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**Developing non-destructive techniques to predict ‘Hayward’
kiwifruit storability**

A thesis presented in partial fulfilment of the requirements for the degree of
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Abstract

A significant portion of New Zealand's kiwifruit production is held as stock in local coolstores for extended periods of time before being exported. Many pre-harvest factors contribute to variation in fruit quality at harvest and during coolstorage, and results in the difficulty in segregating fruit for their storage outcomes. The objective of this work was to develop non-destructive techniques utilised at harvest to predict storability of individual or batches of 'Hayward' kiwifruit based on (near) skin properties. Segregation of fruit with low storage potential at harvest could enable that fruit to be sold earlier in the season reducing total fruit loss and improving profitability later in the season.

The potential for optical coherence tomography (OCT) to detect near surface cellular structural differences in kiwifruit as a result of preharvest factors was demonstrated through quantitative image analysis of 3D OCT images of intact fruit from five commercial cultivars. Visualisation and characterisation of large parenchyma cells in the outer pericarp of kiwifruit was achieved by developing an automated image processing technique. This work established the usefulness of OCT to perform rapid analysis and differentiation of the microstructures of sub-surface cells between kiwifruit cultivars. However, the effects of preharvest conditions between batches of fruit within a cultivar were not detectable from image analysis and hence, the ability to provide segregation or prediction for fruit from the same cultivar was assumed to be limited.

Total soluble solids concentration (TSS) and flesh firmness (FF) are two important quality attributes indicating the eating quality and storability of stored kiwifruit. Prediction of TSS and FF using non-destructive techniques would allow strategic marketing of fruit. This work demonstrated that visible-near-infrared (Vis-NIR) spectroscopy could be utilised as the sole input at harvest, to provide quantitative prediction of post-storage TSS by generating blackbox regression models. However the level of accuracy achieved was not adequate for online sorting purposes. Quantitative prediction of FF remained unsuccessful. Improved ways of physical measurements for FF may help reduce the undesirable variation observed on the same fruit and increase prediction capability.

More promising results were obtained by developing blackbox classification models using Vis-NIR spectroscopy at harvest to segregate storability of individual kiwifruit based on the export FF criterion of 1 kg_f (9.8 N). Through appropriate machine learning techniques, the surface properties of fruit at harvest captured in the form of spectral data were correlated to post-storage FF via pattern recognition. The best prediction was obtained for fruit stored at 0°C for 125 days: approximately 50% of the soft fruit and 80% of the good fruit could be identified. The developed model was capable of performing classification both within (at the fruit level) and between grower lines. Model validation suggested that segregation between grower lines at harvest achieved 30% reduction in soft fruit after storage. Should the model be applied in the industry to enable sequential marketing, \$11.2 million NZD/annum could be saved because of reduced fruit loss, repacking and condition checking costs.

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soft fruit..... 180

List of Abbreviations and Symbols

2D	two dimensional
3D	three dimensional
AAO	all-at-once
ANN	artificial neuron network
AUC	area under curve
CDA	canonical discriminant analysis
CI	chilling injury
DAFB	day after full bloom
DMC	dry matter concentration
DS	decision stumps
DW	dry weight
FF	flesh firmness
FN	false negative
FP	false positive
GA	genetic algorithm
GL	grower line
GLM	general linear model
HC	high crop load
HCG	high crop load with trunk girdling
HSI	hyperspectral imaging
InGaAs	indium gallium arsenide
kg _f	kilogram-force
LC	low crop load
LCG	low crop load with trunk girdling
LDA	linear discriminant analysis
LED	light-emitting diodes
LOOCV	leave-one-out cross validation
LSD	least significant differences
MAE	mean absolute error
MLR	multivariate linear regression

MSC	multiplicative scatter correction
MSE	mean square error
MSEP	mean square error of prediction
MST	minimum taste standard
N	newton
NIPALS	non-linear iterative partial least squares
NIR	near infrared
NZD	New Zealand dollars
OAA	one-against-all
OAo	one-against-one
OCT	optical coherence tomography
PbS	lead sulfide
PC	principal component
PCA	principal component analysis
PCR	principal component regression
PLS	partial least squares
PLS-DA	partial least squares discriminant analysis
PLSR	partial least squares regression
Psa	<i>Pseudomonas syringae</i> pv <i>actinidiae</i>
QDA	quadratic discriminant analyses
R	correlation coefficient
R ²	coefficient of determination
RBF	radial basis function
RC	regression coefficient
RM	reflective mulch
RMSE	root mean square error
RMSEP	root mean square error of prediction
ROC	receiver operating characteristic
S.D.	standard deviation
SD-OCT	spectral-domain optical coherence tomography
SDR	division of standard deviation and RMSEP
SEC	standard error of calibration
SEP	standard error of prediction

SMO	sequential minimal optimisation
SMOTE	synthetic minority oversampling technique
SVM	support vector machines
SVMR	support vector machines regression
TN	true negative
TSS	total soluble solids
TP	true positive
TZG	taste Zespri grade
Vis-NIR	visible near infrared

