LANDTECHNIK
AGRICULTURAL ENGINEERING

Food-scanner applications in the fruit and vegetable sector

Simon Goisser, Sabine Wittmann, Heike Mempel

In the past few years, portable and smartphone-based diagnostic technologies have found their way into the agri-food industry. The aim of this research was to evaluate the performance of portable near-infrared (NIR) spectrometers, so called food-scanners, with regard to their predictive accuracy of important quality parameters of fruit and vegetables. Food-scanner measurements were performed in combination with destructive measurements of the corresponding quality trait (sugar content, dry matter, relative water content) on a wide range of produce from the fruit and vegetable assortment. This study evaluated dry matter content of apple, avocado, blueberry, table grape and tangerine, which yielded cross validation results (r^2) of up to 0.95, 0.87, 0.94, 0.92 and 0.92 respectively. Furthermore, the evaluation of food-scanner spectra for the prediction of sugar content of blueberry, kiwi, mango, persimmon, table grape, tangerine and tomato yielded cross validations (r^2) of up to 0.95, 0.84, 0.80, 0.75, 0.95, 0.93, and 0.87. Furthermore, relative water content of ginger obtained a cross validation correlation of $r^2 = 0.91$. The results show that these traits can be predicted with a high degree of accuracy using non-destructive measurements performed with three commercially available food-scanners SCiO^{TM}, F-750 Produce Quality Meter, and H-100F. Consequently, food-scanners can be used as objective measurement tools along the supply chain of fresh produce to quickly determine fruit quality. In addition, a practical example shows the potential of these instruments for non-destructive quality assessment in incoming goods control at fruit and vegetable wholesalers over a time period of several weeks. Furthermore, possible areas of application of food-scanners along the supply chain of fresh produce are discussed, possibilities for practical applications are presented and time-saving means are highlighted.

Keywords

NIR spectroscopy, food-scanner, non-destructive measurement, quality control

Near-infrared (NIR) technology has many specialist areas of application today. A common application is in the control of chemical, petrochemical and pharmaceutical products. Within the chemical industry, NIR spectrometers are also used in process control and for incoming goods inspection of raw materials. Another area of NIR application is waste separation, where a wide variety of composites and types of plastic are detected and separated through sorting lines. Furthermore, NIR technology is used in process control in the food industry and in the quality analysis of agricultural products (PASQUINI 2003). Within these fields of application and in addition to the control of products for human consumption, quality determination of raw materials is of particular importance. NIR spectrometers therefore are used for quality measurements of cereals, flour, and milk. Further raw products such as feed are analyzed for moisture, protein and raw fiber content using these devices. The technology is also suitable for determining the water content in numerous agricultural products (COZZOLINO 2009). Various pre-

vious experiments on horticultural produce illustrated the potential of using NIR spectroscopy for the prediction of important fruit quality parameters, e.g. sugar content and acidity in apples, oranges, kiwifruit, peaches, as well as kiwifruit dry matter and firmness of peaches and kiwifruit (Wang et al. 2015). Within the last few years, mobile smartphone-based diagnostic technologies have found their way into the agri-food sector. Those devices could replace expensive and bulky laboratory equipment in the near future. Various start-up companies are involved in the development of these measurement tools (Rateni et al. 2017). In particular, the technology of miniaturized and portable NIR spectroscopy has great potential in various areas of application due to its non-destructive use and the link to machine-learning algorithms. Individual companies are already targeting applications in the food industry. They refer to their spectrometers as food-scanners, which provide information on the nutrient content, allergens and contaminations and are intended to determine relevant information on food fraud, food counterfeiting and food quality within a few seconds (Spectral Engines 2020, Tellspec 2020). Other companies are focusing slightly larger yet portable NIR devices specifically designed for the measurement of internal quality parameters such as sugar content and dry matter of various kind of fruit (Felix Instruments 2020, Sunforest 2020). First scientific studies, which employed these portable and miniaturized instruments, indicate good performance and prediction results for a variety of produce and quality parameters, e.g., dry matter content of apple, kiwifruit and stone fruit (Kaur et al. 2017), dry matter and oil content of avocado (Ncama et al. 2018), dry matter and sugar content of mango (Santos Neto et al. 2017), and sugar content of pear (Choi et al. 2017).

A recent qualitative study conducted with actors of the German fresh produce supply chain highlights the potential that these food-scanners could unlock by facilitating future quality control on various levels along the supply chain through non-destructive, objective and fast measurements (Goisser et al. 2020a).

Measurement procedure and data collection of important quality attributes within the assortment of fruit and vegetables

In order to evaluate the applicability of these new types of devices within the practice of fruit and vegetable trade, food-scanners were tested on a large range of available produce within the fruit and vegetable retail sector. Additional fruit and vegetables, of which the application of NIR spectrometers for the prediction of quality traits have not yet been thoroughly researched in the scientific literature (e.g., blueberry, ginger), were analyzed during the course of these studies. Further special features, such as the prediction of relevant quality parameters of thick-skinned fruit (e.g., mango, avocado, citrus fruit) as well as the non-destructive measurement through packaging film were taken into account. Experiments focused on the two quality parameters sugar content and dry matter, as these quality traits often serve as indicators for ripeness and eating quality of fruit. In case of ginger, relative water content of tubers was examined as indicator of freshness.

