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

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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 2021:

The study was conducted in two irrigated growers' peanut fields. Both fields were planted to Georgia-06G. Field 1 was 23 ac in size and divided into fourteen 1.5 ac grids (Figure 1). Field 2 was 75 ac in size and divided into fourteen 5 ac grids. Sampling points were established at center of each grid. Historical satellite images and soil electrical conductivity maps of the fields were analyzed to characterize soil variability. In each field, ten peanut plants were collected from an area approximately 30 ft in radius around the sampling point weekly for the 6 weeks prior to harvest. Approximately 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 calculated for each sampling point. PMI is calculated as the percentage of brown and black pods of the total number of pods. A full 7-day workweek by three students was required to collect, process, and analyze the samples from each field. Figure 2 shows the progression of PMI at each of the 14 sampling points of Field 1 over the six sampling events. The spatial variability of maturity in this field is clearly seen throughout the growing season. On the final sampling date which was the day the peanuts were inverted, PMI ranged from 0.27 to 0.60 at the 14 sampling points.

For each sampling date, multispectral satellite images from the Planet Labs satellite constellation were downloaded. The seven vegetation indices (VIs) and three modified VIs used in the 2019 study are being used to evaluate their maturity prediction strength with the 2021 fields. The average reflectance values for each grid cell are used to calculate the response of the ten VIs for each sampling date. Pearson's correlation ($p<0.001$) and artificial neural networks (ANN) are used to compare the response of the VIs to PMI. The analyses of the 2021 images is still in progress.

An open access scientific journal article describing how we applied ANN to predict PMI from remotely sensed images using data collected during the 2018 and 2019 growing seasons was published in January 2022. The ANN model included VIs from the remotely sensed images and adjusted growing degree days (aGDD) calculated from nearby weather stations as input variables to predict PMI with R^2=0.91 (Figure 3). The full citation of the article is: Santos A.F., Lacerda L.N., Rossi C., Moreno L.d.A., Oliveira M.F., Pilon C., Silva R.P., Vellidis G. 2022. Using UAV and multispectral images to estimate peanut maturity variability on irrigated and rainfed fields applying linear models and artificial neural networks. *Remote Sensing* 14(1):93. https://doi.org/10.3390/rs14010093. The Georgia Peanut Commission is acknowledged for its support of this work.

We believe that we have successfully shown that peanut maturity is spatially variable and that peanut maturity can be predicted using remote sensing. Consequently, we are concluding this work. We greatly appreciate the support that the Georgia Peanut Commission has provided during the life of this project for the past three years.

Figure 1. Field 1 was 23 ac in size and divided into fourteen 1.5 ac grids. Ten peanut plants were collected from an area approximately 30 ft in radius around each sampling point weekly for 6 weeks prior to harvest.

