Field Mapping for Aflatoxin Assessment in Peanut Crops Using Thermal Images

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Abstract. *Aflatoxin is a toxic carcinogenic compound produced by certain species of Aspergillus fungi, which has a significant impact on peanut production. Aflatoxin levels above a certain threshold (20 ppb in the USA and 4 ppb in Europe) make peanuts unsuitable for export, resulting in significant financial losses for farmers and traders. Unmanned Aerial Vehicles (UAVs) are becoming increasingly popular for remote sensing applications in agriculture. Leveraging this advancement, UAV based thermal imaging can be an effective way to detect aflatoxin contamination in the field. It is a non-destructive method, and the ability to provide real-time, large scale field data makes thermal imaging an effective method for field mapping and monitoring aflatoxin contamination. This study aims to compare two image segmentation algorithms in the separation of soil and canopy pixels, and to assess the potential correlation of crop water stress with the presence of aflatoxins in the field. The random forest segmentation was more conservative, resulting in the removal of more pixels, including parts of the canopy that were sparce and likely to show mixed emissivity of canopy and background soil. Average canopy temperature after soil pixels removal was used to calculate the difference between air and canopy temperature and correlated with aflatoxin. The highest correlation between ∆T and aflatoxin levels was observed later in the season, in mid-September with a correlation coefficient of 0.56. Although, based on these initial results that is an indication that canopy temperature may be higher correlated with aflatoxin levels at later stages more data needs to be collected.*

Keywords. *Remote Sensing, Canopy Temperature, Aflatoxin, Peanuts.*

Introduction

Aflatoxin, a mycotoxin produced by Aspergillus fungi, poses significant health risks, and affects crop performance, particularly in peanut production (Payne & Brown, 1998). It can cause acute liver disease, cancer, and birth defects in humans, and various health issues in animals. Various environmental factors, including nutrition, water, temperature, and pH influences aflatoxin biosynthesis (Yu, 2012). Among these factors, water stress in peanut crops significantly increases the risk of aflatoxin contamination. These fungi thrive in hot, dry conditions and can produce aflatoxin as a defense mechanism. Additionally, water stress can weaken plant defenses, making them more susceptible to fungal invasion and subsequent aflatoxin production. Under water stress conditions, plants undergo physiological adjustments to cope with reduced water availability, and stomatal conductance serves as a key mechanism in this response (Carmo-Silva et al., 2012; Pou et al., 2003; Pou et al., 2008). As a plant sense water deficit, stomata close and reduces the stomatal conductance. The impact of reduced stomatal conductance extends beyond water conservation and influences the leaf temperature as transpiration cooling is reduced (Buckley, 2019).

Recent advancements in sensing technologies, particularly the use of UAVs equipped with thermal cameras, offer a more efficient and precise method for monitoring crop water stress (Khorsandiet al., 2018). Thermal imaging can capture these temperature changes, making it an effective tool for identifying water-stressed areas. Therefore, using unmanned aerial vehicles (UAV)-based thermal imaging can be used in early detection of aflatoxin hotspot map. Hence, this study aims to detect the aflatoxin contamination in the field through the use of remote sensing. Specific objectives of this initial study are 1) to compare two image segmentation algorithms in the separation of soil and canopy pixels, and 2) to assess the potential correlation of crop water stress with the presence of aflatoxins in the field.

Methods

Study Site

In 2023, three on-farm trials were carried out in rainfed peanut grower’s fields, located in Douglas, Coffee and Mitchell Counties. The fields were divided into 0.5 hectares grids and sampling points in the center of each plot were used for the ground data collection. For this preliminary study, only the field in Mitchell County was selected for analysis (Fig. 1).

