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Non-destructive firmness assessment of 'SunGold' kiwifruit a three-year study

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ABSTRACT

Kiwifruit (*Actinidia chinensis var. chinensis*) firmness is routinely measured in a destructive manner for decision-making purposes. Thus, a population's quality is inferred by measuring a sample from that population. Consequently, studies have investigated non-destructive techniques for measuring fruit firmness. However, most of these studies have been restricted to a single season or focused on performance over long-term storage. This work compared non-destructive compression (1 mm deformation) and acoustic stiffness with flesh firmness measured with a penetrometer across three seasons. 'SunGold' kiwifruit were harvested from 11, 9 and 3 orchards on multiple occasions in 2020, 2021 and 2022, respectively. Kiwifruit was freighted to Palmerston North and assessed on arrival. Thirty fruit per orchard were measured on lab arrival, whilst 24 fruit per orchard were stored for two weeks at 0°C prior to assessment. The non-destructive methods had a strong ($r^2 > 0.89$–0.92) segmented correlation with flesh firmness (0.52–10 kg_f). Flesh firmness could be adequately estimated with the non-destructive methods within a season. However, segmented regression performance was reduced when predicting for a season outside of the training population. Nonetheless, these non-destructive methods may be useful for estimating flesh firmness at harvest and after short-term storage (2 weeks at 0 °C).

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Introduction

Kiwifruit (*Actinidia chinensis* var. *chinensis*) are often harvested at a stage where they are physiologically mature but unripe and subsequently undergo ripening and quality changes throughout the post-harvest supply chain (Burdon 2019). Throughout the kiwifruit supply chain quality attributes of batches of fruit are assessed by extracting and testing a subsample of a batch. These assessments are crucial for identifying whether kiwifruit should be marketed immediately or can be stored for later sale (Li et al. 2016). Firmness along with sugar content are used to objectively assess the quality and storability of fruit (Muramatsu et al. 1997).

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Firmness can be considered an indicator of the state of kiwifruit ripeness and is used to estimate the storability of the product (Duprat et al. 1997). As a result, firmness in kiwifruit is employed to make several decisions. Firstly, at-harvest firmness can be used to determine whether fruit can be further stored or if it needs to be immediately sold. Secondly, eating ripeness of kiwifruit is considered when the post-storage firmness ≤ 1 kg_f (10 N) and therefore marketing and distribution need to be completed prior to achieving this firmness (Li et al. 2016).

However, the commercially used Magness-Taylor flesh firmness test (FF) is destructive. Therefore, to minimise fruit loss, firmness of a batch of fruit needs to be assumed based on a small sample. Consequently, this estimation can result in some fruit being incorrectly categorised for the desired markets (Muramatsu et al. 1997). Moreover, this sample may not capture the variability that exists in the fruit batch. For instance, Feng et al. (2003) found that almost 29% of all variation within an orchard or batch is accounted for by fruit-to-fruit variability. Subsequently, several non-destructive firmness assessment methods have been investigated to reduce uncertainty and fruit loss. Particularly non-destructive firmness methods such as acoustic stiffness (Aweta), compression, kiwifirm, impact (Sinclair) and NIR have been created and tested to allow for continuous measurements of fruit (Molina-Delgado et al. 2009; Feng et al. 2016b; Li et al. 2016).

This work will focus on two non-destructive mechanical methods which have been continuously revisited, namely compression firmness (CF) and acoustic stiffness (AS). Non-destructive compression firmness is a technique wherein the fruit is minimally compressed (e.g. 1 mm) to deform the whole fruit (Li et al. 2016). Acoustic stiffness utilises the resonant frequency of an object. Particularly, AS relies on the fact that resonant frequencies are resultant from an object's geometry, mass and elastic modulus (Duprat et al. 1997). More specifically, AS is based on a combination of turgor-based tension and the mechanical strength of the cell wall (Hertog et al. 2004). Both CF and AS are considered to provide a global firmness value for the fruit. Contrastingly, FF is considered a point measurement, wherein the obtained values are location-specific (Molina-Delgado et al. 2009). These non-destructive techniques CF and AS have been compared with FF in many crops (Table 1) such as

Table 1. Summary of regression coefficients of non-destructive acoustic and compression firmness with destructive flesh firmness from the literature.