Fruit analyzed during the course of this research are listed in Table 1. Batches of different size of apple, avocado, blueberry, kiwi, mango, persimmon, table grape, and tangerine were purchased from local retail stores as well as fruit wholesale and analyzed at laboratories of the University of Applied Sciences Weihenstephan-Triesdorf in Freising, Germany. In order to obtain the widest possible range of the respective quality parameters of interest, care was taken to integrate different fruit qualities when produce was procured (Table 1). Additional measurements for the determination of quality parameters through packaging film of table grapes and tomatoes were performed during incoming

goods control of a German fruit and vegetable trading company. For the measurement of ginger, fresh plant material of a local plant nursery was obtained and transported to University facilities for subsequent analysis.

During the course of these studies, three commercially available miniaturized and hand-held NIR spectrometers were used: the SCiO^{TM} (version 1.2, Consumer Physics, Hod HaSharon, Israel); the F-750 Produce Quality Meter (Firmware v.1.2.0 build 7041, Felix Instruments, Portland, USA) and the H-100F (Sunforest, Incheon, Korea). All three devices measure in direct contact with fruit samples and utilize interactance mode, therefore only light transmitted through the sample tissue is detected and more information about the actual sample composition and constituents is obtained (Pasquini 2003). The obtained spectra are used to calculate absorbance spectra, which then is utilized for further analysis. The detailed characteristics and operating parameters of these food-scanners, such as spectral resolution and sampling interval, have been elaborately described by Kaur et al. (2017).

Table 1: Products and respective quality parameters examined in this study including reference methods and the source of quality variation

Product	Quality parameter	Reference method	Source of variation in quality
Apple	Dry matter	Drying oven	Integration of various cultivars
Avocado	Dry matter	Drying oven	Combination of different fruit calibres and origins
Blueberry	Dry matter / Brix	Drying oven / refractometer	Pooling of various origins and growing methods (traditional / organic)
Ginger	Water content	Weight loss measurement	Examination of freshly harvested ginger during convective drying
Kiwi (green & gold)	Brix	Refractometer	Merging of fruit with differences in external appearance
Mango	Brix	Refractometer	Combination of air freighted and traditionally transported fruit
Persimmon	Brix	Refractometer	Pooling of various origins and growing methods (traditional / organic)
Table grape (green)	Dry matter / Brix / Brix through PE film	Drying oven / refractometer	Incorporation of various cultivars and origins
Tangerine	Dry matter / Brix	Drying oven / refractometer	Integration of various cultivars
Tomato	Brix through PE film	Refractometer	Combination of various cultivars, types (cherry, salad) and origins

In order to develop NIR prediction models, the first step was the collection of NIR fruit spectra using the respective food-scanner. In contrast to measurements under laboratory conditions, all experiments were performed under condition as realistic and practically relevant as possible. Various factors, such as differences in ambient and fruit temperature (e.g., 4 °C - 22 °C) and variations in lighting conditions, which are often found in incoming goods control of wholesalers and retailers, were therefore integrated into these prediction models. For mango, avocado, tangerine, tomato, apple, kiwi and persimmon, the exact location of spectra collection was used for subsequent reference measurement, whereas for table grapes, blueberries and ginger one spectra per specimen was taken and the whole berry/tuber was used for reference measurement afterwards. For measurements through packaging film, small pre-cut polyethylene (PE) film samples were placed between fruit sample and food-scanner during the recording of spectra.

Spectra collected with the F-750 was transferred from the SD-Card to a computer for further chemometrical analysis using the associated Model Builder Software (version 1.3.0.192 BETA). According to the manufacturer, the software applies non-linear iterative partial least squares (NIPALS) regression and uses the leave-one-out method for cross validation. Absorbance spectra in second derivative form in the wavelength range 729 – 975 nm was utilized for building of prediction models, since these settings are used as standard by the software.

Similarly, absorbance spectra recorded with the SCiO^{TM} was correlated to fruit quality parameters using the cloud-based browser application The Lab (Consumer Physics). The cloud application's default pre-processing settings of spectra were used in this study, 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. The application uses every tenth spectra for cross-validation. The algorithm was set to partial least square regression (PLSR) and additional options for outlier detection as well as additional filters were disabled.

For the H-100F, recorded spectra were exported from the Sunforest H-100 Laboratory Programm (Sunforest). The device provides absorbance spectra in second derivative form in the wavelength range from 650 – 950 nm. Due to the lack of evaluation software provided by the manufacturer, spectra were analyzed with the multivariate data analysis software The Unscrambler® (version 10.5.1, Camo, Oslo, Norway). The H-100F was only used for the evaluation of tangerines, and the two scans per fruit were averaged prior to multivariate analysis. Following the procedure of the F-750, no further pre-processing was applied, and 20 random samples were used for cross-validation.

Coefficient of correlation after cross-validation (r^2_{CV}) as well as the root mean square error after cross-validation ($RMSE_{CV}$) derived from the respective software were used for performance evaluation of the various prediction models (Table 2).

The determination of reference values of the respective quality parameters was performed immediately after collection of fruit spectra. Sugar content in terms of Brix was analyzed by cutting out the area of spectra collection (in case of table grapes and blueberries the whole berry was used), squeezing the fruit tissue with a garlic press and measuring the mixed juice with a digital refractometer (HI 96801, Hanna Instruments, Woonsocket, USA). Dry matter of the area of spectra collection was measured gravimetrically (for table grapes and blueberries whole berries were analyzed). Fresh fruit tissue was weighed and subsequently dried in an oven at 45 °C (avocado) and 80 °C (table grape, blueberry, tangerine, apple) for 48 h. The final dry weight was used for calculation of dry matter as the percentage of dry weight to initial wet weight of each specimen. In order to determine the relative water content of ginger, small tubers fresh from the nursery were examined. Measurement was performed on five consecutive days during which tubers were stored at room temperature (19.8 °C ± 0.9 °C) and relative humidity of 48% ± 3%. After collection of food-scanner spectra, tubers were weighed, and the current weight noted. At the end of day five, dry weight of tubers was determined gravimetrically by drying the tubers in an oven at 80 °C for 48 h. Relative water content was then calculated using the equation provided by Ceccato et al. (2001), on the assumption that fresh tubers showed full turgor weight on day one:

$$Relative\ water\ content\ = \frac{Tuber\ weight\ on\ the\ respective\ day - oven\ dry\ weight}{Tuber\ turgor\ weight\ on\ day\ one - oven\ dry\ weight}$$

Performance of prediction models for fruit quality parameters

Prediction results with respect to r^2_{CV} and $RMSE_{CV}$ obtained from multivariate analysis for every quality parameter and respective food-scanner are listed in Table 2.