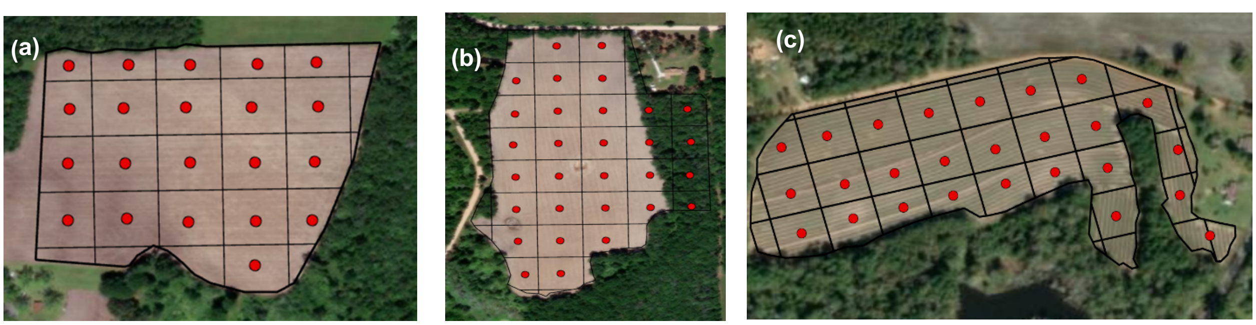

Fig. 1. Peanut grower's fields used in 2023, located in Douglas (a), Coffee (b) and Mitchell (c) counties respectively.

Image Acquisition

The DJI M300 RTK UAV equipped with WIRIS Pro thermal camera (Workswell Infrared Cameras and Systems, Prague, Czech Republic) (Fig. 2) was used to collect canopy temperature data. The WIRIS Pro camera has an uncooled Vox microbolometer sensor with an accuracy of ±2 ^{o}C and temperature sensitivity of 30mK. The camera is also equipped with an RGB sensor, which allows for simultaneous data collections of RGB and thermal images. Images were collected 90 days after planting (DAP) on dates close to ground data measurements. Flight plan was created at the beginning of the season and same flight plan was used for the whole season. Flights were performed with 8 m/s speed with 85% frontal and site overlap. The spatial resolution of images acquired was 15.5 cm. The individual images captured by the camera was stitched using the Pix4D mapper software (Pix4D SA, Lausanne, Switzerland) and the resultant orthomosaic map was analyzed using ArcGIS Pro (ESRI Inc., Redlands, CA) and RStudio.

Fig. 2. DJI M300 RTK UAV equipped with Workswell WIRIS Pro thermal camera.

UAV Image Processing

Both the RGB orthomosaic and thermal reflectance map obtained after stitching were loaded into ArcGIS Pro and Rstudio, where image segmentation was performed. Using FIELDImageR and FIELDimageR.EXTRA, the Green Red Vegetation Index (GRVI) (Equation 1) was calculated and used in two different segmentation methods; k-mean clustering and random forest. Both methods were applied to segment soil and canopy pixels, for soil pixel removal. The GRVI is a reliable measure to distinguish vegetation and soil pixels (Motohka et al., 2010) .

$$\mathrm{GRVI} = \frac{\mathrm{Green}-\mathrm{Red}}{\mathrm{Green}+\mathrm{Red}} \tag{1}$$

In the k-mean clustering method, the resultant GRVI index map was processed for classification giving the two classes as input while with random forest, random soil and plant pixels were trained for the classification. The classified images were used to create a mask that was applied to the thermal images for soil pixel removal.

Ground Data Collection

To detect the presence of aflatoxin in the field, plant samples were collected in two weeks intervals after 90 DAP. Ten plants around the sampling point were randomly selected from each plot for aflatoxin analysis. Samples were separated and sent to a lab for analysis using the ELISA extraction method.

Data Analysis

To normalize the canopy temperature values, the air temperature during the time of the flight was averaged and the canopy temperature measured in each pixel was subtracted to calculate the difference between air temperature and canopy temperature (ΔT). Because canopy temperature is extremely variable due to the weather conditions, especially air temperature, normalizing the canopy temperature values is needed to extract useful information about the canopy water status.

For data analysis the temperature data of the 10-meter diameter circle around the sampling point was extracted from the thermal images. Spearman correlation was used to assess the relationship between crop water stress (represented by ΔT) and aflatoxin concentrations.

Results

Both the K-means clustering and random forest image classification methods achieved a satisfactory result on separating the vegetation and soil pixels as shown in Fig. 3. After image classification the majority of soil pixels were removed using both methods. Due to the very high number of canopy-related pixels compared to exposed soil, the visual identification of common pixel and soil peaks in the histogram is of difficult visualization. However, comparing the histogram of the original unsegmented image with the two images after segmentation and soil pixel removal, it is possible to observe that the number of pixels with temperatures higher than 36˚C significantly decreased. To better compare the performance of both methods, a close-up image of an area of the field after soil pixel removal was shown in Figure 4. It can be observed that the random forest segmentation was more conservative, resulting in the removal of more pixels, including parts of the canopy that were sparce and likely to show mixed emissivity of canopy and background soil. Compared to the K-mean method, random forest performed a better segmentation. Pixels with mixed reflectance can significantly influence the efficiency to evaluate crop water stress to the high temperature values caused by background soil reflectance.

