## Evaluating non-destructive spectral imaging techniques for predicting wine grape attributes

## **Public abstract:**

Grapevines are one of the most important and longest horticulture crops to be cultivated. The United States is one of the biggest producers of grapes and wine. Arkansas, is not the largest wine region in the USA, has long history of planting grape and wine industry. For the wine industry, and the monitoring attributes, such as Soluble Solids content (SSC) and pH, of the ripening process are crucial considerations to determine the grape harvesting timeline. Traditional monitor methods directly take grape berries from vineyard and use diverse instruments to evaluate the attributes in the laboratory, which are destructive and time-consuming procedures. Therefore, non-destructive methods for grape attributes evaluation are critically needed. The objective of this study is to examine the feasibilities to utilize non-destructive hyperspectral imaging systems to predict SSC and pH values for Vignoles grapes growing in Arkansas, and to determine the optimal level of ripeness for harvesting, through monitoring the SSC concentration evolution.

## **Progress report:**

The Vignoles grape samples were collected from Hindsville Farm, located in Hindsville, Arkansas. The grape samples were collected manually and randomly from 2 rows and analyzed on 5 different weeks in the period between July 18th to August 15th, 2022. In each week, 26 berries were taken on one day, for a total of 130 samples. Grapes were then washed and gently dried with absorbent paper when arrived at the laboratory, where the temperature and humidity were controlled at 20 °C±2 °C and 60 % ±5 %, respectively. In this experiment, the samples were placed on a customized 3D printed sample holder, and the holder can 13 berries at one time.

The berries were then scanned by hyperspectral imaging camera (FX10e, GigE, SPECIM, USA) with a resolution of 1024 \* 936 pixels in the spatial dimension and 448 bands in the spectral dimension with the band range of 397.01–1004.52 nm. The imaging system was run in the line scanning model with scanning speed 10mm/s. For each berry sample, hyperspectral images were recorded in five different berry positions. Three positions correspond to berry rotations of approximately 120° on the horizontal side, and the other two positions are collected form berry vertical sides, one position for berry top, another for berry bottom. After the image acquisition, the sample SSC value was measured by using Bausch & Lomb Abbe Mark II refractometer (Scientific Instruments, Keene, NH), and the pH was measured by using pH meter (APERA, pH700, Columbus, OH). The attribute distributions are shown in Fig. 1.

To process the hyperspectral imaging data, the acquired hyperspectral images were corrected with white and dark references. Then, the region of interest of each berry was automatically determined by Otsu's threshold, and the spectral information for each berry was determined by averaging all pixel information in different spatial positions and rotations, as shown in Fig. 2. The spectra signals were then smoothed by SavitzkyeGolay method, as shown in Fig. 3. The signals were then sent into the Partial least squares (PLS) regression models to correlate to predict SSC values through 5-fold cross validation. The optimal number of PLS latent variables is 13, and compared to measured SSC values, the predicted SSC values can achieve  $R^2$  value 0.8113, and mean squared error value 2.0696 Brix, as shown in Fig 4.







0.40 0.30 0.20 0.20 0.10 0.10 0.10 1200 1400 1600 1800 2000

Fig. 2. The raw grape reflectance spectra signals

Fig. 3. The spectra signals after Savitzkye Golay smoothing



Fig. 4. Measured vs predicted values of solid soluble content (Brix) obtained by PLS regression (5-fold cross validation)