A REMOTE VISION ON SUGARCANE: TOWARD THE SUGAR CONTENT ESTIMATION

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Background

For years, researchers worldwide have been focusing their efforts on developing affordable methods for mapping sugarcane properties. For more effective farm monitoring and management, it has been preferable to use remote sensing platforms, which are non-invasive and non-destructive as well as capable of mapping extensive fields and hard-to-reach places. In sugarcane, apply this platform could bring useful information, for example, the amount of sugar in the field, thus overcoming conventional approaches in terms of time, scale, and reliability, which allow farmers to decide the best time and place for harvesting. Moreover, the combination of remote sensing data with artificial intelligence (AI) analysis further increases the truthfulness of the information. Therefore, the Precision Agriculture Laboratory at Louisiana State University (LSU AgCenter) are investigating since 2018 whether remote sensing data could be correlated with sugar content in sugarcane fields.

In 2022, two remote sensing approaches were investigated, they were conducted on two sugarcane fields in Louisiana (Field 1: Houma; Field 2: New Roads). For the first approach were used multispectral images acquired by drones to predict brix and purity in Field 1. The second approach was using a prototype fluorescence sensor to correlate with total recoverable sugar (TRS) in Field 2. The approaches and results are described below.

Multispectral images for brix and purity prediction

Multispectral data and ground truth were collected at the maturity stage in Field 1. Images were captured from a multispectral camera on board of an unmanned aerial system (UAS or drones), while 32 sugarcane samples were collected across the field and sent to the laboratory to extract information on brix and purity. The images were used to generate an orthomosaic and both spectral bands and vegetation indices were used as inputs to the predictive model. Additionally, growing degree days (GDD) were also included in the model for phenological characterization. The dataset was applied to a previously validated predictive AI model trained. Predicted results were plotted and compared to those from ground data, clearly the results were close to each other (Figure 1). Spatially, the field was slightly variable, but the results still showed similar trend, especially for purity. For brix the overall error was 2.3° while the overall error for purity was only 0.5%.

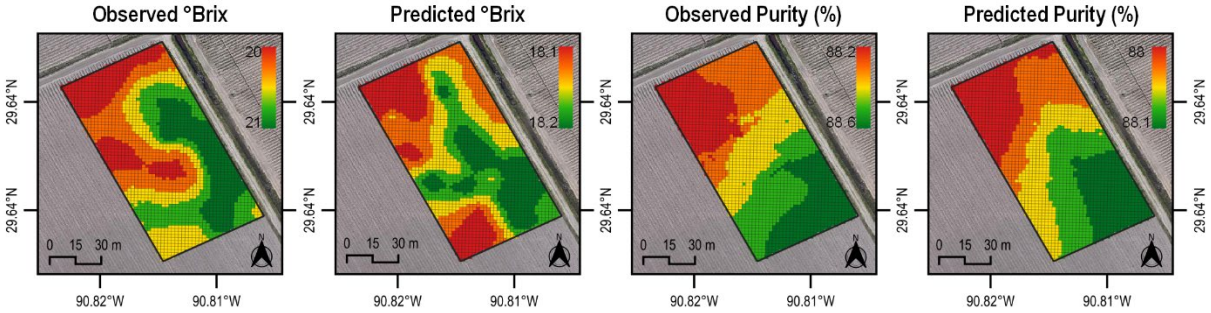

Figure 1. Interpolated maps highlighting observed and predicted results for brix and purity.

Fluorescence sensor data for total recoverable sugar estimation

Unlike multispectral, fluorescence data has a more in-depth and more sensitive relationship with chlorophyll and photosynthetic activities. Therefore, these data could be helpful to sugar content monitoring. Thus, an 18-sample experiment was considered for the data collection (Field 2). The variability for Field 2 was induced by ripener treatments, which allowed a widely range for the sugar content. For this approach, a fluorescence sensor was carried out on the plots and sugarcane samples ware collected for the TRS analysis. The data were analyzed by Pearson's correlation and results showed strong correlation (Figure 2). This strong correlation makes the fluorescence an effective input for sugar content. It can be a timely indicator to be applied individually or added to other inputs in a predictive model in future studies.

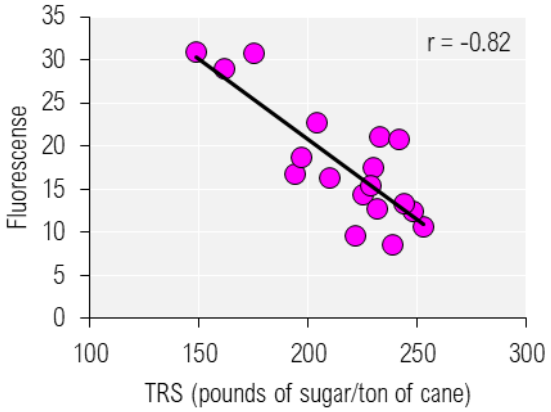

Figure 2. Pearson's correlation between fluorescence data and TRS.

Remote sensing provides timely results and can contribute to farmers making decisions on sugarcane fields. On the one hand, by offering non-destructive assessment, high-level scaling and reliable results. On the other hand, by reducing time consumption and avoiding subjective decisions. Further approaches will integrate a series of remote sensing data to improve the robustness of a predictive models, in addition by including different varieties and field conditions.