Overall, the correlation of spectra with sugar content of fruit yielded good results. Prediction models of high accuracy ($r^2_{CV} > 0.90$) were obtained for blueberries (Figure 1A) and table grapes. Likewise, the measurement through thick-skinned fruit such as tangerines provided very good results. Further good correlations of sugar content were obtained for mango and kiwi ($r^2_{CV} = 0.78 - 0.84$), whereas the prediction of persimmon sugar content yielded better results using the F-750 ($r^2_{CV} = 0.75$) compared to the SCiO^{TM} ($r^2_{CV} = 0.63$). Nevertheless, all values of root mean square errors (RMSE$_{CV}$), which serve as indicator of prediction error, ranged from 0.36 to 0.92 °Brix and can therefore be deemed acceptable for a non-destructive evaluation of fruit quality. Results from this study are comparable to findings reported in the literature, such as the determination of sugar content of kiwi (McGlone and Kawano 1998), mango (Schmilovitch et al. 2000), table grapes (Donis-González et al. 2020) and tangerines (McGlone et al. 2003a) using NIR spectrometers.

Table 2: Performance of selected food-scanners in predicting internal fruit quality of various types of fruit using PLS algorithm. r^2_{CV}: r2 of cross-validation; $RMSE_{CV}$: root mean square error of cross-validation; PC: principal components

Product	Parameter	F-750	SCiO^{TM}	H-100F	n	r^2_{CV}	$RMSE_{CV}$	PC
Apple[1]	Dry matter	X			100	0.95	0.53	6
Avocado[2]	Dry matter	X			195	0.85	1.50	6
	Dry matter		X		195	0.87	1.42	16
Blueberry[1]	Brix	X			275	0.90	0.68	9
	Brix		X		275	0.95	0.47	12
	Dry matter	X			100	0.92	0.59	7
	Dry matter		X		100	0.94	0.51	6
Ginger[2]	Relative water content	X			150	0.91	6.44	5
Kiwi (green)[1]	Brix	X			120	0.84	0.63	8
Kiwi (gold)[1]	Brix	X			120	0.78	0.80	7
Mango[1]	Brix	X			140	0.80	0.58	6
Persimmon[1]	Brix	X			45	0.75	0.76	5
	Brix		X		45	0.63	0.92	3
Table grape (green)[1]	Brix		X		80	0.94	0.51	7
	Brix	X			150	0.95	0.57	5
	Brix (through PE film)	X			75	0.93	0.65	7
	Dry matter		X		80	0.92	0.55	7
	Dry matter	X			160	0.92	0.46	4
Tangerine[1]	Brix			X	80	0.93	0.36	6
	Dry matter			X	174	0.92	0.53	5
Tomato[1]	Brix (through PE film)	X			177	0.87	0.57	7

[1] Various cultivars used for model building [2] Individual cultivars used for model building

Prediction models for sugar content in persimmon obtained the lowest accuracy in our study. These results are inferior to previous literature reports (JANNOK et al. 2014). Additionally, we examined the predictive capability of table grape sugar content through packaging film with the F-750 and obtained prediction models similar to those without packaging (Figure 1B). Similarly, the determination of toma-to sugar content through packaging film yielded prediction models of comparable performance to those reported in earlier experiments (GOISSER et al. 2018). A thorough literature review showed that the prediction of internal quality parameters of fruit through packaging material has not yet been studied.
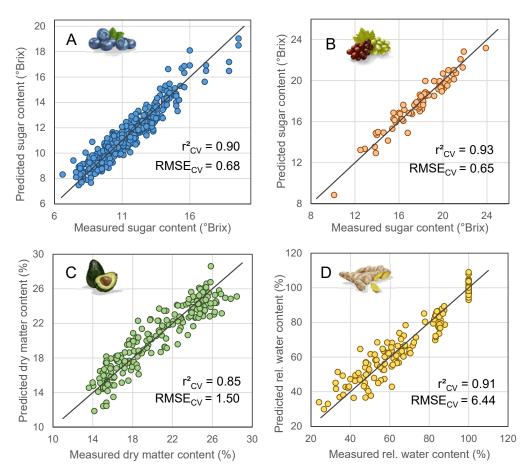

Figure 1: Correlation between NIR food-scanner spectra and quality parameter for A) sugar content of blueberries; B) sugar content of grapes through packaging film; C) dry matter content of avocado; D) relative water content of ginger

