

EXTENDED ABSTRACT

Simulating single band multispectral imaging from hyperspectral imaging: A study into the application of single band visible to near-infrared multispectral imaging for determining table grape quality

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INTRODUCTION

To be accepted by the market and consumers table grapes need to meet certain requirements in terms of physical and chemical quality parameters. Chemical quality parameters of importance include total soluble solids (TSS), total titratable acidity (TA) and pH (Herrera et al., 2003; Jayasena & Cameron, 2008). The standard reference methods used to determine these parameters are generally destructive, time-consuming and may require specialized equipment or complex sample preparation (Daniels et al., 2019; Fernández-Novales et al., 2019). Due to inherent intra-bunch and inter-bunch variability large samples are also required to ensure accurate representation of the vineyard. Alternative methods such as spectroscopy and spectral imaging may be the solution to providing fast, accurate and efficient evaluation of table grapes.

Spectroscopy methods including visible to near-infrared (VNIR) spectroscopy, Fourier-Transform near-infrared (FT-NIR) spectroscopy and short-wave infrared (SWIR) spectroscopy have been proposed and tested for the evaluation of fruit and vegetable quality. These methods are mostly laboratory-based and require highly sophisticated and expensive equipment. Being laboratory-based means that these methods still need samples to be removed from the vine i.e., are also destructive. Some in-field spectrometer options are available, but they remain expensive. Spectroscopy techniques are also generally limited to point measurements

yielding one-dimensional data i.e., a spectral signature for the specific point. This makes it difficult to upscale measurements to a bunch-level investigation because the decision of how many points should be measured and what the distribution of these points across the bunch should be is not an easy one to make. Technologies such as hyperspectral imaging (HSI) and multispectral imaging (MSI) may assist in overcoming this challenge as they provide three-dimensional data comprised of the one-dimensional spectral and two-dimensional spatial data i.e., spectral signatures for each pixel in the image (Nicolai et al., 2007).

HSI and MSI technologies are however not easily transferred to in-field applications due to the potential interference of ambient conditions (light conditions in particular) on the measured spectral data (Nicolai et al., 2007). Some studies have successfully used HSI for in-field applications under specific conditions (Shao et al., 2021). Portable HSI sensors are still expensive and MSI options can provide a cost-effective alternative. MSI technologies have not been widely used in determining fruit quality and to our knowledge no studies on table grapes specifically exist. HSI provides a large amount of information, but MSI is generally limited to much fewer spectral bands or even single bands. This core difference may impact on the successful application of MSI technology for determining table grape quality parameters.

RESEARCH OBJECTIVES

The objective of this study is to investigate the correlation of TSS to specific spectral bands through exploration of data acquired from hyperspectral imaging of intact table grape bunches. The intention of this investigation is to further ascertain whether multispectral imaging which utilizes

a single band approach would be suitable as a method for determining TSS of table grape bunches. This will be done through a simulation of MSI data from the HSI dataset by targeting specific wavelength bands corresponding to those of commercial MSI cameras.

MATERIAL AND METHODS

Description of experimental sites and bunch sampling

The study was conducted using grapes sampled from two commercial table grape blocks in the Bergriver production area, Paarl, South Africa during the 2023/2024 season. The

cultivars included were Crimson Seedless and Sugar CrispTM. The blocks were of similar age, vines were trained on the gable system in both blocks and no overhead nets or plastic

were utilized in either block. Five bunches per cultivar were selected per sample date and there were 19 sample dates in total. Bunches were placed in non-permeable plastic bags and transported on ice to the laboratory at Stellenbosch University.

