Application of hue spectra fingerprinting during cold storage and shelf-life of packaged sweet cherry

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Abstract

Presented work investigated the application of a new color analysis technique in post-harvest life of sweet cherry (*Prunus avium* L. ‘Hudson’). The hue spectra fingerprinting creates a histogram of image colors by summarizing the saturation. The advantage of this calculation method is that vivid colors make peaks while neutral background color is eliminated without object segmentation. Partial Least Squares (PLS) regression was used to estimate reference parameters during 9 d cold storage at 10 ± 0.5 °C ($RH = 90 \pm 1\%$) and following 2 d shelf-life at 20 ± 0.5 °C. The reference parameters of respiration, weight loss, fruit firmness and total soluble solid (TSS) content were measured. Samples were split into seven groups according to the number of perforations of polypropylene film and fructose concentration of moisture absorber. It was observed that parameters TSS and fruit firmness were the most sensitive to the length of storage. Weight loss was affected significantly by packaging. All reference parameters were estimated by PLS model with $R^2 > 0.917$, but weight loss and respiration obtained high estimation error of $RMSE\% = 48.02\%$ and 11.76% , respectively. TSS and fruit firmness prediction were successful with $RMSE\% = 0.84\%$ and 1.85% , respectively. Desiccation and color change of peduncle became visible in the green range of hue spectra. Color change of red fruit was observed with decreasing saturation in the red range of hue spectra. Our findings suggest that hue spectra fingerprinting can be a useful nondestructive method for monitoring quality change of sweet cherry during post-harvest handling and shelf-life.

Keywords Surface color · *Prunus avium* L. · Computer vision · Digital image processing

Introduction

Sweet cherry (*Prunus avium* L.) is very popular and consumed as fresh fruit. The characteristic red color is the major quality attribute and primarily affects consumer acceptance [1–3]. Additionally, cherry contains valuable bioactive compounds, mainly anthocyanins [4, 5]. The quality assignment based on visual observation is supported by the fact that

anthocyanins are the red color pigments of cherry and also contribute to the antioxidant capacity of fruit [6]. Cherry is highly perishable produce and its shelf-life is typically limited in weeks [7]. During the supply chain, appearance changes rapidly by means of color, gloss, surface pitting and peduncle browning [8]. Especially the latter parameter is interesting since peduncle browning was found to reflect changes in water status of peduncle itself and fruit body as well. As a result, color measurements shall include evaluation of both fruit body and peduncle.

The optimum harvest date was estimated by utilizing color for sweet cherry ‘Burlat’ [9], and using pigment specific spectral parameters for ‘Samba’ and ‘Bellise’ [10]. Genetic algorithm utilizing reflectance spectra, including visible range from 580 nm, was able to detect insect infestation of tart cherry above 81% accuracy [11]. Significant change of fruit color was observed for ‘Napoleon’ cherry during cold storage by means of CIELAB a^* , b^* and chroma, but no correlation was found with anthocyanin content [12]. It was observed, that large and more colored

