A Decision-Support Tool to Optimize Mid-Season Maize Nitrogen Fertilizer Management from Red, Green, Blue sUAS Images

Aurelie M. Poncet[1,2*], Thanh Bui[2,3], O. Wesley France[1,2], Trenton L. Roberts[1,2], Larry C. Purcell[1,2], and Jason P. Kelley[4]

[1]Department of Crop, Soil, and Environmental Sciences, University of Arkansas, Fayetteville, AR, USA, [2]Arkansas Agricultural Experiment Station, University of Arkansas System Division of Agriculture, Fayetteville, AR, USA, [3]Department of Computer Science and Computer Engineering, University of Arkansas, Fayetteville, AR, USA, [4]Arkansas Cooperative Extension Services, University of Arkansas System Division of Agriculture, Little Rock, AR, USA

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Abstract

Maize requires more nitrogen (N) fertilizer than other row-crops and optimized application rate and timing are critical components of farm profitability. Three-split strategies can help maintain yields with smaller total fertilizer amounts when the applied rates match the crop requirements. However, site-specific needs are difficult to predict because of complex interactions between the genetic, management, and environmental production factors and scouting is needed to monitor crop N status. While leaf sampling is increasingly used to ground-reference mid-season maize N status, the cost of tissue analysis and lack of guidelines that define where to sample create practical and economic barriers to adoption. Yet, proper characterization of in-field dynamics is needed to infer the optimum sampling strategy and the needed information may be collected using inexpensive small unmanned aerial systems (sUAS) equipped with red, green, blue (RGB) cameras. Previous research demonstrated that the difference between field canopy greenness and that of a high-N reference can be used to predict yield loss from N deficiency and determine the optimize pre-tassel N fertilizer. Canopy greenness is quantified using the dark green color index (DGCI) and characterized from sUAS RGB images collected between the eight expanded (V8) growth stage and tasseling (VT). Calibration equations were developed to compare the field and high-N DGCI values and predict relative grain yield loss from yield-limiting N deficiency. Integration of these findings into a decision-support tool would allow maize producers to fine-tune the current N fertilizer rate recommendations to site-specific crop needs and promote the adoption of optimized practices. The objective of this study was to create a web-tool that automates image processing to assess mid-season maize N status and determine whether additional N should be applied to prevent loss from yield-limiting deficiencies. A high-N reference was established in a N-deficient field trial to generate a test dataset used to support web-tool development. An algorithm was developed to automate image processing and characterize mid-season maize N status and pre-tassel N fertilizer needs from overheard sUAS RGB images. The created algorithm was integrated into a user-friendly web-tool interface. Further research is being conducted to identify the agronomic and economic optimum pre-tassel N fertilizer rates from the predicted relative grain yield information, facilitate high-N reference delineation, and ultimately replace the physical high-N reference with a virtual reference. Findings will be included as new web-tool prototype functionalities, and the final product will be available for public use by 2027.

Keywords: *Aerial Imagery; Automation; Dark Green Color Index; Remote Sensing; Web-tool*

Introduction

Maize (*Zea mays* L.) is a staple crop that requires a large amount of nitrogen (N) per unit area to reach its potential. Therefore, the purchase of N fertilizer accounts for a significant portion of farm expenses and optimized soil N management is a critical component of profitability in maize production systems (Setiyono, et al., 2011). The N fertilizer application rates and timings should match the crop needs to minimize losses and different recommendations are used among regions to account for variations in genotypes, production environments, and management practices (Olfs, et al., 2005). In Arkansas, the recommended rates are determined according to soil texture and yield goal (Slaton, et al., 2014). Approximately 75% to 85% of the recommended rate is applied before the eight expanded leaves (V8) growth stage by means of a pre-planting and sidedress applications to support the crop vegetative growth and ear development (Dos Santos et al., 2021). The remaining 15-25% of N fertilizer is applied pre-tassel to complement the soil N supply and minimize the incidence of yield-limiting N deficiencies during the most critical reproductive stages. Yet, the exact amount of pre-tassel N fertilizer needed to optimize crop development depends on the initial soil supply, weather, and site-specific plant uptake dynamics. Three-split strategies tend to be more beneficial when unfavorable weather conditions increase early-season losses from leaching, runoff, denitrification, or volatilization (Davies et al., 2020), and greater N use efficiency could be achieved if the pre-tassel N fertilizer amounts were adjusted to field conditions within the growing season rather than based on soil texture and yield goals alone (Vanotti and Bundy, 1994a).

While pre-tassel maize N status and fertilizer needs are expected to vary with spatial changes in field conditions and management history, site-specific requirements are difficult to predict because of the number and complexity of production factors at play (Wang, 2021). Yield goal-based approaches tend to overestimate N fertilizer requirements and mid-season assessment of crop N status is an essential aspect of optimized soil fertility management (Vanotti and Bundy, 1994b). Dos Santos et al. (2021) found that a pre-tassel N fertilizer application should be considered when leaf N concentrations less than 3.0% are observed before tasseling, and mid-season leaf tissue sampling is recommended to diagnose and address yield-limiting N deficiencies in maize (Blackmer and Schepers, 1994). However, the cost of tissue analysis and labor remains prohibitive and only scarce information is available to help producers determine where and when the tissue samples should be collected. These economic and practical barriers to tissue sampling hinder the producers' ability to collect relevant ground-reference information for optimized strategic and operational decision-making. Fortunately, recent advances in sensor technology have provided new tools that can be used to map spatial changes in crop development and determine the preferred leaf tissue sampling resolution and locations (Ruiz Diaz et al., 2008). Development of a tool that correlates sensor data with site-specific yield-limiting N stress could be used to maximize scouting efficiency and facilitate the implementation of optimized practices (Ma and Biswas, 2015). Different approaches to the development of data-driven recommendations for real-time and prescription-based N fertilizer rate selection have been investigated in published literature (Reimer et al., 2020).

