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Remote sensing approaches to assess the Fall Armyworm (*Spodoptera frugiperda*) infestation on maize crop: a case study from Sri Lanka

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Abstract

Managing pests and diseases of crops is important to ensuring global food security. Fall armyworm (*Spodoptera frugiperda*) is an invasive pest in Sri Lanka, causing significant damage to maize cultivation on the island. Continuous monitoring of fall armyworms is essential to ensure the high productivity of the crop. Traditional investigation methods used to examine fall armyworm incidence, such as field surveys, are time-consuming and labor-intensive. With the rapid development of remote sensing satellites, spectral reflectance measurements and vegetation indices have been used widely to monitor crop conditions. The present study was initiated to detect the spatial distribution of maize and the fall armyworm incidence in the Moneragala district, Sri Lanka with sentinel-2 multispectral images. The supervised maximum likelihood classification method was performed to determine the extent and spatial distribution of maize in the Moneragala district. Furthermore, remote sensing spectral vegetation indices, i.e., NDVI, SAVI, and NDRE and field surveys were performed to investigate the crop status and disease severity of fall armyworm. In the present study, three disease severity classes were recognized in terms of damage to the leaves, i.e., healthy (no visible leaf damage or less than 5% damage), slightly damaged (5% to 30% damage), and severely damaged (over 30% damage). The results revealed that NDVI, SAVI, and NDRE for healthy maize vegetation are 0.66±0.06, 0.88±0.03 and 0.41±0.02, respectively. Moreover, the disease severity classes of NDVI, SAVI, and NDRE were compared with One-way Analysis of variance (ANOVA) with the Tukey test for multiple comparisons. The results indicated a statistically significant difference between disease severity classes of NDRE ($p<0.05$), suggesting NDRE provides a more accurate measurement to detect fall armyworm incidence. The overall accuracy of the supervised image classification techniques was 89.78%, with a kappa coefficient of 0.88. Results was validated using statistics of maize extent data obtained from the Department of Census and Statistics, Sri Lanka, demonstrating significant accuracy ($p<0.05$). Therefore, present study revealed that remote sensing is an effective tool for mapping maize vegetation cover and early identification of fall armyworm incidence, making it a more economical and effective alternative to conventional methods.

Keywords: Maize, Fall Armyworm (FAW), Remote sensing, Sentinel-2 satellite images, Spectral vegetation indices

Background

Maize (*Zea mays* L.) is one of the most widely cultivated and consumed cereal crops in the world, with a production of 1.1 billion MT in 2019 (World Data Atlas 2021). Maize has excellent economic importance around the world as human food, animal feed, and as a source of industrial products such as biofuels (Sheng et al. 2018; Adom and Liu 2002). It is reported that maize is rich in human nutrition, including proteins (about 5.7%), starch (about 46.2%) and lipids (about 2.2%) (Revilla et al. 2022; Ai and Jane 2016). Consequently, maize has become the most significant food production in the world (Ngie et al. 2014).

Maize is primarily considered a dry zone crop and one of the main crops cultivated in the highlands and shifting (*chena*) types of highland cultivation. Maize currently holds a prominent position in Sri Lankan agriculture, and about 90,000 ha of land are dedicated annually in Anuradhapura, Monaragala, Ampara, Badulla, and Kurunegala districts (Dissanayake et al. 2021). In Sri Lanka, Maize is mainly cultivated under rainfed conditions as a monocrop and a mixed crop with cowpea, green gram, groundnut, chilli, and finger millet (Ranaweera et al. 1988). According to the Department of Agriculture, the annual maize production of Sri Lanka is around 380,000 MT, whereas direct human consumption is estimated at over 50,000 MT (Department of Agriculture Sri Lanka 2021). In Sri Lanka, maize requirements for "*Thriposha"*, which is an additional food very rich in nutritious, is being given to prevent maternal and child malnutrition, and other food industries exceed 18,000 MT annually. Furthermore, according to the Department of Animal Production and health statistics 2020, the total maize requirement for animal feed production approximates 480,000 – 540,000 MT per annum. Thus, maize is the second most important crop on the island (Perera et al. 2019; Malaviarachchi et al. 2007).

The fall armyworm (FAW), *Spodoptera frugiperda* native to tropical and subtropical regions of the western hemisphere from the United States of America to Argentina and is an economically destructive pest of many crop species, including rice, maize, tomato, and cabbage. FAW is an economically important pest of maize. It invaded Africa in 2016, causing a 30% to 60% yield loss (Mitti et al. 2021). Cruzz et al. (1999) reported FAW infest in all growth stages of maize plants. FAW caterpillars are usually found in whorls of young maize plants. In mature plants, they may infect ears, where they feed on soft tissues like kernels, soft inner leaves, and silk hair (Day et al. 2017). They rarely feed on older mature leaves (Makgoba et al. 2021). It is reported that maize yield loss due to FAW infestation in Ghana and Zambia was 45% and 40%, respectively (CABI 2017). Former studies revealed a strong positive relationship between FAW infestation density and yield loss (Overton et al. 2021; De Groote 2020). Application of recommended synthetic pesticides and insecticides are control measures to prevent significant damage to corn fields. However, insecticide use is challenging as FAW can develop resistance to insecticides (Day et al. 2017).

The life cycle of FAW lasts from 30 to 60 days and consists of moths, eggs, larvae, and pupae stages. FAW moths hide during the daytime and become active during the evening. The medium-sized moth has a wingspan of 32 to 40 mm. Forewings are shaded gray and brown. Hind wings are silver-white with a narrow dark border. In the forewing of the male moth, triangular white spots at the tip and near the center can be observed. The moth is a strong flier and can fly up to 100 km per night (Department of Agriculture Sri Lanka 2021). The female moth lays eggs in masses on the underside of the leaves. But sometimes laid on the upper side of the leaves and stems. Eggs are cream, green or brown coloured. Female moths can deposit more than one layer of eggs before they are covered by the whitish anal hairs of the moth (Mitti et al. 2021). FAW usually has six instars (Capinera 2017). The first sign of infection is feeding marks made by the first instars. They only feed on one side of the leaf. Young FAW caterpillars use ballooning to spread to new host plants. Mostly, worm infection gets noticed only after large holes accompanied by the larval droppings in the whorls and on surrounding leaves (Mitti et al. 2021). FAW caterpillars are usually found in whorls of young maize plants. On mature plants, they may infect ears, where they feed on soft tissues like kernels, soft inner leaves, and silk hair. They rarely feed on older mature leaves.