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sweet cherry ‘Kordia’ reached higher amount of edible part with better sugar/acid ratio [13]. More colored fruits were found to be larger (> 8 g, $> \varnothing 26$ mm) and have more soluble solid content (SSC), sugars and anthocyanins compared to less colored ones. On the other hand, neither color nor fruit size affected vitamin C content and amount of total phenolic compounds. Additionally, no significant difference was found in firmness between fruit of different color [13]. The sweet cherry ‘Brooks’ was tested with sensory analysis by trained panel and consumers during 1997–1999 [14]. Trained panel distinguished 4 groups of cherry of different peel color according to the fruit sweetness and cherry flavor intensity. Untrained consumers preferred cherry with $\text{SSC} > 16\%$ and their answers shown significant correlation between peel color and all sensory attributes (sweetness, sourness, cherry flavor intensity). Both sweetness and flavor intensity correlated the best with chroma ($r = -0.976$ and -0.995 , respectively) while sourness obtained the highest correlation with hue among visual attributes ($r = 0.906$). According to the results for ‘Brooks’ and ‘Bing’ sweet cherry, Crisosto et al. [1] concluded that growers should measure SSC at different fruit color to optimize harvesting. The relationship between instrumentally measured color and anthocyanin concentration was evaluated for four cherry cultivars [15]. Standard CIELAB parameters chroma and hue significantly correlated with anthocyanin concentration but not with total phenols. Pre-harvest color rating method was developed for cherry by Wang et al. [16]. The computer vision system calculated ratings were compared to manual scores. The correct rating was over 85% consistently. The major obstacle of surface reflections and inconsistent light in the canopy was solved with camera flash. Finally, seven levels of peel color were distinguished successfully by the system [16]. Instrumental color analysis usually results in standard CIELAB parameters L^* , a^* and b^* [9]. Technology specific color indices, such as browning index, can be calculated from both standard a^* , b^* and changing intensity of images [17]. Fruit color is typically represented by derived parameters of a^* and b^* , namely hue and chroma [3, 13–15, 18]. The relationship between SSC and visual appearance plays an important role in determining consumer acceptance of cherry fruit [1]. However, the number of studies evaluating the mathematical relationship between color and reference parameters of cherry is still limited.

Above mentioned studies show that sweet cherry color, measured on fruit surface, reflects fruit quality and has firm relationship with some key parameters such as anthocyanin concentration, sweetness, fruit specific flavor. Besides fruit surface color, peduncle (stem) color is also a freshness indicator influencing directly the consumer acceptance. Therefore all visible parts of harvested fruit should be included in the evaluation. In this context, the aim of this presented work was to apply hue spectra fingerprinting method on

color images to estimate common reference parameters. Cold storage and shelf-life was followed in the experiment to induce changes and evaluate feasibility of the method in monitoring quality.

Materials and methods

Materials

Sweet cherries (*Prunus avium* L. ‘Hudson’) were harvested at the commercial maturity stage from the farm of Leibniz Institute for Agricultural Engineering and Bioeconomy (Marquardt, Germany) in July, 2019. Collected samples were transported to the laboratory within an hour. Cherries of approximately $\varnothing 25$ mm size, free from damage, greenish stems and uniform external appearance were selected. Fruit were precooled to 10°C .

Samples of 200 ± 5 g were packed in polypropylene tray of 16 cm length $\times$ 11 cm width $\times$ 5 cm depth. Trays were randomly separated into 7 groups (Table 1). One group with open tray served as control during the experiment. The remaining six groups were covered with bi-axially oriented polypropylene film of 25 μm thickness. The lid film was perforated with one or three micro-perforations of $\varnothing 0.7$ mm using a needle. As a result, three groups were perforated with one hole and other three groups with three holes. Additionally, each perforation group was randomly split into three sub-groups. Different absorbers were applied for the sub-groups in order to control humidity inside the package. This is important because the temperature fluctuation during storage or transport causes moisture condensation inside the packages leading to high humidity surrounding the produce, favoring for microbial development [19, 20]. Fructose is hygroscopic and absorbs moisture from the package headspace therefore avoids near saturation condition in package. Cellulose fiber with 30% and 90% of fructose was selected because moisture uptake by absorber was proportional to the concentration of fructose embedded in the FruitPad

Table 1 Sample groups of cherry according to packaging and moisture absorber

Absorber	Micro-perforations		
	Open tray	1	3
None	Control		
None		1-NA	3-NA
30% fructose		1-FP30	3-FP30
90% fructose		1-FP90	3-FP90

Group names show number of perforations, followed by: NA no absorber, FP30 FruitPad with 30% fructose, FP90 FruitPad with 90% fructose

(McAirLaid's Vliesstoffe GmbH, Steinfurt, Germany) [21]. Moisture sorption was expressed as g water per g FruitPad.

The seven groups were expected to show different behavior over storage and help evaluation of hue spectra fingerprinting with wide range of data. All samples were stored at 10 ± 0.5 °C with relative humidity (RH) of $90 \pm 1\%$ for 9 d and additional 2 d for shelf-life at ambient temperature of 20 ± 0.5 °C. Measurements were performed upon arrival to laboratory (0 d), during cold storage (3, 6 and 9 d) and subsequent shelf-life (11 d).