Crop	Non-destructive method	Regression type	Regression coefficient	Reference
Kiwifruit (Hort16A/ Zespri™ Gold)	Compression Acoustic (Aweta)	Linear	0.61	Schotsmans and Mawson (2005)
Kiwifruit (Hayward)	Compression	Richard's function	0.95	Feng et al. (2009)
Kiwifruit ('SunGold')	Acoustic (Aweta)	Logistic	0.82	Feng et al. (2016a)
Kiwifruit (Hayward)	Acoustic (Aweta)	logistic	0.71	
Kiwifruit (Hayward)	Compression	Logistic	0.905	Li et al. (2016)
	Acoustic (Aweta)		0.936	
	Compression	Linear	0.222–0.721	
	Acoustic (Aweta)		0.465–0.688	
Kiwifruit (Gold3)	Compression	Logistic	0.818	
	Acoustic (Aweta)		0.889	
	Compression	Linear	0.869–0.879	
	Acoustic (Aweta)		0.735–0.918	
Apple ('Golden Delicious')	Acoustic impulse	Curvi-linear	0.8391	Duprat et al. (1997)
Tomato		Linear	0.836	
Avocado ('Fuerte')	Acoustic impulse	Linear	0.695	Shmulevich et al. (2003)

kiwifruit (Schotsmans and Mawson 2005; Feng et al. 2009; Feng et al. 2016a; Li et al. 2016), apples (Duprat et al. 1997) and avocado (Shmulevich et al. 2003). Whilst some studies found moderate to strong correlations (R^2 0.6–0.95) between these non-destructive methods and FF (Feng et al. 2009; Feng et al. 2016a; Li et al. 2016; Pourkhak et al. 2017), others reported the contrary. For instance, Schotsmans and Mawson (2005) noted that neither AS nor CF were adequate predictors of FF. This lack of predictive strength is likely related to the different attributes of firmness that these methods measure. Therefore, there is a need to confirm the relationship between these non-destructive and reference methods. Particularly, in the case of kiwifruit most studies have only utilised data from a single season and one or two harvest times. However, to assess the performance of the non-destructive methods multiple seasons are required to build confidence and validate the relationships.

Kiwifruit softening is known to follow a sigmoidal trend, beginning with a slow softening phase, followed by a phase of rapid softening and subsequently a final slow phase (Schroder and Atkinson 2006). This trend is like the disjointed time-based linear relationships (Li et al. 2016) and logistic/sigmoid-like relationships between AS, CF and FF observed in several studies (Feng et al. 2009; Feng et al. 2016a; Li et al. 2016). Segmented regression was chosen as an alternative to sigmoidal regression as the relationship between non-destructive methods and FF was expected to have a more disjointed linear relationship rather than a curvilinear or sigmoidal relationship. Moreover, segmented regression estimates linear segments based on changes in the slope and could therefore be used to quickly assess the firmness of fruit in specific ranges.

To the best of our knowledge few if any studies have investigated the segmented linear relationship between non-destructive firmness assessments and destructive firmness assessments over multiple years. This work aims to achieve two objectives: firstly, identifying whether AS or CF can be used to adequately predict kiwifruit FF using data from three seasons; secondly, whether segmented regression can be used to predict FF across years. The outcomes of this study are intended to provide both increased confidence in non-destructive methods and provide another method of relating non-destructive and destructive firmness methods. Segmented regression would be simple to implement alongside the current industry data analysis, however, some modifications and trials would be required to assess the performance throughout the supply chain.

Materials and methods

Fruit acquisition

This work spans three years of data collection, covering the 'SunGold' kiwifruit commercial harvest seasons in 2020, 2021 and 2022 (Table 2) with a total of 4272 fruit. Multiple orchards were harvested every year, however, not all orchards were harvested in the same ISO week. Specifically, in 2020 and 2021, some orchards were replaced due to a lack of fruit. Additionally, due to time constraints and equipment access during certain harvests, measurements were only captured for 3617 and 3727 fruit for compression and acoustic respectively. Consequently, only those fruit (3481) which were assessed by both methods have been included in this work.

The fruit were all harvested directly from orchards located in the Bay of Plenty except in 2020 (Table 2). These fruit were transported overnight in a chilled linehaul (~5°C)

Table 2. Fruit collection data for the three years included in this research. Average weight and average firmness are reported as the mean and standard deviation.

Season	No of Orchards	Harvest time (ISO week)	Region	Fruit number	Average weight (g)	Average at-harvest firmness (kg_f)	Average Post-storage firmness (kg_f)
2020	14	12	Bay of Plenty,	2280	115.5 ± 17.9	8.27 ± 0.95	7.44 ± 0.90
		18	Hawkes Bay,			4.99 ± 2.14	2.84 ± 1.87
		20	Whangarei,			3.27 ± 2.08	2.04 ± 1.30
		Whole year	Auckland			5.57 ± 2.74	4.18 ± 2.78
2021	9	9	Bay of Plenty	1092	113.2 ± 14.8	N/A	6.64 ± 0.85
		10				6.97 ± 0.74	6.91 ± 0.93
		12				6.66 ± 0.77	6.11 ± 0.91
		16				5.73 ± 1.14	5.27 ± 1.14
		18				5.02 ± 1.63	2.65 ± 1.43
		20				5.99 ± 1.43	3.23 ± 1.62
		Whole year				6.08 ± 1.37	5.15 ± 1.99
2022	3	11	Bay of Plenty	900	112.7 ± 28.2	6.99 ± 0.60	6.4 ± 0.64
		14				6.23 ± 0.95	4.82 ± 1.74
		16				5.93 ± 0.83	4.28 ± 1.94
		18				4.84 ± 1.77	2.25 ± 1.42
		20				1.33 ± 0.68	1.05 ± 0.58
		Whole year				5.07 ± 2.25	3.87 ± 2.32

