly damaged sunflower parcels, providing a comparative visual representation of their biomass characteristics. The results of the TCG analysis were in line with the findings from the other two examined indices. As a general trend, the highly damaged sunflower fields exhibited a distinct deviation from the typical profile observed in healthy vegetation.

Figure 7. Comparison of multitemporal TCG profiles for healthy and highly damaged sunflower parcels.

Afterward, a correlation analysis was conducted to investigate the relationship between the derived image outputs, including spectral transformations and spectral index results, and the corresponding in-situ measurements (i.e., damage ratings) over the time period. Hence, by effectively evaluating the degree of agreement or association between the value-added image products and the in-situ data, valuable information can be obtained for further mapping of the damage.

EVI, CIG, and TCG output data, which provide valuable information on leaf density and biomass in sunflower crops, were considered as variables in the analysis, whereas the damage rates reflect the extent of damage caused by beet webworm moths. The results show that the high damage rate observed in sunflower fields with low index values corresponds to a negative correlation between the variables, indicating an inverse relationship between them (Figure 8). As observed, a strong relationship (R: -0.80%) is evident during the R5-R7 reproductive cycle, spanning from July 16th to July 26th. This result was supported by local agricultural officials and farmers, who confirmed that the damage caused by beet webworm moths was at its maximum during the specified dates.

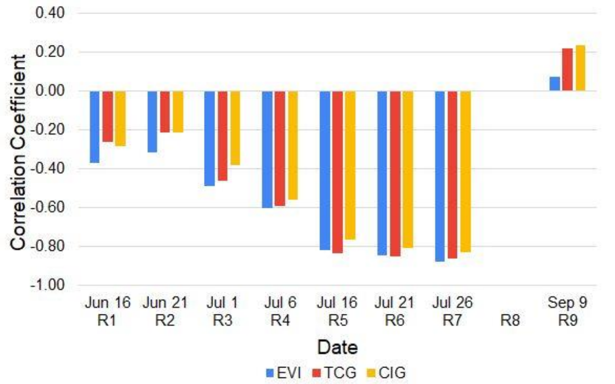


Figure 8. Correlation coefficients between spectral index results and in-situ parcel damage ratings.

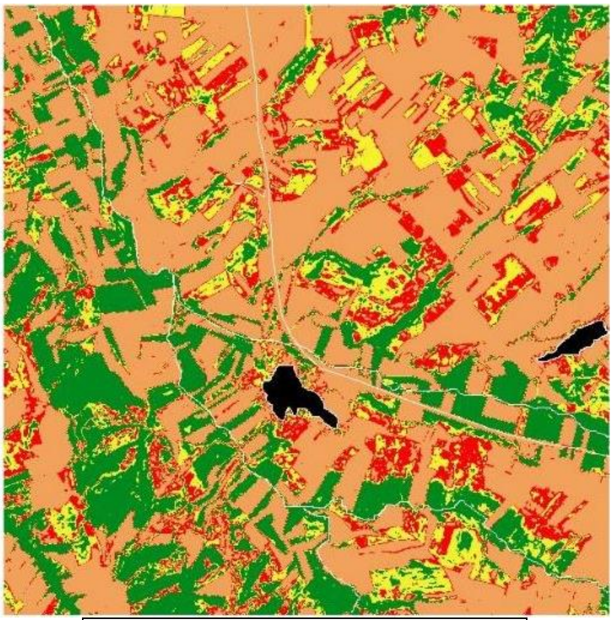
Among the applied indices, EVI showed the highest correlation coefficient (-0.88), indicating its effectiveness in accurately detecting and quantifying the extent of damage. On the other hand, the analysis for the corresponding R8 growth stage could not be evaluated due to the lack of satellite data available for August. Considering the decrease in reflectance values at various growth stages and the strong negative correlation observed with the in-situ data, it is evident that insect infestations in the field can be accurately evaluated. This enables more effective pest control measures and improved crop management strategies in the region.

As the final step, the highest negative correlation observed for EVI during the R5-R7 growth period on July 26th was utilized for damage mapping through the application of the density slicing method. Table 5 shows the specific ranges or segments used for the classification and segmentation of damage levels, using EVI values of 17 training fields (Table 2), for a comprehensive analysis of the consequences of insect infestation in sunflower fields.

	Slight	**Moderate**	**Heavy**	**Fallow Land**
EVI values	1.00-0.43	0.43-0.38	0.38-0.29	0.29-0.00

Tablo 5. Four segment values used for damage mapping in the July 26th EVI image.

The roads and urban areas in the image dated July 26 were digitized prior to the application of the density slicing method. Then, the density slicing method was applied to the image, using the four determined segments (slices), which resulted in the generation of a damage map, as illustrated in Figure 9. Afterwards, accuracy assessment was conducted using the remaining 13 fields for validation purposes (Table 3). While the Overall Accuracy of the produced thematic map was 75%, the Kappa statistics was calculated as 65%.



Legend	
Slight	
Moderate	
Heavy	
Fallow Land	
Urban Areas	

Figure 9. Damage map produced for July 26 image.

5. CONCLUSION

In this study, the assessment of damage to sunflower fields in the Ortaca neighborhood of Tekirdağ province, caused by the invasion of a pest insect known as beet webworm moths, was conducted using satellite imagery and various vegetation indices.

The findings demonstrate that pest insect infestation significantly impacts the growth stage of sunflower crops, particularly during the R5-R7 growth period, with July being the most critical month. Among the applied indices, it was observed that the Enhanced Vegetation Index outperformed the Chlorophyll Index Green and the Tasseled Cap Greenness component in detecting damage.

Despite the limitations imposed by the low number of available in-situ parcels in the accuracy assessment, this study's findings significantly contribute to understanding the detrimental effects of pests on sunflower fields. This understanding is reinforced by the robust correlation (R: -0.88%) observed between spectral indices, particularly EVI, and in-situ data during the critical R5-R7 growth period on July 26th.

Although the accuracy evaluation results yielded an overall accuracy of 75% and a Kappa accuracy of 65%, which fell below the desired level, the strong correlation between the spectral indices and the observed damage provides valuable insights into the impact of pests on sunflower crops. This information plays a pivotal role in comprehending and addressing the effects of pests, guiding farmers, researchers, and agronomists in implementing effective strategies to mitigate and manage the damage caused by these pests.

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