Clearing the smoke for taint detection: Development of rapid, in-field detection systems for grapevine and berries smoke contamination using NIR spectroscopy and machine learning

Vasiliki Summerson, Claudia Gonzalez Viejo, Sigfredo Fuentes*

The University of Melbourne, School of Agriculture and Food, Faculty of Veterinary and Agricultural Sciences, Parkville 3010, Victoria, Australia

*Corresponding author: sigfredo.fuentes@unimelb.edu.au

Introduction and Objective

Bushfires are of common occurrence in Australia and throughout the world. Unfortunately, their incidence, window of opportunity and severity are predicted to rise due to the effects of climate change (CSIRO 2018). Many of these bushfires occur in areas close to wine regions resulting in grapevine smoke exposure. Wine produced from these smoke-affected grapes are characterised by unpleasant smoke aromas such as “burning rubber”, “smoked meats” and “burnt wood” (Bell, Stephens & Moritz 2013). These wines are unprofitable and result in significant financial losses for winemakers. Currently there are no in-field detection systems that growers can use to assess whether their grapevines have been contaminated by smoke and instead they must harvest grapes and conduct mini-fermentations which are then sent off to a commercial laboratory for analysis. This process is time consuming and destructive. This study aimed to use the near-infrared (NIR) spectroscopy and machine learning (ML) modelling for the rapid and non-destructive detection of grapevine smoke exposure by analysing grapevine leaves and/or grape berries.

Materials and Methods

The trial was conducted by Prof. Kerry Wilkinson and Colleen Szeto during the 2018/2019 season at the University of Adelaide’s Waite campus in Adelaide, South Australia (34° 58’ S, 138° 38’ E) and involved the application of five different smoke treatments (high smoke coupled with water misting (HS M) (Fig. 2), high smoke with no water misting (HS NM), low smoke (LS) using half the amount of fuel used in the high smoke treatments to achieve half the smoke density, control with mist (Con J) and control with no mist (Con NM) to Cabernet Sauvignon grapevines at approximately seven days post-veraison. Treatment vines were exposed to straw-derived smoke for one hour under experimental conditions described previously by Kennison et al (2008) and Ristic et al. (2011) (Fig. 1). Near-infrared measurements were then taken daily after smoking using the microPHAZIR TM RX NIR Analyser (Thermo Fisher Scientifc, Waltham, USA), which has a spectral range of 1600-2396 nm. Spectral readings were then used as inputs to train different ML algorithms using a customised code written in Matlab® R2019a (Mathworks Inc., Matick, MA. USA) which resulted in two artificial neural network (ANN) models with the best classification performance for either berry (Model 1) or leaf (Model 2) readings according to the different smoke treatments. The ANN models were trained to classify the leaf or berry NIR readings according to the smoke treatments (HS M, HS NM, LS, Con NM or Con M). The two models were developed using a random data division with 70% (n = 378 for berries and 1132 for leaves) scaled conjugate gradient training algorithm, 15% (n = 81 for grapes and 323 for leaves) for validation and 15% (n = 81 for grapes and 323 for leaves) for testing for the leaf model (Fig. 3a and b).

Results

The models developed were able to correctly classify leaves and berries affected by smoke using the spectral readings as inputs with high accuracy. The leaf models had an overall accuracy of 92% (Model 1), 95% (Model 2) (Fig. 4a and b). Principal component analysis (PCA) performed on the spectral readings resulted in the biplots shown in Figure 5a for berries and b) for Model 2 to classify smoke level in leaves.

Conclusion

Near-infrared spectroscopy and ANN modelling demonstrated to be of great potential for the detection of grapevine smoke contamination in leaves and grapes, which can aid detection using unmanned aerial systems (UAS) for leaves and on-the-go Unmanned Terrestrial Systems (UTS) for automation. Further research is required to relate the spectral readings to the level of volatile phenols in grapes and smoke taint development in wine and the implementation of Artificial Intelligence for automated detection.

Acknowledgements

This research was supported through the Australian Government Research Training Program Scholarship as well as the Digital Viticulture program funded by the University of Melbourne’s Networked Society Institute, Australia. The authors would also like to thank the vineyard managers as well as Prof. Kerry Wilkinson, Dr Roberta De Bei and Colleen Szeto for allowing us to collect data from their experiments and assistance.

References