except when delayed or they were personally collected and driven back to Massey University in Palmerston North, New Zealand (~10°C). Orchards were harvested multiple times to capture a range of firmness, whilst multiple orchards were included to capture greater variability. On arrival to the lab, the fruit were separated into two treatments, with approximately 30 fruit per orchard assessed both non-destructively and destructively immediately (2118 fruit). Whereas approximately 24 fruit per orchard were assessed non-destructively and then stored at 1°C for two weeks prior to non-destructive and destructive assessment (2154 fruit). The storage for two weeks at 1°C was used because these fruit were also involved in another experiment assessing injury (which had minimal impact on firmness). Additionally, this short storage allowed for a more gradual range of firmness to be captured (average 4-unit change in acoustic stiffness).

Acoustic stiffness

Fruit acoustic stiffness was obtained using a portable AWETA acoustic firmness sensor (AFS, first generation Aweta™ Impact and Acoustic Firmness System, Nootdorp, The Netherlands). The settings were as follows: Threshold firmness range of 0–39, tick power of 12 and microphone gain of 50% (Sneddon et al. 2022). The fruit were positioned on a concave foam cup at a 40–50° angle to enable probe contact with the fruit shoulders. Measurements were averaged from both the blossom and stem end (Supplementary 1). The measurements were conducted on the shoulders due to faster measurement speed and greater measurement consistency compared to the equator.

Non-destructive compression and flesh firmness

Non-destructive compression (1 mm deformation) and flesh firmness (penetration test) measurements were performed using an electronic QALink penetrometer (Willowbank

Electronics Ltd, Napier, New Zealand). For both tests, the penetrometer was fitted with an Effegi 7.9 mm convex probe and had the settings: test speed 8 mm/s, reverse speed 25 mm/s and a trigger threshold of 50 g for both methods (Burdon et al. 2016; Li et al. 2016; Li et al. 2017). Both methods were conducted at two locations around the equator with 90° of separation. For non-destructive compression, the skin remained present, and the probe compressed the fruit to 1 mm deformation. Alternatively, for the flesh firmness measurement, the skin was removed, and the measurement distance was set to 8 mm. For both methods peak force was used as the measurement value. Measurement locations were not marked; thus, both these measurements could have been performed in the same locations. All evaluations were conducted in a temperature-controlled lab at 20°C, fruit were assessed on arrival to the lab and ∼12–18 h after removal from the cool room.

Data analysis

The data were filtered to isolate complete sets of firmness measurements and filtered again separately to isolate each year for further analysis. Data analysis was conducted using R (R Core Team 2021), RStudio (Posit team 2023), and the packages dplyr (Wickham et al. 2022), ggplot2 (Wickham 2016), ggpubr (Kassambara 2020), segmented (Muggeo 2008) and caret (Kuhn 2022). Segmented regression provided three distinct regression equations split at points estimated to have a clear change in slope. The predictive power of the segmented regression equations was tested in two scenarios. Firstly, data from all seasons were randomly split 80:20 for a training data set (2786 fruit for calibration, 80% of 3481) and a test set (695 fruit for validation, 20% of 3481), respectively. Secondly, data from 2020 and 2021 ($n = 2600$) were used to develop the segmented regression equations which were used to predict the FF from 2022s non-destructive data ($n = 881$), simulating the scenario where these methods are used in real-world applications. These were conducted to test the performance of segmented regression within a collection/season and across seasons. Additionally, Kolmogorov–Smirnov tests were conducted to assess whether the distributions of the populations were the same. The performance of the regression models was evaluated using the root mean square error of the calibration (RMSEC) and the prediction (RMSEP), mean absolute error (MAE), Akaike information criterion (AIC), and the ratio of prediction to deviation (RPD, referred to as SDR) for the calibration (SDRc) and prediction (SDRp). RMSE measures the square root of the mean squared error and is a metric that is sensitive to outliers, thus providing the true error (Chai and Draxler 2014). Whereas MAE measures the average size of errors within a collection of predictions and is not impacted by extreme outliers (Chai and Draxler 2014). AIC is a metric that considers both the complexity and simplicity of a model. Specifically, the goodness of fit and penalty term will vary with model complexity (Cavanaugh and Neath 2019). SDR is a dimensionless parameter used to quantify predictive ability of models. For RMSEC, RMSEP, MAE and AIC the smaller the resultant value the better the model. Contrastingly, models with greater predictive power will have a higher SDR. Particularly, SDR below 1.5 is useless, above 2.5 is good or excellent accuracy, and SDR values between these vary in predictive accuracy across the range of values.