Real-time and prescription-based data-driven N fertilizer management in maize uses proximal sensing, computer vision, or spectral imaging to characterize field conditions and fine-tune the operational parameters (Pawase, et al., 2023). The most widely adopted systems use multispectral non-imaging sensors mounted on farm machinery to collect crop radiometric reflectance data in the green, red, red-edge, and near-infrared sections of the electromagnetic spectrum (Bausch and Delgado, 2004). The sensor data are georeferenced and collected on-the-go. Vegetation indices such as the normalized difference vegetation index (NDVI) and its derivatives may be used to assess spatial changes in crop health and inform management (Burns, et al., 2022; Maresma et al., 2016). The higher the NDVI and NDVI-derived values, the healthier the crop and comparison of the field values to that of a high-N reference allows for site-specific evaluation of crop N status and fertilizer need requirements (Pettorelli, 2013). At first, the operator would manually determine the fertilizer rate given the ratio between the field and high-N reference values. Today, the normalization of machine learning, artificial intelligence, and computer vision provides opportunities for more autonomous systems with automated N fertilizer rate selection capabilities (Thompson, et al., 2015). Data processing and N fertilizer rate adjustments are performed simultaneously and in real-time during the operation providing that the equipment is equipped with variable-rate fertilization and on-the-go crop monitoring capabilities. Other widely adopted systems use multispectral aerial and satellite images to map in-field changes in crop health prior to the operation (Nawar et al., 2017). The created maps are then used together with geographic information system-based precision agriculture software to generate a N fertilizer prescription that can be implemented into available technology. A high-N reference is still needed to calibrate the N fertilizer prescription. A high-N reference may be established physically in the field, or virtually determined by looking at the mathematical distribution of pixel radiometric values within the collected images (Thompson and Puntel, 2020).

While numerous systems have been developed to support sensor-based N fertilizer rate selection, the technology acquisition cost and need for more effective data-driven software calibration procedures create economic and technical barriers to adoption (Al-Gaadi, et al., 2023). Moreover, not all producers feel comfortable relying on a semi-autonomous system for N fertilizer rate selection. Development of decision-support systems that use inexpensive technology to help inform N fertilizer in cropping systems with intermediate technological capabilities and experience is still needed (Colaço and Bramley, 2018). N is required for chlorophyll synthesis and strong correlations exist between leaf N concentration and canopy greenness. Previous research quantified canopy greenness using the dark green color index (DGCI; Karcher and Richardson, 2003) computed from red, green, blue (RGB) images collected using inexpensive small unmanned aerial systems (sUAS). Calibration equations were established to relate pre-tassel field DGCI values to mid-season crop N status (Purcell et al., 2013; Purcell et al., 2015). Comparison between the field DGCI values to that of a high-N reference allowed for estimation of relative grain yield (RGY) loss from N deficiency independently from lighting conditions at the time of flight (Dos Santos et al., 2020). Pre-tassel N fertilizer application should be considered if more than a specific RGY loss threshold – typically 5% – is expected. Implementation of these equations into a web-tool would help producers optimize their N fertilizer strategy independently from their technological capabilities. The created decision-support system would complement the other solutions found in literature because it would only require the use of RGB cameras that come standard on the least expensive sUAS to inform the producers' management decisions. Moreover, no stitching would be required to allow for use on the turnrow without the need for advanced data processing software and experience. The web-tool would not be used to automate fertilizer rate selection throughout the season. Instead, it would be used to assess crop response to the producers' preferred management strategy and inform ground-referencing needs to help fine-tune pre-tassel N fertilizer rate selection to site-specific crop needs, with or without access to variable-rate fertilization. The objective of this study was to create a web-tool that generates pre-tassel maize N fertilization recommendations from RGB images collected using inexpensive small unmanned aerial systems (sUAS).

Material and Methods

Sample Dataset

A high-N reference was established in a 2-ha N-deficient production maize field at the Pine Tree Research Station, Arkansas (latitude = 35.134806°, longitude = -90.937161°). The field was managed using the University of Arkansas System Division of Agriculture recommendations (Arkansas Cooperative Extension Services, 2008), except for N fertilization. The recommended total N fertilizer rate was 250 kg N ha^{-1} and only 125 kg N ha^{-1} were applied to create visible symptoms of stress. The total N fertilizer amount was delivered in two split-applications with 90 kg N ha-1 applied at planting, and 35 kg N ha^{-1} applied at the six expanded leaves (V6) growth stage for sidedress. In the middle of the field, an additional 145 kg N ha^{-1} were applied at sidedress to create a high-N reference strip. The total N fertilizer amount applied in the high-N reference strip was 10% higher than the total recommended amount to maximize the likelihood of N sufficiency independently from weather conditions. The high-N reference strip was 45-m wide and created parallel to the maximum direction of elongation of the field. Overhead RGB images were captured at the eight, ten, and eleven expanded leaves (V8, V10, and V11) growth stages using a DJI Mavic Air 2 (DJI, Nanshan, Shenzen, China) sUAS. Flight altitude was 75 m above ground level. The images that captured both the N-deficient field conditions and high-N reference were used as sample dataset to facilitate algorithm development.

Automation Steps

Images are processed individually. First, the high-N reference is delineated by the user using a semi-automatic Python (Python Software Foundation, 2022) routine. The delineated high-N area is automatically cropped out of the original image and stored in a separate variable. A reset option was included to allow the user to start over if needed. Then, a function was created to convert the image RGB values into DGCI using equation 1 (Karcher and Richardson, 2003):

$$DGCI = \frac{\frac{H-60}{60} + (1-S) + (1-b)}{3} \tag{1}$$

where DGCI is the computed DGCI value, H, S, and B are the hue, saturation, and brightness values calculated using equations (2) to (6):

$$\text{If max(R,G,B) = R: } H = 60 \cdot \frac{G-B}{\max(R,G,B) - \min(R,G,B)} \tag{2}$$

$$\text{If max(R,G,B) = G: } H = 60 \cdot \left(2 + \frac{B-R}{\max(R,G,B) - \min(R,G,B)}\right) \tag{3}$$