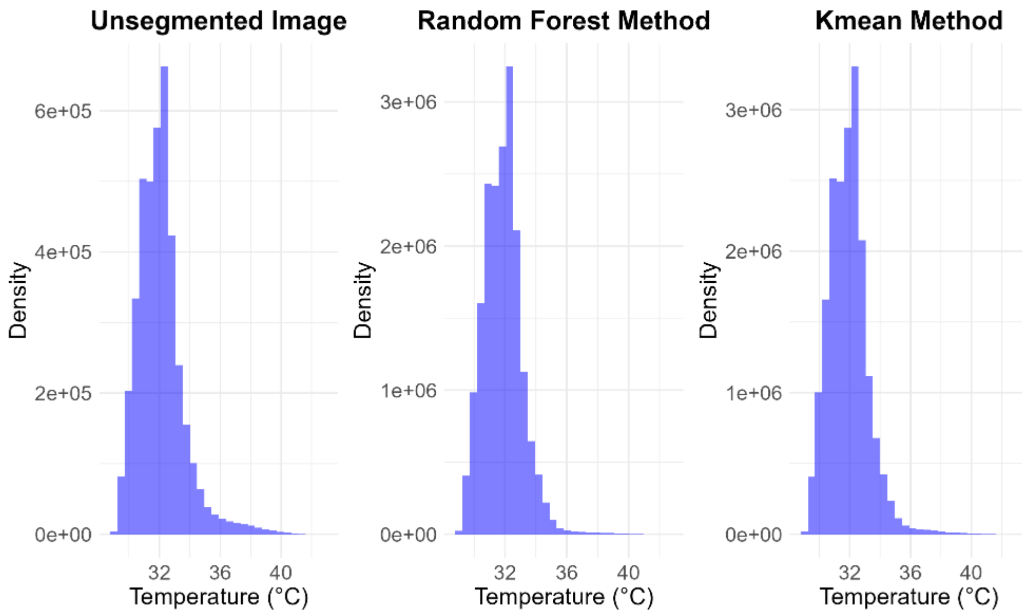

Fig. 3. Histogram of original image and after soil pixel removal using the random forest and the K-means image segmentation methods.

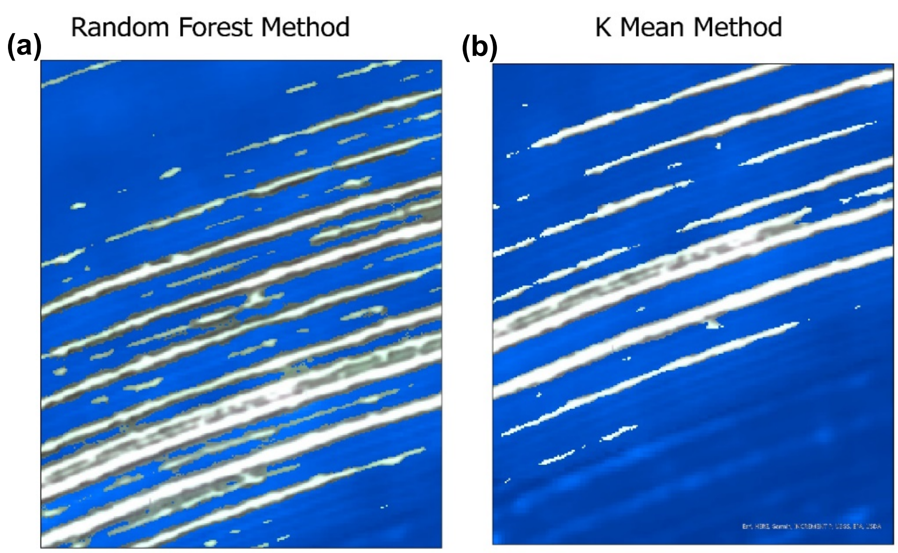

Fig. 4. A close-up image of the peanut field showing the result of both the Random Forest (a), and the K-Means (b) image segmentation methods overlapped with the original image. The blue pixels represent the canopy pixels after image segmentation.

After soil pixel removal, the average temperature data was used to calculate ∆T for each plot and correlate with aflatoxin occurrence in the field. The Spearman correlation between the ∆T and aflatoxin contamination in different dates are shown in Table 1. Significant correlations were observed on two of the three dates tested. The canopy temperature data collected 4 days prior to aflatoxin analysis showed a significant positive correlation with an *r* value of 0.48, while the correlation significance did not hold for data aerial data collected 8 days after aflatoxin analysis. The different results are likely due to the high variation in weather conditions from day to day, and constant changes in crop water status and therefore fluctuations in stress. In mid-September, later in the season, the ∆T showed the highest correlation with aflatoxin levels with a correlation value of 0.56.

