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Monitoring the damage of Armyworm in Summer Corn by Unmanned Aerial Vehicle imaging

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Abstract:

Background: Monitoring armyworm (*Mythimna separata* Walker) damage in crops requires timely, rapid and accurate observations to avoid severe yield losses.

Results: The Random Forest (RF) classifier was more effective at automatically and accurately monitoring armyworm damage compared with Support Vector Machine (SVM), Multilayer Perceptron Classifier (MLPC) and Naive Bayes Classifier (NB) classifiers. Furthermore, the incorporation of an Unmanned Aerial Vehicle (UAV) image-generated digital surface model improved the performance of the RF classifier, increasing the F-score from 0.985 and 0.970 to 0.997 and 0.994, and increasing the Kappa coefficient from 0.955 to 0.990. In addition, we found that Band 3 (735 nm) of the UAV image and Band 6 (740 nm) of a coincident Sentinel-2 image were not sensitive to an armyworm infestation in this study.

Conclusions: We developed an accurate algorithm for the automated identification of armyworm-damaged corn plants using UAV images at the field scale. The study also indicated the feasibility of the developed method for monitoring corn armyworm damage at regional scale when combined with Sentinel-2 images.

Keywords: armyworm monitoring; summer corn; Unmanned Aerial Vehicle; Random Forest; Sentinel-2

Background

The incidence of insect pests in crops in China is increasing due to the frequent occurrence of extreme weather, simultaneous sowing over large areas and the increase of pests resistance to insecticides [1]. Curtis et al. [2] showed that crop pests increase with global temperatures and that an average global surface temperature increase of 2°C can lead to corn production declines of 23% in China and of 32% in the United States. Armyworm (*Mythimna separata* Walker) is one of the most serious insect pests for cereal crops and can result in great crop production losses every year [3, 4]. Summer corn is one of the favorite hosts of armyworm because high temperatures and rain during the growing season of summer corn make the crop grow rapidly and create a suitable environment for insect reproduction. Armyworm, with its high field density, long duration of the infestation and rapid migration [5], can result in devastating damages to corn. In 2012, one of the most serious armyworm infestations ever recorded broke out in most corn planted areas of China, covering about 7.4 million hectares [6]. Large losses of grain production lead to price increases in the agricultural product futures market when supply is low and demand is high, and vice versa. At present,

application of chemical pesticides is the main method of armyworm control. However, the blind application of a large amount of pesticides damages the ecological environment and can leave pesticide residues harmful to human health. It is thus of great significance to rapidly and timely determine the occurrence area, severity and diffusion pattern of a pest infestation, so that precise spraying of pesticides in the field can be deployed with precision farming [7, 8]. Traditional methods of monitoring plant insect pests mainly depend on field inspection by plant protection personnel. This approach is time-consuming and laborious. Additionally, the field campaign can only be done in finite sampling areas and does not provide information about the degree of infestation over a region [9]. Armyworms mainly feed on corn leaves and ears, especially in the tasseling-filling stage, interfering with the normal physiological activities of corn and resulting in plant dwarfing and changed canopy spectra. In consideration of this fact, remote sensing can provide a promising approach for non-destructively identifying crop diseases and insect pests quickly and automatically on a regional scale.

