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[1]Department of Horticulture and Food Technology, University of Applied Sciences Weihenstephan-Triesdorf, Freising, Germany
[2]Department of Applied Artificial Intelligence, Deggendorf Institute of Technology, Technology Campus Grafenau, Grafenau, Germany
[3]Division Urban Plant Ecophysiology, Faculty of Life Sciences, Humboldt-Universität zu Berlin, Berlin, Germany

Evaluating the practicability of commercial food-scanners for non-destructive quality assessment of tomato fruit

Simon Goisser[1,3], Michael Fernandes[2], Sabine Wittmann[1], Christian Ulrichs[3], Heike Mempel[1]*

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Summary

The assessment of tomato fruit quality depends on a variety of extrinsic and intrinsic quality parameters such as color, firmness and sugar content. Conventional measurement methods of these quality parameters are time consuming, require various measurement devices, and in case of intrinsic quality, involve destructive measurements. Latest research focused on the non-destructive determination of these parameters by using spectroscopic measurements. The goal of this study was to evaluate the capability of three commercially available portable and miniaturized VIS/NIR spectrometers, so called food-scanners, in predicting various tomato quality attributes in a non-destructive way. Additionally, this study evaluated the software provided by manufacturers for building of prediction models by comparing the results derived from those software tools to state-of-the-art software for multivariate analysis. Evaluation of food-scanner spectra resulted in prediction models of high accuracy ($r^2 > 0.90$) for tomato fruit firmness, dry matter, total soluble solids and color values L*, a* and h°. Prediction models computed with manufacturer's software showed similar accuracy to those derived from state-of-the-art evaluation software. Results of this study illustrate the great potential of commercial food-scanners for non-destructive quality measurement. Further important features of food-scanners with respect to the application along the fresh produce supply chain are addressed.

Keywords: NIR spectroscopy; tomato; quality control; non-destructive measurement; food-scanner

Introduction

Fresh tomato fruit (*Solanum lycopersicum* L.) is the vegetable species most consumed in Germany in terms of quantity with an average amount of 2.3 Mio t per year (Statista, 2019). When it comes to cultivation, distribution and marketing of tomatoes, various commercial quality parameters are of high relevance. These commercial quality attributes differ depending on the position in the supply chain. Producer prioritize qualities beneficial for an unproblematic cultivation of plants such as disease resistance, cultivation work, fruit weight, fruit size and appearance. In order to meet the requirements of a demand driven supply chain, additional postharvest characteristics such as uniformity, shape, color and firmness as well as shelf life are of importance (Folta and Klee, 2016). From the perspective of the consumer, taste and flavor are relevant quality attributes, and lack of flavor was identified as the primary reason for consumer dissatisfaction for tomatoes (Bruhn et al., 1991). A recent study on consumer acceptance of tomatoes cultivated for fresh consumption attested the importance of sensory traits like juiciness, sweetness and taste intensity, which influence consumer purchase preference (Casals et al., 2019). Additionally, tomato firmness and color are vital quality parameters which influence acceptability and marketability (Batu, 2004).

Some of the above mentioned quality parameters of tomato fruit must meet certain standards within the European Union regarding the marketing and commercial quality control (BLE, 2019). Besides these standards required by law, retail companies impose additional requirements which oftentimes exceed those statutory provisions. These provisions regarding quality relate primarily to extrinsic attributes that are important for marketing and trading, e.g. appearance or absence of damage and deterioration. Firmness is used as an indicator for the classification of tomatoes into three classes (Extra, Class I, Class II), yet the quoted indications „firm, reasonably firm, slightly less firm than Class I" and severity of defects (UNECE, 2018) are prone to subjectivity. Visual and haptical impressions dominate quality assessment along the fresh fruit supply chain, therefore the evaluation of these traits highly depends on experience of staff in quality control (Goisser et al., 2020a). The application of instrumental measurements for these commercially important traits could help to reduce the variation between individual controller, offer higher precision and supply a standardized language of fruit quality among industry, consumers and research (Abbott, 1999). Furthermore, the measurement of intrinsic quality parameters such as sugar content (°Brix) as well as acidity, which relate to tomato flavor and sweetness (Causse et al., 2007), could allow the estimation of sensory traits such as tomato taste.

Traditional instrumental measurement methods of extrinsic and intrinsic quality parameters are often time consuming and require trained personal in combination with various measurement devices. The determination of firmness via penetrometer and sugar content per refractometer demands destructive measurement methods, in the case of acidity handling of chemicals is necessary for titration. Besides these destructive measurement methods of internal quality parameters, optical measurement methods like visible and near infrared (VIS/NIR) spectroscopy have been successful in determining important quality parameters of agricultural and horticultural products. NIR spectroscopy can be applied for qualitative applications, such as identification and classification of samples, as well as quantitative applications in order to determine major constituents in samples such as fruit and vegetables (Pasquini, 2003). As emphasized in the recent guidelines on objective tests for fruit and vegetables (OECD, 2018), NIR spectroscopy comprises the ability to simultaneously predict multiple quality attributes using only a single spectrum, therefore serving as multidimensional predictor of fruit quality. A summary provided by dos Santos et al. (2013) highlights successful reported applications for analysis of various quality attributes along a variety of fruit and vegetable species using portable spectrometers instead of traditional laboratory NIR devices. Ongoing technological developments promoted the miniaturization and commercialization of NIR sensors, so called food-scanners. Some of these devices are particularly designed for end-consumers and should enable them to identify macronutrients, allergens, calories or food contaminants (Rateni et al., 2017).

First studies on the predictability of individual tomato quality para-

* Corresponding author

meters such as sugar content and lycopene (SHENG et al., 2019; GOISSER et al., 2020b) using portable handheld NIR spectrometers indicate the potential of these miniaturized devices for non-destructive quality evaluation. Commercially manufactured portable NIR instruments are relatively new and previous research either compared the performance of various instruments for the prediction of single quality traits such as dry matter (KAUR et al., 2017) or used individual devices for the prediction of multiple quality attributes within selected fruit such as kiwi (LI et al., 2018) or avocado (NCAMA et al., 2018). The results of these studies illustrate the potential of food-scanners for fast and non-destructive quality measurement. With regard to the practical use of these devices along the fresh produce supply chain, a recent study identified important requirements as stated by supply chain actors, e.g., ease of use and robustness of devices and reliability and accuracy of prediction models (GOISSER et al., 2020a).

The aim of the study is to examine the assessment of the most important quality attributes of tomato fruit by using three commercially available portable food-scanners. Contrary to previous research, which focused on prediction accuracy and spectral pre-processing, this study investigates user friendliness and potential of an application in practice along the fresh fruit supply chain. Therefore, this study used manufacturer's software for building of prediction models as well as state-of-the-art software for multivariate analysis. By comparing the results derived from both software tools, the accuracy and reliability of prediction models computed with manufacturer's software can be assessed. For the evaluation of the full potential of each food-scanner, the full available spectral range was used during building of NIR prediction models. In order to generate a high variability for different quality parameters, two different experimental approaches were used in this study. In one experiment, different ripening stages from one tomato cultivar were examined, whereas the second experiment analyzed tomatoes of uniform ripening levels but different cultivars and origins. These different approaches highlight the fact that users have to adhere to certain requirements in order to create good prediction models. Further important aspects with respect to usability and applicability by non-experts are discussed.

Materials and methods

Experimental setup and sample material

All research was conducted at facilities of the University of Applied Sciences Weihenstephan-Triesdorf. In order to examine tomato fruit quality in its entirety the experiment comprised two separate parts. Within the first part, quality of one tomato variety (*Solanum lycopersicum* cv. Avalantino) was monitored from fruit ripening during cultivation throughout harvest up to postharvest storage. Tomatoes were cultivated during summer 2019 in a greenhouse at the University of Applied Sciences Weihenstephan-Triesdorf (48°24'12''N, 11°43'50''E) under commercial growth conditions. A hydroponic recirculating drip irrigation system was utilized for tomato cultivation. The average air temperature during cultivation within the greenhouse was 20.1 ± 8.1 °C and relative humidity was 74.5 ± 17.7%. In total, 245 tomatoes were used for the first part of the experiment. Evaluation of tomato quality during ripening was conducted from the middle of July until start of August 2019 on five days with two to five days in between. Five different ripening stages were determined for harvest by using the USDA Color Chart (USDA, 1975) as orientation: 1) Green (tomato surface of full green color) 2) Breaker (shift in color from green to yellow) 3) Turning (break in color from yellow to orange) 4) Light red (change in color from orange to light red) 5) Red (tomato surface of full red color). On any measurement day five tomatoes of every ripening stage were randomly selected and harvested, resulting in batches of 25 tomatoes each day and 125 fruit total. Calyx was removed and samples were numbered for recording of spectra and subsequent reference measurements. In order to monitor fruit quality during postharvest storage, 120 tomatoes of the ripening stage (5) were randomly selected and harvested from the greenhouse in the fourth week of August, 2019. After numbering the tomatoes were positioned on a metal grid to allow full air circulation at room temperature of 22.4 ± 1.7 °C and relative humidity of 67.4 ± 3.0% for the storage period of 22 days. Measurement of fruit quality was conducted on the day of harvest and 8, 13, 17, 20, and 22 days after harvest in batches of 20 randomly selected samples.