Prediction models developed for dry matter content in various types of fruit yielded good results (r^2_{CV} = 0.85 - 0.95). Models of high accuracy could be derived for dry matter of apples, blueberries, ta-ble grapes and tangerines (r^2_{CV} > 0.92; $RMSE_{CV}$ = 0.46 - 0.59). Our prediction models derived for dry matter in apples are superior to findings of MØLLER et al. (2013) and similar to results of McGLONE et al. (2003b). Results from our experiments yielded better correlations for the prediction of table grape dry matter compared to findings reported in the literature (DONIS-GONZÁLEZ et al. 2020), whereas the performance for dry matter prediction in intact tangerines was analogous to results of GUTHRIE et al. (2005). The portable devices used in our study performed good in predicting dry matter of blueberries (r^2_{CV} > 0.92). However, no comparable reports were found for dry matter prediction of blueberries

within the scientific literature. The prediction of dry matter content of avocado (Figure 1C) resulted in models of slightly lower accuracy (r^2_{CV} = 0.85 - 0.87) and higher prediction errors ($RMSE_{CV}$ = 1.42 - 1.50). This slight deviation in model accuracy compared other fruit could be explained by the dark skin of avocados, since a large part of NIR radiation is intercepted, which results in loss of spectral information. Nevertheless, our findings are in line with results achieved by OLAREWAJU et al. (2016) for the prediction of avocado dry matter.

The determination of the relative water content of ginger (Figure 1D) obtained good results (r^2_{CV} = 0.91; $RMSE_{CV}$ = 6.44). Comparable findings have been reported by LI et al. (2011) by applying PLS models and using a laboratory spectrometer for the determination of moisture content in ginger.

For almost all quality parameters examined, in particular sugar content and dry matter of various important fruit types, the developed prediction models yielded a high and therefore practical accuracy. In most cases, relatively small sample sizes were used to create prediction models. With regard to the utilization of these devices along the fruit and vegetable supply chain, the creation of new and separate prediction models is easy and can be realized quickly. It should be noted that the number of principal components has been automatically chosen by the respective software, which in some cases (e.g. avocado dry matter and blueberry sugar content for SCiO^{TM}) resulted in a very high number of PLS factors. Additionally, the models were validated using cross-validation from the same sample set. Due to the variability within some of the presented prediction models as well as the high number of PCs, validation with external samples must be performed to guarantee model robustness for practical applications. This is especially important if quality is predicted for fruit varieties or fruit origins not yet present within the sample pool.
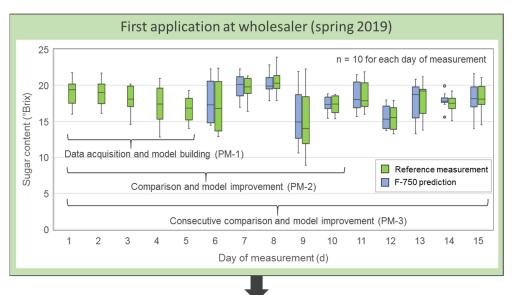
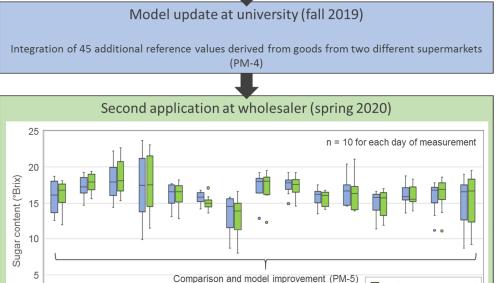## Validation in practice – utilizing a food-scanner for incoming goods control

In order to demonstrate the potential of food-scanners for the quality assessment during incoming goods control, a practical experiment was carried out. For this purpose, the F-750 Produce Quality Meter from Felix Instruments was selected in coordination with the fruit trader and used in two consecutive years within an incoming goods quality control department of a German fruit trader for the prediction of table grape sugar content. Table grapes are usually marketed as a type of produce with no particular focus on cultivars. Therefore, the GLOBALG.A.P. number (GGN) was used as principal indicator of grapes emanating from different producers and therefore of different orchard origin. The procedure is described in Figure 2, the performance of the various prediction models built during the experiment is shown in Table 3. In order to illustrate the time saved by using a food-scanner, the time required for destructive and NIR measurements was recorded and compared (Table 4).

In a first step, data was collected during three consecutive weeks of quality assessment in the spring of 2019. Within the first week, NIR spectra of ten green table grapes per day were recorded and the respective sugar content was measured destructively using a digital refractometer (HI 96801, Hanna Instruments, Woonsocket, USA). Using the resulting 50 reference values and fruit spectra, a first prediction model (PM-1) was developed with the software provided by Felix Instruments (Model Builder Software version 1.3.0.192 BETA). During the second week of quality assessment, NIR predictions for sugar content of ten green table grapes were performed and the actual sugar content of each table grape was destructively determined with the refractometer. As illustrated by the comparative Boxplot in Figure 2 only slight deviations between F-750 predictions and destructive measurements of the overall daily quality could be detected.

Table 3: Performance of various prediction models built with the F-750 Produce Quality Meter and Model Builder Software for the prediction of table grape sugar content during the practical experiments. r^2_{CV}: r^2 of cross-validation; $RMSE_{CV}$: root mean square error of cross-validation; r^2_{V}: r^2 of validation by external samples; $RMSE_V$: root mean square error of validation by external samples

Model label	No. of cultivar	No. of GLOBALG.A.P. numbers	n	r^2_{CV}	$RMSE_{CV}$	r^2_{V}	$RMSE_V$
PM-1	2	3	50	0.87	0.74	0.75	0.84
PM-2	2	5	100	0.96	0.56	0.93	0.65
PM-3	2	9	150	0.95	0.57	-	-
PM-4	2	13	195	0.95	0.52	0.92	0.77
PM-5	2	19	345	0.93	0.62	-	-

Figure 2: Procedure for utilizing the F-750 Produce Quality Meter for the non-destructive measurement of sugar content of green table grapes during incoming goods control at a German fruit wholesaler

The additional data collected during the second week was used for the improvement of the first prediction model (PM-1), which led to the building of a second prediction model (PM-2) using the provided software.