Many studies have revealed the effectiveness of satellite images in monitoring crop diseases and insect pests. Yuan et al. [10] presented Fisher's linear discriminant analysis for monitoring crop diseases and pests based on the Worldview-2 and Landsat 8 satellite data. Chemura et al. [11] used Sentinel-2 images to discriminate coffee leaf rust infection levels and achieved high overall accuracy of 76.2%. Meigs et al. [12] mapped tree mortality based on long time-series of Landsat images and forest inventory data and analyzed the spatiotemporal dynamics of insect pests. Unfortunately, the long revisit period, low spatial resolution and the requirements for clear weather of optical satellite images hampered the ability of monitoring armyworm infestations, which break out in short times [13, 14]. Recently, unmanned aerial vehicles (UAV) with different sensors are increasingly being used in precision agriculture for monitoring crops growth condition [15-17]. With advances in the flexibility of operation and high spatial, spectral, and temporal resolution, UAV images can be used to accurately identify damaged plants and monitor their condition at the field scale [18, 19]. Dobbels and Lorenz [20] used a UAV system to monitor soybean chlorosis caused by iron deficiency for developing tolerant soybean varieties and gained better results than those of traditional ground-based visual assessments. Yue et al. [21] extracted pest information from UAV images with an improved scale-invariant feature transform algorithm. Huang et al. [22] explored the potential of using the photochemical reflectance index for quantifying yellow rust in wheat from airborne hyperspectral images. Because UAVs can observe the land surface with high resolution images from different perspectives by flying on prescribed routes, UAV images can be used to generate digital surface models (DSM) through photogrammetry, such as with an image-based modeling (IBM) algorithm, offering a cost-effective way to collect crop canopy structure information [23, 24]. As a co-product of UAV optical imaging, the DSM can be used in crop land classification, crop growth monitoring, and yield estimation. Yang et al. [25] extracted the lodging area of rice successfully using UAV images and derived a DSM by developing a decision tree classification model with an accuracy of 96.17% and a Kappa coefficient of 0.941. Diaz-Varela et al. [26] automatically identified agricultural terraces by applying object-oriented classification to UAV multispectral images and high-resolution DSM, and their overall accuracy was 90%. However, the joint use of UAV spectral images and DSM features for monitoring armyworm infestations is relatively less common in published studies.

Remote sensing data are massive and high-dimensional. Consequently, efficient and automated approaches are critical to their analysis and interpretation [27]. There are two groups of remote sensing image classification methods for pest identification: supervised classification methods, such as maximum likelihood method, machine learning method, and unsupervised classification methods, such as k-means and ISODATA. The Random Forest (RF) algorithm has been extensively used for monitoring the damage of pests on vegetation. RF is a machine learning method with ensemble learning, which uses multiple decision trees to predict samples [28, 29]. Because of ensemble learning, RF can avoid errors due to a single model or due to a single group of parameters; it has higher accuracy and better stability compared with using a single classifier. Moreover, it is not sensitive to abnormal values (noise) or overfitting [30] and is a nonparametric algorithm [31], which

means that it does not need to assume any parametric distribution of the data. Therefore, RF can be applied to various types of data [32]. In addition, RF can also output the importance of each feature to the classification and regression, helping feature selection to reduce data dimension and improve efficiency [33]. RF has been successfully applied to remote sensing images. Adelabu et al. [34] used RF and Support Vector Machine (SVM) classification algorithms to identify different levels of insect defoliation in an African savanna based on RapidEye imagery. Xu et al. [35] detected the damage of *Dendrolimus punctatus* Walker by Backpropagation neural networks and RF models. Aparecido et al. [36] developed a disease and pest warning system for coffee to predict the incidence of various diseases and insect pests by machine learning algorithm, such as the RF Regressor, Artificial Neural Networks, etc.

In this study, we used the RF algorithm to identify the damage of armyworm in a summer corn field by extracting the pest damage from UAV images of the study area. The spectral characteristics of different incidences of the pest in Sentinel-2 images were also analyzed. The contributions of this paper were: i) to evaluate the performance of RF for monitoring the damage of armyworm as a pest of summer corn and compare it with other machine learning classifiers including SVM, Multilayer Perceptron Classifier (MLPC) and Naive Bayes Classifier (NB); ii) to explore the potential of corn canopy DSM for identifying the damage of corn armyworm; and iii) to identify the importance of the UAV image features for the identification of armyworm infestation.