$$\text{If max(R,G,B) = B: } H = 60 \cdot \left(4 + \frac{R-G}{\max(R,G,B,) - \min(R,G,B)}\right) \tag{4}$$

$$S = \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)} \tag{5}$$

$$B = \max(R,G,B) \tag{6}$$

where R, G, and B are the image red, green, and blue pixel digital numbers. Equations 1 to 7 were applied to each pixel in the original overhead images and delineated high-N reference area. The computed DGCI values quantify canopy greenness. Then, a function was created to convert the DGCI values to RGY using equation 7 (Dos Santos et al., 2020):

$$RGY = \frac{e^{0.47 + 19.6 \cdot DGCI - 18.2 \cdot DGCI_{ref}}}{1 + e^{0.47 + 19.6 \cdot DGCI + 18.2 \cdot DGCI_{ref}}} \tag{7}$$

where RGY is the computed RGY values, DGCI is the DGCI value from the original overhead image, and $DGCI_{ref}$ is the median high-N DGCI value computed for the cropped image. Equation 7 was applied to each DGCI value computed from the original overhead image. The computed RGY values range from 0 to 100% and predict yield given crop N status. If RGY ranges from 95% to 100%, less than 5% yield loss is expected from N deficiency and the crop is considered N-sufficient. If RGY is less than 95%, more than 5% yield loss is expected from N deficiency and the crop is considered N-deficient. The lower the RGY value, the greater the predicted yield loss and the more N-deficient the crop. A N status function was created to classify the RGY data according to their N status (e.g., sufficient versus deficient).

The original sUAS overhead images and corresponding user-delineated high-N references are inputted into the DGCI function. A parameter was added to allow the user to choose to exclude non-canopy pixels – defined by max(R,G,B) ≠ G - from the analysis. A second parameter allows the user to re-scale images at coarser spatial resolutions to minimize high-frequency noise. The dimensions of the re-scaled images are determined by the original dimensions multiplied by a scaling factor ranging from 0.05 to 1.00. For instance, if an image with 256 x 192 pixels is resampled using a scaling factor of 0.5, the dimensions of the re-scaled image are 256*0.5 = 128 pixel wide, and 192*0.5 = 96 pixel tall. The overhead DGCI images and the high-N DGCI areas generated by the DGCI function are imputed into the RGY function. The output from the RGY function is inputted into the N status function. A main function was created to execute the DGCI, RGY, and N functions as one. All computations were performed using the image_utilities, python-opencv (Bradski, 2000), matplotlib (Hunter, 2007), numpy (Harris, et al., 2020), and utm Python packages. The process was further automated by creating a rudimentary software package executable through command line.

Algorithm Integration with a User Interface

The created Python package was integrated into a web-tool user interface using R Shiny (R Core Team, 2024; Chang, et al., 2024) and the following R packages: base64enc (Urbanek, 2015), imager (Barthelme, 2024), reticulate (Ushey and Tang, 2024), DT (Xie and Tan, 2024), future.apply (Bengtsson, 2021), magick (Ooms), shinydashboard (Chang and Borges Ribeiro, 2021), shinyjs (Attali, 2021), shinywidgets (Perrier, et al., 2024), terra (Hijmans, 2024), and tidyverse (Wickham, et al., 2019). The web-tool prototype was designed so that the user completes each data processing step in order. First, the user is prompted to upload RGB sUAS images featuring both field conditions and a high-N reference. Duplicate images are automatically excluded. No stitching is required to allow use on the turnrow without advanced computing capabilities and experience. The user cannot move forward until at least one image is uploaded. The user is also given the option to delete images that were imported by mistake, or reset the web-tool (e.g., reload the webpage). Then, the user is prompted to delineate the high-N reference in each uploaded image before being able to execute the created python algorithm. If multiple high-N references are selected for any one image, only the most recent one is processed. By default, non-canopy pixels are excluded from the analysis, 95% RGY threshold is used to characterize crop N status, and the uploaded images are not re-scaled. However, the user may choose to change these parameters at any stage of the process and re-process images providing all other requirements have been met.

Results

Step-by-step demonstration of the created web-tool prototype is provided in figures 1 to 9. First, the user is prompted to browse one or multiple images from their device (figures 1 and 2). The selected images are uploaded into the created interface and displayed in a table (figure 3). New images may be browsed, selected, and added by repeating the steps illustrated in figures 1 and 2.

Duplicates are automatically excluded based on image path and name. Uploaded image size can be adjusted to accommodate device screen size or resolution, and personal preferences (figure 4). Uploaded images may also be selected and removed as needed. Next, a high-N reference must be delineated in each image to allow for data processing. A sidebar menu and toolbar allow the user to navigate between images and draw within an image (figure 5). The images that still require a high-N reference are listed in the sidebar menu (figure 6). Once a high-N reference has been identified within all images, the user may proceed with data processing and analysis (figure 7). A pop-up window reminds the user to define a high-N reference in all images if at least one is missing.

Image processing is fully automated providing that the user uploads at least one image and identify a high-N reference area within each image. Canopy greenness quantified using the DGCI, the associated RGY prediction, and maize N status outputs are displayed within their respective tabs (figures 7 and 8). The user may change the image processing parameters (e.g., non-canopy pixel exclusion, RGY threshold, and re-sampling) and re-process the images as needed. Demonstration of the re-scaling functionality is provided in figure 9. The images used for illustration in this proceeding were collected at the ten expanded leaves (V10) growth stage.