Reference measurements

Headspace gas concentration

Three trays per group were randomly withdrawn from storage and the headspace gas concentration of O₂ and CO₂ in the package were measured. One needle was pierced into the package, then gases were pumped out through the needle and injected into gas analyzer (CheckMate3, Dansensor, Denmark). Results were expressed as percentage of O₂ and CO₂ inside the package [22].

Respiration

Carbon dioxide release from the cherries was measured in a closed respiratory system over 3 h in closed Perspex® cylinders with infra red sensors (FYA600CO2, Ahlborn Mess- und Regeltechnik GmbH, Holzkirchen, Germany). From the increase in CO₂ concentration over time, respiration activity was calculated as milligram of CO₂ produced per kilogram of fruit in 1 h (mg CO₂ kg⁻¹ fruit h⁻¹) [8].

Weight loss

Weight loss was determined by weighing the cherries at the beginning of the experiment and each interval with an electronic balance (BP 210 S, Sartorius AG, Göttingen, Germany). Results were expressed as percentage loss of initial readings according to Serrano et al. [3].

Firmness

Fruit firmness was measured with TA.XT.plus Texture Analyzer (Stable Microsystems, UK) instrument. Firmness of cherry was determined using a spherical steel probe (Ø6.35 mm). Force, deformation and time data were

recorded, from which firmness was calculated as the maximum force used to achieve 2% deformation of the fruit diameter [3].

Total soluble solid content

Total soluble solid (TSS; %) content was obtained with a digital refractometer (ATAGO PR 1, Leo Kuebler GmbH, Karlsruhe, Germany) using freshly squeezed liquid according to Rux et al. [23].

Digital image processing

Images of Full HD size (1920 × 1080 pixel) were captured using a color camera (Samsung WB350F). Optical zoom of 4.0 was adjusted. Samples of 8–12 fruit were placed on white background at the same time. This background was used as color reference and all images were adjusted to have the same white balance. Pictures were processed using GNU Octave (version 4.4.1) software [24]. After white balance adjustment, the whole picture was scanned and hue spectra fingerprint was collected as summary of saturation for all hue values (Eq. 1).

$$F(i) = \frac{1}{N} \sum_{x,y} S(x,y)^{H(x,y)=i}_{S(x,y)>0.05} \quad (1)$$

where N is the number of pixels, $F(i)$ is the value for hue angle i , $S(x,y)$ is the saturation value for pixel at coordinates x and y , and $H(x,y)$ is the hue angle for pixel at coordinates x and y . Hue and saturation are calculated for each pixel according to the following equations (Eq. 2).

$$H = \tan^{-1} \frac{b}{a}, S = \sqrt{a^2 + b^2}, a = R - \frac{G+B}{2}, b = \frac{\sqrt{3}(G-B)}{2} \quad (2)$$

where H is the hue angle in 0–360°, S is the saturation scaled in 0–1, and R , G , B are red, green and blue intensity values, respectively. The Octave function `atan2` can avoid failure with division by zero.

The advantage of the calculation is that neutral colors, such as black and white, have zero saturation, therefore they are not visible on spectra. In order to remove potential noise, the threshold value of 5% was applied with $S(x,y) > 0.05$. As a result, $F(i)$ has peaks at the observed colors and zero value for others. This data vector has 360 elements for hue angle in the range of 0–360°. Color change is expected to move peaks and changing homogeneity will alter width of peaks. This hue spectra is the color representation of the picture, like a fingerprint. This data vector can be processed with all mathematical tools used in chemometry and spectra analysis. Since neutral pixels of low saturation are removed, computation can be

fast because there is no need for segmentation and object recognition.

Statistical evaluation

The statistical software of R (version 3.6.2, R Foundation for Statistical Computing, Vienna, Austria) was used with package Partial Least Squares and Principal Component Regression (PLS, version 2.7–2) [25]. Groups were compared with Analysis of Variances (ANOVA) and significant differences were tested with Tukey's post-hoc test ($p < 0.05$). Effectiveness of PLS prediction was evaluated with determination coefficient (R^2) and root mean squared error (RMSE). Figures represent data with mean value and standard deviation (SD).