Surveillance and monitoring systems for early diagnosis of the FAW are essential to combat the threat posed by pests. Conducting extensive field surveys over a large area to detect the presence of pests and plant damage has become inefficient due to inadequate human, infrastructure, and financial resources. Misidentification and late identification of the pest result in yield loss and incorrect use of synthetic pesticides. Since the FAW is a transboundary pest, countries must collaborate to control the pest infestation (Mitti et al. 2021). Therefore, improved information systems and forecasting have been identified as essential in developing an effective management strategy for integrated pest management of FAW. Remote sensing technology can be used as an effective method to make a timely diagnosis of affected plants on a field scale. Remote sensing is a fast, non-destructive, less labour-intensive, and relatively cost-effective method for studying the biochemical and physical parameters of vegetation across large spatial areas. Since the images in remote sensing provide early detection before the symptoms become evident on ground surveys, there is sufficient time to take corrective actions before any economic losses occur (Hatfiels and Pinter 1993). Various spectral vegetation indices have been developed to detect plant stress based on spectral measurements (Xue and Su 2017; Ngie et al. 2014). Khan et al. (2018) mentioned that spectral vegetation indices derived from multi-spectral images could evaluate moisture content, crop health, and nutrient content. Furthermore, remote sensing spectral analysis can predict crop disease, pest disease and weed infestation (Homolova et al. 2013). The visible, near-infrared microwave portions of the electromagnetic spectrum region are primarily used in agricultural studies since these spectral regions include wavelengths sensitive to the crops' biological and physiological functions (Lillesand et al. 2008). Normalized difference vegetation index (NDVI) derived with reflectance measurements of RED and NIR is the most common and widely related to leaf area index and canopy photosynthesis. Normalized Difference Red Edge (NDRE) is a spectral index that estimates chlorophyll content and vegetation damage ranging from nutrient deficiencies to pest and disease damage. NDRE is derived with reflectance measurements for Near-infrared and vegetation red edge bands. Soil-Adjusted Vegetation Index (SAVI) derived from reflectance measurements for visible red and Near-infrared bands, which measures the vegetation cover of arid zones by minimizing soil brightness influenced by soil brightness (Eos.com 2019; Xue and Su 2017). Former studies reported that spectral vegetation indices play a significant role in detecting yellow rust, powdery mildew, aphid in wheat, late blight in tomatoes, and spider mite in cotton (Fitzgerald et al. 2004; Yang 2010; Sankaran et al. 2010; Huang et al. 2007). Moreover, the accuracy of mapping pests is reported to be approximately equal to hyperspectral and multi-spectral remote sensing images (Yang 2010). Zhang et al. (2015) suggested that multi-spectral data-based analysis is convenient due to its lower costs and higher availability.

Currently, the main challenge of maize production reported by Sri Lankan farmers is yield reduction owing to pests and diseases. FAW is a new pest in Sri Lankan soil and was first reported in August 2018 it is reported that FAW is a destructive and rapidly spreading insect which causes significant damage to the crop. It caused massive damage to large-scale maize monocropping systems (Perera et al. 2019). The outbreaks of this pest can devastate the economy, food, and nutrition security of the entire country. Monaragala district, located in the dry zone in Sri Lanka, is one of the districts with the highest area under maize cultivation and one of the first districts where FAW infestation was reported (Perera et al. 2019). Dry and intermediate zones in Sri Lanka are best suited for commercial cultivation. MI maize hybrid 01, 02, 03, 04 and 05 are locally produced hybrid varieties. Seed requirements of open-pollinated varieties are varied from 15kg per hectare, and for hybrids, it is 12kg per hectare (Department of Agriculture Sri Lanka 2021). According to the Department of Agriculture statistics, 55% of the cultivated extent of maize was affected in 2018 and 75% in 2019. Furthermore, a 15% yield loss was caused by the FAW during the early years of the invasion (Weligamage et al. 2020). Therefore, rapid assessment of the extent and severity of damage caused by FAW is important for decision-making in crop production. Farmer education and community action are critical in management of FAW population using an integrated pest management approach (Mitti et al. 2021). Although in-depth studies to determine the infestation of FAW are scanty, this knowledge is vital to determine the fate of maize cultivation in the country. Intensive research needs remote sensing techniques to be developed to implement management measures due to FAW infestation. The current study, therefore, focuses on investigating FAW damage in maize fields in the Monaragala district, Sri Lanka. Moreover, such information helps agricultural administrators and policymakers to decide

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whether to implement price regulation or provide financial subsidies/ agricultural insurance in damaged regions.

Methods

Study site

Monaragala district, the second-largest district in Sri Lanka, which faces the east and southeast direction of Sri Lanka, was selected for the study (Figure 1). The total area of the Monaragala district is 5659 km^2 (6° 17", 7° 28" N; 80° 50", 80° 35" E). The primary livelihood of the people living in the district is agriculture. The district receives a mean annual rainfall of 1500 mm, usually limited to 4-5 months of the year. The eastern, south, and south-eastern parts of the district are relatively drier than the higher north-western parts. Monaragala district has a mean annual temperature ranging from 22.5^{o}C to 27.5^{o}C. The major soil types of the district are reddish-brown earth, red, yellow podzolic, and low-humic clays. It is reported that Monaragala district contributes to more than 30% of the maize production in Sri Lanka (Department of Census and Statistics 2022).