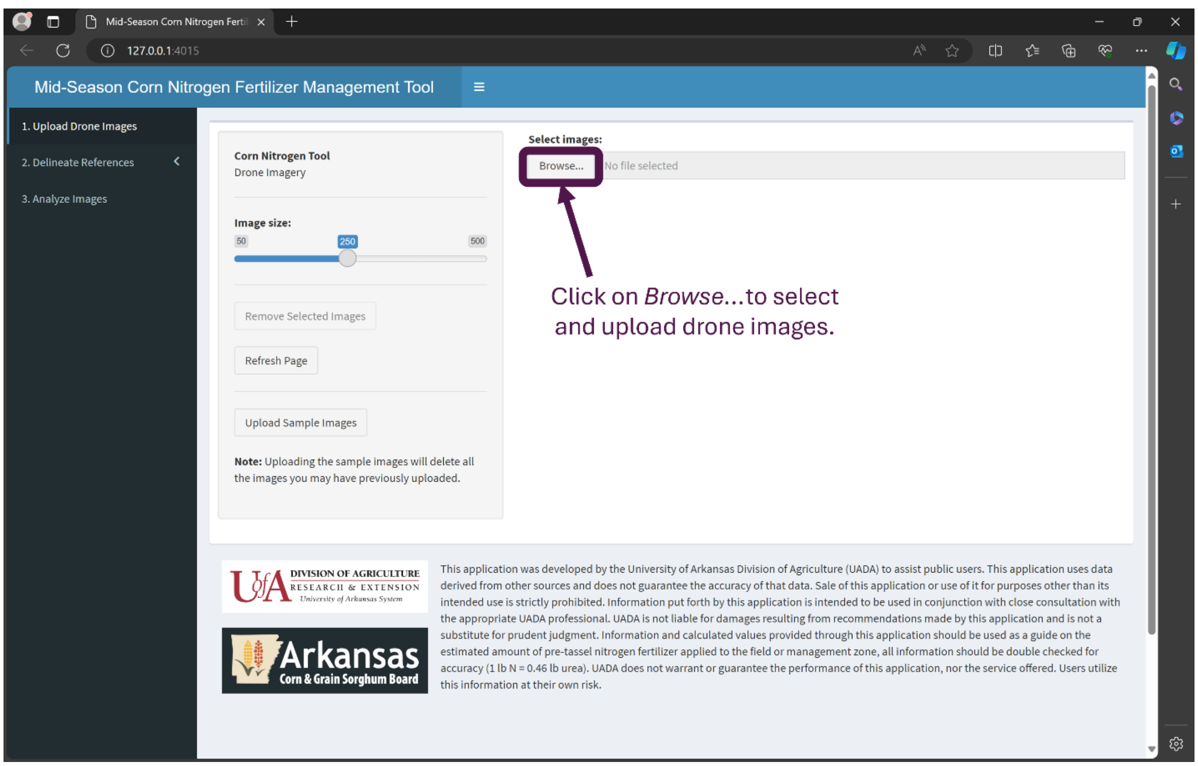

Figure 1. User interface of the created web-tool prototype. The *Upload Drone Images* menu is displayed by default. Users must upload overhead images before proceeding to the next step.

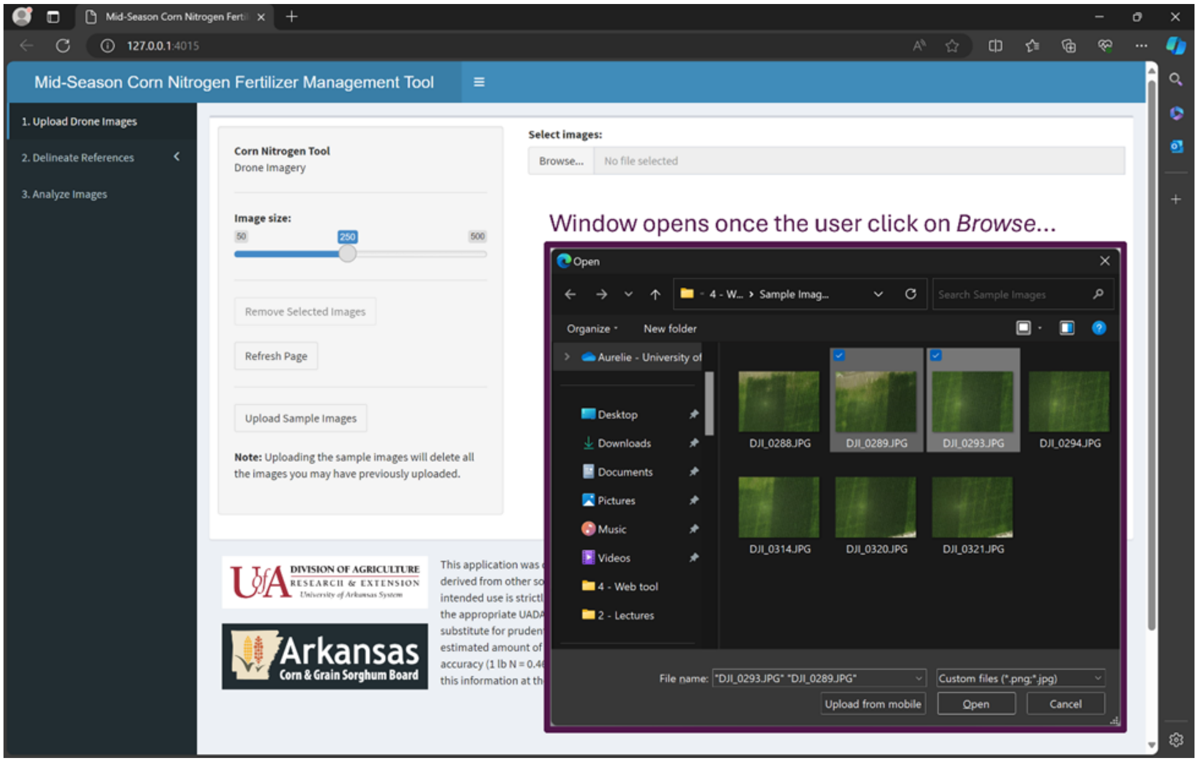

Figure 2. Browsing window requesting the user to find and select individual red, green, blue overhead images for upload into the web-tool prototype. Multiple images may be selected at once. Additional images may be added later by repeating the same steps. Duplicates are automatically excluded based on file path and name.