Results

Hue spectra

Sweet cherry has dark red color on fruit surface and its stem is green (Fig. 1a), therefore two color segments were expected to show peaks on the spectra. It was observed, that peaks became smaller due to the color change from vivid red or green toward dark color and they also moved along hue angle during storage and shelf-life (Fig. 1b). Especially the stem, changed its color and moved peak from green toward brown.

Hue spectra was used to build PLS prediction models for reference parameters. The PLS loadings confirmed that data below 100° and above 320° contributed to the models.

Fig. 1 Sweet cherry sample arranged in front of the camera (a) and average hue spectra at the beginning and end of the experiment (b)

Headspace gas concentration and respiration

Headspace O_2 concentration decreased to 15.5% during cold storage and finally to 10.0% after shelf-life. At the same time, CO_2 concentration increased to 3.6% during cold storage and reached approximately 10.0% after shelf-life (data not shown).

The respiration rate for all samples increased during the experiment (Fig. 2). Groups overlapped each other during cold storage, and separated according to the number of perforations in shelf-life. Considering all respiration rate data, there was significant difference among certain perforation groups (ANOVA $F=9.442$, $p<0.001$). Moisture absorber did not contribute significantly to the changes of respiration rate.

The respiration rate increased rapidly at ambient temperature, after 9 d. As a result, readings did vary from 14.74 to 47.89 $mg\ CO_2\ kg^{-1}\ h^{-1}$. PLS model was created to estimate respiration data based on surface color represented by hue spectra. The number of latent variables (LV) was adjusted to 30, which is 8.33% of the data vector. Data did not distribute uniformly within the range, but model obtained good result with $R^2=0.917$ and $RMSE=2.42\ mg\ CO_2\ kg^{-1}\ h^{-1}$. Figure 3 shows the PLS prediction result in comparison with collected data. There is some fluctuation, but majority of data at respiration below 22 $mg\ CO_2\ kg^{-1}\ h^{-1}$ was estimated well and resulted in the relative prediction error of $RMSE\%=11.76\%$.

Fruit firmness

The firmness of all samples decreased slightly throughout 9 d of cold storage, followed by a stronger decline in shelf-life,

particularly for control fruit (Fig. 4). Control fruit became the softest and packaging could slow down softening process. There was difference between certain groups, but no clear separation was found according to the number of perforation. Observed behavior of cherry firmness is in agreement with literature [26]. Moisture absorber did not affect cherry firmness significantly.

PLS model was created to estimate fruit firmness based on the hue spectra of color images ($LV=30$). The model fits well to data points ($R^2=0.971$) with small error of $RMSE=0.024\ N$. Prediction result is presented in comparison with collected data on Fig. 5. Small fluctuation of prediction is visible, but model accuracy is very good with $RMSE\%=1.85\%$. Firmness was found to have strong linear correlation with total soluble solid content ($r=-0.924$).

Total soluble solid content

Total soluble solid content of sweet cherry increased gradually over cold storage period for all samples, later on more rapidly when moved to ambient temperature ($20\pm0.5\ ^\circ C$). There was high variability within sample groups and average readings were close (Fig. 6). Comparing the initial and final values, significant differences can be observed among certain groups. However, no clear distinction can be made due to the large overlap of data. Obtained results of TSS are in agreement with literature [7]. The range of TSS accounts for 11–20° Brix and it typically remains almost in the same range during cold storage or modified atmosphere packaging.

PLS model was created to estimate TSS content of sweet cherry ($LV=30$) based on hue spectra (Fig. 7). This model fits data with $R^2=0.960$, and the prediction error of

Fig. 2 Respiration rate of sweet cherry during 9 d cold storage and 2 d shelf-life

Fig. 3 PLS prediction result of respiration rate based on hue spectra

Fig. 4 Firmness of sweet cherry during 9 d cold storage and 2 d shelf-life

Fig. 5 PLS prediction result of fruit firmness based on hue spectra

Fig. 6 Total soluble solid content of sweet cherry during 9 d cold storage and 2 d shelf-life

RMSE=0.13%. The relative error was the smallest among other reference parameters with RMSE%=0.84%. Besides the strong relationship with fruit firmness, TSS correlated significantly with respiration ($r = 0.827$).