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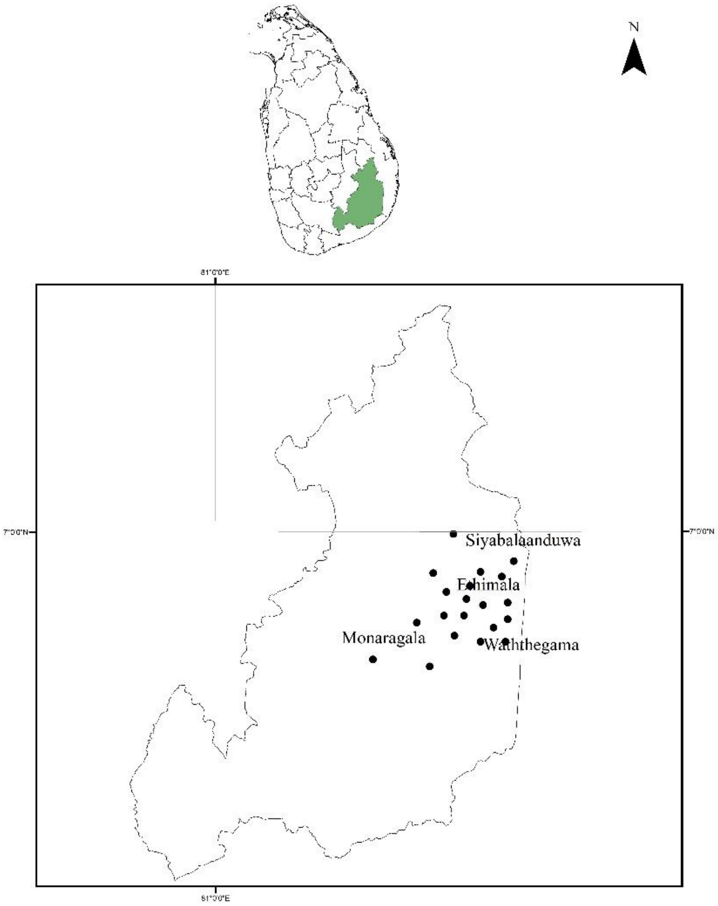

Figure 1. Map of the study area, including maize farms in Monaragala District.

Satellite data processing

The current study used freely available multi-temporal data from optical sensor, Sentinel – 2(L2A) satellite images. The satellite image of less than 10% of cloud cover was downloaded from QGIS 3.16 (QGIS 2021). The cropping seasons on the island are synonymous with two monsoons, i.e., Northeast-monsoon and Southwest-monsoon seasons. The major maize cultivation period of Sri Lanka falls during the North-east monsoon from September to March in the following year. Satellite images of maize cultivation at mature stages of the major rice cultivation season of Sri Lanka in 2019, 2020, and 2021 were utilized to map maize fields in Moneragala district, Sri Lanka. Moreover, it is reported that FAW feeds on maize cultivation during the late whorl stage of plants (Lowry et al. 2022). Therefore, the current study utilized satellite images at the late whorl stage fell in November of maize cultivation to investigate FAW incidence (Table 1). The current study selected 20 maize farms with more than 1 ha of continuous monocropping as study sites. Farm locations were collected using Garmin E-Trex GPS receiver (Figure 1). The image classification algorithm supervised Maximum Likelihood Classification (MLC) approach was performed to classify maize vegetation cover from the other land use types. Ground Reference Points (GRPs) were collected through field visits as described by Rwanga and Ndambuki (2020) to perform image classification. The GRPs were collected from the homogeneous areas of maize vegetation to avoid mixed pixels. The area of maize fields each year was calculated considering pixel area estimation. Thus, the extent of maize cultivation over the study period was calculated. The image classification accuracy was evaluated with the kappa coefficient. Furthermore, the area estimated based on satellite remote sensing was compared with maize extent obtained from the Department of Census and Statistics, Sri Lanka.

Table 1. Acquisition dates of satellite images for mapping of maize vegetation extent and Fall armyworm incidence.

Satellite image acquisition	Cropping season		
	2018/2019	2019/2020	2020/2021
Maize vegetation extent mapping	2019.01.03	2020.03.03	2020.11.28
Fall armyworm incidence mapping	2018.11.14	2019.11.14	2020.11.28

Computation of spectral vegetation indices

The sensitivities of spectral features for FAW damage analysis were examined using three spectral vegetation indices related to leaf area index and canopy morphology variations. Vegetation indices, i.e., NDVI (equation 1), SAVI (equation 2), and NDRE (equation 3), were computed to evaluate the growth dynamics at the foliar level (Table 2).

Table 2. Remote sensing spectral indices derived with reflectance measurements for visible red and near infrared and red edge bands. L represents the soil brightness correction factor (0.5).

Equation no.	Spectral index	Equation
1	Normalized Difference Vegetation Index	$NDVI = \frac{NIR - Red}{NIR + Red}$
2	Soil-Adjusted Vegetation Index	$SAVI = \frac{NIR - Red}{NIR + Red\ + L}(1 + L)$
3	Normalized Difference Red Edge	$NDRE = \frac{NIR - Red\,Edge}{NIR + Red\,Edge}$

Reference data collection

Ground truth data regarding the total extent of healthy and damaged maize cultivation were collected from the Monaragala provincial Department of Agriculture and the Department of Census and Statistics. Moreover, meteorological parameters in terms of monthly rainfall, monthly average minimum, maximum temperature, and relative humidity were collected from the Department of Meteorology to examine the climatic factors that influence the infection of FAW.

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Assessment of the FAW infestation through field scouting

The damage severity of the FAW was surveyed through field scouting in a semi-systematic pattern according to the scouting protocols of FAO (Food and Agriculture Organization of the United Nations) and CIMMYT (International Maize and Wheat Improvement Centre). Scout walking was done in a “W” pattern stopping at five different locations to cover the entire field. To reduce the edge effect, two border rows were avoided. At each location, ten plants were investigated for signs and symptoms of the FAW. The signs in the upper three leaves were observed and categorized according to the severity of the damage. Based on the degree of foliar damage, the infection status (the extent of the leaf damage) of each sampling point of the field was assessed and assigned to one of the three severity classes, i.e., healthy, slightly damaged, and severely damaged (Figure 2). The scoring scale used is shown in Table 3.