For the second part, 200 tomatoes consisting of eight different varieties à 25 fruit were purchased at four different supermarkets in Freising, Germany, from January to March, 2019. Only plastic-wrapped tomatoes of commercial grade one were selected. In order to generate variability, various tomato types (Roma, Salad, Cherry) from different countries of origin were analyzed (Tab. 1). Not all fruit cultivars could be identified due to missing indications on packaging labels. All spectral and related reference measurements in both parts of the experiment were conducted on a single fruit basis. Prior to spectroscopic and reference analysis fruit was kept at room temperature to allow acclimatization. Temperature of fruit surface was measured immediately before recording of spectra using an infrared meter (AMiR 7834, Ahlborn Meßtechnik GmbH, Holzkirchen, Germany) and averaged 19.1 ± 0.4 °C.

Tab. 1: Sample composition of supermarket tomatoes.

Tomato type	Variety	N	Origin
Salad	n/a	25	The Netherlands
Salad	n/a	25	The Netherlands
Salad	Prince	25	Germany
Roma	n/a	25	Spain
Miniature Roma	Aromatica	25	The Netherlands
Miniature Roma	Sunstream	25	The Netherlands
Cherry	Romantic	25	Spain
Cherry	n/a	25	Germany

Acquisition of spectra using portable NIR devices

Fruit spectra of intact tomato fruit were recorded with three different portable and commercially available food-scanners (Fig. 1). At first, two spectra for each tomato were acquired on opposite sides of the fruit equator using the F-750 Produce Quality Meter (Firmware v.1.2.0 build 7041, Felix Instruments, Portland, USA). During each recording of a new measurement, the F-750 uses a reference shutter for normalization of the spectrometer output and accounts for dark current and ambient light by recording dark scans. After recording of spectra data was transferred from the SD-Card to a computer for subsequent analysis. In a next step, the portable NIR spectrometer H-100F (Sunforest, Incheon, Korea) was used for recording of spectra on same two spots on opposite sides of the fruit equator as the F-750. To ensure scan quality, the white standard attached in the protective cap of the measurement head was used for referencing at the beginning and after every 20 measurements. Raw spectra was saved to a computer by linking the H-100F via USB and running the Sunforest H-100 Laboratory Program (V 1.1, Sunforest, Incheon, Korea). At last, spectra of each tomato was recorded using the SCiO™ Molecular Sensor (SCiO™ version 1.2, Consumer Physics, Hod HaSharon, Israel). The SCiO™ applies a LED light source which illuminates a considerably smaller surface area compared to the halogen lamps of the F-750 and H-100F. In order to depict an appropriate average fruit spectra, four equidistant scan points (approximately 90° apart) around the fruit equator were deemed more suitable, covering the two measurement points used with the F-750 and H-100F. The device

Fig. 1: Commercially available portable NIR food-scanner: (left) SCiO™ Molecular Sensor with protective plastic case, (middle) F-750 Produce Quality Meter, (right) H-100F portable spectrometer with protective plastic cap.

possesses a white standard within its protective plastic case, which was used for referencing at the start and after every 20 measurements. The technical features of all three devices have been elaborated in several previous works (Kaur et al., 2017; Li et al., 2018).

Depending on the respective device, two to four spectra were recorded for each fruit. For each device, all spectra belonging to one tomato fruit were averaged and the averaged spectra used for correlation with quality parameters and subsequent model building.

Measurement of fruit quality parameters

Measurements of external and internal quality parameters were performed immediately after recording of spectra and followed a defined operating procedure (Fig. 2). At first, fruit color was measured around the fruit equator with a colorimeter (PCE-CSM 2, PCE Instruments, Meschede, Germany) consistent with the spots of NIR spectra acquisition. Color readings were automatically averaged by the colorimeter and the averaged values used for subsequent reference. Firmness of each fruit was recorded in N as an average of two measuring points using a penetrometer (Fruit Texture Analyser, GUESS Manufacturing Ltd., Cape Town, South Africa). The applied probe head was 1 cm² in surface and used a measurement speed of 5 mm/s and test depth of 7.5 mm.

After acquisition of external quality parameters fruit were randomly selected for dry matter (DM) measurement. Within the first part of the experiment, dry matter of 50 tomatoes was analyzed during the ripening period, consisting of two tomatoes of each of the five ripening stages on five measurement days. During analysis of stored fruit, five tomatoes were selected randomly for DM measurement on each of the six days of measurement, resulting in 30 tomatoes. In total, 80 samples were analyzed for DM within the first part. In the second part, ten tomatoes within the batch of 25 fruit of each of the eight varieties were drafted randomly for DM measurement, resulting in 80 samples in total. Tomatoes were cut into four parts, put in small aluminum containers and placed in a dry oven for 48 h at 80 °C until constant dry weight was reached. Afterwards the ratio of dry weight to initial fresh weight was used to calculate % DM.

The remaining tomatoes within each part of the experiment were blended using a conventional smoothie mixer (WMF Kult X Mix&Go 300 Watt, WMF Group GmbH, Geislingen/Steige, Germany). The purée was filtered using filtering paper. 2-3 drops of stirred filtrate were used for measurement of total soluble solids (TSS) using a digital refractometer (HI 96801, Hanna Instruments, Woonsocket, USA). 10 mL stirred filtrate was used for the determination of titratable acidity with a titrator (HI 902 Potentiometric Titrator and HI 921 Autosampler, Hanna Instruments, Woonsocket, USA). Results were expressed as g/L citric acid in fresh weight. TSS concentration and amount of titratable acidity were used to calculate Brix/Acid ratio as stipulated by OECD guidelines (OECD, 2018).

Statistical and chemometrical analysis

General data analysis such as calculation of average values and standard deviations (SD) was performed with Microsoft® Excel® 2016.

The evaluation of a linear relationship between recorded spectra and tomato quality attributes was performed with the respective analysis software tools from the device manufacturer for the SCiO™ and F-750. In order to evaluate the performance of the manufacturer's software and to carry out a neutral overall evaluation of food-scanner predictability of quality parameters, raw spectra of both devices was additionally analyzed with the multivariate data analysis software The Unscrambler® software (version 10.5.1, CAMO, Oslo, Norway). In comparison, the H-100F is not provided with an end-user tool for creating prediction models, therefore spectra was only analyzed with The Unscrambler® software. Software such as The Unscrambler® allow the computation of the correlation coefficient of both calibration

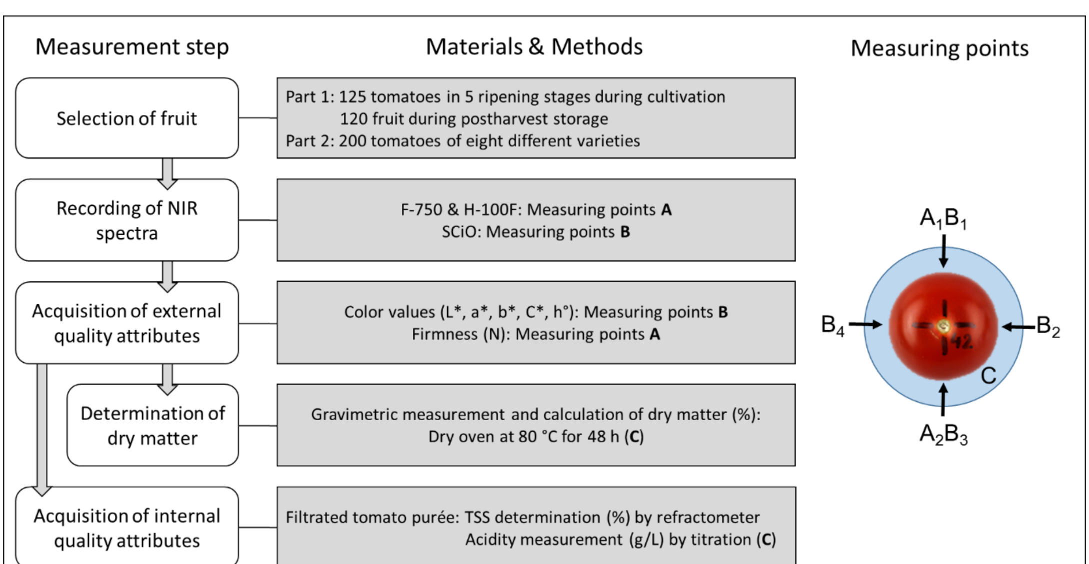

Fig. 2: Illustration of the measurement procedure and measuring points for NIR spectra as well as quality parameters within this experiment.

