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Non-destructive prediction of soluble solids and dry matter content using NIR spectroscopy and its relationship with sensory quality in sweet cherries

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ABSTRACT

Near infrared spectroscopy (NIR) models developed in the spectral region between 729 and 975 nm for a handheld instrument have been demonstrated to be accurate, robust and versatile for the rapid and non-destructive evaluation of soluble solids (SSC) and dry matter (DMC) content in sweet cherries at two different temperatures, 0 and 23 °C. Coefficient of determination (R^2) values for model calibrations ranged from 0.922 to 0.946 for SSC and from 0.910 to 0.933 for DMC, with standard errors of calibration from 0.612 to 0.792 and from 0.687 to 0.911% for SSC and DMC, respectively, depending on the variety and the temperature of the fruit. External validation of the models demonstrated they could be confidently used for 'Chelan' and 'Bing' sweet cherries; R^2 values for SSC ranged from 0.726 to 0.891 and for DMC from 0.670 to 0.725 between the predicted and the observed values in the external validation set, respectively. Consumer preference evaluation for 'Bing' and 'Chelan' sweet cherries with differing SSC (16.38–28.45) and DMC (17.67–31.62%) revealed higher acceptance by consumers for cherries with high DMC as well as for cherries with high SSC. DMC was equal to or superior to SSC for predicting flavor intensity and balance of sweet to sour taste as assessed by consumers. Considering the revealed importance in sensory evaluation of DMC, as well as SSC, in the eating quality of sweet cherry, the use of handheld NIR devices, which are rapid, lightweight and user-friendly should be considered for routine, non-destructive analysis of sweet cherry quality.

1. Introduction

Cost effective and nondestructive quality-control analysis systems can enhance the ability of agro-food industries to manage product quality. Fast optical techniques such as near-infrared (NIR) spectroscopy are playing a prominent role in process analysis. The potential to measure quality components non-destructively, on-line and quickly (milliseconds to seconds) makes NIR spectroscopy an interesting alternative to classical (frequently destructive) measurement methods. Several studies of on-site application of NIR to characterize internal and external quality of fruits and vegetables have been presented in recent years. Using NIR, complex quality traits such as soluble solids content (SSC), titratable acidity (TA), ascorbic acid, anthocyanins, flavonoids and/or lycopene, among others, can be non-destructively analyzed under commercial conditions (Alander et al., 2013; Costa et al., 2006; Nicolaï et al., 2007, 2014; Slaughter et al., 2003; Slaughter and Abbott, 2004; Walsh et al., 2004).

Harvesting fruit at optimal physiological maturity is essential for good eating quality (Kader, 2002). One of the standard parameters for determining fruit quality at harvest is SSC, frequently measured in quality control programs for diverse fruit, including sweet cherry (Crisosto et al., 2003; Escribano and Lázaro, 2012; Walsh, 2006). However, recent studies have suggested that dry matter content (DMC) could be an equal or superior predictor of flavor in numerous fruit (Bally et al., 2000; Burdon et al., 2004; Harker et al., 2009). Fruit DMC is basically comprised of all components except water, including both soluble and insoluble carbohydrates (Gibson, 2012). DMC has been measured to assess fruit maturity and consumer preference (Gamble et al., 2010;

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Harker et al., 2009; Palmer et al., 2010). As these authors revealed, the improvement in consumer preference in ripe kiwifruit, avocado and apple was intimately related to DMC and not simply associated with higher SSC. Despite its increasing importance in fruit quality, DMC has not been studied for non-climacteric fruit, like cherry, that do not have starch accumulation at harvest.

Traditionally, measurement of SSC and particularly DMC has been destructive, and DMC, in particular, was time consuming and laborious. In comparison, NIR spectroscopy offers the possibility of measuring these internal attributes non-destructively, quickly and with reasonable accuracy (Nicolaï et al., 2007). NIR has been tested for measurement of SSC in several types of fruit (Nicolaï et al., 2014). Carlini et al. (2000) and Lu (2001) used benchtop NIR spectrophotometers to successfully develop high-accuracy models to predict cherry SSC, showing the potential to use NIR with commercial cultivars to improve uniformity and/or to grade fruit for eating quality. The success of NIR spectroscopy for analysis of DMC in fruit is due to the strong absorbance of NIR light by water molecules, and the fruit's high water and carbohydrate contents. Prediction of DMC with NIR spectroscopy has been successfully applied to kiwifruit (Slaughter and Crisosto, 1998; Walsh et al., 2004), banana, mango, avocado, tomato and potato (Walsh et al., 2004), apple (McGlone et al., 2003), prune (Slaughter et al., 2003), and pear (Travers et al., 2014), but has not been tested in cherry.