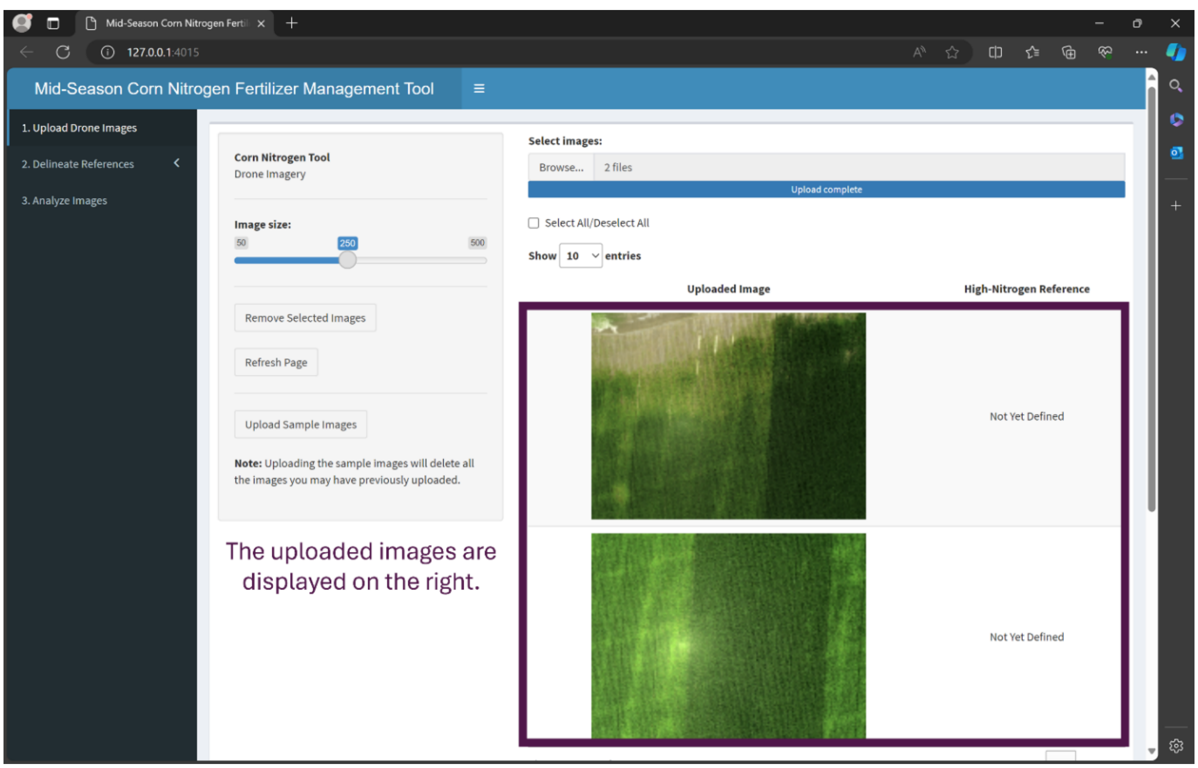

Figure 3. Uploaded red, green, blue overhead images are displayed in the web-tool user interface.

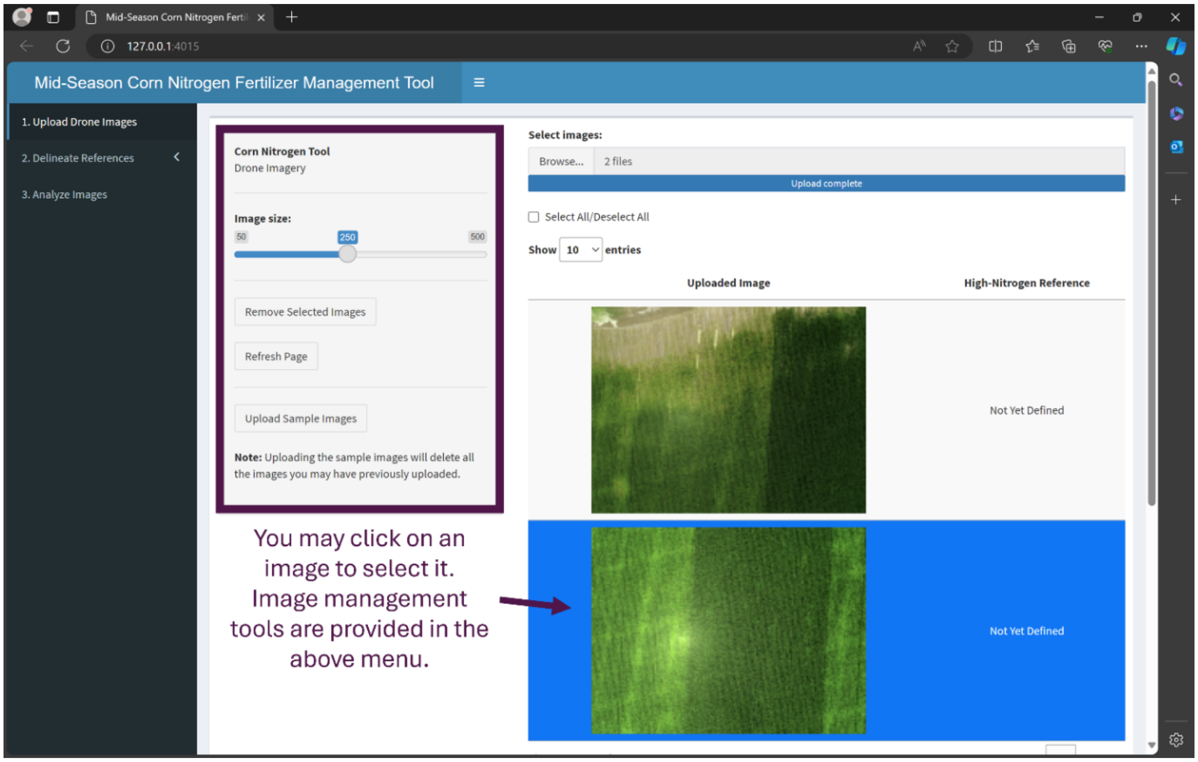

Figure 4. Overhead image manipulation. The user may change image display size, select (highlighted in blue) and remove one or more images, or refresh the page. The user may also upload a set of sample images for practice. If all uploaded images are removed at once the web-tool is refreshed and all parameters are reset to their default settings.