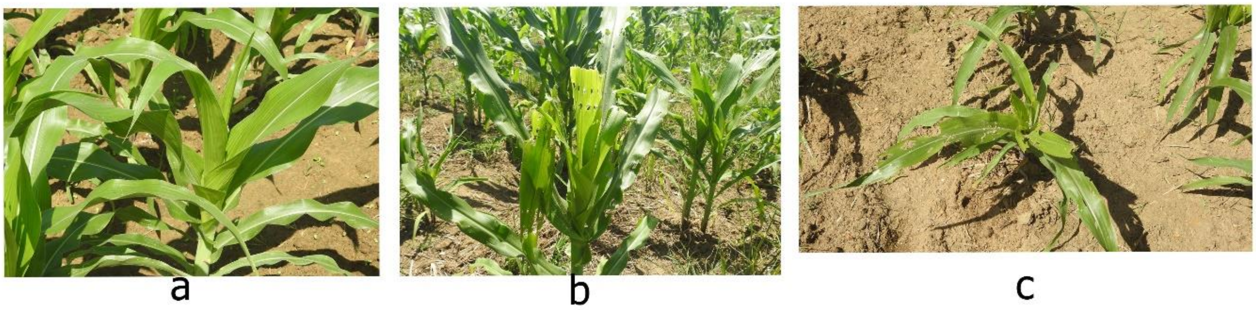

Figure 2. Visually assessment of the leaf damage severity (a) Healthy (b) Slightly damaged, and (c) Severely damaged.

Table 3. The scoring scale of damage level of fall armyworm (Source: Zhang et al. 2015; Prasanna et al. 2018).

Explanation/definition of damage	Severity Classes
No visible leaf damage or total leaf damage is less than 5% of the surveyed plants	Healthy
5% to 30% damage to upper three leaves	Slightly damaged
Over 30% damage to upper three leaves	Severely damaged

Data analysis

Two sample t-test ($p < 0.05$) was performed to determine whether there was a significant difference between the maize extent estimated based on remote sensing techniques and those published by the Department of Census and Statistics, Sri Lanka. Spectral vegetation indices values of each maize field obtained in 2019, 2020, and 2021 were statistically compared with One-Way ANOVA and Tukey HSD pairwise comparison ($p < 0.05$). Furthermore, Pearson's correlation analysis was performed to determine the correlation between spectral vegetation indices and climatic factors in terms of rainfall, temperature, and relative humidity. Time series data of the FAW population over three years (from 2019 to 2021) was collected from the Department of Agriculture, Monaragala. These ground-truth data were compared with the results from the statistical analysis to examine the sensitivity of spectral vegetation indices to FAW incidence.

Results

Figure 3 (a, b, and c) depicts the classification of maize fields based on time-series remote sensing images. According to the classification results, the maximum overall accuracy and kappa coefficient of extent mapping of the present study is 89.74% and 0.88, respectively. Interestingly, overall accuracy and kappa coefficient are similar for all cases (Table 4). Moreover, the comparison between maize area estimated with remote sensing techniques and those published in the Department of Census and Statistics was not statistically significant ($p < 0.05$; Table 5). Results show that the highest NDVI, SAVI and NDRE values were obtained from 2020/2021 cultivation season, and consequently, the highest yield was obtained from a 2020/2021 cultivation. Furthermore, NDVI, SAVI, and NDRE values of 2020/2021 cultivation season show a significant difference (Figure 3 d, e, and f; $p <0.05$) from the other cultivation seasons. This result is consistent with the maize area calculation (Table 5).

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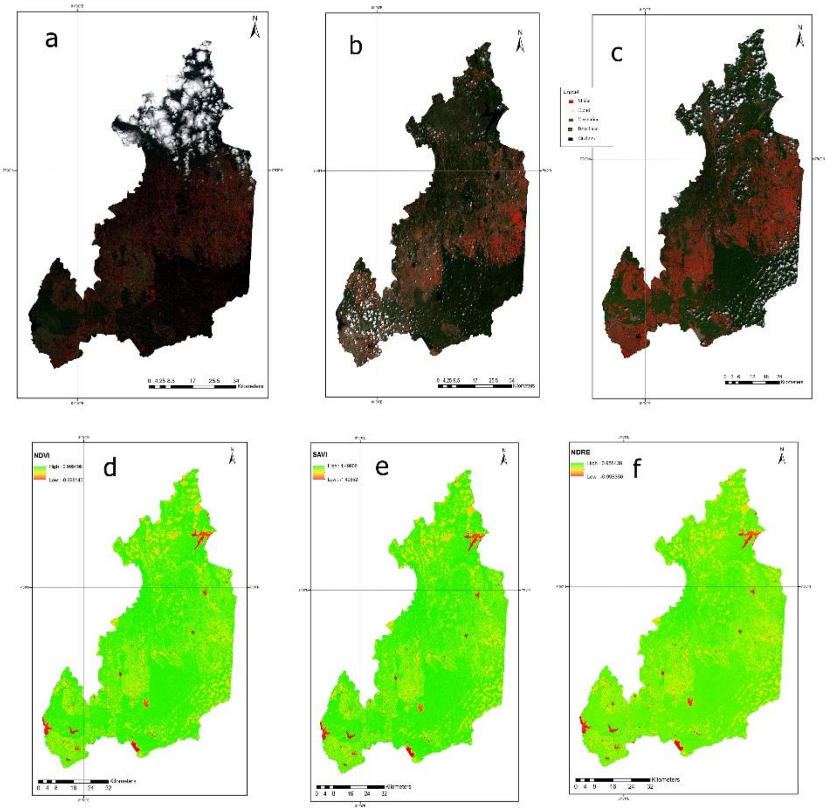

Figure 3. Spatial distribution of maize cultivated area in Monaragala district based on remote sensing analysis. Maize grown area for major cropping seasons of (a) 2018/2019 (b) 2019/2020 (c) 2020/2021; Remote sensing spectral indices d) NDVI, (e) SAVI, and (f) NDRE for major cropping season of 2020/2021.

Table 4. Overall accuracy and Kappa coefficient of extent mapping.

Season of cultivation	Overall accuracy (%)	Kappa coefficient
2018/2019	75.63%	0.72
2019/2020	74.47%	0.71
2020/2021	89.74%	0.88

Table 5. Comparison of maize extent estimated based on remote sensing techniques with those published at the Department of Census and Statistics.

