Using Remote Sensing to Map In-Field Variability of Peanut Maturity

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Objective: Determine the feasibility of using remote sensing to map in-field variability of peanut maturity and quality

Work Conducted in 2019:

The study was conducted in two grower peanut fields – a rainfed field in Tift County and an irrigated field in Worth County and on research plots at the UGA Lang Farm. All fields were planted to GA-06. Historical satellite images of the fields were analyzed to select a block of the grower fields with the most soil variability. The block was divided into twelve 2.5 ac grid cells (Figure 1). Ten peanut plants were collected from an area approximately 30 ft in radius at the center of the grid cells weekly for the 6 weeks prior to harvest (Figure 2). Two hundred peanut pods were removed from each group of plants and pressure-washed to expose the mesocarp. The pods were placed on the Peanut Profile Board (PPB) and the number of nuts in each color class recorded. The peanut maturity index (PMI) was also calculated for each sample. At the Lang Farm, peanuts were planted in two week intervals to simulate maturity differences. In addition to sampling for maturity, a large number of physiological parameters were also measured.

During each sampling day, a Parrot Sequoia camera attached to a 3DR Solo quadcopter UAV (Figure 2) was used to capture multispectral images in 4 different bands; Green (530-570 nm), Red (640-680 nm), NIR (770-810 nm) and Red Edge (730-740 nm). All UAV flights were performed within 2 hours of solar noon from an altitude of 90 m with 70% overlap. At 300 ft, the spatial resolution of the camera was 3.75 in. Pix4D software was used to create mosaics of reflectance maps in each one the four bands and the ArcGIS software was used to extract an average reflectance value for the pixels in each of the 24 grid cells. A full 7-day workweek by two PhD-level graduate students was required to collect, process, and analyze the samples from each field.

Seven vegetation indices (VIs) that have been used by other studies to predict crop maturity and three modified VIs were selected for evaluation. The average reflectance values for each grid cell were then used to calculate the response of the ten VIs for each sampling date (Figure 1). Pearson's correlation ($p<0.001$) and regression analysis were used to compare the response of the VIs to PMI.

All VIs had a negative linear relationship with PMI where the value of the VI decreased as PMI increased. The best results in 2019 were for four VIs. These were the Nonlinear Index (NLI), Nonlinear Index using Red Edge (NLI_{RE}), the Modified NLI (MNLI), and the Modified NLI Red Edge ($MNLI_{RE}$). Three of the four VIs also performed the best during the 2018 study. *The results are very promising.*

The relationship between PMI and the VIs was the strongest for the irrigated fields. Because the 2019 growing season included extended periods without precipitation, the peanuts in the rainfed field experience severe drought stress and likely shed maturing pods thus skewing the hull-scrape data.

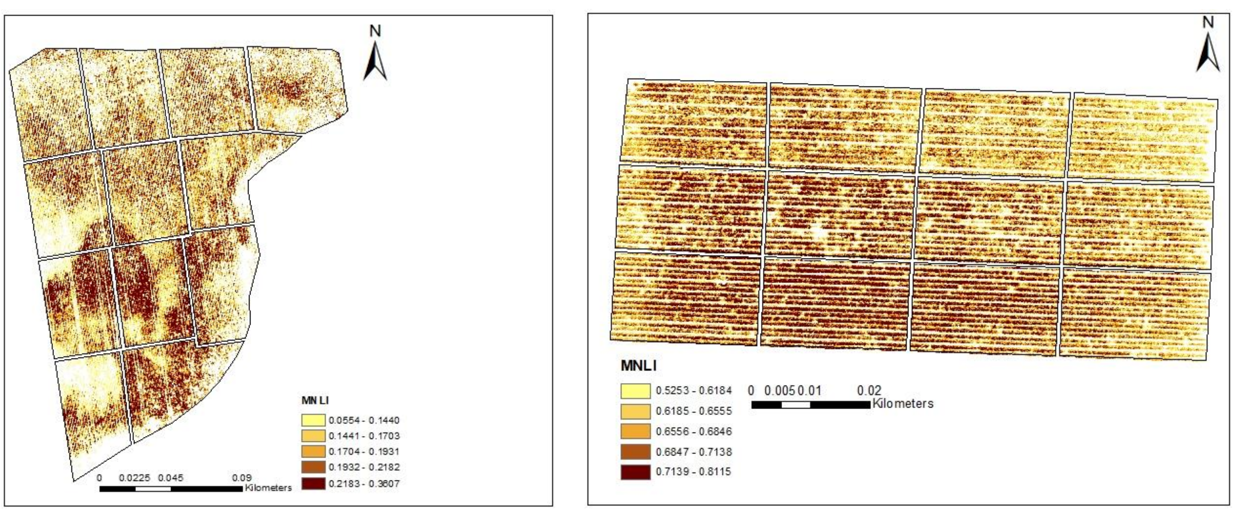

Figure 1. Vegation index (MNLI) images of the 30 ac block in the rainfed field which was divided into twelve 2.5 ac sampling plots (left) and the 12 Lang Farm plots (right). In both fields lighter areas indicate more mature peanuts and darker areas