During the third week, the procedure from the second week was repeated. The comparison between F-750 prediction and destructive measurement showed high conformity (Figure 2). At the end of the third week of the first experiment part, all data was pooled in a third prediction model (PM-3).

In preparation for the next practical application, the third prediction model (PM-3) was updated at the University of Applied Sciences Weihenstephan-Triesdorf in the fall of 2019 by adding 45 additional spectra and reference values of green table grapes bought from two different local supermarkets. Data was again pooled and a fourth prediction model was developed (PM-4).

In the spring of 2020, the updated prediction model (PM-4) was again used during quality assessment of incoming goods at the same wholesale company for a second three-week practical experiment. Every day, fruit spectra, NIR predictions for sugar content and destructive reference measurements of ten green table grapes were performed and recorded. Analog to the first practical application, the NIR prediction model in 2020 was updated weekly by integrating the recorded spectra and reference values. As indicated by the second Boxplot in Figure 2, the second experiment initially showed only a slight deviation of prediction and reference values. The overall coverage of the daily fruit quality using non-destructive NIR predictions can be described as very satisfying. Furthermore, the continuous improvements resulted in an increase of conformity of NIR prediction values and real reference values towards the end of the three-week period. At the end of the second practical experiment, all data was aggregated in a final fifth model (PM-5). The models PM-1 and PM-2 developed in 2019 have been tested for model robustness using the data of the consecutive week for model validation. Similarly, PM-4 was validated using the data collected in 2020 (Table 3).

In an additional experiment the time needed to measure the sugar content of 25 table grapes via refractometer and food-scanner was recorded and compared (Table 4). An essential advantage of the NIR measurements is the fact that the measurements can be carried out non-destructively and directly on the working platform and therefore no additional working time is required for cleaning of equipment and transport to an adjacent laboratory. Furthermore, no additional equipment (e.g., paper towels, knife, cutting board, deionized water) is needed when measurements are performed via food-scanner compared to a refractometer.

Table 4: Comparison of the time required for sugar measurements using refractometer and NIR-device

Measurement procedure	Refractometer	F-750 Produce Quality Meter
Number of samples	25	25
Measurement time / sample (s)	30	15
Time for cleaning and transport / sample (s)	15	0
Total time (min)	18:45	6:15

The presented experiment illustrates the great potential of portable and miniaturized NIR food-scanners for a non-destructive quality assessment of internal fruit quality during incoming goods control. As shown on the example of table grapes, the creation of new prediction models is easy and can be realized quickly by utilizing the software provided by device manufacturers. Furthermore, the experiment demonstrated that prediction models of high accuracy built for specific type of fruit can be used

at a later time while still showing high conformity with destructive measurements. Moreover, fruit of origin previously not included within the data pool, as illustrated through the growing number of new producers, could be predicted with high accuracy. Treating this new data as samples for external validation resulted in high model robustness for PM-2 and PM-4. In addition, the experiment shows that prediction models can be updated quickly and easily at any time by entering small new data sets. Compared to conventional destructive measurements, which are usually necessary to determine the respective quality parameters, food-scanners are comparatively easy to handle and demonstrated to save valuable working time. In addition, fewer produce has to be destroyed for quality assessment. The ability to measure non-destructively through the packaging film with high prediction accuracy, as indicated in previous experiments (Table 2) makes these devices attractive for use along the fruit and vegetable supply chain. Although only a practical validation for the prediction of table grape sugar content is shown in this study, we assume that it is similarly feasible for other fruits at reasonable expense. Thus, a practical application could become quite realistic for the future. In order to guarantee model robustness and prediction accuracy, a periodic validation and re-calibration is necessary.

Potential applications along the supply chain of fruit and vegetables

Based on our findings there are numerous possible applications for food-scanners along the fresh produce supply chain.

At the producer level, food-scanner can be used to monitor fruit quality during growth and maturing of fruit. Due to the portability of these devices, some of the relevant ripening parameters can be determined directly on the plant and harvest predictions can be derived at an early stage. Furthermore, harvesting operations in large orchards can be better coordinated. Certain manufacturers of portable NIR devices have specialized in this area of application and already offer devices specifically designed for various types of fruit (FELIX INSTRUMENTS 2020). Therefore, important ripening parameters such as sugar content and dry matter of tropical fruit (e.g., avocado, mango, kiwi) can be predicted in a non-destructive way. Once these products have been transported, food-scanners can be used to verify fruit quality at the next level of the supply chain. Some produce, especially fruit from overseas, are ripened in special ripening facilities just after arrival in the importing country. The possibility of non-destructive quality assessment enables fruit wholesalers to better control and organize these post-ripening processes.

During incoming goods control of fruit and vegetables at wholesale companies, defined quality criteria must be satisfied. For various types of fruit, statutory minimum requirements are specified (Table 5). Compliance with these standards and additional requirements imposed by retail chains is necessary for an efficient marketing of produce within the European market (UNECE 2019). However, these parameters can often not easily be determined, especially in the case of packaged produce. As stated in the latest draft of the OECD guidelines, NIR spectrometers comprise the ability to simultaneously predict various fruit quality parameters from a single NIR spectrum, therefore serving as "multidimensional predictors of consumer acceptance" (OECD 2018). The prediction results of various quality parameters using food-scanners in our studies indicate the potential of food-scanners, however further validations have to be performed. Following this, several quality parameters of fruit types provided with limited values could be predicted in a non-destructive way with high accuracy (e.g., avocado, kiwi, table grape, citrus). As we demonstrated for table grapes and tomatoes, there is

great potential for the assessment of fruit quality through packaging film, which could facilitate incoming goods control even further.