(r^2_C) and cross-validation model (r^2_{CV}) as well as the corresponding calibration and cross-validation root mean square error ($RMSE_C$, $RMSE_{CV}$). These factors are used to evaluate the performance of the respective prediction model. Additionally, the software offers numerous possibilities for data pre-processing and further analysis. Outliers detected with The Unscrambler®, which indicated errors during spectra collection, were omitted from evaluation.

After recording of spectra with the SCiO™, the spectra are uploaded to a cloud-based browser application (The Lab, Consumer Physics, Hod HaSharon, Israel) which allows building of prediction models. The default pre-processing settings within the cloud-application were used in order to build prediction models, namely logarithm, averaging all four scans per sample, first derivative (window of 35 and polynom degree of 2), selecting the full wavelength range from 740-1070 nm and subtracting the average. Every tenth spectra was used for cross-validation. The algorithm was set to partial least square regression (PLSR) and outlier detection as well as additional filters were disabled. Raw spectra were then exported from the cloud-based samples library to an Excel-file and analyzed with The Unscrambler®, applying the same pre-processing settings as set in the cloud-application as well as PLSR, using 20 random segments for cross-validation.

The F-750 comes with a free software tool for analysis of spectra and building of prediction models. Spectra recorded with the F-750 was loaded into the most recent Model Builder Software (version 1.3.0.192 BETA, Felix Instruments, Portland, USA). The software uses non-linear iterative partial least squares (NIPALS) regression and leave-one-out method for cross-validation. Spectra in second derivative form, which is used by default by the software, was transferred from the Model Builder Software to an Excel-file and loaded into The Unscrambler® for additional evaluation. The whole wavelength range from 477-1059 nm was utilized for building prediction models. Both spectra per sample were averaged and no further pre-processing was applied. PLSR algorithm was utilized for building of prediction models, using 20 random segments for cross-validation.

For the H-100F, raw spectra in second derivative form was exported from The Sunforest H-100 Laboratory Program in the wavelength range from 650-950 nm. After averaging the two scans per sample no further pre-processing was applied. 20 random segments were used for cross-validation.

The SCiO™ application as well as the F-750 Model Builder Software allow the selection of a specific spectral range for evaluation. Within this study, the full wavelength range of all food-scanners was selected in order to evaluate the full potential of these devices. Since both software programs of the F-750 and H-100F do not allow access to raw spectra, the automatically computed second derivative of spectra was used.

Gathering of information on usability characteristics

A qualitative study regarding the application of food-scanners along the fresh produce supply chain identified several important requirements for food-scanners to allow the utilization in daily quality control processes, e.g., high prediction accuracy, convenience in handling and robustness of food-scanners (Goisser et al., 2020a). Based on these results as well as personal experience of the authors through collaborations with supply chain actors, characteristics of high importance with respect to the usability and applicability of food-scanners were identified within four categories, namely device independency, data handling, practical handling and available accessories. Manufacturer's specifications were used to evaluate device independency and available accessories, whereas personal assessments of the authors were used besides manufacturer's specifications for the evaluation of data handling and practical handling of food-scanners. In order to determine a practice-oriented scan speed for each device, 30 consecutive measurements on various tomatoes were conducted with each food-scanner and measured using a stop watch. Based on these measurements, arithmetic mean as well as standard deviation of scan speed for each device were calculated.

Results

Distribution of tomato fruit quality for both parts of the experiment

Value ranges, arithmetic mean and standard deviation (SD) for all quality parameters measured in both parts of the experiment are shown in Tab. 2. As indicated by the value range, variance within the first part of the experiment was greater for quality parameters L*, a*, C*, h°, firmness and Brix/Acid ratio. Vice versa, quality attributes such as DM, TSS and titratable acidity showed higher variability within the second part of the experiment. Variance of color value b* differed only slightly between both parts of the experiment.

Food-scanner spectra vs. quality parameters (manufacturer's software)

The Model Builder software allocated by Felix Instruments for the F-750 provides the user with information on model linearity of the calibration set (r^2_C) as well as the correlation coefficient after performing a leave-on-out cross-validation (r^2_{CV}). Root mean square errors for both calculations are also provided ($RMSE_C$, $RMSE_{CV}$). For the purpose of this study, these values were chosen as denominator of performance (Tab. 3). The cloud application provided by Consumer Physics for the evaluation of SCiO™ spectra with respect to its correlation to reference values does not differentiate between calibration and validation models and therefore only displays a single r^2 and RMSE value (Tab. 3).

Evaluation of spectra collected with the F-750 in the first part of the experiment yielded models of high prediction accuracy ($r^2_{CV} > 0.90$)

Tab. 2: Distribution of reference values of quality parameters within each part of the experiment. L*, a*, b*, C*, h°: colorimetric values; DM: dry matter; TSS: total soluble solids; SD: standard deviation

Parameter	Experiment part	N	Range	Mean	SD
L*	1	245	29.13 - 51.36	36.03	5.40
	2	120	32.33 - 41.88	36.12	2.11
a*	1	245	-7.97 - 31.69	17.08	13.19
	2	120	11.55 - 28.46	22.29	2.87
b*	1	245	18.01 - 39.27	27.65	3.34
	2	120	16.49 - 27.99	21.16	2.57
C*	1	245	21.49 - 49.26	34.74	6.11
	2	120	23.66 - 39.59	30.85	2.79
h°	1	245	40.87 - 106.54	62.07	22.50
	2	120	35.18 - 63.39	43.56	5.02
Firmness (N)	1	245	6.14 - 90.75	30.53	19.26
	2	120	12.67 - 42.24	24.43	7.21
DM (%)	1	80	5.50 - 7.58	6.09	0.38
	2	80	4.02 - 9.69	6.72	1.74
TSS (%)	1	165	4.50 - 7.30	5.54	0.59
	2	120	3.1 - 9.00	5.78	1.84
Acidity (g/L)	1	165	2.43 - 6.02	3.73	0.77
	2	120	2.40 - 9.21	5.08	1.32
Brix/Acid ratio	1	165	8.63 - 27.21	15.60	3.98
	2	120	7.38 - 18.22	11.42	2.39

Tab. 3: Prediction of tomato quality parameters of the F-750 Produce Quality Meter and SCiO™ Molecular Sensor using the respective manufacturer's software. L*, a*, b*, C*, h°: colorimetric values; TSS: total soluble solids; r^2_C: r^2 of calibration; $RMSE_C$: root mean square error of calibration; r^2_{CV}: r^2 of cross-validation; $RMSE_{CV}$: root mean square error of cross validation; PC: principal components

			F-750 (λ = 477 - 1059 nm)					SCiO™ (λ = 740 - 1070 nm)		
Parameter	Experiment part	N	r^2_C	$RMSE_C$	r^2_{CV}	$RMSE_{CV}$	PC	r^2_P	SEP	PC
*L**	1	245	0.90	1.68	0.90	1.70	3	0.89	1.83	9
	2	120	0.54	1.44	0.52	1.46	3	0.47	1.54	3
*a**	1	245	0.95	2.83	0.95	2.88	4	0.92	3.81	12
	2	120	0.21	2.54	0.19	2.58	3	0.37	2.28	3
*b**	1	245	0.27	2.85	0.25	2.89	3	0.42	2.56	5
	2	120	0.66	1.49	0.65	1.52	3	0.72	1.36	4
*C**	1	245	0.74	3.15	0.72	3.24	4	0.80	2.76	7
	2	120	0.41	2.14	0.39	2.17	2	0.62	1.73	4
h°	1	245	0.96	4.60	0.96	4.71	4	0.91	6.95	12
	2	120	0.42	3.84	0.40	3.90	3	0.39	3.91	2
Firmness (N)	1	245	0.92	5.40	0.92	5.53	4	0.91	5.84	10
	2	120	0.49	5.16	0.47	5.25	3	0.46	5.29	6
DM (%)	1	80	0.08	0.59	0.03	0.61	1	0.07	0.37	1
	2	80	0.94	0.41	0.93	0.47	6	0.97	0.31	8
TSS (%)	1	165	0.56	0.39	0.56	0.39	2	0.71	0.32	7
	2	120	0.93	0.47	0.92	0.51	6	0.97	0.30	8
Acidity (g/L)	1	165	0.03	2.00	0.02	2.01	2	0.00	2.00	1
	2	120	0.51	0.92	0.49	0.94	3	0.66	0.77	6
Brix/Acid ratio	1	165	0.43	3.09	0.42	3.13	2	0.49	2.92	4
	2	120	0.46	1.76	0.46	1.77	2	0.51	1.68	3

for color values L*, a*, h° as well as firmness. Prediction models of moderate performance were obtained for chroma C* (r^2_{CV} = 0.72) as well as TSS (r^2_{CV} = 0.56), whereas color value b* and Brix/Acid ratio yielded predictions of poor performance. No feasible calibration and cross-validation could be acquired for DM (r^2_{CV} = 0.03) and titratable acidity (r^2_{CV} = 0.02). Within the second part of the experiment, prediction models computed for DM and TSS showed high predictive capabilities (r^2_{CV} > 0.90). Models of moderate performance were acquired for color value L* (r^2_{CV} = 0.52) and b* (r^2_{CV} = 0.65), whereas predictions of color value a*, chroma C*, hue h°, firmness, titratable acidity and Brix/Acid ratio displayed poor accuracy (r^2_{CV} < 0.50).