Materials and Methods

Study area

The study area was located in Beicuizhuang Village, Langfang City, Hebei Province, China (39°21'N~39°22'N, 116°44'E~116°46'E), in the central-eastern part of the North China Plain, covering an area of about 70 ha (Figure 1). There were various crops planted, including summer corn (mainly Zhengdan 958), soybean, peanut, fruit trees, and others. This is a typical small-holding farming area with flood irrigation by pumping water, so the crop management (e.g., sowing, irrigation, fertilization and weeding) is varied. Conventionally, in the study area, summer corn is seeded at the end of June and harvested in the beginning of October. Through on-site investigations and inquiries to local farmers, it was determined that the summer corn in this area was seriously attacked by armyworm in the middle of August 2019.

Figure 1. Study area: (a) location on the map; (b) UAV multispectral image, R/G/B=Band 2/ Band 3/ Band 1 of the experiment field; (c) UAV image-generated digital surface model (DSM).

UAV image collection

The UAV images were collected on 18 August 2019 between 10:50 and 11:25 local time, almost simultaneously with the acquisition time of a Sentinel-2 image. The meteorological conditions were sunny and windless. The Parrot Disco-Pro AG fixed-wing UAV system was used to collect the UAV images. The system, developed for agricultural applications, carried an automated multispectral sensor – the Parrot Sequoia camera (Table 1). The camera was connected to an irradiance sensor which had the same spectral bands as the multispectral sensor and recorded the light conditions [37].

Table 1. The band information of the Parrot Sequoia Multispectral sensor.

Band	Central wavelength (nm)	Bandwidth
Band 1- Green	550	40
Band 2- Red	660	40
Band 3- Red-edge	735	10
Band 4- NIR	790	40

Before the flight, the Parrot Sequoia camera took photos of the calibration board for radiation correction after photo splicing (Figure 2). The operator kept the calibration board facing the sun in order to guarantee there the absence of shadows on the board. Figure 2 (a)–(d) were the captured green, red, red-edge, and NIR band images for radiometric calibration in the study area. The aboveground height of the flight lines was 120 meters, the longitudinal overlap and lateral overlap were all 80%, yielding a ground sample distance (GSD) of 0.135 m/pixel; the flight duration was 20 minutes. The georeferencing was achieved by Global Positioning System (GPS) built into the Parrot

Sequoia camera and five ground control points (GCPs) were provided by using a Huace i80 real-time kinematic (RTK) GPS receiver (Huace Ltd., Shanghai, China) with 2.0 cm of positioning accuracy. In addition, the UAV photos, the calibration photos and GCPs were input into the Pix4Dmapper Pro 4.1 software following the “Ag Multispectral” template for automatic splicing and point cloud modeling [38]; finally, the spliced multispectral image (Figure 1b) and the UAV image-generated DSM (Figure 1c) were generated [23, 24], with spatial resolution of 0.135 m/pixel and accuracy of 0.131 m. Therefore, the Parrot Disco-Pro AG fixed-wing UAV system was suitable for plot scale precision agricultural research.

Figure 2. Shooting the calibration board on different bands.

Sentinel-2 image acquisition and pre-processing

Sentinel-2 images are one of the most widely used satellite multispectral images in view of their advantages in temporal, spatial and spectral resolution, and a free data policy. The cloudless Sentinel-2B Level-1C products used for this study were acquired on 18 August 2019 at 10:55 UTC with the UTM/WGS84 projection. The atmospheric correction of images was done by Sen2cor (version 2.8.0). The Sentinel-2 images adopted different spatial resolutions in different spectral bands (as shown in Table 2). Therefore, the SupReME algorithm [39] was used to generate a unified 10-m resolution image set. The algorithm depended on the observation model of the imaging (blurring and down-sampling), and fully exploited the textural information from the high resolution bands and the correlation of spectral bands, to transfer all lower resolution super-bands to the maximum resolution quickly in one step. Existing studies have shown that such super-resolved images can improve the classification accuracy of images [40] and thus the ability of quantitative remote sensing [41]. Then, the spectral profiles of five different pest infection levels were extracted and analyzed based on the super-resolution images of Sentinel-2.