Weight loss

The weight loss of all samples increased during cold storage and shelf-life (Fig. 8). There was significant difference

Fig. 7 PLS prediction result of total soluble solid content based on hue spectra

Fig. 8 Weight loss of sweet cherry during 9 d cold storage and 2 d shelf-life

Fig. 9 PLS prediction result of weight loss based on hue spectra

between control group and others in any packaging. Fruit covered with perforated foil suffered weight loss of 0.64% within 6 d and 1.92% after shelf-life, while control fruit obtained 1.75% within first 6 d and 6.97% final value after shelf-life.

There was significant difference in weight loss between control and the other groups (ANOVA $F = 96.434$, $p < 0.001$). Significant correlation was observed between weight loss and firmness ($r = -0.867$) and TSS ($r = 0.745$).

Weight loss was also estimated by PLS model (LV = 30) based on hue spectra (Fig. 9). The determination coefficient was high ($R^2 = 0.925$) but estimation error reached $RMSE = 0.33\%$. Especially at low values, the prediction error is high resulting in the relative error of $RMSE\% = 48.02\%$. According to these result, weight loss could not be estimated using surface color.

Role of moisture absorber

The FruitPad absorbed moisture from the environment of fruit (Fig. 10). No sign of water condensation was observed for packages with FruitPad, whereas condensed water occurred on the inner part of lid film at 5 d of cold storage for the packs without FruitPad. Small fluctuation of

temperature can result in condensation with high RH, its prevention is critical [7]. Fructose concentration of absorber did not result significant effect on measured parameters. Observed differences in sorption curves (Fig. 10) show the response of absorber to environment inside packaging.

As a result, the combination of perforations and moisture absorbers provided adequate packaging to prolong shelf-life of sweet cherry.

Comparison of parameters

The reference parameters showed strong relationship to each other according to Pearson correlation coefficient (Table 2). The agreement of parameters clearly indicates the quality change of sweet cherry during the experiment.

There was difference among the reference parameters in terms of response to storage time, number of perforations on packaging and absorber concentration. According to the Fisher score of ANOVA, parameters TSS and firmness were more sensitive to the length of storage, while weight loss showed clear difference based on packaging (Table 3).

All PLS prediction models used the same number of latent variables (LV = 30). The number of latent variables is only 8.33% of the available hue spectra data. All models

Fig. 10 Moisture sorption of FruitPad used in packaging **Table 2** Linear correlation (Pearson) coefficient of reference parameters

	Weight loss	TSS	Firmness
Respiration	0.471**	0.827***	-0.782***
Weight loss		0.745***	-0.867***
TSS			-0.924***

**p < 0.01

***p < 0.001

reached high determination coefficient ($R^2 > 0.917$), but two models can be considered successful with the relative prediction error of $RMSE\% < 2.00\%$. Collected data represent one harvest and season, therefore validation was performed according to the sample groups (Table 1). PLS models were created excluding data of a specific group and estimation of parameters of selected group was used for validation. Evaluation of firmness prediction model by groups is summarized in Table 4. The total number of evaluated pictures were 124, including the initial 12 taken

Table 3 Sensitivity and prediction results of reference parameters

Reference parameter	ANOVA F			PLS regression (LV = 30)		
	Time	Packaging	Absorber	R ²	RMSE	RMSE (%)
Total soluble solid	883.495	10.070	8.772	0.960	0.13	0.84
Firmness	806.993	17.049	0.024	0.971	0.024	1.85
Weight loss	577.233	96.434	0.014	0.925	0.33	48.02
Respiration	204.302	9.442	0.006	0.917	2.42	11.76