Prediction models of high accuracy (r^2_P > 0.90) computed for the SCiO™ device in the first experiment part were obtained for color value a*, hue h° and firmness, while models for L*, chroma C* and TSS were of good performance with r^2_P of 0.89, 0.80 and 0.71, respectively. Models of poor predictive capability were acquired for color value b* (r^2_P = 0.42) and Brix/Acid ratio (r^2_P = 0.49), whereas the prediction of DM and titratable acidity was not feasible. Analysis of spectra gathered in the second part of the experiment resulted in prediction models of high accuracy (r^2_P = 0.97) for DM and TSS. Moderate r^2_P were obtained for color value b*, chroma C*, titratable acidity and Brix/Acid ratio, however the prediction models computed for color values L*, a*, hue h° as well as firmness showed low performance.

Food-scanner spectra vs. quality parameters (The Unscrambler®)

The evaluation of raw spectra of all three commercially available food-scanners using The Unscrambler® software showed great differences in the accuracy of quantitative prediction of certain tomato quality attributes (Tab. 4).

Within the first part of the experiment, tomato fruit quality was monitored from fruit ripening during cultivation up to postharvest storage. The evaluation of all three portable food-scanners within this part of the experiment resulted in cross-validation models of high accuracy (r^2_{CV} > 0.90) for color values L* and a*, hue h° as well as firmness (Fig. 3A). Validated models of color value b* showed low to moderate accuracy for the F-750 (r^2_{CV} = 0.29), SCiO™ (r^2_{CV} = 0.55) and H-100F (r^2_{CV} = 0.48) instrument. Prediction models of chroma C* yielded good results for all three devices, ranging from r^2_{CV} = 0.73 to 0.80 and 0.83 for F-750, H-100F and SCiO™ respectively. Unlike the second part of the experiment, calibration models for dry matter indicated only small predictive capability for all three instruments, and subsequent cross-validation resulted in a significant drop in r^2, which overall led to prediction models of poor performance. The validation of models for TSS achieved predictions of moderate (F-750 and H-100F) to good (SCiO™) performance, whereas cross-validation of prediction models for titratable acidity only yielded models of moderate accuracy for all three food-scanners. Prediction models for the Brix/Acid ratio ranged from r^2_{CV} = 0.69 over 0.70 to 0.74 for the F-750, H-100F and SCiO™, respectively, indicating moderate to good predictability.

In the second part of the experiment, fruit quality of eight different tomato varieties was determined. The evaluation of prediction models computed with food-scanner scans and reference measurements yielded models of high accuracy (r^2_{CV} > 0.90) for both dry matter and TSS (Fig. 3). Additionally, all three sensors obtained cross-validated prediction models of moderate accuracy (r^2_{CV} ranging from 0.54 to 0.75) for color values L* and b*, hue h°, firmness, acidity as well as the Brix/Acid ratio for all three devices. Low to moderate predictability was achieved for color value a*, where r^2_{CV} ranged from 0.48 over 0.49 to 0.54 for F-750, SCiO™ and H-100F, respectively. Prediction of chroma C* was poor for the F-750 (r^2_{CV} =

Tab. 4: Prediction of tomato quality parameters of three commercially available NIR devices using The Unscrambler® software for evaluation. L*, a*, b*, C*, h°: colorimetric values; TSS: total soluble solids; r^2_C: r^2 of calibration; $RMSE_C$: root mean square error of calibration; r^2_{CV}: r^2 of cross-validation; $RMSE_{CV}$: root mean square error of cross validation; PC: principal components

			F-750 (λ = 477 - 1059 nm)					SCiO™ (λ = 740 - 1070 nm)					H-100F (λ = 650 - 950 nm)				
Parameter	Experiment part	N	r^2_C	RMSEC	r^2_{CV}	RMSECV	PC	r^2_C	RMSEC	r^2_{CV}	RMSECV	PC	r^2_C	RMSEC	r^2_{CV}	RMSECV	PC
*L**	1	245	0.90	1.70	0.90	1.74	1	0.91	1.61	0.90	1.74	9	0.93	1.39	0.93	1.44	3
	2	120	0.71	1.14	0.62	1.32	6	0.62	1.31	0.57	1.40	4	0.75	1.05	0.70	1.16	6
*a**	1	245	0.97	2.44	0.96	2.53	4	0.93	3.41	0.92	3.71	9	0.96	2.65	0.96	2.74	3
	2	120	0.61	1.78	0.48	2.08	6	0.55	1.91	0.49	2.05	5	0.63	1.74	0.54	1.95	7
*b**	1	245	0.31	2.78	0.29	2.83	3	0.60	2.12	0.55	2.26	8	0.53	2.30	0.48	2.43	5
	2	120	0.68	1.45	0.66	1.51	3	0.76	1.25	0.73	1.35	4	0.78	1.22	0.72	1.38	7
*C**	1	245	0.75	3.04	0.73	3.20	4	0.85	2.36	0.83	2.54	8	0.82	2.58	0.80	2.71	5
	2	120	0.43	2.10	0.42	2.14	1	0.69	1.56	0.65	1.67	5	0.60	1.78	0.49	2.00	7
h°	1	245	0.96	4.52	0.96	4.70	3	0.93	6.04	0.92	6.50	9	0.95	4.86	0.95	4.95	2
	2	120	0.72	2.66	0.64	3.03	6	0.61	3.15	0.54	3.45	5	0.78	2.37	0.73	2.64	6
Firmness (N)	1	245	0.93	5.17	0.93	5.31	3	0.90	6.07	0.89	6.55	9	0.92	5.35	0.92	5.46	2
	2	120	0.73	3.77	0.64	4.37	6	0.66	4.19	0.54	4.95	11	0.72	3.80	0.67	4.18	6
DM (%)	1	80	0.47	1.58	0.18	1.99	7	0.54	0.28	0.32	0.33	6	0.33	0.32	0.16	0.36	5
	2	80	0.96	0.33	0.94	0.43	7	0.98	0.25	0.97	0.32	8	0.96	0.35	0.94	0.42	7
TSS (%)	1	165	0.80	0.26	0.69	0.32	8	0.85	0.23	0.81	0.26	10	0.77	0.28	0.67	0.34	11
	2	120	0.94	0.46	0.92	0.51	5	0.97	0.32	0.96	0.35	6	0.97	0.32	0.96	0.38	7
Acidity (g/L)	1	165	0.60	0.49	0.51	0.54	6	0.63	0.46	0.57	0.51	8	0.68	0.43	0.63	0.47	5
	2	120	0.74	0.67	0.64	0.79	6	0.71	0.71	0.66	0.78	6	0.82	0.57	0.75	0.67	8
Brix/Acid ratio	1	165	0.74	2.11	0.69	2.30	6	0.75	2.06	0.70	2.25	7	0.77	1.96	0.74	2.10	6
	2	120	0.62	1.47	0.54	1.64	5	0.77	1.15	0.65	1.42	12	0.71	1.29	0.64	1.45	7

0.42) as well as the H-100F (r^2_{CV} = 0.49), whereas the evaluation of the SCiO™ device yielded moderate results (r^2_{CV} = 0.65).

Differences in usability characteristics

Important features with respect to device independency, data handling, practical handling and available accessories of food-scanners derived from manufacturer's specifications and personal assessment of the authors are compiled in Tab. 5.

With respect to the independent use of these devices without additional equipment, the necessity of internet access and additional devices during scanning as well as the need for external white-referencing of these spectrometers was evaluated. The investigation showed that the F-750 and H-100F can be used as stand-alone and offline instruments that require no additional devices for scanning or displaying of results. Both instruments are equipped with on-board prediction models for evaluation of NIR spectra and displays for the illustration of the respective measurement results. In contrast, the SCiO™ requires constant internet access during scanning as well as an additional mobile device. For the SCiO™, an additional device (e.g., smartphone, tablet) is mandatory, works as an intermediate link between the miniaturized NIR spectrometer and the cloud database, and serves as display for measurement results. The SCiO™ as well as the H-100F provide protective plastic caps, which on the one hand serve as protection during transportation and on the other hand contain the respective white standard for regular referencing of the spectrometer. Contrary to this, the F-750 uses a shutter with gold-coated foil as its reference standard, which is calculated for every sample measurement, therefore an external white reference is not needed.