Table 2. List of Sentinel-2A image band parameters

Band	Spatial resolution (m)	Central wavelength (nm)	Band width (nm)
Band 1- Coastal aerosol	60	443	20
Band 2 - Blue	10	490	65
Band 3 - Green	10	560	35
Band 4 - Red	10	665	30
Band 5 - Red edge	20	705	15
Band 6 - Red edge	20	740	15
Band 7 - Edge of the NIR plateau	20	783	20
Band 8 - NIR	10	842	115

Band 8a - Narrow NIR	20	865	20
Band 9 - Water vapor	60	945	20
Band 11 - SWIR	20	1610	90
Band 12 - SWIR	20	2190	180

Classification by machine learning algorithms

The Scikit-learn open-source Python package [42] was used in this study to perform data classification and prediction by machine learning algorithms, including RF [28, 29], SVM [43], MLPC [44] and NB [45].

The damage of corn plants infected by armyworm shows with a decrease in leaves, which leads to changes in physiological activities, morphological characteristics and canopy spectrum of corn. The classifiers used image features to classify individual corn pixels into different categories. According to the ground survey and visual interpretation methods, there were 193,369 pixels of healthy corn plants; 96,825 pixels of corn damaged by armyworm were selected from UAV images with spatial resolution of 0.135 m/pixel. Furthermore, the datasets were used to create a dataset consisting of only UAV multispectral images and a dataset consisting of both UAV multispectral images and DSM information. A 10-fold cross-validation [46] was adopted to evaluate the accuracy of the classification. Through this approach, the dataset was divided randomly into ten groups, of which nine acted as training data and one group acted as the test data for training. The correct rate (or error rate) was obtained for each test. Finally, the average of the correct rate (or error rate) of ten iterations was used as the estimation of the accuracy of the algorithm. For the other three classifiers (SVM, MLPC and NB), the cross-validation method and the evaluation measures were the same as that for RF. Note that all test and validation datasets of the RF experiments were saved and used in the SVM, MLPC and NB classification experiments to ensure a fair comparison of these classifiers with RF.

Three measurements were used to assess the performance of the classifiers, including overall accuracy (OA), F score (F-health & F-pest) and Kappa coefficient (Kappa) [47]. These measurements were calculated from a confusion matrix [48] of classification results (Figure 3). In Figure 3, TP (true positive) and FN (false negative) were the numbers of correct and wrong classifications of samples in the healthy corn category; FP (false positive) and TN (true negative) were the number of wrong and correct classifications of samples in the insect pest category.

The OA (Eq. 1) indicates the proportion of correctly predicted pixels including both healthy and attacked by insect pests. The F-score (Eq. 2) is an index that combines precision (p, Eq. 4) and recall (r, Eq. 5), and it is calculated for either healthy or infested corn. In Eq. 2, β is to control the weights of p and r: when $\beta = 1$, the two weights are the same; when $\beta > 1$, the weight of p is significant; and when $\beta < 1$, the weight of r is significant. In this study, $\beta = 1$. The Kappa coefficient (Eq.3) is a statistical indicator of interrater reliability [49], which is calculated by the OA and the probability of random agreement (Pe, Eq.6).

The RF classifier can perform an implicit feature selection to process the high-dimensional data efficiently. The outcome of this implicit feature selection of RF can be expressed with the Gini importance [32, 50] (Eq.7). In Eq. 7, k is each of the classes analyzed and $P(k)$ is the proportion of observations in the k_{th} class.

		assignment	
		Healthy	Insect attack
Label	Healthy	TP	FN
	Insect attack	FP	TN

Figure 3. Confusion matrix of separation results.