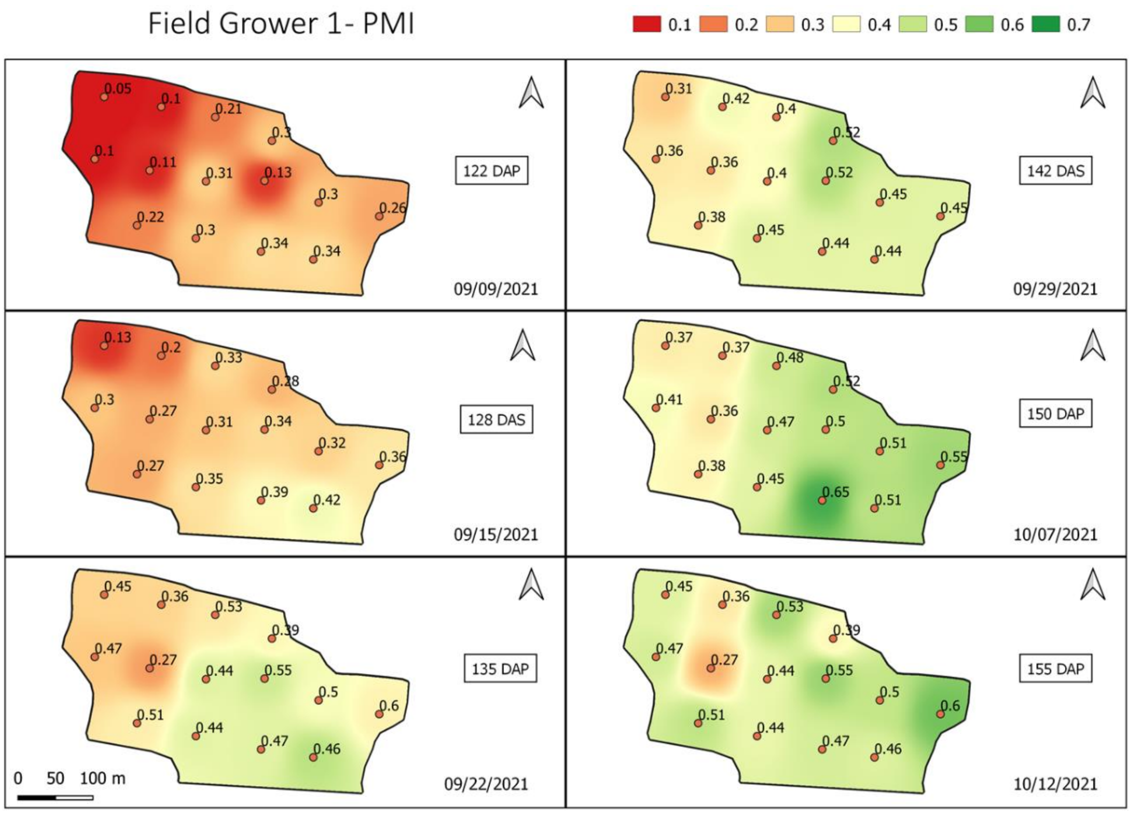

Figure 2. Progression of PMI at each of the 14 sampling points of Field 1 over the six sampling events. The spatial variability of maturity in this field is clearly seen throughout the growing season. PMI = (brown + black) / total.

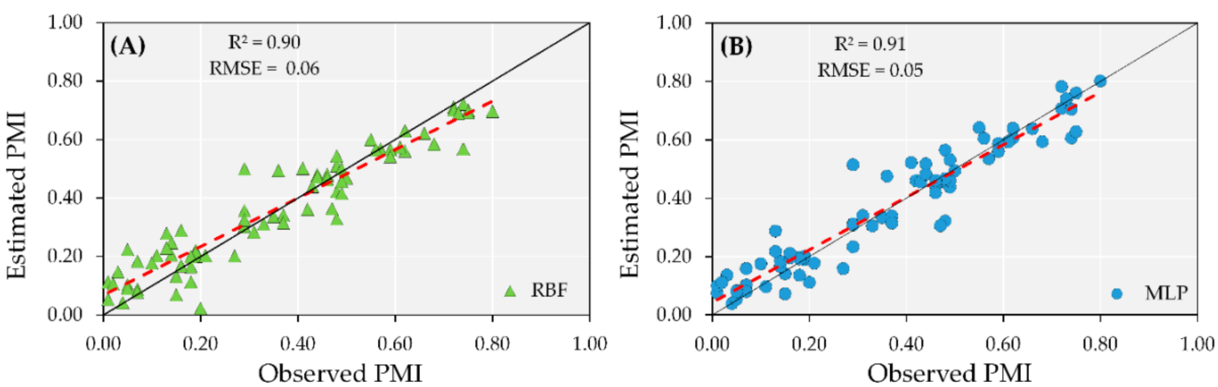

Figure 3. Performance of two types of artificial neural networks (ANN) models using data from irrigated and rainfed fields from 2018 and 2019.