Table 5: Overview of fresh fruit and vegetables with specific limits of fruit quality parameters according to the United Nations Economic Commission for Europe (UNECE 2019).

Produce	Limiting parameter	Respective document number (UNECE 2019)
Apple	Brix	FFV-50
Avocado	Dry matter	FFV-42
Citrus fruit	Brix, sugar/acid ratio, juice content	FFV-14
Kiwi	Brix, dry matter	FFV-46
Melon	Brix	FFV-23
Peach, Nectarine	Brix, firmness	FFV-26
Pineapple	Brix	FFV-49
Table grape	Brix, sugar/acid ratio	FFV-19
Watermelon	Brix	FFV-37

Portable NIR spectrometers can be integrated into the practical quality control process and the quality of produce can be examined on site directly on the pallet. On the one hand, workflow can be facilitated, which on the other hand saves valuable working time. Additionally, the application of food-scanners allows better objective, reliable and thus comparable quality recording in contrast to oftentimes subjective evaluations by test personnel (GOISSER et al. 2020a).

An extensive evaluation of the data that was recorded during incoming goods control of a German fruit and vegetable wholesaler shows the additional benefit of implementing NIR food-scanners. In this way, the daily recorded an already digitized values can be used to identify differences in delivered produce quality non-destructively, as illustrated by predictions of the F-750 Produce Quality Meter (Figure 3A). In order to protect the anonymity of the cooperation partner, the varieties are not listed in detail in the example shown. The comparison of the destructively determined and non-destructively measured sugar content values of table grapes during our incoming goods control experiment showed that the vast majority of the measured values (> 90%) were within an error range of ± 1 °Brix (Figure 3B). During incoming goods control at wholesalers, a reliable statement about the averaged sample is more relevant than the quality of a single product. Therefore, the accuracy determined in our experiments can be deemed appropriate for the determination of averaged values of a larger sample. Due to this measurement accuracy, fluctuations in the course of the season, individual supplier performance and quality differences depending on the region of origin can be recorded quickly. If necessary, appropriate measures (e.g., special advertising, discount campaigns) can be initiated.

Food-scanners can also be used for end-consumers as well as retail stores to distinguish entry-level products from premium products within the assortment of fruit and vegetables. Differences between these products are often primarily communicated through the layout and design of packaging. We used the data collected during the course of our incoming goods control project and combined the destructively recorded sugar contents of different commercial tomato varieties with the respective retail prices (Figure 3C). As illustrated, fruit qualities that can be clearly distinguished from one another are already offered at different prices. Oftentimes, these differences in internal fruit quality are

not visible for unexperienced end-consumers, which makes the different pricing strategies difficult to understand. By using food-scanners in retail stores, these differences in internal fruit quality can be communicated to the end-consumer, e.g. by demonstrating live measurements in combination with sensory tasting of fruit. Dynamic pricing strategies, as described by Duan and Liu (2019), which are based on a transparent fruit quality, could help retailers to profit from high-quality produce in the future. However, handling of these devices by unexperienced consumers is a challenge and must be taken carefully into account. Incorrectly performed measurements and false results could cause severe brand damage for retail markets and producers and lead to unnecessary food waste and recalls (Pöpping and Bourdichon 2018).
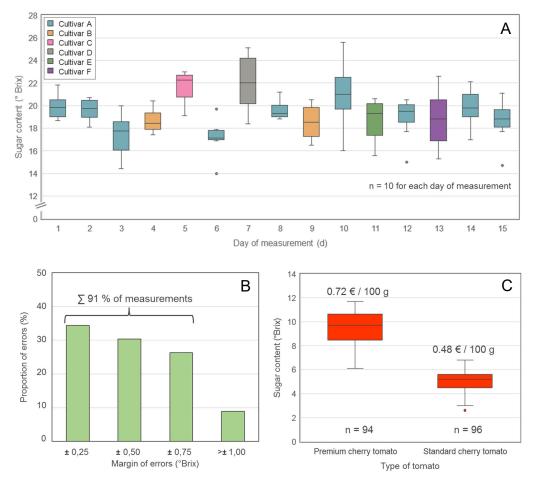

Figure 3: (A) Differences in sugar content of table grapes measured on 15 days during incoming goods control using the F-750 Produce Quality Meter; (B) margin of errors for food-scanner measurements compared to destructive measurements; (C) distinction of different types of tomato due to their sugar content and retail price (according to data from 2020, calendar week 33) using the F-750 Produce Quality Meter

Figure 4 summarizes the possible applications of food-scanners along the fresh produce supply chain. In order to allow a reasonable handling by end-consumers, additional aspects such as handling by inexperienced people and the correct interpretation of the displayed measurements must be taken into account (Pöpping and Bourdichon 2018). With regard to future application of these devices, the estimation of shelf life of fruit and vegetable became the focus of attention within the last few years. First studies conducted on selected produce such as apple (Correa et al. 2015), asparagus (Sánchez

et al. 2009) or lettuce (Giovenzana et al. 2014) indicate the possibility of modelling the shelf life of produce by using NIR spectrometry. Another future area of food-scanner application could be the prediction of sensory taste patterns. The results of initial studies on the combination of NIR spectra with sensory analysis on apples and grapes indicate that taste patterns and consumer preferences can be recognized using NIR spectroscopy (Mehinagic et al. 2003, Parpinello et al. 2013).