Table 4 Firmness prediction model and validation on sample groups

Sample group	N	Calibration*			Validation**		
		R ²	RMSEC	RMSEC (%)	R ²	RMSEV	RMSEV (%)
Control	20	0.976	0.019	1.51	0.450	0.153	12.36
1-NA	13	0.980	0.020	1.62	0.674	0.086	6.36
3-NA	18	0.978	0.021	1.64	0.734	0.072	6.13
1-FP30	15	0.978	0.021	1.66	0.796	0.084	6.15
1-FP90	15	0.983	0.019	1.47	0.657	0.088	6.54
3-FP30	15	0.975	0.022	1.82	0.755	0.079	6.73
3-FP90	16	0.982	0.019	1.45	0.640	0.115	8.78

*Calibration model is built excluding selected group, model is tested on the others

**Validation is performed only on the selected group

Table 5 Total soluble solid content prediction model and validation on sample groups

Sample group	N	Calibration*			Validation**		
		R ²	RMSEC	RMSEC (%)	R ²	RMSEV	RMSEV (%)
Control	20	0.974	0.11	0.69	0.438	0.55	3.49
1-NA	13	0.976	0.10	0.64	0.526	0.48	3.02
3-NA	18	0.967	0.12	0.78	0.847	0.32	2.00
1-FP30	15	0.967	0.12	0.77	0.782	0.34	2.15
1-FP90	15	0.979	0.10	0.60	0.758	0.41	2.69
3-FP30	15	0.971	0.11	0.72	0.729	0.36	2.27
3-FP90	16	0.969	0.12	0.74	0.700	0.35	2.22

*Calibration model is built excluding selected group, model is tested on the others

**Validation is performed only on the selected group

before separation of sample groups. Calibration models obtained high R^2 with the average of 0.979 and low average relative error of $RMSEC\% = 1.60\%$. Validation of groups reached lower average R^2 of 0.672 and higher average relative error of $RMSEV\% = 7.58\%$. Especially validation of control group, stored in open tray, was less successful with $RMSEV\% = 12.36\%$.

Evaluation of PLS model performance on TSS prediction is presented in Table 5. Calibration models obtained high R^2 with average of 0.972 and low average relative error of $RMSEC\% = 0.71\%$. Similar to firmness validation results, TSS validation also reached lower R^2 and higher error. The determination coefficient fell to similar average of $R^2 = 0.683$ like that of firmness, but relative error of validation did not increase so high with average of $RMSEV\% = 2.52\%$. All group validation achieved small relative error of $RMSEV\% < 3.5\%$.

Total soluble solid content and fruit firmness prediction obtained promising results in calibration (Table 3). Validation confirmed the potential of TSS prediction using hue spectra fingerprinting (Table 5). Firmness prediction achieved error above 5% but average was less than 10% (Table 4). Both TSS and firmness estimation based on hue spectra of fruit and peduncle can be recommended for monitoring, but TSS model outperformed all others.

Discussion

Sweet cherry is very sensitive, perishable produce with short shelf-life. Its storage potential is low and limited in few weeks even under optimal conditions [27]. Consequently, several studies investigated potential techniques to prolong postharvest life. Near freezing temperature of $-1.5\text{ }^{\circ}\text{C}$ and $-1.9\text{ }^{\circ}\text{C}$ were used to maintain physicochemical parameters of sweet cherry ‘Hongdeng’ and ‘Lapins’, respectively [18]. This cold storage obtained better firmness, TSS, acidity and decrease weight loss for 100 d storage than that of $0\text{ }^{\circ}\text{C}$ and $5\text{ }^{\circ}\text{C}$. Near freezing temperature requires accurate control