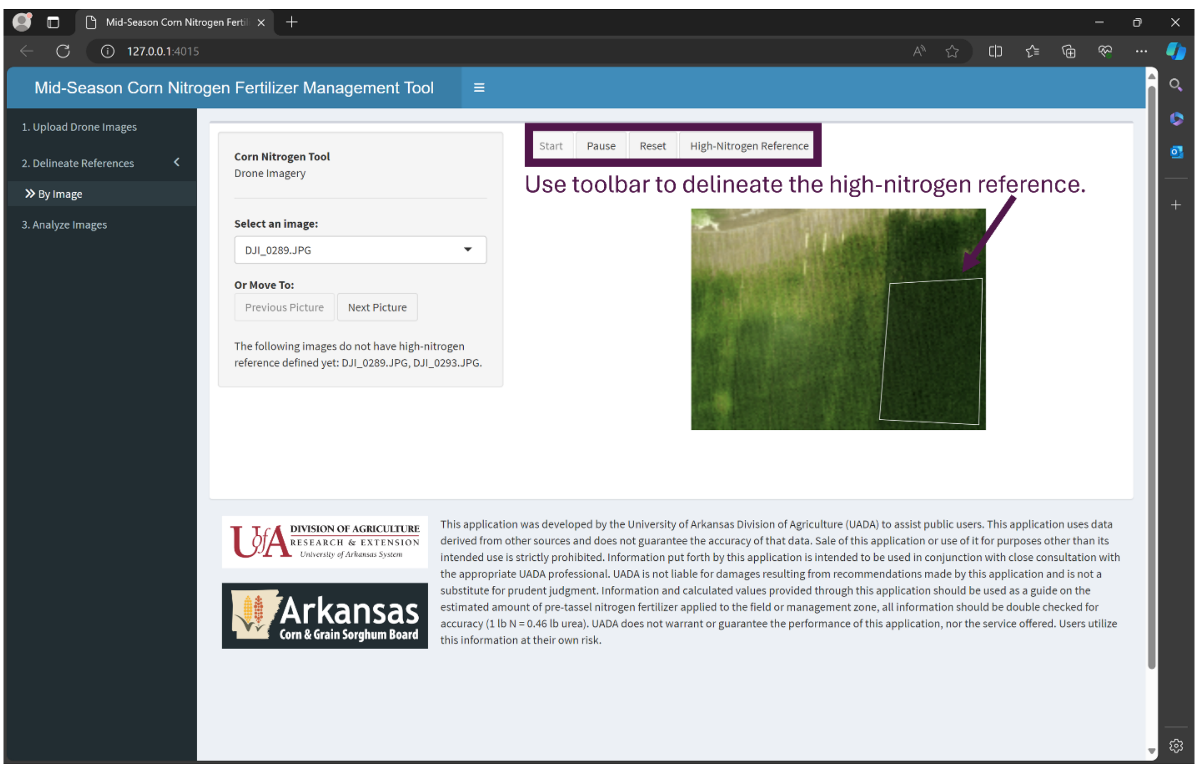

Figure 5. High-nitrogen delineation process completed within the *Delineate References* menu. The user may use the *Start, Pause,* and *Reset* (do-over) tools as needed to delineate the reference area within each image. The delineated area appears as a white polygon overlayed over the selected image. The *High-Nitrogen Reference* button completes the process.

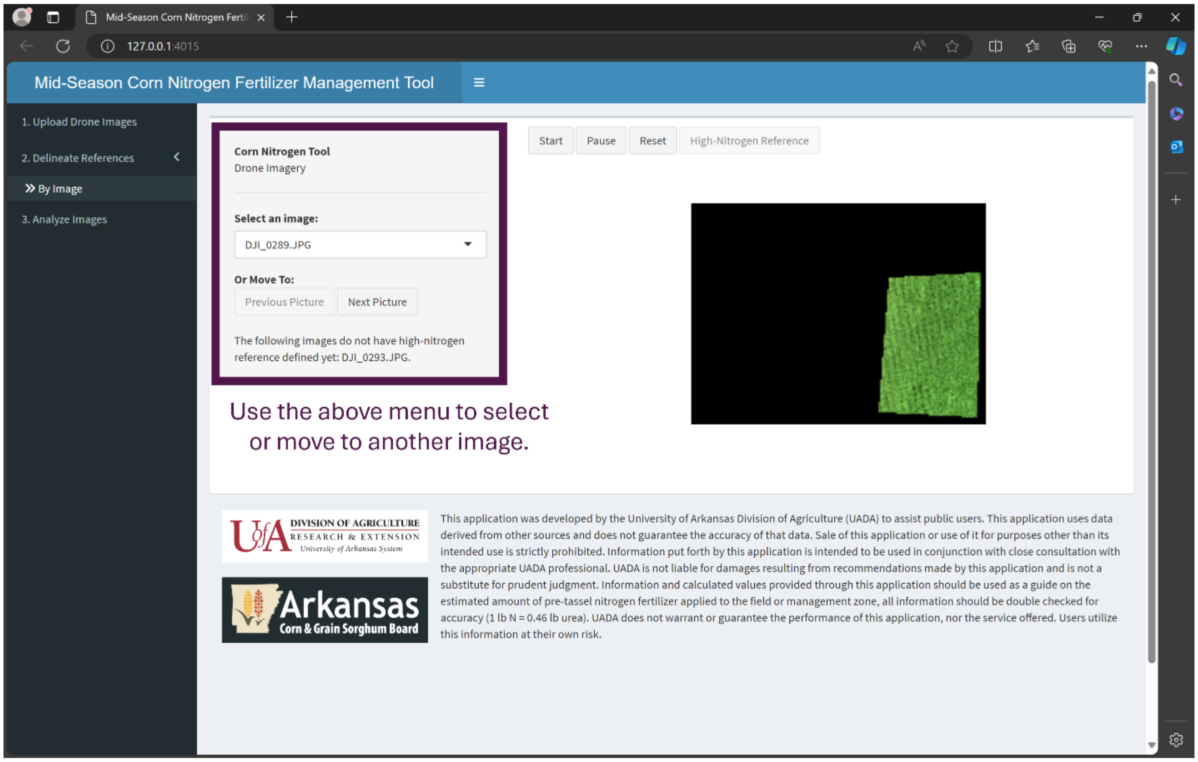

Figure 6. Completion of the high-nitrogen reference delineation. The pixels outside the delineated area are blacked out. The user may then select or move to another image using the tools provided in the sidebar menu. A high-nitrogen reference must be selected in each image before the user can proceed with processing.