With regard to the development of new prediction models for the utilization of these devices in daily practice, as illustrated by the presented case study, a broad range of fruit quality and respective reference values must be considered in order to retain good prediction models. As demonstrated in previous studies (Wedding et al. 2013, Fan et al. 2019), the integration of biological and seasonal variability of fruit can help to build more robust and reliable prediction models and thereby unlock a great potential of non-destructive quality assessment via NIR food-scanners in practical applications for fresh produce.
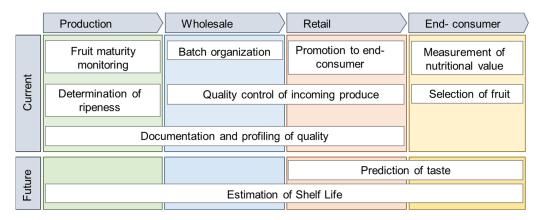

Figure 4: Areas of food-scanner applications along the fresh produce supply chain in current and future quality control

Conclusions

Our study illustrated the possible application of food-scanner at various levels of the fresh produce supply chain. Measurements made possible by food-scanners add value to the quality assessment within the trade of fruit and vegetables. Therefore, the quality of fresh produce can be communicated and tracked quickly and objectively along the supply chain. Our study also shows that further simplifications with regard to the practical use of these devices will be possible in the future. As demonstrated, food-scanners can be used for the building of various prediction models from data collected during incoming goods control or measuring fruit quality directly through packaging film. With regard to the use and benefit of these devices for end-consumers, further applications, such as the prediction of taste, are of great interest. Food-scanners could help to cluster the sensory quality of fruit into taste profiles (e.g., sweet, sour, fruity), which overall enables both retailers and end-consumers to select the desired quality in a targeted manner.

With regard to future investigations, the combination of information derived from NIR spectroscopy with additional data such as temperature and humidity during storage could constitute a new method of shelf life estimation of fresh produce. Using an improved assessment of shelf life at an early stage, the flow of produce along the supply chain can be controlled more specifically. Consequently, produce not suitable for the fresh market can be sent to alternative paths of food processing (e.g., smoothies, juices, dried produce), which helps saving valuable resources and avoids redundant food loss.

References

Ceccato, P.; Flasse, S.; Tarantola, S.; Jacquemoud, S.; Grégoire, J.-M. (2001): Detecting vegetation leaf water content using reflectance in the optical domain. Remote Sensing of Environment 77, 22-33. https://doi.org/10.1016/S0034-4257(01)00191-2

Choi, J.-H.; Chen, P.-A.; Lee, B.; Yim, S.-H.; Kim, M.-S.; Bae, Y.-S.; Lim, D.-C.; Seo, H.-J. (2017): Portable, non-destructive tester integrating VIS/NIR reflectance spectroscopy for the detection of sugar content in Asian pears. Scientia Horticulturae 220, 147-153. https://doi.org/10.1016/j.scienta.2017.03.050

Correa, A.R.; Quicazán, M.C.; Hernandez, C.E. (2015): Modelling the Shelf-life of Apple Products Accoring to their Water Activity. Chemical Engineering Transactions 43, 199-204. https://doi.org/10.3303/CET1543034

Cozzolino, D. (2009): Near infrared spectroscopy in natural products analysis. Planta medica 75, 746-756. https://doi.org/10.1055/s-0028-1112220

Donis-González, I.R.; Valero, C.; Momin, M.A.; Kaur, A.C.; Slaughter, D. (2020): Performance Evaluation of Two Commercially Available Portable Spectrometers to Non-Invasively Determine Table Grape and Peach Quality Attributes. Agronomy 10, 148. https://doi.org/10.3390/agronomy10010148

Duan, Y.; Liu, J. (2019): Optimal dynamic pricing for perishable foods with quality and quantity deteriorating simultaneously under reference price effects. International Journal of Systems Science: Operations & Logistics 6, 346-355. https://doi.org/10.1080/23302674.2018.1465618

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 Biology and Technology 151, 79-87. https://doi.org/10.1016/j.postharvbio.2019.02.001

Felix Instruments (2020): Food science instruments. https://www.felixinstruments.com/food-science-instruments/portable-nir-analyzers/f-750-produce-quality-meter/, accessed on 21 June 2020

Giovenzana, V.; Beghi, R.; Buratti, S.; Civelli, R.; Guidetti, R. (2014): Monitoring of fresh-cut Valerianella locusta Laterr. shelf life by electronic nose and VIS-NIR spectroscopy. Talanta 120, 368-375. https://doi.org/10.1016/j.talanta.2013.12.014

Goisser, S.; Fernandes, M.; Ulrichs, C.; Mempel, H. (2018): Non-destructive measurement method for a fast quality evaluation of fruit and vegetables by using food-scanner. DGG-Proceedings 8, 1-5. https://doi.org/10.5288/DGG-PR-SG-2018

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

Guthrie, J.A.; Walsh, K.B.; Reid, D.J.; Liebenberg, C.J. (2005): Assessment of internal quality attributes of mandarin fruit. 1. NIR calibration model development. Aust. J. Agric. Res. 56, 405. https://doi.org/10.1071/AR04257

Jannok, P.; Kamitani, Y.; Kawano, S. (2014): Development of a Common Calibration Model for Determining the Brix Value of Intact Apple, Pear and Persimmon Fruits by near Infrared Spectroscopy. Journal of Near Infrared Spectroscopy 22, 367-373. https://doi.org/10.1255/jnirs.1130

Kaur, H.; Künnemeyer, R.; McGlone, A. (2017): Comparison of hand-held near infrared spectrophotometers for fruit dry matter assessment. Journal of Near Infrared Spectroscopy 25, 267-277. https://doi.org/10.1177/0967033517725530