Image acquisition

HSI imaging was done at the Vibrational Spectroscopy Unit at the Department of Food Science, Stellenbosch University using a HySpex VNIR-1800 camera (HySpex, Oslo, Norway) which operated in the 400 – 1000 nm spectral range and has a spectral resolution of 4 nm. The camera is fitted with a 30 cm lens and has a field of view of 9.733 cm. The imaging setup was configured with a frame period of 6502 μ s and an integration time of 6500 μ s. The sample stage moved at a speed of 5 cm/s. The samples were illuminated with 2 x

800W tungsten halogen lamps which were allowed to warm up for 15 min prior to imaging. Calibration was done prior to sample imaging using a standard grey reflectance reference (75 % reflectance). HySpex Ground v4.11.2 software (HySpex, Oslo, Norway) was used for image acquisition and HySpex Rad v2.5 software (HySpex, Oslo, Norway) was used to convert the images to reflectance files. Further conversions and data extraction was done using MATLAB software (The MathWorks Inc, 2024).

Data extraction

Manual and automatic data extraction protocols were applied to the HSI images. Both protocols were carried out using MATLAB codes written for this purpose. The manual protocol involved selecting nine targeted berries in the bunch image and extracting data from four points of each berry. The average of the spectral data extracted from these combined points was exported in an Excel sheet. Automatic

data extraction was based on the *activecontour* image segmentation method (The MathWorks Inc., 2023) in which the image is segmented into foreground and background using active contours (snakes) region growing technique. The average spectral data of the foreground (bunch) segment of the image is then exported to an Excel sheet.

MSI data simulation from HSI

Spectral ranges related to the red (R), green (G), blue (B), and near-infrared (NIR) areas of the spectrum were identified and the data corresponding to these ranges extracted from HSI datasets. The ranges were as follows: Red: 620 – 650 nm; Green: 495 – 570 nm; Blue: 407 – 500 nm and near-

infrared: 950 – 980 nm. Two additional ranges corresponding to RedEdge (RE) and NIR ranges in which commercial MSI cameras operate were also identified and these ranges corresponded to 710 – 740 nm and 830 – 870 nm respectively.

Reference chemical measurements

Reference chemical measurements were done for total soluble solids (TSS). The samples were juiced for this measurement. All berries from a bunch (single sample) were blended using a stick-blender (household type) and the juice sieved through

a tea-sieve to remove pulp and skin solids. TSS was then determined using the clear juice using a handheld digital refractometer (Atago PAL-1, Tokyo, Japan).

Statistical analysis

Statistical analysis to determine the correlation of TSS to specific wavelengths was conducted using the *lars* package in R (Lares, 2024). The top 40 wavelengths corresponding to TSS was identified for the full HSI dataset through this process and the correlation coefficient (r) for each determined

to indicate the strength and nature of the relationship between the reflection value of the wavelengths and TSS. The same process was applied to the smaller HSI datasets (MSI range simulations), but the r-value was evaluated for the average reflection value across all the wavelengths within each range.

RESULTS

The investigation of the relationship between the reflectance values of wavelengths and TSS was done on the full HSI dataset for each cultivar (Crimson Seedless and Sugar Crisp TM) separately and for the two cultivars combined (Figure 1). The weakest relationships were found in the case of the combined dataset (Figure 1C) where the maximum and minimum r-value was 0.509 and 0.290 respectively. Some positive relationships are observed in the ranges of 710 – 740 nm ($r = 0.429 - 0.492$) and 640 – 650 nm ($r = 0.480 - 0.509$). Results were much different between the Crimson Seedless

and Sugar Crisp TM datasets (Figure 1A and Figure 1B). In the case of Crimson Seedless negative relationships with TSS are observed for the wavelengths in the range 490 – 550 nm ($r = -0.691$ to -0.439). This corresponds to the green region of the spectrum and this relationship is to be expected since the chlorophyll in red grape varieties degrades during ripening i.e., reflectance in the green spectrum will decrease as TSS increases with ripening progression. A slight positive relationship is observed in the range of 710 – 732 nm ($r = 0.362 - 0.412$), similar to what is noticed in the combined

dataset results. TSS has been linked to the wavelengths between 720 – 740 nm (Zhao et al., 2023). For Sugar CrispTM the relationships were quite constant for all the wavelengths identified with *r*-values between 0.601 and 0.640. The strongest relationship is noticed between 621 – 640 nm. This corresponds to the red spectrum and could be ascribed to changes in pigments in the grape skins such as carotenoids (yellow) and flavonoids (red to purple) which occurs during ripening of green skinned grape varieties.