Results

Model validation

The performance of segmented regression was assessed using a segmented model developed using the training data set (80% of data $n = 2786$) and fit to the test data set (20% of data $n = 695$). This process was conducted separately for both AS (Figure 1(A)) and CF (Figure 1(B)). Both non-destructive segmented models fit relatively well across the whole FF range. However, there was a greater performance at the low (< 2–3 kg_f) and high (> 5 kg_f) than in the middle FF ranges (3–5 kg_f). These segmented models (Figure 1(A,B))

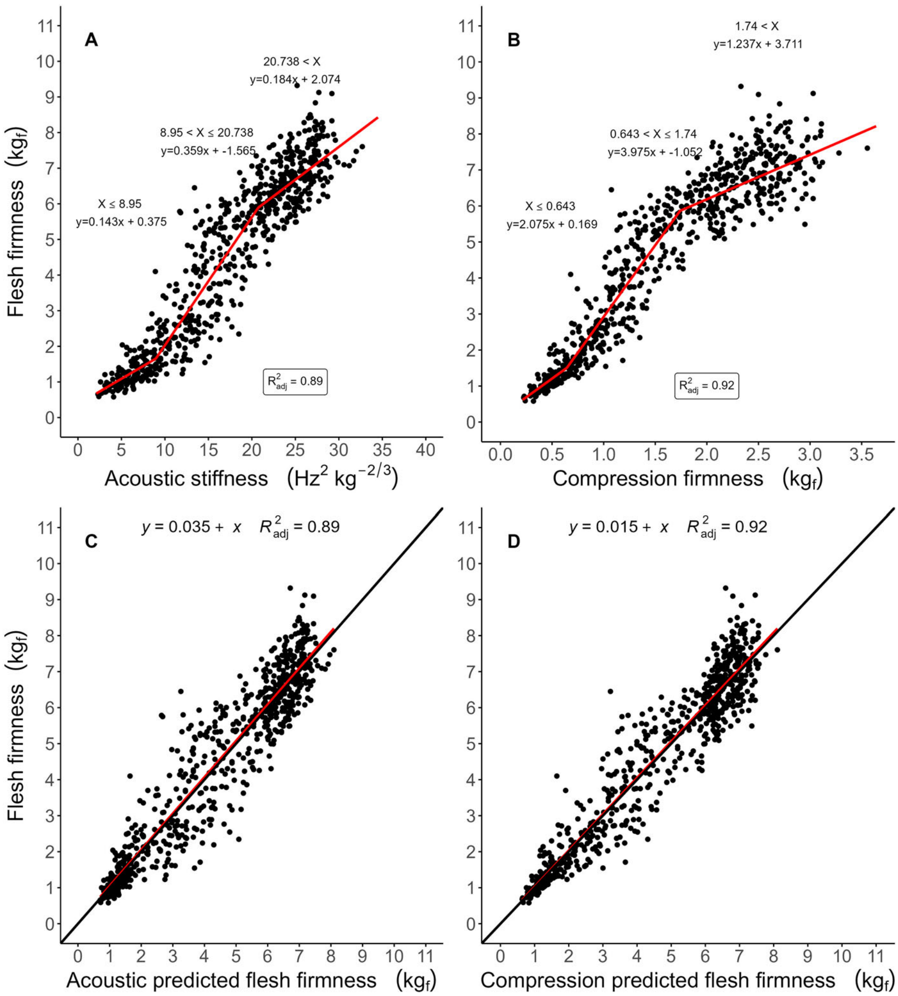

Figure 1. Segmented linear regression (A & B) and simple linear regression (C & D). The segmented lines of best fit were developed using segmented regression models from the training data set for Acoustic stiffness (A) and Compression firmness (B). The simple linear regression depicts the values predicted using the segmented regression models for Acoustic stiffness (C) and Compression firmness (D). The linear best fit line is in red and the $x = y$ line is depicted in black. Data points in both the segmented and linear regressions are from the test data set ($n = 695$).

show relatively high performance as shown in Table 3. Particularly, the RMSEC are 0.79 and 0.69 and the MAE are 0.59 and 0.52 for AS and CF, respectively. The RMSEC suggests that the average difference between the predicted and actual values of FF are 0.79 and 0.69 kg_f for AS and CF respectively. Interestingly, under both RMSEC and MAE the CF segmented model performed better than the AS segmented model. This performance is reinforced by both the AIC (6650 and 5868 for AS and CF respectively) and the SDRc where both AS and CF have good or excellent accuracy (> 2.5) but the SDRc for AS is marginally lower than that of CF.

The segmented predicted values versus the observed values showed a very strong linear relationship (Figure 1(C,D)). Particularly the data showed a near 1:1 relationship. However, when comparing the line of best fit with the $x = y$ line, the best fit line appears to be slightly above the $x = y$ line. This difference appears to increase gradually as the fruit firmness increases. However, this difference is very minimal (<0.04 kg_f) and could be neglected. Although the divergence with greater firmness suggests that the segmented regression models slowly lose predictive power as firmness increases. This observation agrees with the SDRp values which are reduced compared to the SDRc values but still above 2.5 and thus have good to excellent accuracy.