Li, J.; Xue, L.; Liu, M.H.; Lv, P.; Yan, L.Y. (2011): Determination of Moisture Content in Ginger Using PSO Combined with Vis/NIR. AMR 320, 563-568. https://doi.org/10.4028/www.scientific.net/AMR.320.563

McGlone, V.A.; Fraser, D.G.; Jordan, R.B.; Künnemeyer, R. (2003a): Internal quality assessment of mandarin fruit by vis/NIR spectroscopy. Journal of Near Infrared Spectroscopy 11, 323-332. https://doi.org/10.1255/jnirs.383

McGlone, V.A.; Jordan, R.B.; Seelye, R.; Clark, C.J. (2003b): Dry-matter—a better predictor of the post-storage soluble solids in apples? Postharvest Biology and Technology 28, 431-435. https://doi.org/10.1016/S0925-5214(02)00207-7

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

Mehinagic, E.; Royer, G.; Bertrand, D.; Symoneaux, R.; Laurens, F.; Jourjon, F. (2003): Relationship between sensory analysis, penetrometry and visible–NIR spectroscopy of apples belonging to different cultivars. Food Quality and Preference 14, 473-484. https://doi.org/10.1016/S0950-3293(03)00012-0

Møller, S.M.; Travers, S.; Bertram, H.C.; Bertelsen, M.G. (2013): Prediction of postharvest dry matter, soluble solids content, firmness and acidity in apples (cv. Elshof) using NMR and NIR spectroscopy: a comparative study. Eur Food Res Technol 237, 1021-1024. https://doi.org/10.1007/s00217-013-2087-6

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. Biosystems Engineering 174, 41-49. https://doi.org/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

Olarewaju, O.O.; Bertling, I.; Magwaza, L.S. (2016): Non-destructive evaluation of avocado fruit maturity using near infrared spectroscopy and PLS regression models. Scientia Horticulturae 199, 229-236. https://doi.org/10.1016/j.scienta.2015.12.047

Parpinello, G.P.; Nunziatini, G.; Rombolà, A.D.; Gottardi, F.; Versari, A. (2013): Relationship between sensory and NIR spectroscopy in consumer preference of table grape (cv Italia). Postharvest Biology and Technology 83, 47-53. https://doi.org/10.1016/j.postharvbio.2013.03.013

Pasquini, C. (2003): Near Infrared Spectroscopy: Fundamentals, Practical Aspects and Analytical Applications. Journal of the Brazilian Chemical Society 14, 198-219. https://doi.org/10.1590/S0103-50532003000200006

Pöpping, B.; Bourdichon, F. (2018): Consumer food testing devices: threat or opportunity? New Food 21, 30-33

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

Sánchez, M.-T.; Pérez-Marín, D.; Flores-Rojas, K.; Guerrero, J.-E.; Garrido-Varo, A. (2009): Use of near-infrared reflectance spectroscopy for shelf-life discrimination of green asparagus stored in a cool room under controlled atmosphere. Talanta 78, 530-536. https://doi.org/10.1016/j.talanta.2008.12.004

Santos Neto, J.P. dos; Assis, M.W.D. de; Casagrande, I.P.; Cunha Júnior, L.C.; Almeida Teixeira, G.H. de (2017): Determination of 'Palmer' mango maturity indices using portable near infrared (VIS-NIR) spectrometer. Postharvest Biology and Technology, 130, 75-80. https://doi.org/10.1016/j.postharvbio.2017.03.009

Schmilovitch, Z.; Mizrach, A.; Hoffman, A.; Egozi, H.; Fuchs, Y. (2000): Determination of mango physiological indices by near-infrared spectrometry. Postharvest Biology and Technology 19, 245-252. https://doi.org/10.1016/s0925-5214(00)00102-2.

Spectral Engines (2020): Food Scanner. The world's smartest, fastest and easiest way to measure food content. https://www.spectralengines.com/products/nirone-scanner/foodscanner, accessed on 21 June 2020.

Sunforest (2020): Portable Nondestructive Fruit Quality Meter. http://sunforest.kr/index.php?sm_idx=eng, accessed on 3 August 2020

Tellspec (2020): Empowering a Healthier World. with Real-Time Analysis Using Portable Low-Cost Sensors. https://tellspec.com/, accessed on 21 June 2020

UNECE, 2019: Fresh Fruit and Vegetables - Standards. http://www.unece.org/trade/agr/standard/fresh/ffv-standardse.html, accessed on 21 June 2020

Wang, H.; Peng, J.; Xie, C.; Bao, Y.; He, Y. (2015): Fruit Quality Evaluation Using Spectroscopy Technology: A Review. Sensors 15, 11889-11927. https://doi.org/10.3390/s150511889

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 Biology and Technology 75, 9-16. https://doi.org/10.1016/j.postharvbio.2012.04.016

Authors

M.Sc. Simon Goisser, Research assistant at University of Applied Sciences Weihenstephan-Triesdorf, Department of Greenhouse Technology and Quality Management, Am Staudengarten 10, 85354 Freising, Germany

M.Sc. Sabine Wittmann, Research assistant at University of Applied Sciences Weihenstephan-Triesdorf, Department of Greenhouse Technology and Quality Management, Am Staudengarten 10, 85354 Freising, Germany

Prof. Dr. Heike Mempel, Professor at University of Applied Sciences Weihenstephan-Triesdorf and head of the department of Greenhouse Technology and Quality Management, Am Staudengarten 10, 85354 Freising, Germany.
E-Mail: heike.mempel@hswt.de

Acknowledgements