The investigation of the relationship between the reflectance values of wavelengths and TSS was also done on the simulated MSI dataset for each cultivar (Crimson Seedless and Sugar CrispTM) separately and for the two cultivars

combined (Figure 2). For Crimson Seedless the strongest relationship was in the HSI_G range ($r = -0.737$) (Figure 2A). For Sugar CrispTM the strongest correlation was in the HSI_R range ($r = 0.639$) (Figure 2B) and for the combined data set the HSI_RE range had the best relationship to TSS ($r = 0.452$). As with the HSI dataset the combined MSI datasets had the lowest *r*-values. In all cases (cultivars separately and combined) the HSI_NIR2 range (general NIR range) shows slightly better correlations to TSS than the HSI_NIR1 range (NIR range related to MSI cameras). This could be due to the fact that the HSI_NIR1 range (830 – 870 nm) is not reported to coincide with TSS as strongly as the range of HSI_NIR2 (950 – 980 nm) (Gomes et al., 2017).

CONCLUSION

From the results it is clear that the reflection data of cultivars differ with red and white cultivars exhibiting distinctive trends. When combining the dataset to include results from both cultivars the correlation results were not as strong as in the case of when the two cultivars were analysed separately. This could point to difficulty in creating general correlations for application to multiple cultivars, but this study only

included two cultivars and this may be improved by including more cultivars. Some correlations are observed for the ranges corresponding to that in which commercial MSI cameras operate and this can indicate that these cameras may be suitable to apply to table grape quality determination, but more investigations into this is needed to make a definitive decision.

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REFERENCES

- Daniels, A. J., Poblete-Echeverría, C., Opara, U. L., and Nieuwoudt, H. H. (2019). Measuring internal maturity parameters contactless on intact table grape bunches using NIR spectroscopy. *Front. Plant Sci.*, 10(November), 1–14.
- Fernández-Navales, J., Garde-Cerdán, T., Tardáguila, J., Gutiérrez-Gamboa, G., Pérez-Álvarez, E. P., and Diago, M. P. (2019). Assessment of amino acids and total soluble solids in intact grape berries using contactless Vis and NIR spectroscopy during ripening. *Talanta*, 199(November 2018), 244–253.
- Gomes, V. M., Fernandes, A. M., Faia, A., and Melo-Pinto, P. (2017). Comparison of different approaches for the prediction of sugar content in new vintages of whole Port wine grape berries using hyperspectral imaging. *Comput. Electron. Agric.*, 140, 244–254.
- Herrera, J., Guesalaga, A., and Agosin, E. (2003). Shortwave-near infrared spectroscopy for non-destructive determination of maturity of wine grapes. *Meas. Sci. Technol.*, 14(5), 689–697.
- Jayasena, V., and Cameron, I. (2008). °brix/Acid ratio as a predictor of consumer acceptability of crimson seedless table grapes. *J. Food Qual.*, 31(6), 736–750.
- Lares, B. (2024). lares: Analytics & Machine Learning Sidekick. R package version 5.2.9.9005, commit 666295d16d42da33b58d066b7a142b5c64621cea, <https://github.com/laresbernardo/lares>
- Nicolaï, B. M., Beullens, K., Bobelyn, E., Peirs, A., Saeys, W., Theron, K. I., and Lammertyn, J. (2007). Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review. *Postharvest Biology and Technology*, 46(2), 99–118.
- Shao, Y., Wang, Y., and Xuan, G. (2021). In-field and non-invasive determination of internal quality and ripeness stages of Feicheng peach using a portable hyperspectral imager. *Biosyst. Eng.*, 212, 115–125.
- The MathWorks Inc. (2023). MATLAB version 9.10.0 (R2021a), Natick, Massachusetts: The MathWorks Inc. <https://www.mathworks.com>
- Zhao, J., Hu, Q., Li, B., Xie, Y., Lu, H., and Xu, S. (2023). Research on an improved non-destructive detection method for the soluble solids content in bunch-harvested grapes based on Deep Learning and hyperspectral imaging. *Appl. Sci. (Switzerland)*, 13(11).