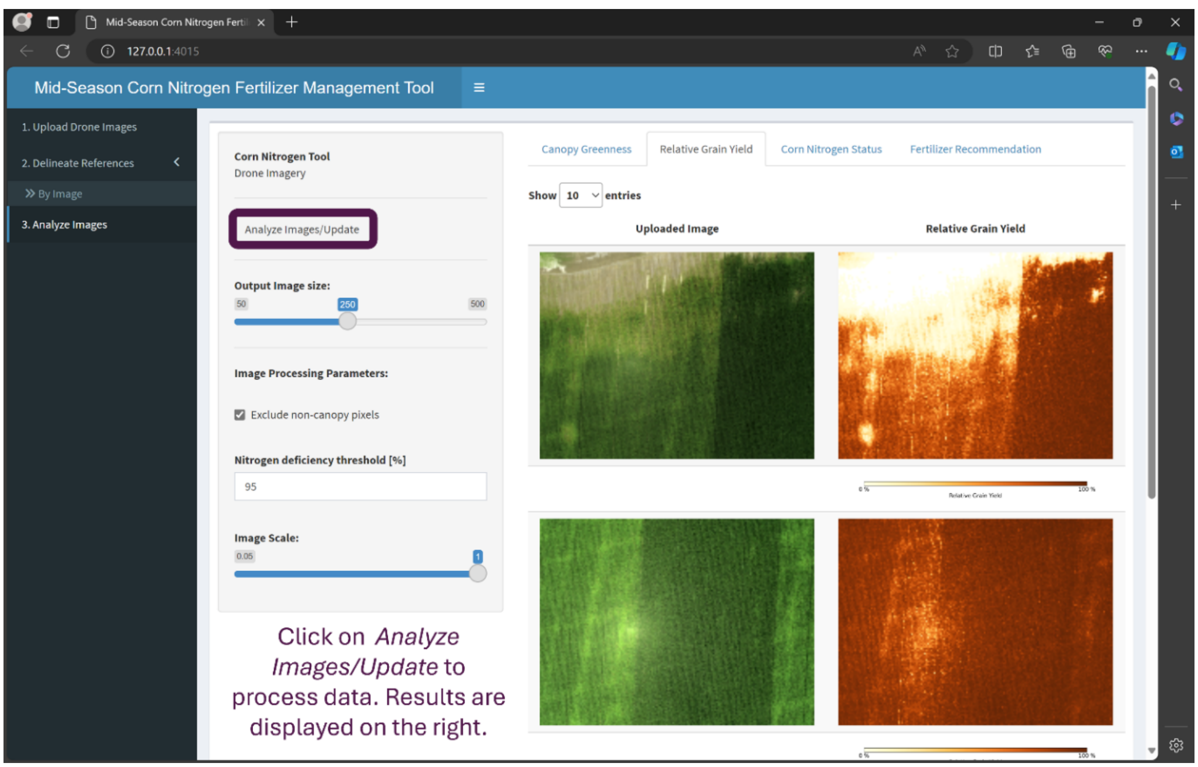

Figure 7. Overhead image processing. The user clicks on *Analyze Images/Update* to process the uploaded images. Results are displayed within a set of relevant tabs. The relative grain yield predictions are shown by default. Algorithm outputs are displayed side-by-side with their corresponding red, green, blue overhead images.