Season of cultivation	Area estimation (ha)	
	Remote sensing method	Data available at the Department of Census and Statistics
2018/2019	25,519	28,253
2019/2020	24,873	25,716
2020/2021	26,844	27,587

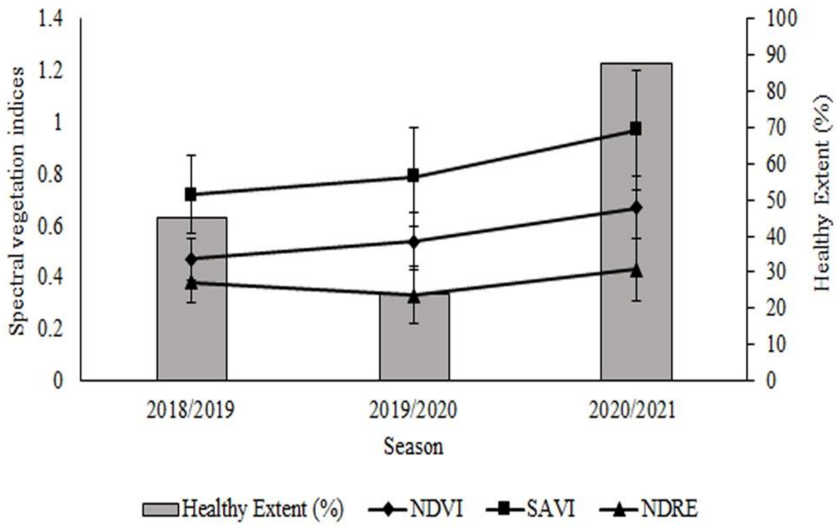

Figure 4. Comparison of ground truth data and remote sensing spectral vegetation indices (Bars show the standard deviation of the spectral vegetation indices).

The different spectral values indicated the disease severity. The spectral vegetation indices values obtained for the healthy category of NDVI, SAVI and NDRE were 0.66 ±0.06, 0.88

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±0.03, and 0.41 ±0.02, respectively (Table 6). The severity analysis results show a significant difference between the healthy and damaged classes in NDVI and SAVI spectral features but not a substantial difference between the slightly and severely damaged classes. NDRE spectral feature shows a significant difference ($p < 0.05$) between all three severity classes (Table 6). The healthy extent of maize cultivation shows that the estimated area based on spectral vegetation indices is consistent with the ground truth data (Figure 4). Hence, the accuracy of the method is further confirmed. Furthermore, according to Figure 5, the highest average rainfall and relative humidity have been recorded in the 2019/2020 cultivation season, in which the greatest FAW damage was recorded.

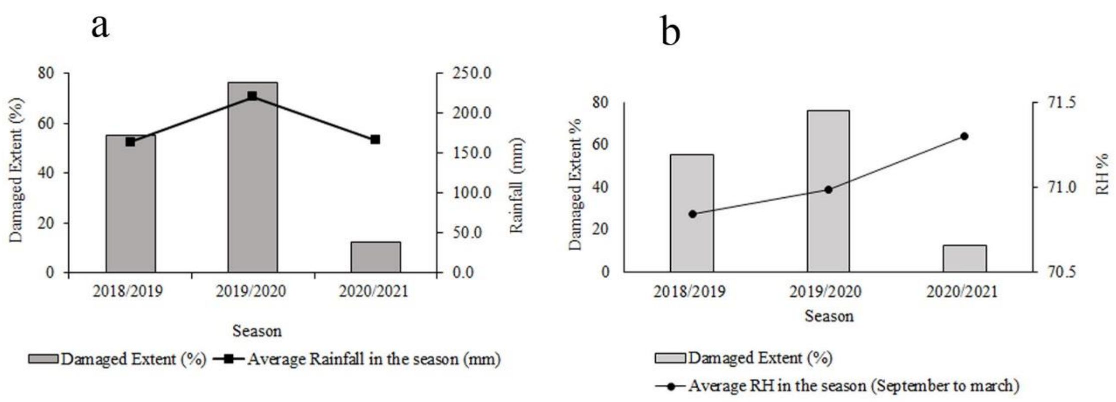

Figure 5. Relationship between damage extent by army fall worm and climatic factors in terms of rainfall (a) and relative humidity (b) during the major cropping seasons 2018/2019, 2019/2020, 2020/2021; in Moneragala district.

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Table 6. Means of the spectral features in disease severity classes.

Severity Class	NDVI	SAVI	NDRE
Healthy	$0.66^{a} \pm 0.06$	$0.88^{a} \pm 0.03$	$0.41^{a} \pm 0.02$
Slightly Damaged	$0.53^{b} \pm 0.04$	$0.73^{b} \pm 0.06$	$0.36^{b} \pm 0.00$
Severely Damaged	$0.45^{b} \pm 0.02$	$0.68^{b} \pm 0.05$	$0.29^{c} \pm 0.01$

The mean of spectral features within a column followed by the same superscripts are not significantly different ($p < 0.05$). (± shows the standard deviation of the spectral vegetation indices in each severity class).

Discussion

FAW is an invasive pest in Sri Lanka and increases the risk of food insecurity on the island. Early detection of FAW is essential to prevent significant yield loss. Therefore, continuous monitoring of FAW incidence is essential to ensure the high productivity of crops.

Prasanna et al. (2018) mentioned that the growth stages of maize are divided into the early whorl stage, late whorl stage, tasseling/ silking, and maturity. At the early stages of the crop, the soil surface is hardly covered by the canopy, but good ground cover can be observed at the maturity stage. Therefore, satellite images acquired in the late whorl stage show more soil background since plants are small. The good ground cover by the canopy ensures that each pixel of the training samples for maize crops in supervised classification represents the crop. Therefore, satellite images acquired in the maturity stage of maize were used for extent mapping in this study. According to field observations and information from the Department of Agriculture, Sri Lanka, the major maize cultivation period usually begins on 15th September and lasts until 15th March of the following year. Thus, extent mapping of maize cultivation was performed using multispectral images acquired between late November and March.

