Progress in the Application of Remote Sensing to White Mold Management in Snap Bean

Ethan W. Hughes[1], Jan van Aardt[1], Sarah Jane Pethybridge[2], Julie R. Kikkert[3], and Carl Salvaggio[1].
[1]Rochester Institute of Technology, [2]Cornell University, and [3]CCE Cornell Vegetable Program.

White mold caused by the fungus, *Sclerotinia sclerotiorum* is a severe disease of snap bean that results in crop loss by reducing the number of harvestable pods. The industry standard is for snap bean fields to apply a fungicide for white mold control when 10% of the plants have at least one bloom. However, rapid and accurate detection of white mold risk remains evasive, and currently is, at best, a manual and labor-intensive exercise. The overarching goal of this research therefore is to develop a spatially-explicit white mold risk model, derived from remote sensing imaging systems, mounted on unmanned aerial systems (UAS). We have three main objectives to address this challenge: i) identify spectral signatures for the onset of blooming to optimally time fungicide application, ii) investigate spectral characteristics of white mold onset in the snap bean crop, and iii) evaluate the coupling of white mold with UAS-based metrics, such as leaf area index (LAI), row and plant spacing, and digital elevation models.

The study area was located at the New York State Agricultural Experiment Station, Cornell University (Geneva, NY, USA). Field trials were designed to study the effects of planting time on the occurrence and severity of white mold. This staggered planting time design allowed the UAS to capture snap bean plants at different stages of blooming and white mold onset, all in the same imagery. A DJI Matrice-600 UAS was utilized to acquire the imagery; the system boasts a camera platform with a high spatial resolution color (RGB) camera, Headwall Photonics Nano imaging spectrometer (272 color bands/channels; ranging between 400-1000 nm), and a Velodyne VLP-16 light detection and ranging (LiDAR) system. High frequency flights were executed when portions of the field started to bloom.

To accomplish the first two objectives, the hyperspectral imagery from the Headwall Nano imaging spectrometer had to be ortho-rectified, calibrated into reflectance, and then mosaicked using GPS/IMU (inertial measurement unit) information. The empirical line method (ELM) was used to calibrate the radiance images into reflectance. The empirical line method uses white and black panels (with known reflectance spectra) in the field to develop calibration coefficients that will force the radiance spectra of each pixel in the scene to reflectance. Figure 1 shows what the calibration step does to the spectra of the calibration panels.

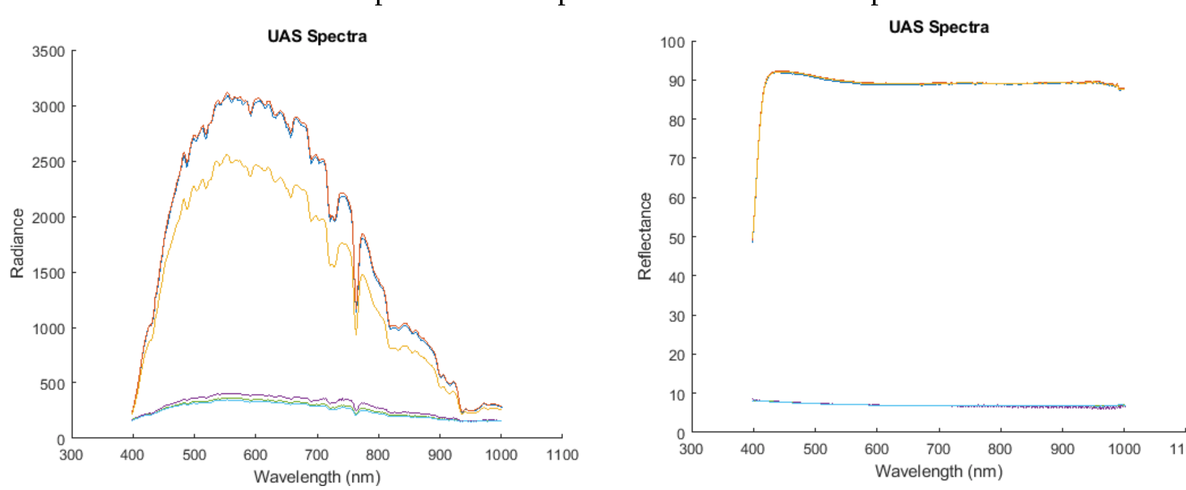

Figure 1: Radiance spectra (left) of calibration panels, converted to reflectance (right) using the Empirical Line Method.

The ELM method allows for conversion of the atmosphere effects in the radiance spectra (left) to reflectance results in a bright, flat reflectance curve for the white panel (Figure 1; right, topmost curve), and a dark, flat curve for the black panel (Figure 1; bottom-right). This step is crucial to growers that ensure that imagery and associated products are illumination-independent, i.e., that observed changes are not due to illumination differences between days or viewing geometry (sun-plant-sensor angles). This approach is crucial to the adoption of UAS-based precision agriculture.

Pure pixels, or pixels that contain a single, specific object, i.e., these pixels are not mixed spectra of various crop components, of snap bean plants were separated using a supervised classification process, followed by stepwise discriminant analysis to determine which wavelengths are critical to differentiating between blooming and non-blooming snap bean plants. This same method was used on imagery later in the season to discriminate between plants that were affected by white mold or not. An example of pure pixels being separated (highlighted in red) is shown in Figure 2.

Figure 2: Pure pixels separated using the Spectral Angle Mapper (SAM) technique; the red pixel only contain plant (foliage) material

First stage classification models will be developed using linear discriminant analysis and principal components analysis (PCA), while partial least squares (PLS) regression will be used to create binary logistic regression models to differentiate between bloom/no bloom and mold/no mold categories. These models will be evaluated for accuracy andprecision, using snap bean ground truth data from the fields, monitored intensively by Cornell University researchers. Figure 3 below shows a portion of ground truth locations in the snap bean field.

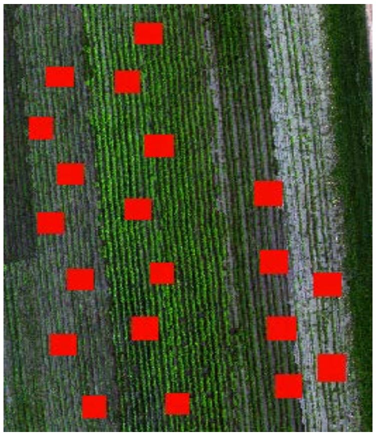

Figure 3: Ground truth plots used to evaluate the efficacy of bloom and white mold detection methods in snap bean fields

We envision that the risk models created during this study will lead to more judicious use of fungicide in snap bean fields, with both financial and sustainability benefits. We will present early results of this project, focusing on the 2017 summer field season, data collection, and UAS-based snap bean bloom detection. We also will highlight the lessons learned and discuss the potential for UAS sensing in precision agriculture applications.