As a second aspect, the handling of the generated data was examined. Spectra collected with the F-750 can be accessed either by removing the SD card on which spectra is stored and transferring the data to a computer or using the Wi-Fi function of the SD card. Although a special file format is used for the spectra, the transfer to other multivariate analysis software is easily possible due to the free software and open format. SCiO™ spectra is only accessible through an online database by using a web browser or the corresponding SCiO™ mobile app. Furthermore, the SCiO™ requires a separate development license for the access of raw spectra, which can be downloaded in a simple file format. Spectral data stored on the H-100F can either be transferred via USB to a computer or accessed via Bluetooth using a smartphone. Spectra provided by the H-100F can either be accessed with special software for multivariate data analysis, e.g., The Unscrambler®, or by using data analysis software such as R or Python combined with syntax analysis of the respective file format. The ability of building own prediction models and the knowledge necessary for doing so differs significantly between the three devices. The manufacturer of the F-750 provides a free software tool for analysis of spectra and building of own prediction models and supports users with a systematic instruction on how to build custom tailored models. By following these instructions step by step, unexperienced users are able to build own prediction models without specialized knowledge in NIR spectroscopy. As for the SCiO™, the manufacturer provides a cloud-based browser application that allows the building and evaluation of prediction models. However, the utilization of these self-developed prediction models for future predictions requires the programming of separate mobile applications. In contrast to this, building of own prediction models by end-users is not possible with the H-100F.

Additional differences were identified with respect to features in practical handling of the three food-scanners. Regular handling of

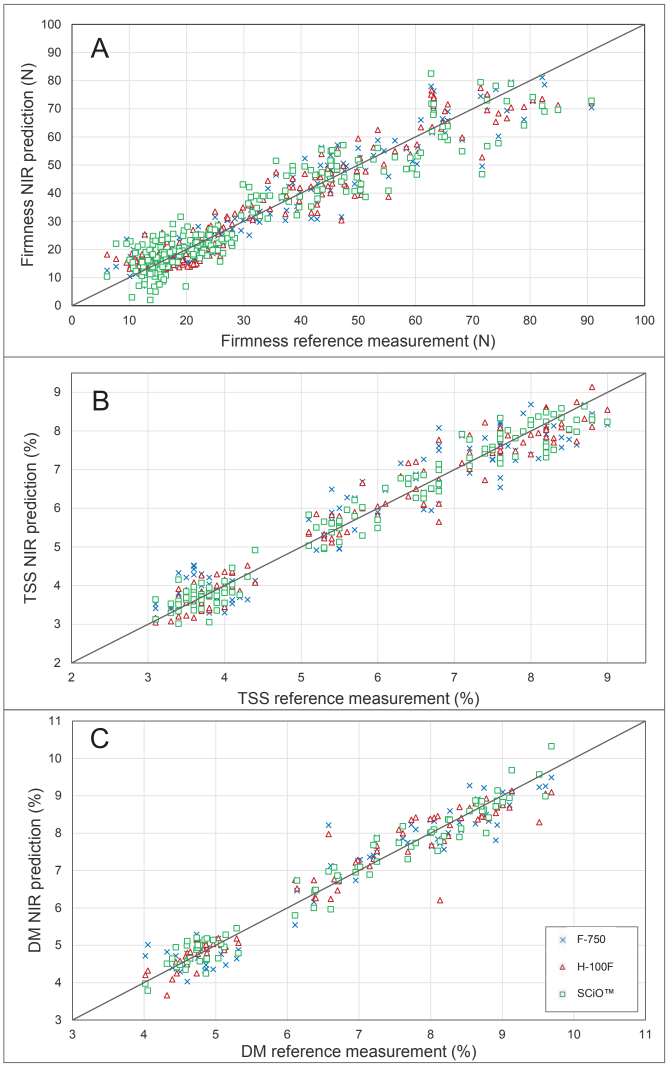

Fig. 3: Correlation between measured and predicted firmness (A), TSS (B), and DM (C) of cross validated models built with The Unscrambler® of all three food-scanners used in this study. The black line symbolizes the line of best fit.

fruit and vegetables leads to light soiling of food-scanners, e.g., through adhering water and dirt or particles of rough and hairy fruit skins. Therefore, lens and light source of the SCiO™ and H-100F device have to be cleaned regularly to guarantee undistorted measurements. Due to the design of the F-750, the lens protects the light source, therefore only the lens requires regular cleaning. According to manufacturer's specifications, the F-750 battery lasts over 1600 scans and the H-100F battery over 2000 scans. Results of our own measurements estimate the battery life of the SCiO™ at 250 scans. Own measurements identified differences in scan speed, ranging from 4.9 s (H-100F), 8.2 s (SCiO™) to 14.3 s (F-750). It should be noted that the whole time interval from the beginning of one to the beginning of the next possible scan was recorded instead of just measuring the time until the measured value was displayed. Due to the built-in technology and the focus on different end-user groups, there are also differences in the weight and dimensions of the three food-scanners. The F-750 is robustly designed for the utilization within the orchard through farmers and producers, whereas the SCiO™'s small and lightweight design was initially targeted for end-consumer use. The H-100F has similar dimensions to the F-750, but since plastic is used for the casing instead of metal, it weighs significantly less.

All three devices provide accessories for the measurement of smaller objects and fruit. In addition, the H-100F features a built-in radio-frequency identification (RFID) reader for the identification of individual tagged trees or areas, whereas the F-750 has a GPS sensor for online mapping of non-destructive quality readings. Manufacturers offer supplementary accessories for additional areas of application such as liquids (F-750, SCiO™) and powders (F-750).

Discussion

Prediction results of food-scanner spectra

By using two different experimental designs (tomatoes during ripening and different tomato cultivars from the supermarket) we were able to generate great variance for almost every quality parameter examined. Color values L*, a*, C*, h° and firmness showed great variation in reference values in the first part of the experiment due to ripening-related changes during cultivation and storage. The combination of different tomato cultivars in the second part of the experiment resulted in a wide range of reference values for DM and TSS. The evaluation of NIR prediction models using food-scanners yielded a higher coefficient of determination (r^2) for the respective part of the experiment with a wide range in fruit quality of the samples used in calibration and validation sets (Tab. 2). These findings are in line with Su et al. (2014) and highlight the importance of the variability of samples for building a feasible NIR prediction model of the quality trait of interest. This wide range of reference values also makes prediction models more robust, since both bad and good qualities are integrated. Thus a realistic range of values is represented. When creating future prediction models during practical application of food-scanners along the fresh fruit supply chain, attention should be paid to a large variance of the desired quality trait of interest. In order to guarantee this variance, users responsible for building prediction models must have extensive knowledge of fruit quality.

For the following comparison of our results to scientific literature, results computed with the independent software The Unscrambler® are used as reference. The models with the best accuracy due to the wide range of reference values are used for comparison (Tab. 3). Utilizing NIR spectra for the determination of tomato firmness during cultivation and storage resulted in good prediction models (r^2_{CV} > 0.89) for all three food-scanners. These results are superior to findings achieved on intact tomatoes using portable and laboratory NIR instruments reaching from r^2_{CV} = 0.78 (Ecarnot et al., 2013) to r^2_{CV} = 0.82 (He et al., 2005). Similar results for firmness prediction (r^2 = 0.89) on intact tomatoes were achieved by Kusumiyati et al. (2008) using portable NIR spectroscopy.

Tomato dry matter content varies greatly depending on the tomato cultivar (Ercolano et al., 2008). Screening of one tomato cultivar from cultivation to storage in our study showed a smaller range of dry matter distribution (2.08%) compared to screening multiple tomato cultivars (5.67%). Prediction of dry matter with only one tomato cultivar yielded no feasible models (r^2_{CV} = 0.16-0.32). These findings are in line with poor prediction results (r^2_{CV} = 0.39-0.49) for one tomato cultivar using a laboratory NIR instrument (Torres et al., 2015). Contrary to this, NIR prediction models of high accuracy (r^2_{CV} > 0.90) could be created for the model containing multiple cultivars with all three food-scanners. Prediction of dry matter in apple, kiwifruit and stone fruit applying the same food-scanners we used showed similar predictive capabilities of this fruit trait (Kaur et al., 2017).