Model prediction

Segmented regression models have reduced efficacy when predicting the FF of data outside of the training population. Specifically, the segmented models developed using data from the 2020 and 2021 seasons struggled to accurately predict the FF observed in the 2022 season. This lack of predictive power is likely related to the training and test sets possessing different distributions (Kolmogorov–Smirnov $p < 0.05$). The fit segmented regression lines appear to be displaced from the 2022 data for both AS (Figure 2(A)) and CF (Figure 2(B)). Particularly, the slopes and breaks derived using the 2020 and 2021 data do not coincide or agree with the breaks or slope gradients observed in the 2022 data. This misplacement is most noticeable in segment one for AS (Figure 2 (A)) and at segment three for CF (Figure 2(B)). Despite this, the model performance

Table 3. Model performance parameters for the internal validation (80:20 split data) and external validation. For external validation the model performance was evaluated by using an individual year as the test set and the remaining years as the model calibration. For example, 2020s data were the test set for the model calibrated from 2021 and 2022 data. RMSEC and RMSEP are root mean square error of the calibration and prediction respectively. SDRc and SDRp are the ratio of prediction to deviation for the calibration and prediction, respectively.

	Internal validation							
Test set	Calibration model	Non-destructive method	RMSEC	RMSEP	MAE	AIC	SDRc	SDRp
20% of all data	80% of all data	Acoustic	0.79	0.79	0.59	6650.3	3.50	2.82
		Compression	0.69	0.69	0.52	5867.5	4.69	3.28
	External validation							
2020	2021 and 2022	Acoustic	0.80	0.81	0.60	4692.9	3.05	2.74
		Compression	0.74	0.66	0.58	4357.4	3.67	3.32
2021	2020 and 2022	Acoustic	0.82	0.75	0.61	5900.7	3.41	2.17
		Compression	0.69	0.72	0.51	5049.7	4.96	2.42
2022	2020 and 2021	Acoustic	0.75	0.96	0.56	5869.6	4.03	2.43
		Compression	0.64	0.84	0.49	5075.3	5.60	2.80