$$OA = \frac{TP + TN}{TP + FN + FP + TN} \quad (1)$$

$$F \text{ score} = (1 + \beta^2) \frac{r \times p}{r + \beta^2 \times p} \quad (2)$$

$$Kappa = \frac{OA - Pe}{1 - Pe} \quad (3)$$

$$p = \begin{cases} \frac{TP}{TP + FP} & \text{Healthy} \\ \frac{TN}{TN + FN} & \text{Insect attack} \end{cases} \quad (4)$$

$$r = \begin{cases} \frac{TP}{TP + FN} & \text{Healthy} \\ \frac{TN}{TN + FP} & \text{Insect attack} \end{cases} \quad (5)$$

$$Pe = \frac{(TP + FN) \times (TP + FP) + (FP + FN) \times (FN + TN)}{TP + FN + FP + TN} \quad (6)$$

$$Gini = \sum k \times P(k) \times (1 - P(k)) \quad (7)$$

201 Results

202 Identification of armyworm damage with machine learning algorithms

203 We evaluated the performance of the RF classifier using OA, F-health, F-pest, Kappa and
 204 running time. We compared the armyworm identification accuracy with UAV multispectral images
 205 alone with that obtained from combining the multispectral images with the DSM. The combination
 206 of DSM with the UAV multispectral images improved the performance of the RF classifier (Figure 4):
 207 the OA, F-health, F-pest, Kappa values improved while the running speed decreased, from 0.980,
 208 0.985, 0.970, 0.955 and 69.6s using multispectral UAV images alone to 0.996, 0.997, 0.994, 0.990 and
 209 62.7s by combining the multispectral UAV images and DSM, respectively. Particularly, the OA
 210 improved by 0.016. The values of F-health, F-disease and Kappa were greater than 0.97 for both
 211 datasets, indicating that the RF classifier was highly accurate in distinguishing healthy corn from
 212 infested corn in this experiment.

213 Apart from RF, three classifiers were compared using these two types of datasets, including
 214 SVM, MLPC and NB classifiers (Figure 4). For these three classifiers, we observed the following
 215 three results. First, using the multispectral UAV images alone (Figure 4 (a)), the SVM had the best
 216 overall classification performance compared with MLPC and NB, with the OA, F-health, F-disease
 217 and Kappa values of 0.982, 0.986, 0.927 and 0.959 respectively. The OA of SVM (0.982) was even
 218 higher than that of RF (0.980). Second, for the combined dataset of both multispectral UAV images
 219 and DSM (Figure 4 (b)), the NB had the highest classification accuracy, and the OA, F-health,
 220 F-disease and Kappa values were 0.988, 0.991, 0.982 and 0.972, respectively. The combination with
 221 the UAV image-generated DSM improved the performance of the NB classifier, in which the OA
 222 increased by 0.029 (from 0.959 for the multispectral images alone). Nonetheless, the OA of RF (0.996)
 223 was still higher than that of NB (0.988). Third, the running speed of the three classifiers was quite
 224 different. With our computing resources (Intel Core™i7-4790 CPU and Win7 64-bit operating
 225 system), it took 3087.4s and 3176.2s for the MLPC method and 1488.1s and 1374.4s for the SVM
 226 method when using the multispectral UAV images and the combined multispectral images with
 227 DSM, respectively. This revealed that the addition of the UAV image-generated DSM could
 228 effectively speed up the running time of the machine learning classifiers (except for NB, but it was
 229 the fastest of the four classifiers).

230

Figure 4. Results of the machine learning algorithms: (a) the multispectral images alone; (b) combined dataset (multispectral + DSM).

Figure 5 shows the distribution of the corn armyworm infestation obtained by applying the RF classifier to the UAV multispectral image and the DSM. The armyworm infestation mainly occurred in the southern portion of plot A, the top center of plot B and nearly the whole of plots C and D. This is consistent with field observations. In the early stages of armyworm infestation, the farmers of plots A, B, C and D might have not found out in time or taken effective measures to prevent the spread of the pests; we also observed that in these plots the weeds, which were even higher than the corn plants, had not been removed in time, increasing humidity and limiting air circulation, which might have been one of the important reasons for the outbreak of armyworm [1, 6, 10]. Some field photos were taken at four points (p1)-(p4) in Figure 5. The photos in Figure 5 (b) and Figure 5 (c) were from points attacked by armyworm in plots A and B, respectively. We can see that most of the corn leaves have been eaten by the armyworm, and only a small part of the stalk was left. For comparison, at points (p3) and (p4) there were no pests and the corn plants were healthy.