Models containing only one cultivar yielded moderate predictions of TSS (r^2_{CV} = 0.67-0.81), which is in range of previous studies using only one tomato cultivar and laboratory NIR instruments (Flores et al., 2009; Torres et al., 2015; Clément et al., 2008). Building of TSS prediction models using multiple tomato cultivars in our study yielded accurate results (r^2_{CV} > 0.90). Previous studies using labo-

Tab. 5: Compilation of food-scanner characteristics with respect to usability and applicability

Features	Device		
	F-750	SCiO™	H-100F
Device independency			
Necessity of internet access during scanning	No	Yes	No
Additional devices needed for scanning	None	Smartphone / Tablet	None
Internal / external white-referencing	Internal	External	External
Data handling			
Access of spectra	Free, SD-Card	Licenced, online database	Free, USB, Bluetooth
Ability for building own prediction models	Free software available	Programming of own apps necessary	No
Specialized knowledge necessary for model building	No	Yes	Yes
Practical handling			
Instrument maintenance	Lens cleaning	Lens and LED cleaning	Lens and light source cleaning
Running costs	None	None	None
Durability of battery life	> 1600 scans[a]	> 250 scans[b]	~ 2000 scans[a]
Scan speed (mean and standard deviation)	14.3 ± 0.1 s[b]	8.2 ± 0.7 s[b]	4.9 ± 0.1 s[b]
Device weight	1.05 kg	36 g	440 g
Device dimension	18 × 13.5 × 6 cm	5.5 × 3.7 × 1.4 cm	19 × 17 × 10.7 cm
Available accessories			
Provided accessories	Small fruit adaptor, GPS	Small object holder	Rubber mold for small fruit, built-in RFID reader
Purchasable accessories	Liquids and powders kit	Liquid accessory	n/s

[a]According to manufacturer's specifications
[b]Results of own measurements

ratory NIR instruments (He et al., 2005; Saad et al., 2016) and a miniaturized NIR sensor (Sheng et al., 2019) obtained similar prediction models.

In the first part of the experiment all three food-scanners yielded prediction models of high accuracy for lightness L* and color value a* ($r^2_{CV} > 0.90$, Tab. 3), which is in the range of findings from previous work using benchtop UV-VIS-NIR spectrometer and portable NIR instrument (Clément et al., 2008; Kusumiyati et al., 2008). Prediction of color value b* yielded best results in the second part of the experiment for all three food-scanners (r^2_{CV} = 0.66 - 0.73). However, previous studies demonstrated better correlations of r^2 = 0.82 - 0.92 (Kusumiyati et al., 2008; Clément et al., 2008). Correlation of food-scanner spectra to chroma C* in our study obtained moderate to good results (r^2_{CV} = 0.73 - 0.83) in the first part of the experiment. Various previous research using portable NIR spectrometer yielded slightly better prediction models of r^2 = 0.90 - 0.87 (Ecarnot et al., 2013; Kusumiyati et al., 2008). Evaluation of hue h° yielded prediction models of high accuracy ($r^2_{CV} > 0.90$), which is similar to findings in the literature on portable NIR instrument performance (Ecarnot et al., 2013; Kusumiyati et al., 2008).

Previous studies applying laboratory NIR instruments demonstrated the difficulty of predicting acidity in intact tomato fruit (Flores et al., 2009; Oliveira et al., 2014) and yielded prediction accuracies comparable to our results. As elaborated by Oliveira et al. (2014), tomatoes generally show low concentration and a heterogeneous composition of TSS and acidity. Compared to other fruit species, tomatoes have no homogeneous composition of flesh since they are divided into different loculi. This structure can cause interference when NIR radiation is penetrating fruit and could be the reason for these moderate correlations in both parts of the experiment (r^2_{CV} = 0.51 - 0.75).

This moderate predictability of acidity combined with the mathematical relation yielded prediction models for Brix/Acid ratio of likewise moderate accuracy (r^2_{CV} = 0.54 - 0.74) in both experiments. No literature reports could be found regarding prediction models for Brix/Acid ratio in intact tomatoes. However, previous research on tomato juice using a laboratory NIR instrument obtained slightly superior accuracies (r^2 = 0.74 - 0.86) for comparable wavelength regions (Jha and Matsuoka, 2004).

All three food-scanners had similar accuracies for the prediction of each quality trait within each part of the experiment (Tab. 3). The slight differences in model accuracy can be explained by the differences in wavelength ranges of the respective scanners. Kaur et al. (2017) evaluated the spectral features of all three food-scanners used in this study and found strong correspondence to the water absorbance bands at 760 nm, 840 nm and 960 nm, with slight variations between instruments. As demonstrated by McGlone and Kawano (1998) using kiwifruit, the water and carbohydrate absorbance bands at 840 nm and 960 nm strongly correlate to prediction models developed for TSS and DM. The good correlation of food-scanner spectra and tomato TSS and dry matter in our study are in line with these findings. With respect to the determination of color values, the F-750 covers almost the whole visible spectrum up to near infrared (477 - 1059 nm), whereas the H-100F comprises the red wavelength range of the visible spectrum (650 - 950 nm). Contrary to this, the SCiO™ covers a small range of the far-red end of the visible spectrum.

Performance of manufacturer's software compared to The Unscrambler®

Various previous studies tried to determine the performance of the three food-scanners used in this study for the prediction of internal quality traits of selected fruit and vegetables. However, most studies only used the portable NIR spectrometers for collection of spectra and utilized the corresponding software tools provided by manufacturers for data extraction. In many scientific studies, the subsequent multivariate data analysis was performed by using specialized software for multivariate data analysis such as MATLAB (Kaur et al., 2017; Teye et al., 2019) or The Unscrambler® (Ncama et al., 2018). To the best of our knowledge, a direct comparison of these provided software tools to specialized software has only been done by Li et al.

(2018) for the SCiO™ device with three kiwi quality parameters during a quality estimation trial. The authors obtained similar predictive performance for dry matter, TSS and firmness using SCiO™ Lab as well as The Unscrambler®. However, such a comparison has not yet been conducted for the F-750, which also provides its own software for evaluation and building of prediction models. In order to evaluate the potential application of these portable food-scanners in practice along the fresh fruit supply chain, this study used manufacturer's software as well as The Unscrambler® software for building of prediction models for a variety of tomato fruit quality traits. By comparing the results derived from both software tools, the accuracy and reliability of prediction models computed with manufacturer's software can be assessed.

A direct comparison of the prediction models created with The Unscrambler® (Tab. 3) to models developed using manufacturer's software (Tab. 4) indicates similar predictive performances for models of high accuracy ($r^2_{CV} > 0.90$) for both devices. The small variations in model performance was most likely due to slightly deviating numbers of principal components (PC), which are selected automatically and individually by each respective software. Additionally, the variability in sampling during cross-validation could cause these minor differences. Some prediction models of poor to moderate accuracy ($0.40 < r^2_{CV} < 0.80$) achieved similar results for both The Unscrambler® and manufacturer's software (e.g., color values b* and C* for the F-750 as well as color value C* for SCiO™ within both parts of the experiment). However, most prediction models within this area of accuracy computed with The Unscrambler® surpass those derived from F-750 or SCiO™ manufacturer's evaluation software. Whereas the evaluation of DM and acidity with The Unscrambler® within the first part of the experiment indicated merely moderate predictive capabilities, neither F-750 or SCiO™ software obtained any form of linear correlation between food-scanner spectra and reference values.

It should be noted that the evaluation of spectra using manufacturer's software yielded similar results to evaluations applying The Unscrambler® software for prediction models of high accuracy ($r^2_{CV} > 0.90$). In particular, these models of high accuracy are relevant when it comes to the practical application of food-scanners. This study therefore was able to demonstrate that existing food-scanners, including the software supplied, are suitable for creating feasible prediction models for fruit quality traits. Therefore, actors along the fresh fruit supply chain can use these devices independently and are not reliant on additional professional software for data evaluation. These results are in line with findings of Li et al. (2018), who found similar model accuracies for kiwi quality attributes using both The Unscrambler® and SCiO™ software. The results of this study demonstrate the great predictive potential and informative value of commercially available portable food-scanners. By combining multiple prediction models of high accuracy of various quality traits within one global prediction model, portable food-scanners can be used as multidimensional and non-destructive measurement tools of fruit quality. Therefore, future users can gain a comprehensive picture of fruit quality using only one single scan.

This study used two different experimental approaches in order to generate high variability of tomato fruit quality parameters. The utilization of fruit during ripening and storage resulted in a larger range of reference values L*, a*, b*, C*, h° and firmness compared to fruit from retail stores. Vice versa, differences in variety and origin within the second experiment increased variability of reference values DM, TSS and acidity. With the exception of color value b*, NIR prediction models yielded higher correlation for the experiment with a larger range of reference values. When it comes to the development of new prediction models by users in daily practice, a broad range of fruit qualities and respective reference values must be taken into account in order to obtain good prediction models. As highlighted in previous research (Fan et al., 2019; Wedding et al., 2013), additional integration of biological and seasonal variability of fruit can contribute to build more reliable and robust prediction models and thereby unlock potential of non-destructive quality assessment via NIR food-scanners in practical applications.