FIGURES

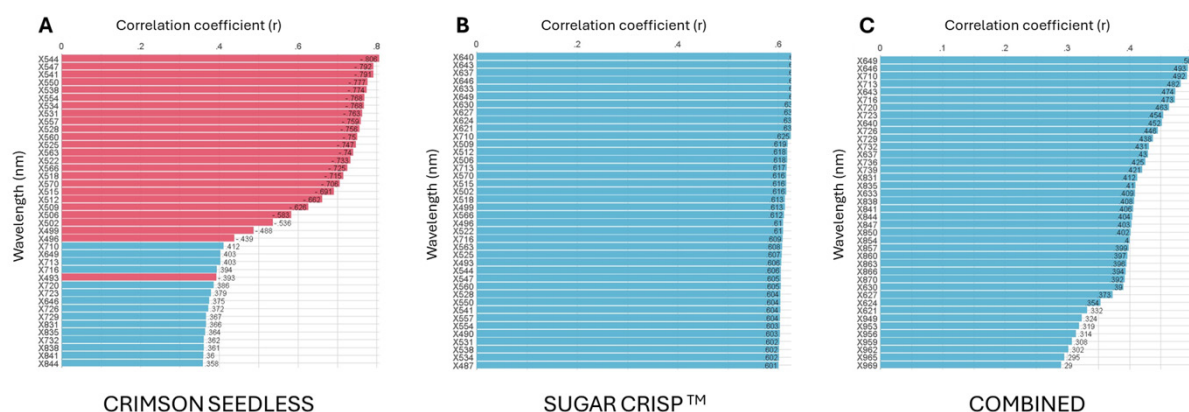


Figure 1. Correlation coefficients (r) for the top 40 wavelengths from the HSI dataset showing correlation to TSS for A) Crimson Seedless only, B) Sugar Crisp™ only and C) the two cultivars combined.

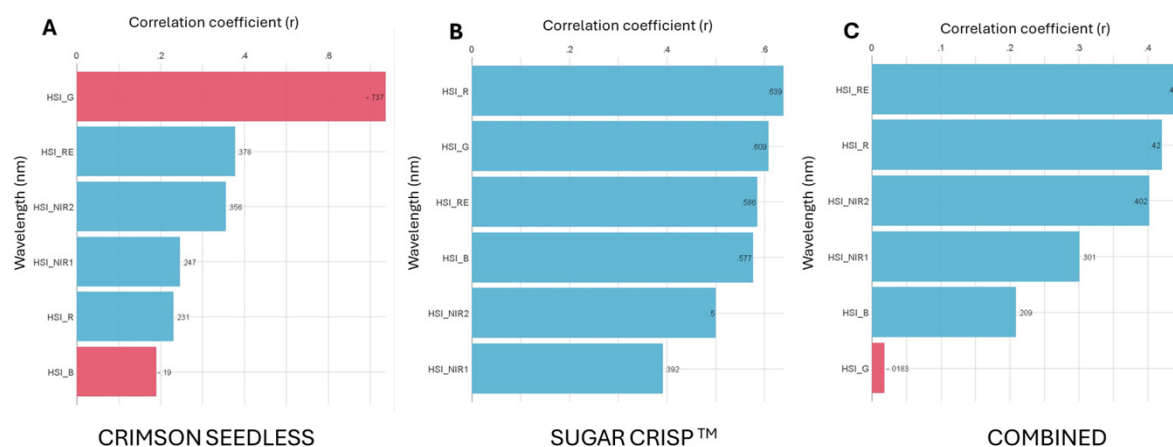


Figure 2. Correlation coefficients (r) for averaged simulated MSI wavelength ranges dataset showing correlation to TSS for A) Crimson Seedless only, B) Sugar Crisp™ only and C) the two cultivars combined.

HSI_R = Red region;

HSI_G = Green region;

HSI_B = Blue region;

HSI_RE = RedEdge region (Related to MSI camera);

HSI_NIR1 = NIR region (related to MSI camera);

HSI_NIR2 = NIR region related to (general).