Figure 5. Monitoring of the armyworm attack on summer corn by RF: (a) map of corn damaged by armyworm; (b) and (c) are the photos of points (p1) and (p2) in the area damaged by armyworm, respectively; (d) and (e) are the photos of points (p3) and (p4) in the healthy area, respectively.

243 Pest incidence levels classifying results

244 The percentage of pest pixels in a 10 m × 10 m grid (generated from the Sentinel-2 image) was
 245 calculated based on Figure 5 (a), and classified into five pest incidence levels of corn (Figure 6). The
 246 pest incidence is most serious in the southern portion of plot A, the top center of plot B and whole
 247 of plots C and D, mostly 60%-100%. This situation is consistent with field observations. In terms of

incidence, plots A and B, C and D are adjacent to each other, and the infested areas are connected. Therefore, that could be the cause of the local armyworm outbreak in the cornfield.

Figure 6. Pest incidence levels of corn in each 10 x 10 m grid.

An infestation of armyworm in summer corn changes the canopy structure and affects the transmission path of light radiation, causing changes in canopy reflectance. The loss of leaves will also affect photosynthesis and transpiration of corn, and induce yellowing and withering of the plants because of inadequate nutrients and water, which further change the spectral characteristics of the corn canopy. The spectral characteristics of different levels of infestation of the Sentinel-2 image were analyzed (Figure 7). Figure 7 (a)-(e), (k) and (l) show that, as the infestation declines, the reflectivity of each band decreases, except at levels 4 to 5. However, in Figure 7 (g)-(j), as the pest declines, the reflectivity of each band increases. In Figure 7 (f), the relationship between reflectivity and disease incidence is not very clear.

Figure 7. Spectral characteristics of different pest incidence levels in the Sentinel-2 image: the x-axis represents levels of armyworm incidence (%) in corn (0-20, 20-40, 40-60, 60-80, 80-100). Plots (a)-(l) correspond to Band 1-Band 8, Band 8a, Band 9, Band 11 and Band 12 of Sentinel-2.

Discussion

Sensitivity to damage by armyworm

To analyze the relationship between the five features of the UAV images (Band 1 - Green, Band 2 - Red, Band 3 - Red-edge, Band 4 - NIR and DSM) and classification accuracy, the Gini importance of each feature was calculated. In order of importance, the five features of the UAV images for the identification of armyworm diseases were Band 2 - Red (0.33) > Band 1 - Green (0.28) > DSM (0.21) > Band 4 - NIR (0.17) > Band 3 - Red-edge (0.01). It is clear that the three most important features for classification are the Red Band, the Green Band and the UAV image-generated DSM. The corn area damaged by armyworm (Figure 5 (a) and (b)) led to an abnormal canopy spectrum since the morphological and chemical characteristics of the leaves have an intense effect on the spectral characteristics of the canopy, which showed that the reflectivity of the red band and the green band increased and that of the NIR band decreased. Because the corn plants infested by armyworm are shorter than healthy ones, the DSM is also sensitive to the pests. The red-edge band is one of the most sensitive bands to vegetation diseases [51-53], and is located where the slope of the spectrum changes the most. However, contrary to our prior knowledge, the red-edge band (735 nm) has the lowest importance for classification in this case.

Figure 7 (e)-(g) were the spectral characteristics of Band 5, Band 6 and Band 7 with corn armyworm incidence (%) at 0-20, 20-40, 40-60, 60-80, 80-100 intervals, respectively. These three narrow bands were red-edge bands which was very sensitive to vegetation changes, lying between

the Red band and the NIR band. The central wavelengths of these three red-edge bands, which have the largest slope change in the whole spectrum, were 705 nm, 740 nm and 783 nm, respectively. The spectral range of Band 6 of the Sentinel-2 image corresponds to Band 3 of the UAV image (Table 1). With the decrease of corn armyworm, the reflectance of Band 5 decreases and that of Band 7 increases. Band 6 of Sentinel-2 (740 nm) and Band 3 - Red-edge of UAV (735 nm) were between the changes of Band 5 and Band 7, and the spectral intervals for these three bands was only about 40 nm, which makes the sensitivity of the two bands to the pest change lower than other bands [54, 55]. This revealed that Band 6 was not sensitive to the damage of corn armyworm in this study. This result was consistent with the ranking of the feature importance in the RF output.