Table 1. Spearman correlation between ∆T and aflatoxin levels at different dates.

Flight Date	Aflatoxin Measurement Date	Correlation Coefficient (r)
August 11	August 15	0.48*
August 23	August 15	-0.20
September 12	September 07	0.56*

*Significant correlations

Conclusions

The analysis demonstrates that the random forest model using RGB images to mask thermal images can be used to segment soil and vegetation pixels and enhance the segmentation performance for thermal images. This approach leverages the strengths of random forest algorithms to handle complex relationship and feature interactions leading to a better separation between canopy and soil pixels. Further analysis will be performed testing other segmentation approaches to improve separation of soil and canopy temperature pixels for peanuts.

The correlation analysis reveals a higher correlation between the ∆T, an indicator of crop water stress and aflatoxin levels at a later stage of peanut crops. Although, based on these initial results that is an indication that canopy temperature may be higher correlated with aflatoxin levels at later stages more data needs to be collected. Aflatoxin data and peanut water stress is being evaluated in two additional fields. These initial findings are promising to show that UAV-based canopy temperature may be a good indicator of aflatoxin risk areas to assist growers in mitigating contamination.

References

Buckley, T. N. (2019). How do stomata respond to water status? *New Phytologist*, *224*(1), 21–36. https://doi.org/10.1111/NPH.15899

Carmo-Silva, A. E., Gore, M. A., Andrade-Sanchez, P., French, A. N., Hunsaker, D. J., & Salvucci, M. E. (2012). Decreased CO 2 availability and inactivation of Rubisco limit photosynthesis in cotton plants under heat and drought stress in the field. *Environmental and Experimental Botany*, *83*. https://doi.org/10.1016/j.envexpbot.2012.04.001

Khorsandi, A., Hemmat, A., Mireei, S. A., Amirfattahi, R., & Ehsanzadeh, P. (2018). Plant temperature-based indices using infrared thermography for detecting water status in sesame under greenhouse conditions. *Agricultural Water Management*, *204*. https://doi.org/10.1016/j.agwat.2018.04.012

Loreto, F., Centritto, M., & Chartzoulakis, K. (2003). Photosynthetic limitations in olive cultivars with different sensitivity to salt stress. *Plant, Cell and Environment*, *26*(4). https://doi.org/10.1046/j.1365-3040.2003.00994.x

Matias FI, Caraza-Harter MV, Endelman *JB.* FIELDimageR: An R package to analyze orthomosaic images from agricultural field trials. The Plant Phenome **J.** 2020; https://doi.org/10.1002/ppj2.20005

Motohka, T., Nasahara, K. N., Oguma, H., & Tsuchida, S. (2010). Applicability of Green-Red

Vegetation Index for remote sensing of vegetation phenology. *Remote Sensing*, *2*(10). https://doi.org/10.3390/rs2102369

Pawar P. & Matias FI. FIELDimageR.Extra: Advancing user experience and computational efficiency for analysis of orthomosaic from agricultural field trials. The Plant Phenome **J.** 2023; https://doi.org/10.1002/ppj2.20083

Payne, G. A., & Brown, M. P. (1998). GENETICS AND PHYSIOLOGY OF AFLATOXIN BIOSYNTHESIS. *Annual Review of Phytopathology*, *36*(1), 329–362. https://doi.org/10.1146/annurev.phyto.36.1.329

Pou, A., Flexas, J., Alsina, M. D. M., Bota, J., Carambula, C., De Herralde, F., Galmés, J., Lovisolo, C., Jiménez, M., Ribas-Carbó, M., Rusjan, D., Secchi, F., Tomàs, M., Zsófi, Z., & Medrano, H. (2008). Adjustments of water use efficiency by stomatal regulation during drought and recovery in the drought-adapted Vitis hybrid Richter-110 (V. berlandieri x V. rupestris). *Physiologia Plantarum*, *134*(2). https://doi.org/10.1111/j.1399-3054.2008.01138.x

Yu, J. (2012). Current understanding on aflatoxin biosynthesis and future perspective in reducing aflatoxin contamination. In *Toxins* (Vol. 4, Issue 11). https://doi.org/10.3390/toxins4111024