The current study used freely available Sentinel-2 satellite images since Sentinel-2 provides 13 spectral bands of multispectral images with a high spatial resolution (Sentinel-2 User Handbook 2015). Moreover, Sentinel-2 has an appropriate spatial and spectral resolution in the near-infrared region, with three additional vegetation red edge bands with 20 m spatial resolution compared to the latest Landsat OLI/TIRS (Astola et al. 2019; Kumbula et al. 2019). The results of this work indicated that the overall accuracy of the image classification procedure was 89.78% with a kappa of 0.88, suggesting the Maximum Likelihood algorithm is more reliable in maize field extent mapping. Our results corroborate those former studies (Valero and Alzate 2019; Mustapha et al. 2010), reporting that the supervised maximum likelihood classification algorithm can be considered a reliable technique regarding vegetation mapping. Moreover, Rwanga and Ndambuki (2017) mentioned that if the kappa coefficient is greater than 0.7, the strength of agreement is good. These results were further confirmed by comparing of the area estimated with remote sensing techniques and maize cultivated area published in the Department of Census and Statistics in which there is no significant difference ($p < 0.05$) between maize area estimations. Hence, our result suggested that mapping the spatial distribution of the maize is effective using the sentinel-2 multispectral images.

However, identifying FAW incidence in the tasseling / silking or maturity stages is too late to minimize the economic loss. A former study reported that the most vital stage for maximum production of maize is the late whorl stage. This is because, at the late whorl stage, eight to twelve leaves are fully unfolded (Ngie et al. 2014). Therefore, the suitable period for FAW incidence mapping is the late whorl stage which falls 28 to 42 days after emergence. Considering the life cycle of maize, and the crop calendar in the Moneragala district, the late whorl season falls in mid-November for the major maize cultivation season. Therefore, multispectral satellite images acquired in November were used to map FAW incidence.

FAW typically has six larval instars. The young FAW larvae feed on the undersides of leaves, sucking chlorophyll from the leaves, leaving a transparent window. The third to sixth instars have developed jaw and cause the most extensive defoliation resulting in leaf holes (Mitti et al. 2021). These damage symptoms cause a significant reduction in leaf area, biomass and chlorophyll content. Therefore, NDVI, SAVI, and NDRE vegetation indices related to analyzing leaf area index and canopy morphology variations were used in this study to examine the sensitivity of spectral features candidates for FAW infestation. The current study revealed that NDRE is more effective in investigating FAW incidence as NDRE is calculated using the combination of the NIR and red edge bands (Table 6; Figure 4). Corroborating our finding, Datt et al. (2005) found the red edge region as a good estimator of chlorophyll-related stress. Furthermore, former studies mentioned that the red edge index is more effective in determining canopy chlorophyll content of maize (Adamczyk and Osberger 2015; Li et al. 2014; Delegido et al. 2013).

Our field observation revealed FAW causes patchy damage in the field. Corroborating this observation, Zhang et al. (2015) showed that most of the upper leaves of slightly damaged plants remain undamaged owing to the feeding pattern of the FAW from the bottom to the top of crops. Consequently, such plants might have a slight spectral change, thus lacking a clear spectral signature to be sensed. Thus, the results of the severity analysis with NDVI and SAVI of the current study manifested a statistically significant difference between the healthy and damaged classes, whereas there is no statistically significant difference ($p < 0.05$) between the slightly and severely damaged classes. However, our result manifested statistically significant between ($p<0.05$) all the three severity classes obtained with NDRE index. Former studies reported that NDRE is a sensitive index to examine crops with lower chlorophyll content and hence the chlorophyll content variation throughout the foliage (Boiarskii and Hasegawa 2019; Li et al. 2014). Hence, NDRE is the most suitable spectral feature candidate to predict FAW damage.

The spectral vegetation indices values obtained for the healthy category by this study are lower than the standard values for the healthy category. For example, if the crop is healthy NDVI value is between 0.66 and 1. If moderately healthy, it ranges from 0.33 to 0.66. The NDRE value in the healthy crop is between 0.6 and 1 (Eos.com 2019). However, the NDVI and NDRE values obtained for the healthy category in this study were 0.66 ± 0.06 and 0.41 ± 0.02, respectively. This is because the maize fields in the late whorl stage were used in the study, and the standard values are for mature stages. Ngie et al. (2014) revealed that spectral vegetation indices values gradually increased with the growth of the crop life cycle of maize.

Capinera (2017) mentioned that warm and humid weather conditions influence the propagation of FAW and hence can cause severe crop damage. According to the current study, the highest average rainfall and relative humidity have been recorded for the cultivation season in 2019/2020, in which the most significant FAW damage is recorded, suggesting wet conditions with abundant rainfall result in lush vegetation, which is favourable for an expansive FAW population. A former study showed that NDVI is proportional to the precipitation and inversely proportional to the temperature (Ghebrezgabher et al. 2020). Corroborating this observation, the present study shows that all three vegetation indices were negatively correlated with the minimum monthly average temperature. Thus, the result further suggests FAW infestation is rapid at low temperature and humid conditions.

Remote sensing technologies have yet to be widely used in the Sri Lankan context. The present study shows the ability to use remote sensing for early identification of FAW incidence leading to site-specific control. Also, it reduces the cost of field investigation, making it a more economical and effective alternative to conventional methods. Moreover, the study revealed that free access to Sentinel-2 imagery facilitates the implementation of pest management strategies. Hence, remote sensing is an effective tool for the early identification of FAW incidence in Sri Lanka.

Conclusions

Invasive pests, FAW increases the risk of food security. Therefore, early detection of FAW is essential to prevent significant yield loss. This study examined the feasibility of using sentinel-2 multi-spectral images to detect the spatial distribution of maize and the FAW incidence using the Monaragala district. The results suggest that sentinel-2 multispectral images can be used to map the spatial distribution of maize cover in Moneragala district while remote sensing spectral index, i.e., NDRE is the best to sense the severity of FAW damage of maize vegetation. The recent availability of free access to Sentinel-2 imagery facilitates the use of remote sensing technology in implementing of pest management strategies, which is essential to enhancing food security.

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Declaration

No potential conflict of interest was reported by the authors.