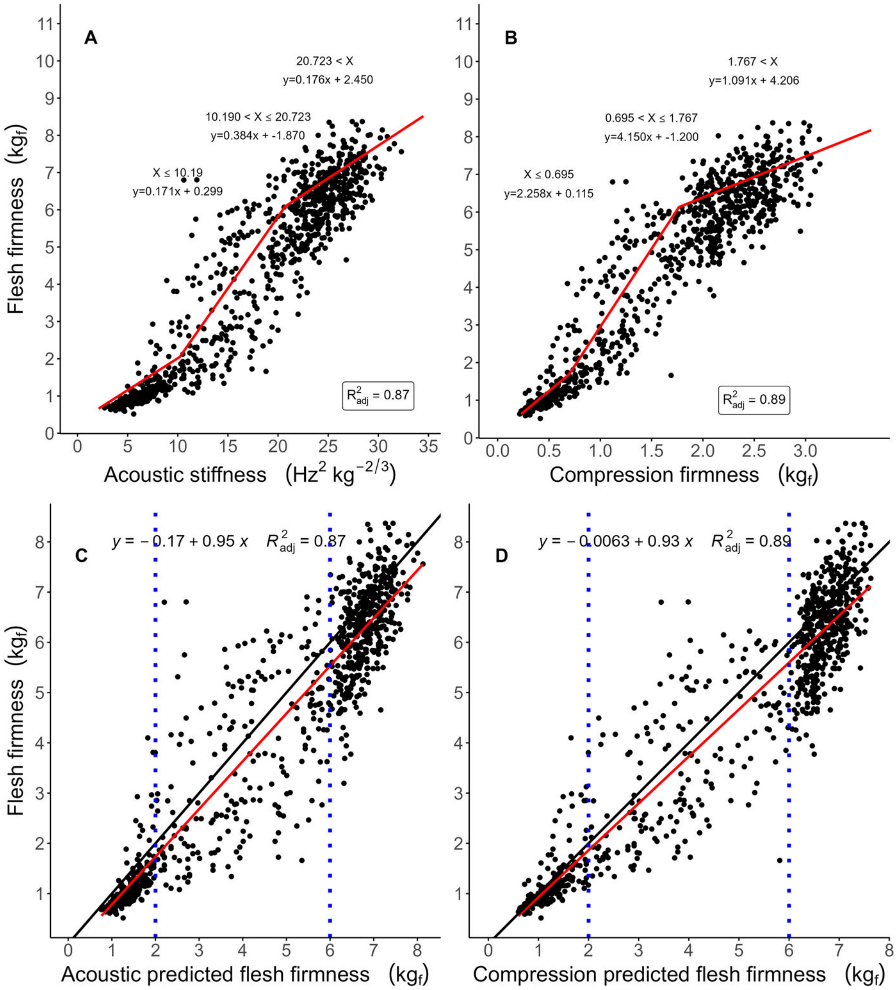

Figure 2. Segmented linear regression (A & B) and simple linear regression (C & D) of the 2022 seasons data. Segmented lines of best fit were developed using segmented regression models developed from the 2020 and 2021 data ($n = 2600$) for both Acoustic stiffness (A) and Compression firmness (B). The simple linear regression depicts the values predicted using the 2020 and 2021-built regression models for acoustic stiffness (C) and compression firmness (D). The linear best-fit line is in red and the $x = y$ line is depicted in black. Blue dotted lines indicate the rough threshold locations of changes in data distribution. The data in both the segmented and linear regressions are from the 2022 season ($n = 881$).

appears to be relatively good with an RMSEC of 0.75 and 0.64 for AS and CF, respectively. This suggests that the average difference between observed and predicted FF values are 0.75 and 0.64 kg_f for AS and CF, respectively. Additionally, this suggests that there is marginally greater performance with the calibration for 2022 than with the 80:20 model. Similar RMSEC performance can be observed for 2020 and 2021 in Table 3. Moreover, MAE suggests that the calibration model (2020 and 2021 data) tested on 2022 also performed marginally better (0.56 and 0.49 for AS and CF, respectively) than in the 80:20 model. Additionally, like the 80:20 model CF was observed to perform better than AS in terms of both AIC and SDRc. Interestingly, SDRc was greater in this model than the 80:20 model reinforcing an improved performance in the calibration. However, the prediction of the 2022 data had reduced performance below that of the 80:20 model. Specifically, RMSEP increased and SDRp dropped below 2.5 for AS but was still slightly above for CF (2.80). This suggests that there is greater error when predicting outside of the training season. This decline in performance in terms of SDRp was observed for both 2020 and 2021 predictions as well.

The reduced model performance was more noticeable after comparing the predicted FF values with the observed FF values in 2022 (Figure 2(C,D)). Particularly, the variability between the predicted and observed values is obvious in the middle firmness ranges (2–6 kg_f). Moreover, there is an apparent shift in the relationship at high firmness (>6 kg_f) for both AS (Figure 2(C)) and CF (Figure 2(D)). However, despite these issues, a strong relationship appears to remain at low firmness (<2 kg_f). Furthermore, the linear fitted line appears to be located close to the $x = y$ line at low firmness and then deviates rather significantly as the firmness increases. This suggests that these non-destructive methods may only be used with confidence between seasons when assessing the fruit of low firmness.

Discussion

Establishing a segmented regression

Acoustic stiffness and compression firmness were not immediately linearly correlated to FF. Specifically, there were at least three distinct changes in slope visible in the raw data, which is also observed in the subsample in Figure 1(A,B). This pattern has been observed previously for kiwifruit stored for varying lengths of time (Li et al. 2016). Subsequently, a segmented regression method was employed to capture these groupings and relationship changes in the present study. The implementation of this segmented model appeared to capture more of the natural variability than the single linear regression (data not shown). This improvement in regression strength was not unexpected. Previous studies using linear regression have shown moderate relationships between non-destructive firmness measurements and flesh firmness. For example, AS and CF were observed to have a linear R^2 of 0.61 between 0 and 20 N FF (Schotsmans and Mawson 2005). On the contrary, when using a larger firmness range (0–100 N FF) and regression methods which account for shifts in relationship, stronger relationships have been captured. Particularly an R^2 of 0.82 (Feng et al. 2016a) and 0.89 (Li et al. 2016) were captured for AS when using logistic regression. Similarly, R^2 of 0.82 (Li et al. 2016) and 0.95 (Feng et al. 2009) were captured for CF using a logistic and Richard's function (sigmoidal), respectively. Therefore, the results of segmented regression agree with previous work. Specifically, accounting for shifts in relationships can improve the regression strength.

Estimating flesh firmness model validation

The FF could be accurately predicted when using the segmented models developed from 80% of the data. Specifically, the segmented models were observed to accurately fit the test data (20%) (Figure 1(A,B)) with relatively low RMSEC and MAE (<0.8) and a relatively high correlation coefficient (>0.85). However, the RMSEC and MAE do suggest that there is a fair margin of error when considering specific firmness ranges. For example, RMSEC suggests that there will be a 0.79 and 0.69 kg_f difference for firmness values estimated by AS and CF, respectively. This error is negligible at high firmness (>6 kg_f) wherein fruit will be stored regardless of the exact firmness. However, this error is an issue for fruit at the marketable stage wherein a 1 kg_f fruit could be classified as either 0.21 or 1.79 kg_f. Particularly, the fruit classified below 1 kg_f may be discarded, whilst the fruit classified above 1 kg_f may remain in storage. However, both RMSEC and MAE may be reduced if the middle firmness range (3–5 kg_f) was excluded. This is particularly important for the low firmness range (>2 kg_f) where there appears to be an almost 1:1 relationship.