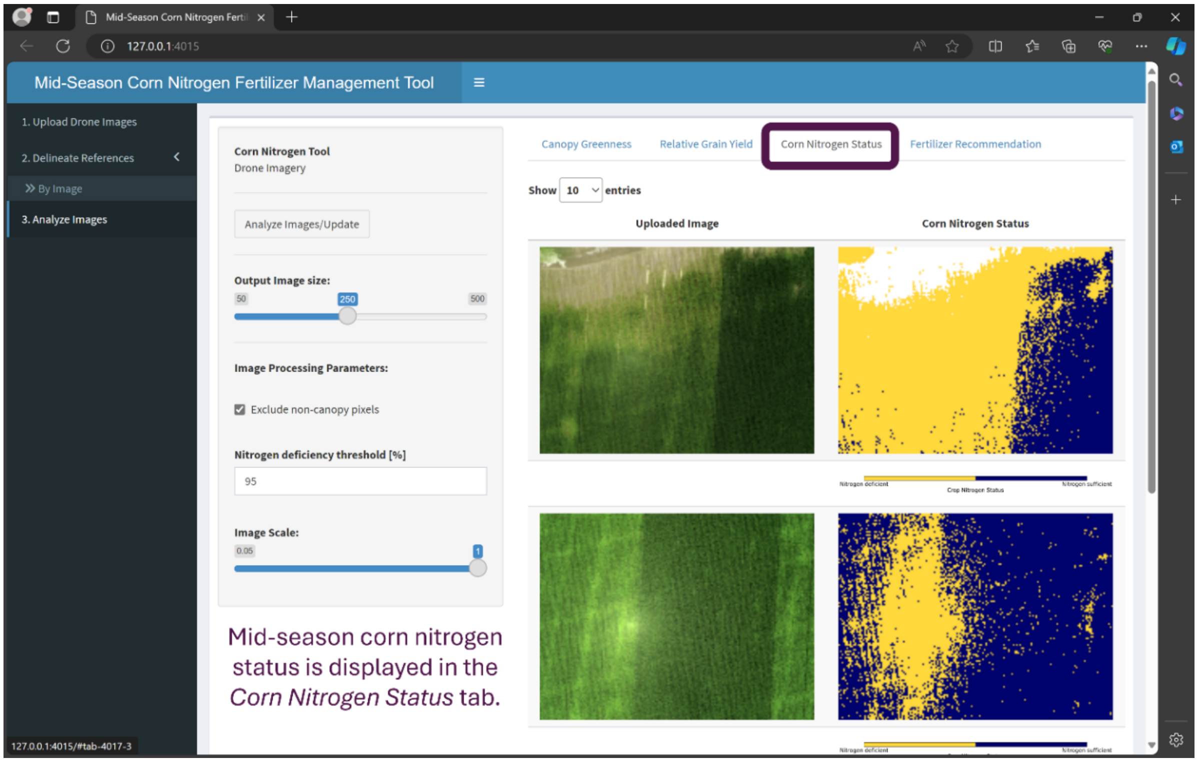

Figure 8. Mid-season maize nitrogen status assessment. The user may move between tabs without re-processing images.

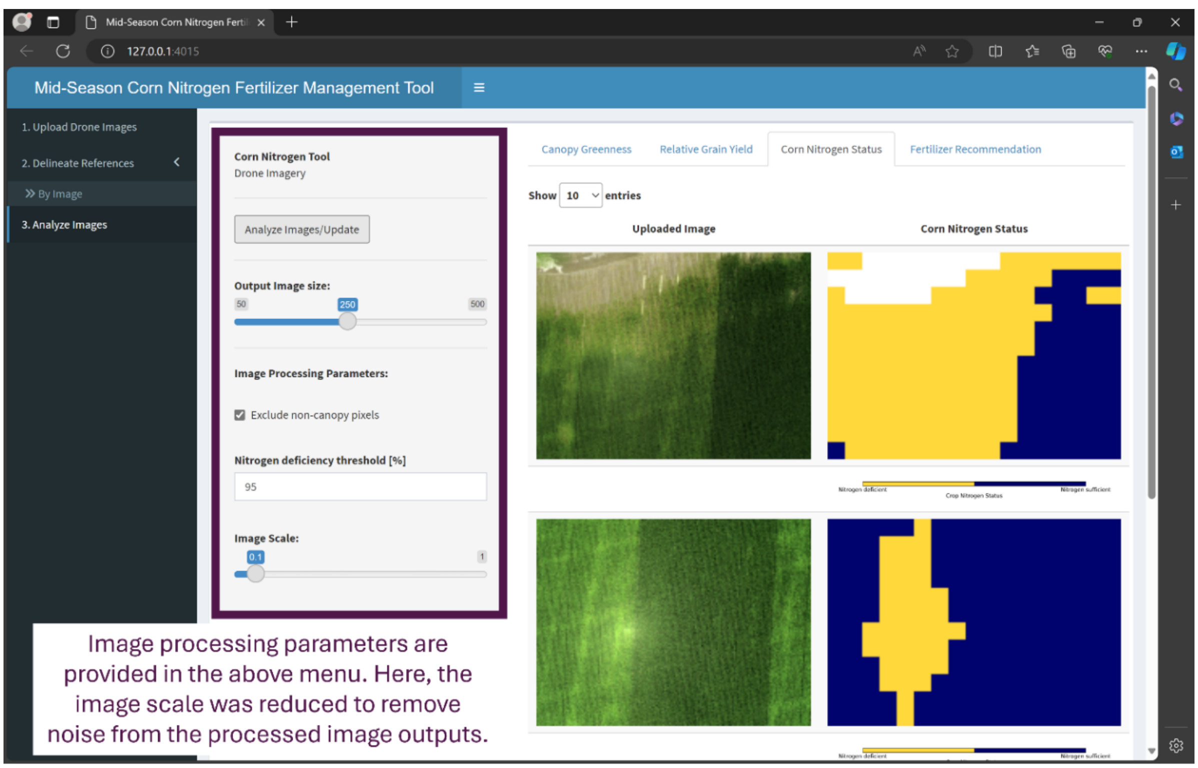

Figure 9. Processed image manipulation. The user may adjust the image display size to different screen sizes or resolutions. The user may also choose whether to exclude non-canopy pixel from the data processing (excluded pixels are shown in white). The user may also change the relative grain yield threshold for yield limiting nitrogen deficiency detection (95% by default), and re-scale the image to a coarser spatial resolution to minimize noise.

Discussion

A web-tool prototype was developed to help producers assess mid-season maize N status with overhead RGB images collected using inexpensive sUAS. No stitching is required to allow image processing on the turnrow without advanced data computing capabilities. The current web-tool prototype is still in development, and additional functionalities will be added before deployment in 2027. The additional functionalities will increase user friendliness and relevance to promote widespread adoption. The following additions are currently in the pipeline: automation of the high-N reference area delineation across images from coordinates or shapefile; delineation of a virtual high-N reference as a substitute from the establishment of a physical high-N reference at sidedress; determination of a mid-season agronomic and economic N fertilizer rate recommendation to optimize maize N fertilizer management; combination of the individual image outputs into a single product, and development of an algorithm that will identify the best tissue sampling locations for ground-truthing.

In terms of development stack, Python and R were used to complete this project because of their popularity among the scientific community, modularity, capabilities, and interoperability. These made it possible for agronomists without formal computer science background to drive algorithm and web-tool development. It also provided flexibility for the addition of additional functionalities. Both programs also allow for rapid image processing and the development of a system that can be deployed and improved quickly with a small budget. In addition to the new functionalities listed above, future efforts will emphasize technology commercialization and on-farm validation.

Conclusions

The following conclusions can be drawn from this study:

- Overhead RGB images collected using inexpensive sUAS can be used to inform ground-scouting efforts and optimize maize production independently from the producers' technological capabilities.
- Automation and decision-support tool development was used to bring research findings back to the farm and promote optimized N fertilizer management through precision agriculture.
- Development-stack selection was carefully considered to allow for continued web-tool development along with ongoing research efforts.
- The created workflow provides a proof-of-concept that may be applied to other similar applications.

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