List of Abbreviations

ANOVA	- Analysis of Variance
CIMMYT	- International Maize and Wheat Improvement Centre
FAO	- Food and Agriculture Organization
GPS	- Global Positioning System
GRP	- Ground Reference Points
MLC	- Maximum Likelihood Classification
NDRE	- Normalized Difference Red Edge
NDVI	- Normalized Difference Vegetation Index
NIR	- Near – Infrared
QGIS	- Quantum Geographic Information System
OLI/TIRS	- Operational Land Imager and Thermal Infrared Sensor
SAVI	- Soil-Adjusted Vegetation Index
Tukey’s HSD	- Tukey’s Honestly Significant Difference

References

Adamczyk J, Osberger A (2015) Red-edge vegetation indices for detecting and assessing disturbances in Norway spruce dominated mountain forests. International Journal of Applied Earth Observation and Geoinformation 37:90-99. doi: 10.1016/j.jag.2014.10.013.

Adom KK, Liu RH, (2002) Antioxidant activity of grains. J Agricultural and Food Chemistry 50: 6182–6187**.**

Ai Y and Jane J (2016) Macronutrients in Corn and Human Nutrition. J Comprehensive Reviews in Food Science and Food Safety 15:582-598. doi: 10.1111/1541-4337.12192.

Astola H, Häme T, Sirro L, Molinier M, Kilpi J (2019) Comparison of Sentinel-2 and Landsat 8 imagery for forest variable prediction in boreal region. J Remote Sensing of Environment 223:257-273. doi: 10.1016/j.rse.2019.01.019.

Boiarskii B, Hasegawa H (2019) Comparison of NDVI and NDRE Indices to Detect Differences in Vegetation and Chlorophyll Content. J International Conference on Applied Science, Technology and Engineering J. Mech. Cont.& Math. Sci., Special Issue 4:20-29. doi: 10.26782/jmcms.spl.4/2019.11.00003.

CABI (2017) Fall armyworm: Impacts and Implications for Africa, Commonwealth Agricultural Bureau International, Wallingford. Available via https://www.cabi.org/cabi-publications/fall-armyworm-impacts-and-implications-for-africa-2/. Accessed 7 May 2022.

Capinera JL (2017) Fall armyworm, *Spodoptera frugiperda* (J.E. Smith) (Insecta: Lepidoptera: Noctuidae). Available via http://edis.ifas.ufl.edu/in255._Accessed 10 March 2021.

Cruz I, Figueiredo MLC, Oliveira AC, Vasconcelos CA (1999) Damage of *Spodoptera frugiperda* (Smith) in different maize genotypes cultivated in soil under three levels of aluminium saturation. International Journal of Pest Management 45(4): 293–296. doi: 10.1080/096708799227707.

Datt A, Datt B, Kelly R, Apan A (2005) Detection of pests and diseases in vegetable crops using hyperspectral sensing: a comparison of reflectance data for different sets of symptoms. Available via https://eprints.usq.edu.au/553/1/Apan_etal_SSIMelb2005_2.pdf. Accessed 8 May 2022.

Day R, Abrahams P, Bateman M, Beale T, Clottey V, Cock M, Colmenarez Y, Corniani N, Early R, Godwin J, Gomez J, Moreno PG, Murphy ST, Oppong-Mensah B, Phiri N, Pratt C, Silvestri S, Witt A (2017) Fall armyworm: impacts and implications for Africa. Out looks on pest management 28(5):196-20. doi: 10.1564/v28_oct_02.

De Groote H, Kimenju SC, Munyuaa B, Palmasa S, Kassie M, Brucea A (2020) Spread and impact of fall armyworm (*Spodoptera frugiperda* J.E. Smith) in maize production areas of Kenya. J Agriculture, Ecosystems and Environment 292:106804.

Delegido J, Verrelst J, Meza CM, Rivera JP, Alonso L, Moreno J (2013) A red-edge spectral index for remote sensing estimation of green LAI over agroecosystems. European Journal of Agronomy 46: 42-52. doi: 10.1016/j.eja.2012.12.001.

Department of Agriculture, Sri Lanka. https://doa.gov.lk/FCRDI/index.php/en/crop/43-maize-e. Accessed 10 March 2021.

Department of Census and Statistics, Sri Lanka. http://www.statistics.gov.lk/HIES/HIES2006_07. Accessed 8 February 2022.

Dissanayake SP, Gunaratne LHP, Sivanathewer T, Ginigaddara G.A.S (2021). Comparative analysis of sustainability in paddy monoculture and paddy-maize rotation farming systems in Sri Lanka. Tropical Agricultural Research 32(3): 265-275.

Fitzgerald GJ, Maas SJ, Detar WR (2004) Spider mite detection and canopy component mapping in cotton using hyperspectral imagery and spectral mixture analysis. J Precision Agriculture 5:275–289.

Ghebrezgabher M, Yang T, Yang X, Eyassu ST (2020) Assessment of NDVI variations in responses to climate change in the Horn of Africa. The Egyptian Journal of Remote Sensing and Space Science 23(3):249-261.

Hatfield PL, Pinter PJ (1993) Remote sensing for crop protection. J Crop Protection 12(6): 403–413. doi:10.1016/0261-2194(93)90001-y.

Homolova L, Maenovsky Z, Clevers J, Garcia-Santos G, Schaepman ME (2013) Review of optical-based remote sensing for plant trait mapping. J Ecological Complexity15: 1–16.

Huang W, Niu Z, Liu L (2007) Identification of yellow rust in wheat using in-situ spectral reflectance measurements and air borne hyperspectral imaging. J Precision Agriculture 8:187–197.

Khan Z, Rahimi-Eichi V, Haefele S, Garnett T, Miklavcic S (2018) Estimation of vegetation indices for high-throughput phenotyping of wheat using aerial imaging. J Plant Methods14(1). doi 10.1186/s13007-018-0287-6.

Kumbula S, Mafongoya P, Peerbhay K, Lottering R, Ismail R (2019) Using Sentinel-2 Multispectral Images to Map the Occurrence of the Cossid Moth (*Coryphodema tristis*) in Eucalyptus Nitens Plantations of Mpumalanga, South Africa. J Remote Sensing11(3):278. doi:10.3390/rs11030278.