However, there appear to be a few curiosities in the data. Firstly, the non-destructive methods prior to prediction possess high variability in the 3–5 kg_f FF range (Figure 1(A, B)). Secondly, the predicted FF data (Figure 1(C,D)) appears to have a slight underprediction at the high firmness range, expressed as a change in slope above 7 kg_f. The reasons for these phenomena are unclear. However, the variability between 3 and 5 kg_f may relate to the differential rate of changes occurring during softening. Particularly, Schroder and Atkinson (2006) noted that cell wall swelling, and pectin solubilisation occur in the second phase of softening (1–6 kg_f). Moreover, they noted that pectin degradation and loss of middle lamellae initiated in the second phase but peaks in the final phase. Additionally, with the loss and degradation of pectin there appeared to be an associated movement of water, which coincided with cell wall swelling. Furthermore, they noted that differential softening can be observed across tissue and even within cells. Therefore, the poor performance in the 3–5 kg_f firmness range may be associated with these changes occurring at varying rates throughout the fruit. Thus, the FF point measurement may not capture enough data to get the exact firmness during this phase of rapid change. Whereas the non-destructive methods may provide a better overview of whole fruit softening. Alternatively, because the non-destructive methods are sensitive to water content (Hertog et al. 2004; Róth et al. 2005; Schotsmans and Mawson 2005; Schotsmans et al. 2005) they detect greater variability due to differential swelling of cells (caused by water movement). Therefore, FF may underperform in this phase of rapid softening due to the limited area assessed. Likewise, the non-destructive methods may be overly influenced by changes in cell water content in this phase leading to greater variability. This variability has been observed to varying extents in several studies. Particularly in tomatoes there was a larger dispersion between 2 and 6 kg_f when using NIR for firmness prediction (Kumar et al. 2022). Moreover, in 'SunGold' kiwifruit using CF, AS, and impact firmness there were increases in data spread observed above 15 N when using logistic regression and noticeable spread between 20 and 40 N in linear regressions for 0–6 weeks of storage (Li et al. 2016).

Regardless of this variability, the correlation coefficients observed in this study are comparable or better than those observed previously using other non-destructive methods. Specifically, previous work on tomatoes observed R^2 of 0.89–0.92 and 0.90–0.92 for calibration and validation (prediction) sets respectively using spatially resolved spectroscopy (Huang et al. 2018). Moreover, using NIR the R^2 ranged from 0.58–0.66 and 0.58–0.72 for calibration and validation sets respectively depending on the wavelengths investigated (Kumar et al. 2022). Furthermore, pear firmness assessed using acoustic vibration achieved an R^2 of 0.81 and 0.72 for calibration and validation, respectively (Zhang et al. 2014). Ultimately, both AS and CF show promise as options for non-destructively predicting the FF of kiwifruit.

Presently, CF appears to have a greater predictive power than AS in all metrics (RMSEC, MAE, AIC and SDRc). This is more pronounced in the AIC of the segmented models with an AIC of 6650 and 5868 for AS and CF, respectively. Thus, focusing purely on model performance the better option for FF prediction is CF. This is not unexpected as both CF and FF use the same equipment and assessment process, whereas AS is measured with different equipment and at different locations on the fruit. Besides the model performance, there are other factors which should be considered when deciding which method to implement. Particularly, AS measured with a first-generation Aweta struggles to provide consistent readings for fruit of low mass (<60–70 g). Although this may be less of an issue in the later generations of the Aweta. Conversely, CF as measured in this study can induce white markings on the flesh. These white markings arose after repeat measurements and on fruit which were below 2 kg_f. However, this marking may also arise on firmer fruit. Consequently, for certainty of non-destructive action and relatively similar performance, AS is the preferable method for assessing FF non-destructively.

Predicting flesh firmness in 2022

Contrastingly, when the segmented regression models were used to predict FF in a season outside of the training data there is poor fitting (Figure 2). Particularly, the fitted segmented regressions appear to be slightly above the centre of the test data in both AS and CF (Figure 2(A,B)). This displacement is most noticeable at the low and high firmness ranges, but less noticeable between 2 and 6 kg_f due to the large spread of data. The variability between 2 and 6 kg_f could be related to the variability in this range between seasons. Moreover, the lack of consistency in firmness across seasons may be compounded by the variability between the non-destructive methods and FF in this FF range.