Comparison of usability characteristics

A direct comparison of the three food-scanners used in this study shows clear differences with regard to usability and applicability characteristics (Tab. 5).

Both F-750 and H-100F are not reliant on internet access during scanning and can therefore be used independently at all points of the fresh produce supply chain, from orchards to incoming goods control in warehouses to retail stores. In contrast, the SCiO™ requires constant internet access during scanning as well as an additional mobile device (e.g., smartphone, tablet). This finding is contrary to statements on the SCiO™ website, where offline scanning is advertised (Consumer Physics, 2020). However, personal experience as well as communication with SCiO™'s manufacturer revealed that offline scanning is not possible (Consumer Physics, 2017). Therefore, the SCiO™ can not be used as an independent measuring device. Additionally, the device can only be used effectively in places with a stable internet connection, which is not always guaranteed in large warehouses or remote orchards.

Data handling of the F-750 can be described as very user-friendly. On the one hand, spectra are provided freely, on the other hand the gratis software and instructions for model building allows non-experts of NIR spectroscopy the building of new prediction models. With respect to the practical use of food-scanners for fresh produce quality control, new quality parameters could be developed by users along the supply chain themselves. In contrast, users of the SCiO™ device need to purchase an additional license to access raw spectra for building of own prediction models. To enable the use of these models for future predictions, further know-how in app programming is required. For the H-100F, spectra are also freely accessible, but the manufacturer does not provide software for building of own prediction models. According to the manufacturer, a short form of model building program was provided in the past, but deemed not useful. In order to analyze the spectra and respective reference data and produce calibration models in a suitable data format with the H-100F, model building programs such as The Unscrambler® can be used (Sunforest, 2018). However, these specialized programs are not suitable for many users in day-to-day practice, since on the one hand they are very expensive and on the other hand they require a lot of training.

The evaluation of the practical handling of all three food-scanners showed comparable effort in device maintenance. Additionally, none of these devices requires further running costs. Both F-750 and H-100F are characterized by very long battery runtimes and can therefore be used for several days in practical applications. The battery of the SCiO™ lasts for approximately 250 measurements. When used continuously, e.g., during quality assessment in the orchard or incoming goods control, this number can be reached within a short period of time. Theoretically, the battery life of the SCiO™ can be extended by using a mobile powerbank and charging the device parallel to scanning. However, an additional device and thus another dependency would be necessary. An important aspect in practical handling is the scan each device requires for one measurement, since it serves as indication for labor efficiency. Previous work identified rapid measurements as important feature of portable food-scanners (Goisser et al., 2020a). Our measurement results for scan speed (Tab. 5) surpass those reported in previous studies (Kaur et al., 2017) as well as manufacturer's specifications (Sunforest, 2020; Consumer Physics, 2020). It should be noted that in contrast to these references, we recorded the whole time interval from the start of one scan to the beginning of the next possible scan. For the SCiO™, quality and stability of the internet connection is essential with regard to scan speed. Both F-750 and H-100F display the scan result a few seconds before the next scan is possible, which most likely explains these deviations from manufacturer's specifications. However, the scan speed measured in our study is much more practice-oriented. Assuming a fixed timeframe for the application of food-scanners in quality control processes, different numbers of scans can be performed with each device. Depending on the device, different numbers of measuring points would be available for quality assessment. Due to the built-in technology, weight and dimension differs notably between devices. These features have to be considered when the devices are used portable in the orchard or warehouse and have to be physically carried around by the users.

All manufacturers provide accessories that enable the measurement of fruit and vegetables of various sizes. Therefore, users along the fresh produce supply chain are not limited in their use of these devices due to fruit size. However, additional fruit properties such as the color and thickness of fruit skin have to be considered when applying NIR spectroscopy, since these properties could greatly influence the accuracy and reliability of NIR prediction models. The F-750 provides a GPS function, which enables the measurement values to be displayed in a map view. By using RFID tags in orchards in combination with the built-in RFID reader, the H-100F takes a similar approach. On the one hand, fruit ripeness can be monitored in orchards, on the other hand, this function can also be used to verify the origin of produce as well as quality of origin by measurements at production companies. Additional accessories for the measurement of liquids can be purchased for the SCiO™, the F-750 provides a purchasable liquids and powders kit. Users are therefore able to use these portable NIR instruments for testing various substances within the food industry (e.g., fruit juices, beverages, dried herbs) or completely different areas of application in other industries.

Conclusion

The predictability of various tomato quality parameters using three commercially available portable food-scanners was analyzed and the software for building of own prediction models provided by manufacturers of these devices evaluated through comparison to state-of-the-art software for multivariate analysis. The results highlight the capability of these devices in predicting various internal fruit quality parameters in a non-destructive way. Our findings are consistent with previous research, which in many cases used laboratory NIR instruments compared to portable and miniaturized NIR devices. Quality control of fruit and vegetable along the fresh produce supply chain is often limited to optical inspections and in some cases not performed at all. Through the combination of a multitude of internal quality measurements within a single scan, food-scanners provide a comprehensive and objective picture of fruit quality. Food-scanners can be used on various points along the fresh produce supply chain and replace traditional time-consuming and elaborate destructive measurement methods of internal fruit quality. Therefore, food-scanners can be an important tool in making fruit quality along the whole fresh produce supply chain more transparent and comprehensible.

The comparison of software provided by manufacturer to state-of-the-art software shows that the provided software delivers good results, especially for models of high prediction accuracy. Applied to the practical application of these devices in day-to-day processes of quality control this means that special expertise in the field of NIR spectroscopy and model building is not necessary. Since some manufacturers provide basic software solutions in combination with operating instructions, users are enabled to build their own prediction models.

As highlighted in this study, variation in fruit quality is of great importance in order to build accurate prediction models. The variation of the respective fruit quality parameter can be influenced in various ways, e.g., through different ripening stages, variation in origin and cultivars or seasonal differences. With regard to the practical use and long term application of food-scanners along the fresh produce supply chain, it is vital that users of these devices are aware of the importance of the variability of reference values when it comes to creating new, reliable and robust prediction models.

Based on previous studies and personal experience with supply chain actors, an exemplary framework evaluating food-scanner characteristics with respect to usability and applicability was designed. The evaluation of these usability characteristics showed various differences between the three devices used in this study, especially with regard to the independent use of these devices and handling of generated data. Potential users of food-scanners must inform themselves in advance and make sure that the respective device meets their company's requirements, especially in day-to-day work processes of fruit quality control. For a further spread and effective use of these devices in practice, manufacturers must pay attention to user-friendliness and simple model building solutions.

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Conflict of interest

No potential conflict of interest was reported by the authors.

References

Abbott, J.A., 1999: Quality measurement of fruits and vegetables. Postharvest Biol. Tech. 15, 207-225. DOI: 10.1016/S0925-5214(98)00086-6

Batu, A., 2004: Determination of acceptable firmness and colour values of tomatoes. J. Food Eng. 61, 471-475. DOI: 10.1016/S0260-8774(03)00141-9

BLE, 2019: Obst und Gemüse von A bis Z. Vermarktungsnormen frisches Obst und Gemüse. Retrieved from https://www.ble.de/DE/Themen/Ernaehrung-Lebensmittel/Vermarktungsnormen/Obst-Gemuese/Vermarktungsnormen-Hilfen-zur-Anwendung/ObstundGemueseA_Z.html?nn=8904900.

Bruhn, C.M., Feldman, N., Garlitz, C., Harwood, J., Ivans, E., Marshall, M., Riley, A., Thurber, D., Williamson, E., 1991: Consumer perception of quality: apricots, cantaloupes, peaches, pears, strawberries, and tomatoes. J. Food Quality 14, 187-195. DOI: 10.1111/j.1745-4557.1991.tb00060.x

Casals, J., Rivera, A., Sabaté, J., Romero del Castillo, R., Simó, J., 2019: Cherry and Fresh Market Tomatoes: Differences in Chemical, Morphological, and Sensory Traits and Their Implications for Consumer Acceptance. Agronomy 9, 9. DOI: 10.3390/agronomy9010009

Causse, M., Damidaux, R., Rousselle, P., 2007: Traditional and Enhanced Breeding for Quality Traits in Tomato, 153-192. In: Razdan, M.K. (ed.), Genetic improvement of solanaceous crops. Enfield, NH: Science Publ.

Clément, A., Dorais, M., Vernon, M., 2008: Nondestructive measurement of fresh tomato lycopene content and other physicochemical characteristics using visible-NIR spectroscopy. J. Agr. Food Chem. 56, 9813-9818. DOI: 10.1021/jf801299r

Consumer Physics, 2017: Customer Support. Personal communication, Freising, Germany.