of $\pm 0.1\text{ }^{\circ}\text{C}$ to decrease fluctuation and avoid damage induced by ice crystals. Storage temperature of $1\text{ }^{\circ}\text{C}$ was found to be effective in control of biosynthesis of anthocyanins [28]. The combination of cold storage temperature and modified atmosphere packaging was able to delay the ripening according to firmness, weight loss and color change [3]. Sweet cherry stored at $1\text{ }^{\circ}\text{C}$ and $RH = 90\%$ (with additional 1 d shelf-life at $20\text{ }^{\circ}\text{C}$) responded sensitively to essential oils in modified atmosphere packaging. Natural antifungal agents of eugenol, thymol, menthol and eucalyptol affected significantly the changes of respiration, weight loss, chroma index and firmness [3]. In our work, the common physicochemical parameters, measured as reference, were in agreement with literature: respiration, soluble solid content, weight loss and firmness. Studies investigating cherry quality typically measure color as a quality index related to anthocyanins and ripeness. Color is also considered to be the most important parameter determining acceptability by consumers [2]. Consumers are looking for cherry with red fruit color and green stem [1]. However, application of color measurement in estimation of quality parameters of cherry is still limited. Muskovic et al. [29] found exponential relationship between firmness and CIELAB hue angle ($R^2 = 0.923$) for sweet cherry during fruit development and ripening. They found that hue angle of fruit surface change follows logistic curve within 30–70 d after anthesis for ‘Alex’, ‘Carmen’ and ‘Krupnoplodnaja’ cherry. The inflection point of the curve was suggested for characterizing the fruit development process. This firmness model is limited to the time of fruit development.

Crisosto et al. [1, 14] obtained significant correlation between appearance and sensory attributes of cherry. Four groups of cherry were made based on color as full light red, 50% bright red, full bright red and full dark red for ‘Brooks’, and salmon, red, mahogany, dark mahogany for ‘Bing’. Reference parameters of TSS, titratable acidity, pH, weight and firmness were found to be different for selected groups. Although authors concluded that red color and $SSC > 16\%$ were preferred the most by expert panel and consumers,

no model was created for prediction. In another study, hue, chroma and brightness (L^*) changes during storage were in agreement with chemical (ascorbic acid content, total anthocyanins content), physical (weight loss, firmness) and sensory (juiciness, texture, acceptability) parameters according to reported statistical analysis [18]. ANOVA test was performed to evaluate contribution of storage temperature and storage time to consumer acceptance and sensory attributes. However, no further analysis of mathematical relationship with color was presented. Hue spectra fingerprinting obtained similar agreement among measured parameters and resulted in estimation models. Computer vision is able to measure color and its pattern on the whole visible surface to evaluate ripeness, detect defects [16, 30]. Surface color analysis usually include removal of glaring reflection and segmentation of region of interest (fruit and stem) [16]. These procedures are not necessary with hue spectra fingerprinting, since low saturation areas (surface reflection, white or gray background) are removed due to the low saturation. The green stem was identified as one expectation of consumers [1], and it was proved to indicate water status and quality of sweet cherry fruit [8]. The water loss via peduncle was found to be around 40% at the beginning of shelf-life and decrease exponentially. Strong relationship was observed between water content and maximum photochemical efficiency (F_v/F_m) during storage [8]. Authors concluded that water deficit contributes 73% to the reduction of the photochemical efficiency. Peduncle has low resistance to vapor transfer and causes much higher water loss than fruit body, therefore stem color change is an important freshness indicator and it should be included in the quality evaluation. In agreement with this demand, hue spectra includes all visible colors of the picture in analysis, like a color fingerprint. Our results are coincident with previous study on peduncle [8], since hue spectra showed peaks in green color range and those peaks changed during cold storage and shelf-life. Green peaks of the hue spectra moved to lower hue values and peak values decreased due to the lower saturation as stem lost its fresh green color. The PLS prediction models also obtained valuable loadings (model coefficients) in green and red color range. The previously reported color change of stem from green to brown was observed in this work as well.