These data abnormalities become more obvious once the predicted FF values and observed FF values are compared (Figure 2(C,D)). Particularly two major abnormalities become apparent. Firstly, the spread of the relationship appears more exacerbated in the 2–6 kg_f range. Secondly, there is a noticeable change in slope above 6 kg_f. Moreover, the best-fit line rapidly diverges away from the $x = y$ line as firmness increases. This suggests that the segmented regression did not adequately capture the high firmness ranges (>6 kg_f) thus resulting in an under prediction. This is likely related to 2020 and 2021 having statistically different distributions of AS and CF compared to 2022, particularly above 6 kg_f (data not shown). FF predictions across years inherit a larger margin of error, particularly RMSEP was greater and SDRp was lower than in the 80:20 model (Table 3). Overall, the variability and underprediction in both non-destructive methods suggest that in this study, segmented regression could not adequately predict FF across years. However, the minimal change observed between the R^2, MAE and RMSEC of the 80:20 model and the 2022 model suggests that AS and CF have potential as non-destructive assessments of FF. Particularly, the performance across years may be improved by incorporating more seasons and fruit into the training model.

Similar model performance issues have been observed with NIR assessments of firmness. For example, Rungpichayapichet et al. (2016) observed relatively poor performance when using NIR-built models to predict mango firmness across years. Specifically, the models achieved an R^2 of 0.45, 0.64 and −0.66 when predicting mango firmness in 2009, 2012, and 2013, respectively. Likewise, Li et al. (2018) observed strong performance with NIR on kiwifruit firmness in model calibration ($R^2 > 0.9$) but observed reduced performance ($R^2 = 0.56$) during external model validation. Therefore, for the best performance, segmented models will need to be trained and assessed on data within a season.

Moreover, it is possible that the performance of the model is hindered by the inherent variation of FF. For example, the environmental conditions or orchard can have a significant impact on the resulting firmness (Chagné et al. 2014; Zushi et al. 2023). Moreover, season and location within a plant can have a significant impact on fruit firmness (Moggia et al. 2017; Lobos et al. 2018). For example, Snelgar and Hopkirk (1988) found that shaded kiwifruit vines produced fruit with low firmness. Additionally, the nutrition during growth can impact firmness and firmness decay. Specifically, Prasad et al. (1988) observed that fruit softened at variable rates when grown with low nitrate levels, whereas high nitrate led to rapidly softening fruit. Thus, several pre-harvest factors may impact the firmness of fruit within an orchard and across seasons. Furthermore, Li et al. (2017) suggested that non-destructive model performance may be influenced by both model robustness and the precision of the FF measurement. Particularly Li et al. noted that two FF measurements on the same fruit (90° apart at the equator) possessed large variability. Specifically, they found FF measurement variability may account for up to 80% of the calculated RMSEC. However, further studies (including sensory evaluations) are required to determine whether these non-destructive methods could be used as an alternative to FF (penetrometer) as a standard for kiwifruit quality evaluations. These findings suggest that AS or CF could be utilised with some accuracy across seasons with fruit of low firmness. Specifically, these methods should be able to estimate the firmness of fruit below 2 kg_f with decent efficacy. However, these methods will require further data collection to improve the accuracy of FF prediction between 2 and 6 kg_f. Therefore, it may be possible to implement these methods in the industry after long-term storage prior to repacking or shipping.

Conclusion

Segmented regression can be used to adequately predict the FF using either AS ($R^2 = 0.89$; RMSEP = 0.79) or CF ($R^2 = 0.92$; RMSEP = 0.69). However, segmented regression has reduced efficacy when predicting outside of the training seasons ($R^2 = 0.87$ and 0.89; RMSEP = 0.96 and 0.84 for AS and CF respectively). Particularly, the 2022 prediction models tend to underestimate the FF values and diverge from the $x = y$ line as FF increases. Moreover, there is a large spread of data in the 2–6 kg_f range which may be related to either natural variation in fruit populations or due to accuracy issues with either FF or the non-destructive methods. However, despite the issues, this work has shown that AS or CF can be used within a season to estimate FF presuming there is an existing library of adequate correlative data.

The current standard of FF assessment may not be as appropriate for firmness assessment as the non-destructive methods. Particularly, FF was a handheld puncture method and was adopted due to the lack of alternatives. Thus, everything has been compared to FF, even though this method is destructive and imperfect especially with natural variation. Specifically, FF measured firmness can vary for numerous reasons across seasons and orchards. Particularly, the macro and micro-climate and cultural practices may impact firmness. This is especially true for a spot measurement like FF but could be less impactful in a global measurement such as AS or CF.

Future work could investigate harvesting and marketing thresholds for non-destructive methods and compare their acceptability with that of FF. Moreover, research could be conducted to observe the variability captured by FF and non-destructive methods throughout the growing season. This would enable us to observe which of the methods has greater variability in the resultant measurements, thus identifying potential weaknesses or strengths of the methods. Furthermore, both AS and CF have the potential to accurately estimate FF within a season at harvest (>6 kg_f) and potentially after storage (<1 kg_f). Moreover, the current work suggests that fruit of low firmness (<2 kg_f) may be adequately predicted between seasons with AS or CF.

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