Rapid progress in the use of NIR has led to the development of a few battery-powered, handheld devices that enable new applications that can be implemented in situ. Portable NIR spectrophotometers, such as the NIRVana (Greensill and Walsh, 2000) and its second generation, the F-750 (Felix Instruments, WA, USA), offer additional advantages: small size, low cost, robustness, user-friendly interface and portability. Since the chemical information about the sample is empirically extracted from the details of the spectrum, NIR spectroscopy requires calibration against a reference method with the ingredient of interest (Alander et al., 2013). Once a predictive model is developed, it can be uploaded into these handheld instruments to enable prediction of the trait value of future samples for real-time use. Partial least square (PLS) regression, which defines the latent variables based on the covariance between the spectral data and the component of interest, has been demonstrated to be one of the most successful multivariate model development methods, especially in NIR spectroscopy (Næs et al., 2004; Nicolaï et al., 2014). However, multivariate NIR calibration models are subject to disruption by external fluctuations, such as temperature, and could perform poorly when external effects on the NIR spectra are not considered in the experimental design for the model development process (Maeda et al., 1995). In addition, models would be more robust if they remained accurate when used among varieties within a species and also season to season.

Our goal was to develop models to predict SSC and DMC with NIR interactance measurements in 'Chelan' and 'Bing' sweet cherries, and to further explore the relationship between SSC and DMC with consumer preference. Our specific objectives were to 1) reveal and compare the impact of cherry DMC and SSC on consumer preference scores, 2) test the ability of a new handheld NIR device (F-750, Felix Instruments, Camas, WA, USA) to predict SSC and DMC in sweet cherry, and 3) develop robust and accurate SSC and DMC models to be applied in cold and room temperature environments by the sweet cherry industry.

2. Materials and methods

2.1. Fruit material

In 2014, an experiment was conducted to explore the relationships between consumer sensory quality and objective quality parameters. 'Chelan' and 'Bing' cherry (*Prunus avium*) fruit, size 9 to 11.5, were harvested from a commercial orchard near Sacramento, California. The fruit were picked from 12 representative trees per variety, one week before commercial harvest for that variety and every 3 to 5 d thereafter to capture three (light, medium, dark) color stages of ripeness. Fruit were packed into cardboard boxes and transported in an air conditioned vehicle to the University of California, Davis within 2 h of harvest. Upon arrival in the laboratory, fruit with stems attached were sorted for uniform appearance quality and only those with a lack of defect, such as splits, sunburn, bruises or cuts, were selected for study. Three hundred fruit per variety were selected for their broad range of external color, assuming a broad range of ripeness, DMC and SSC for consumer taste testing and destructive quality analysis.

In 2015, cherry samples from the same varieties were harvested to build and test a model using NIR spectroscopy to predict SSC and DMC. Fruit of each variety were chosen using the same criteria as in 2014 for NIR spectra collection and destructive quality analysis for the reference dataset and NIR model building. An independent set of 100 fruit per variety were also sampled at commercial harvest to provide an external validation set to test the final NIR models. All fruit were cold-stored at 0 °C for 16 h before NIR assessment or consumer sensory evaluation.

2.2. Consumer evaluation

A total of 535 untrained consumers of sweet cherries participated in the tasting. Two taste sessions were conducted on the University of California Davis campus, one per variety. The total number of consumers that participated in each test was 243 for 'Chelan' and 292 for 'Bing'. Twenty six to 43% of the consumers were male and 57% to 74% were female. More than 75% of the individuals surveyed were within the ages of 18 and 25, 13% to 16% were between 26 and 49 and only 4% to 9% were age 50 and above. At the beginning of the session, tasters had to respond to the question 'which is the most important factor you consider when purchasing cherries?' with the options "flavor", "price", "nutritional content" or "none of these", with an additional space to freely add a different factor. Bottled mineral water and unsalted crackers were provided as a palate cleanser before tasting the sample. At each session, every panelist received one half of a single fruit from one of the three stages of ripeness to evaluate. The remaining half of the fruit was used for determination of SSC and DMC as described below. The samples were randomly selected and the taster was not able to see or try any other samples to prevent any influence from comparison, order or carryover. Assessments were made using 10 cm line hedonic scales, where '0' represented 'dislike very much' and '10' represented 'like very much' for the attributes 'sweet and sour balance', 'intensity cherry flavor' and 'overall quality'. To avoid bias, consumers did not receive any monetary incentive for participation.

2.3. Spectral measurements

Interactance spectral measurements from the fruit selected for model building were taken on opposite cheeks of the same fruit at 0, 5, 20 and 25 °C, in this order. Measurements were made on the widest part of the fruit at its equator: point 1) 'suture' side and point 2) directly opposite. To make sure that the model set of fruit was at the correct temperature before measurement, a set of additional cherries handled in the same manner were monitored with a fruit probe thermometer (Dual Probe Temperature Tester SH44A, Cooper Instruments, Warrenton, VA, USA). Three models per variety and trait were developed from the dataset: cold model (C; 0 and 5 °C data), room temperature model (RT; 20 and 25 °C data) and cold + room temperature model (C + RT; 0, 5, 20 and 25 °C