Figure 8. Canopy spectral response of UAV image in summer corn

Figure 9. Canopy spectral response of Sentinel-2 image in summer corn

The infestation of armyworm in corn growth leads to changes in leaf area of the affected tissue or plant directly [9, 10]. As the main organ of photosynthesis and other physiological activities, the loss of leaves causes a domino effect in the corn plants. As the plants lack sufficient nutrients and water to sustain the various physiological activities, the concentration of chemical pigments in tissues declines, and the cell and tissue structure is destroyed. Figure 8 shows the UAV image representative average reflectance from the corn area damaged by pests and healthy summer corn canopies. The reflectance of corn damaged by pests is higher than that of healthy corn in Band 1 - Green and Band 2 - Red, and it is lower than that of healthy corn in Band 4 - NIR. However, in Band 3 -Red-edge, the reflectance is almost the same in both cases. Figure 9 shows the Sentinel-2 representative average reflectance from the armyworm infested (pest incidence level at 80%-100%) and healthy (pest incidence level at 0%-20%) summer corn canopies. The two curves intersect at two inflection points, located at about 740 nm and 1150 nm, respectively. The armyworm damage area has higher canopy reflectance from 443 nm to 705 nm and from 1610 nm to 2190 nm than healthy summer corn. From 783–945 nm, the canopy reflectance from healthy summer corn is higher when than that of armyworm damage area. This indicates that a reduced amount of leaves in the corn canopy influences the light distribution. In Figure 7 and Figure 9, the section of 443–665 nm was located in the visible spectrum band where the leaves could rely on various pigments (i.e., chlorophyll, carotenoids) to absorb this energy. The decrease of corn canopy pigment led to the

decrease of visible light absorption, which resulted in the increase of canopy reflectance of this part of the spectrum (Figure 7 (a)-(d)). The canopy spectrum of 783–945 nm in the near-infrared band tends to be highly reflective and is closely related to the cell structure. The canopy reflectance at 783–945 nm was lower than that of healthy corn, indicating that the armyworm had seriously damaged the cell structure of the plants (Figure 7 (g)-(j)). From 443–945 nm, the red edge position shifted to a shorter wavelength due to the infestation of armyworm, with a “Red Edge-Blue Shift” in the spectrum, which decreased the slope of the red edge. Moreover, from 1610 nm to 2190 nm, the canopy reflectance is related to the water content of vegetation. In the area damaged by armyworm, the leaves of vegetation canopy decreased, the plants gradually withered, and the water content decreased, which led to the increase in spectral reflectance compared to that of normal vegetation (Figure 7 (k)-(l)).

Broader implications for future agriculture applications

First, our study shows the effectiveness of the RF classifier in mapping damages of armyworm infestation based on UAV images, especially when information about the canopy structure (i.e., the DSM) is added. Armyworm mainly eats the leaves and ears of corn, directly damaging the canopy structure, changing the physiological activities, morphological characteristics and canopy spectrum of corn [8, 56]. In general, canopy structural features could supplement information on the health status of crops, and improve the accuracy of the identification of armyworm damage area [57, 58].

Second, in this study, four machine learning classifiers, RF, SVM, MLPC and NB, were used to extract the regions in which armyworm outbreaks occurred in the field, with OA of more than 95%, with the OA of RF reaching 99.57%, indicating the advantages of applying machine learning classifiers to agricultural applications. Agricultural remote sensing also includes many crop growth simulation models (e.g., WOFOST, DSSAT) and radiation transfer models (e.g., PROSAIL, DART), which can accurately describe material and energy exchanges between crops and the external environment [55, 59–61]. However, these models are often complex and cannot directly retrieve crop growth parameters. Combining these models with machine learning techniques can improve the retrieval of crop growth parameters [62–64].