Consumer Physics, 2020: Technology. Technical Specifications. Retrieved 28 April 2020, from https://www.consumerphysics.com/technology/.

dos Santos, C.A.T., Lopo, M., Páscoa, R.N.M.J., Lopes, J.A., 2013: A review on the applications of portable near-infrared spectrometers in the agro-food industry. Appl. Spectrosc. 67, 1215-1233. DOI: 10.1366/13-07228

Ecarnot, M., Bączyk, P., Tessarotto, L., Chervin, C., 2013: Rapid phenotyping of the tomato fruit model, Micro-Tom, with a portable VIS-NIR spectrometer. Plant Physiol. Biochem. 70, 159-163. DOI: 10.1016/j.plaphy.2013.05.019

Ercolano, M.R., Carli, P., Soria, A., Cascone, A., Fogliano, V., Frusciante, L., Barone, A., 2008: Biochemical, sensorial and genomic profiling of traditional Italian tomato varieties. Euphytica 164, 571-582. DOI: 10.1007/s10681-008-9768-4

Fan, S., Li, J., Xia, Y., Tian, X., Guo, Z., Huang, W., 2019: Long-term evaluation of soluble solids content of apples with biological variability by using near-infrared spectroscopy and calibration transfer method. Postharvest Biol. Tech. 151, 79-87. DOI: 10.1016/j.postharvbio.2019.02.001

Flores, K., Sánchez, M.-T., Pérez-Marín, D., Guerrero, J.-E., Garrido-Varo, A., 2009: Feasibility in NIRS instruments for predicting internal quality in intact tomato. J. Food Eng. 91, 311-318. DOI: 10.1016/j.jfoodeng.2008.09.013

Folta, K.M., Klee, H.J., 2016: Sensory sacrifices when we mass-produce mass produce. Hortic. Res. 3, 16032. DOI: 10.1038/hortres.2016.32

Goisser, S., Mempel, H., Bitsch, V., 2020a: Food-Scanners as a Radical Innovation in German Fresh Produce Supply Chains. International Journal on Food System Dynamics, Vol. 11, No 2 (2020), 101-116. DOI: 10.18461/IJFSD.V11I2.43

Goisser, S., Wittmann, S., Fernandes, M., Mempel, H., Ulrichs, C., 2020b: Comparison of colorimeter and different portable food-scanners for non-destructive prediction of lycopene content in tomato fruit. Postharvest Biol. Tech. 167, 111232. DOI: 10.1016/j.postharvbio.2020.111232

He, Y., Zhang, Y., Pereira, A.G., Gomez, A.H., Wang, J., 2005: Nondestructive Determination of Tomato Fruit Quality Characteristics Using Vis/NIR Spectroscopy Technique. Int. J. Inf. Technol. 11, 97-108.

Jha, S.N., Matsuoka, T., 2004: Non-destructive determination of acid-brix ratio of tomato juice using near infrared spectroscopy. Int. J. Food Sci. Tech. 39, 425-430. DOI: 10.1111/j.1365-2621.2004.00800.x

Kaur, H., Künnemeyer, R., McGlone, A., 2017: Comparison of hand-held near infrared spectrophotometers for fruit dry matter assessment. J. Near Infrared Spec. 25, 267-277. DOI: 10.1177/0967033517725530

Kusumiyati, Akinaga, T., Tanaka, M., Kawasaki, S., 2008: On-tree and after-harvesting evaluation of firmness, color and lycopene content of tomato fruit using portable NIR spectroscopy. J. Food Agric. Environ. 6, 327-332.

Li, M., Qian, Z., Shi, B., Medlicott, J., East, A., 2018: Evaluating the performance of a consumer scale SCiO™ molecular sensor to predict quality of horticultural products. Postharvest Biol. Tech. 145, 183-192. DOI: 10.1016/j.postharvbio.2018.07.009

McGlone, V.A., Kawano, S., 1998: Firmness, dry-matter and soluble-solids assessment of postharvest kiwifruit by NIR spectroscopy. Postharvest Biol. Tech. 13, 131-141. DOI: 10.1016/S0925-5214(98)00007-6

Ncama, K., Magwaza, L.S., Poblete-Echeverría, C.A., Nieuwoudt, H.H., Tesfay, S.Z., Mditshwa, A., 2018: On-tree indexing of 'Hass' avocado fruit by non-destructive assessment of pulp dry matter and oil content. Biosyst. Eng. 174, 41-49. DOI: 10.1016/j.biosystemseng.2018.06.011

OECD, 2018: OECD Fruit and Vegetable Scheme. Guidelines on objective tests to determine quality of fruit and vegetables, dry and dried produce. Retrieved from www.oecd.org/agriculture/fruit-vegetables/.

Oliveira, G.A. de, Bureau, S., Renard, C.M.-G.C., Pereira-Netto, A.B., Castilhos, F. de, 2014: Comparison of NIRS approach for prediction of internal quality traits in three fruit species. Food Chem. 143, 223-230. DOI: 10.1016/j.foodchem.2013.07.122

Pasquini, C., 2003: Near Infrared Spectroscopy: Fundamentals, Practical Aspects and Analytical Applications. J. Brazil. Chem. Soc. 14, 198-219. DOI: 10.1590/S0103-50532003000200006

Rateni, G., Dario, P., Cavallo, F., 2017: Smartphone-Based Food Diagnostic Technologies: A Review. Sensors (Basel, Switzerland) 17. DOI: 10.3390/s17061453

Saad, A., Jha, S.N., Jaiswal, P., Srivastava, N., Helyes, L., 2016: Non-destructive quality monitoring of stored tomatoes using VIS-NIR spectroscopy. Eng. Agric. Environ. Food 9, 158-164. DOI: 10.1016/j.eaef.2015.10.004

Sheng, R., Cheng, W., Li, H., Ali, S., Akomeah Agyekum, A., Chen, Q., 2019: Model development for soluble solids and lycopene contents of cherry tomato at different temperatures using near-infrared spectroscopy. Postharvest Biol. Tec. 156, 110952. DOI: 10.1016/j.postharvbio.2019.110952

Statista, 2019: Gemüsekonsum in Deutschland. Retrieved from https://de.statista.com/statistik/studie/id/42820/dokument/gemuesekonsum-in-deutschland/.

Su, H., Sha, K., Zhang, L., Zhang, Q., Xu, Y., Zhang, R., Li, H., Sun, B., 2014: Development of near infrared reflectance spectroscopy to predict chemical composition with a wide range of variability in beef. Meat Sci. 98, 110-114. DOI: 10.1016/j.meatsci.2013.12.019

Sunforest, 2018: Application of Sunforest H-100F. Personal communication, Freising, Germany.

Sunforest, 2020: H-100F. Portable Nondestructive Fruit Quality Meter. Retrieved 29 April 2020, from http://sunforest.kr/category_main.php?sm_idx=169.

Teye, E., Amuah, C.L.Y., McGrath, T., Elliott, C., 2019: Innovative and rapid analysis for rice authenticity using hand-held NIR spectrometry and chemometrics. Spectrochim. Acta A 217, 147-154. DOI: 10.1016/j.saa.2019.03.085

Torres, I., Pérez-Marín, D., La Haba, M.-J.D., Sánchez, M.-T., 2015: Fast and accurate quality assessment of Raf tomatoes using NIRS technology. Postharvest Biol. Tech. 107, 9-15. DOI: 10.1016/j.postharvbio.2015.04.004

UNECE, 2018: UNECE Standard FFV-36 concerning the marketing and commercial quality control of tomatoes. 2017 Edition. Retrieved from https://www.unece.org/trade/agr/standard/fresh/ffv-standardse.html.

USDA, 1975: USDA Color Chart: Color Classification Requirements in Tomatoes. Retrieved from https://ucanr.edu/repository/view.cfm?article=83755%20&groupid=9.

Wedding, B.B., Wright, C., Grauf, S., White, R.D., Tilse, B., Gadek, P., 2013: Effects of seasonal variability on FT-NIR prediction of dry matter content for whole Hass avocado fruit. Postharvest Biol. Tech. 75, 9-16. DOI: 10.1016/j.postharvbio.2012.04.016

ORCID
Simon Goisser https://orcid.org/0000-0002-7685-8893
Sabine Wittmann https://orcid.org/0000-0002-8669-4132
Christian Ulrichs https://orcid.org/0000-0002-6733-3366
Heike Mempel https://orcid.org/0000-0002-5820-663X

Address of the corresponding author:
Heike Mempel, Greenhouse Technology and Quality Management, University of Applied Sciences Weihenstephan-Triesdorf, Am Staudengarten 10, 85354 Freising, Germany
E-mail: heike.mempel@hswt.de