Li F, Miao Y, Feng, G, Yuan F, Yuea S, Gao X, Liu Y, Liu B, Ustin SL, Chen X (2014) Improving estimation of summer maize nitrogen status with red edge - based spectral vegetation indices. J Field Crops Research 157:111–123. doi:10.1016/j.fcr.2013.12.018.

Lillesand T, Kiefer R, Chipman J (2015) Remote sensing and image interpretation, 7th edn. Wiley, New York.

Lowry A, Durocher-Granger L, Oronje M, Mutisya D, Mfune T, Gitonga C, Musesha B, Taylor B, Wood S, Chacha D, Beale T, Finch EA, Murph ST (2022) Optimizing the timing of management interventions against fall armyworm in African smallholder maize: Modelling the pattern of larval population emergence and development. J Crop protection 157:105966. doi: 10.1016/j.cropro.2022.105966.

Makgoba MC, Tshikhudo PP, Nnzeru LR, Makhado RA (2021) Impact of fall armyworm (*Spodoptera frugiperda*) (J.E. Smith) on small-scale maize farmers and its control strategies in the Limpopo province, South Africa Jamba 13(1): 1016. doi: 10.4102/jamba.v13i1.1016.

Malaviarachchi MAPWK, Karunarathne KM, Jayawardane SNJ (2007) Influence of plant density on yield of hybrid maize (zea mays L.) under supplementary irrigation. Journal of Agricultural Sciences 3 (2): 58-66.

Mitti M, Luchen S, Hove L, Tanyongana R (2021) Training manual on fall armyworm. Food and Agriculture Organization of the United Nations.

NDRE: Normalized Difference RedEdge Index for Agriculture (2019) EOS Data Analytics, England. https://eos.com/industries/agriculture/ndre. Accessed 30 December 2021.

Mustapha MR, Lim HS, Jafri MZM (2010) Comparison of Neural Network and Maximum Likelihood Approaches in Image Classification Journal of Applied Sciences
10 (22): 2847-2854. doi: 10.3923/jas.2010.2847.2854

Ngie A, Ahmed F, Abutaleb K (2014) Remote sensing potential for investigation of maize production: review of literature. South African Journal of Geomatics 311. 27-559. doi: 10.4314/sajg.v3i2.4.

Overton K, Maino JL, Day R, Umina PA, Bett B, Carnovale D, Ekesi S, Meagher R, Reynolds OL (2021). Global crop impacts, yield losses and action thresholds for fall armyworm (*Spodoptera frugiperda*): A review. Crop Protection 145:105641.

Perera N, Magamage M, Kumara A, Galahitigama H, Dissanayake K, Wekumbura C, Iddamalgoda P, Iddamalgoda P, Siriwardhana C, Yapa P (2019) Fall Armyworm Epidemic in Sri Lanka: Ratnapura District Perspectives. International Journal of Entomological Research 7(1): 09-18.

Prasanna B, Huesing J, Eddy R, Peschke V (2018) Fall armyworm in Africa: a guide for integrated pest management. Feed the Future. Available via https://www.feedthefuture.gov/resource/fall-armyworm-in-africa-a-guide-for-integrated-pest-management-first-edition. Accessed 14 May 2021.

QGIS. https://www.qgis.org/en/site/index.html. Accessed 30 July 2021.

Ranaweera N, De Silva G, Fernando M, Hindagala H (1988). Maize Production in Sri Lanka. In: The CGPRT Centre. Available via https://books.google.lk/books/about/Maize_Production_in_Sri_Lanka.html?id=UMA6AAAAMAAJ&redir_esc=y. Accessed 4 June 2021.

Revilla P, Alves ML, Andelković V, Balconi C, Dinis I, Mendes-Moreira P, Redaelli R, Ruiz de Galarreta JI, Vaz Patto MC, Žilić S, Malvar RA (2022) Traditional Foods From Maize (*Zea mays* L.) in Europe. J Frontiers in Nutrition 8:683399. doi: 10.3389/fnut.2021.683399.

Rwanga SS, Ndambuki JM (2017) Accuracy assessment of Land Use/ Land Cover classification using remote sensing and GIS. International Journal of Geosciences 8: 611-622. doi: 10.4236/ijg.2017.84033.

Sankaran S, Mishra A, Ehsani R, Davis C (2010) A review of advanced techniques for detecting plant diseases. J Computers and Electronic in Agriculture 72:1–13. doi:10.1016/j.compag.2010.02.007.

Sentinel-2 User Handbook (2015) European Space Agency. Available via https://sentinels.copernicus.eu/web/sentinel/user-guides/document-library/-/asset_publisher/xlslt4309D5h/content/sentinel-2-user-handbook. Accessed 4 June 2021.

Sheng S, Li T, Liu RH (2018) Corn phytochemicals and their health benefits. J Food Science and Human Wellness 7:185–195. doi: 10.1016/j.fshw.2018.09.003.

Valero M JA, Alzate ABE (2019) Comparison of maximum likelihood, support vector machines, and random forest techniques in satellite images classification. Tecnura, 23(59), 13-26. https://doi.org/10.14483/22487638.14826

Weligamage S, Mathimaaran E, Nishantha K, Bandara K (2020) Diversity and abundance of predatory arthropods of fall armyworm. ASDA.

World Data Atlas (2021). https://knoema.com/atlas/World/topics/Agriculture/Crops-Production-Quantity-tonnes/Maize-production. Accessed 7 March 2021.

Xue J, Su B (2017) Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. Journal of Sensors 2017: 1-17. doi:10.1155/2017/1353691.

Yang CM (2010) Assessment of the severity of bacterial leaf blight in rice using canopy hyperspectral reflectance. J Precision Agriculture11:61–81. doi: 10.1007/s11119-009-9122-4.

Zhang J, Huang Y, Yuan L, Yang G, Chen L, Zhao C (2015) Using satellite multispectral imagery for damage mapping of armyworm (*Spodoptera frugiperda*) in maize at a regional scale. J Pest Management Science 72(2):335–348. doi:10.1002/ps.4003.