Third, as a low-cost, flexible and easy to operate field monitoring method, UAV remote sensing is playing an increasingly important role in agricultural development. Using UAV images, we can quickly understand the growth of crops in the field, and quickly identify the region and level of infestation of armyworm [24]. As a large agricultural country, China represents a broad application prospect for agricultural insurance. However, rapid and accurate claim settlements have always been a problem hindering the development of the agricultural insurance industry. The application of UAV in insect pest identification, damage assessment and yield estimation can provide effective means for the rapid settlement of agricultural insurance claims. In addition, we can combine multi-temporal UAV images and satellite images to dynamically detect insect pests in the field, understand the source and diffusion patterns of pests, and manage the farmland more intelligently.

Conclusions

Armyworm is one of the most serious insect pests of corn. In this paper, we proposed a method to successfully monitor the damage of armyworm as a pest in summer corn in the study area based on UAV images and the RF algorithm.

The conclusions that can be drawn from this study are as follows: 1) RF could monitor the damage of armyworm (*Mythimna separata* Walker) infestation on summer corn by UAV images from the heading stage to the milk stage in the study area; 2) the addition of UAV image-generated DSM will not only improve the classification accuracy of RF, but also improve its operation efficiency; 3) the order of importance of five features of UAV for the identification of armyworm is Band 2 > Band 1 > DSM > Band 4 > Band 3, while Band 3 (735nm) of UAV and Band 6 (740nm) of Sentinel-2 are not sensitive to pest information in this study.

However, due to the small geographical coverage of UAVs, our experimental area is relatively small. In the future, we will expand our research to explore the armyworm infestation of other similar crops (wheat and rice) and monitor the damage of insect pest on a larger scale.

Author Contributions: This work was a cooperation of our research team, and the contributions were as follows: Conceptualization, Mingzheng Zhang, Jing-Hao Xue and Wei Su; Formal analysis and Writing – review & editing, Jing-Hao Xue; Investigation, Xinsheng Wang, Wei Su and Dehai Zhu; Methodology and Writing – original draft, Mingzheng Zhang; Software, Mingzheng Zhang and Wancheng Tao; Validation, Zixuan Xie, Tian Jin and Chan Yao.

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Availability of data and materials

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Author details

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Figures

Figure 1

Study area: (a) location on the map; (b) UAV multispectral image, R/G/B=Band 2/ Band 3/ Band 1 of the experiment field; (c) UAV image-generated digital surface model (DSM).

Figure 2

Shooting the calibration board on different bands.

		assignment	
		Healthy	Insect attack
Label	Healthy	TP	FN
	Insect attack	FP	TN

Figure 3

Confusion matrix of separation results.

Figure 4

Results of the machine learning algorithms: (a) the multispectral images alone; (b) combined dataset (multispectral + DSM).

Figure 5

Monitoring of the armyworm attack on summer corn by RF: (a) map of corn damaged by armyworm; (b) and (c) are the photos of points (p1) and (p2) in the area damaged by armyworm, respectively; (d) and (e) are the photos of points (p3) and (p4) in the healthy area, respectively.

Figure 6

Pest incidence levels of corn in each 10 x 10 m grid.

Figure 7

Spectral characteristics of different pest incidence levels in the Sentinel-2 image: the x-axis represents levels of armyworm incidence (%) in corn (0-20, 20-40, 40-60, 60-80, 80-100). Plots (a)-(l) correspond to Band 1-Band 8, Band 8a, Band 9, Band 11 and Band 12 of Sentinel-2.

Figure 8

Canopy spectral response of UAV image in summer corn

Figure 9

Canopy spectral response of Sentinel-2 image in summer corn