Overbeck et al. [10] predicted optimal harvest date of sweet cherry 'Samba' and 'Bellise' with ± 2 d on the basis of NDVI (normalized chlorophyll index) and NAI (anthocyanin index) spectroscopic parameters. The Vis/NIR spectroscopy is able to predict SSC and fruit firmness, based on the specific pigment absorbance change during storage [31–33]. The advantage of spectroscopy is its high accuracy which is also reflected by the prediction quality ($RMSE\% < 1\%$). Hue spectra fingerprinting also covers the visible color range in 400–900 nm, depending on the camera sensor. Color camera offers limited color range and lower accuracy compared to

a spectroscopy instrument, but on the other hand, is able to measure on the whole fruit surface and stem color as well. Colorimeter and spectrophotometer instruments collect data only from the selected small surface area. Due to the size limitation of this technique, typically fruit body color is measured, neglecting the stem color. Similarly to reflectance spectra, hue spectra was utilized in PLS models. Single type of PLS with $LV = 30$ was used to apply one method to all parameters. The relatively high number of LV is probably the result of narrow peaks that change location, width and value with changing color.

Weight loss was predicted with good $R^2 = 0.925$ but high relative error of $RMSE\% = 48.02\%$. The value of weight loss was small and moderately increased during cold storage and control fruit accelerated at ambient temperature. The significant correlation of weight loss with TSS and firmness indicate that fruit reached advanced ripening. The significant difference between open tray control and packaging groups shows the advantage of applied packaging (absorber and perforations). Control group exceeded accepted 3% of weight loss [34] already in cold storage, while packed fruit were below 2.00% within 11 d, including 2 d shelf-life. Observed weight loss and fruit behavior is similar to that of for carrot [35]. Moisture absorber did not affect significantly weight loss of sweet cherry.

Respiration obtained better estimation but still high relative error of $RMSE\% = 11.76\%$. Similar tendency was observed for respiration with small changes in cold storage and sharp increase in shelf-life. The distribution of data was not balanced, what is likely to contribute to the low prediction efficacy.

Fruit firmness decreased gradually and more rapidly after withdrawal to ambient temperature. Open tray control fruit obtained the smallest firmness values and had stronger decline than others in shelf-life. This behavior is in agreement with previous study on cherry [26]. The PLS calibration of fruit firmness estimation achieved the best $R^2 = 0.971$ and small relative error of $RMSE\% = 1.85\%$. Validation of firmness prediction model was less successful with $RMSEV\% = 7.58\%$, but still can contribute to quality monitoring.

Total soluble solid content showed similar tendency, changed gradually during cold storage and shelf-life. The calibration of TSS estimation achieved $R^2 = 0.960$ and the best $RMSE\% = 0.84\%$. The TSS prediction model outperformed all others including good validation result of $RMSEV\% = 2.52\%$. It can be observed, that gradually changing reference parameters of fruit firmness and TSS obtained good prediction. Both parameters can be estimated using fruit and peduncle color.

The results are in agreement with literature in terms of the best prediction of TSS like the Vis/NIR analysis of fruit quality [32]. Our observations suggest that hue spectra

fingerprinting is a useful and rapid method for color analysis based on the combination of digital image processing and chemometrics. This non-contact and nondestructive measurement can be applied in online sorting and commercial practice.

Conclusions

Hue spectra fingerprinting represented the color of sweet cherry fruit and peduncle as well. The peaks of specific colors moved position and became wider with changing fruit color, and peak values reduced with decreasing color saturation. The reference parameters of respiration, weight loss, firmness and total soluble solid (TSS) content were measured during the experiment. Firmness and TSS changed gradually and values were distributed more evenly than that of respiration and weight loss. This behavior affected probably the prediction quality of PLS models. Firmness and TSS obtained acceptable small relative error. Firmness obtained the best $R^2=0.971$ and TSS obtained the best $RMSE\%=0.84\%$. Both red and green color ranges contributed to prediction models confirming the importance of peduncle color in evaluation of fruit quality. Hue spectra fingerprinting can be suggested for rapid and nondestructive monitoring of fruit quality during postharvest processes and shelf-life.

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Author contributions LPLN: measurement, data analysis and manuscript editing. AV: control measurement and data analysis. LB: data analysis and manuscript editing. LF: manuscript editing. PVM: design of experiment and manuscript editing.

Data availability Not included, available upon request.

Compliance with ethical standards

Conflicts of interest Authors declare no conflict of interest.

Informed consent Not applicable.

Code availability Not included, R scripts are available upon request.

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