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Apple Fruitlet Abscission Prediction. I. Development and Evaluation of Reflectance Spectroscopy Models

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Abstract. **Chemical thinning, the most common and cost-effective thinning method, is conducted during early apple fruit development over a 3- to 4-week period using multiple applications of plant growth regulators. It is critical to provide apple growers with tools to assess the efficacy of chemical thinners quickly and accurately because visible responses are not apparent for up to 2 weeks after application. The objective of this study was to build a model to predict apple fruitlet abscission following a chemical thinner application with in situ reflectance data obtained with a portable visible and near infrared (Vis/NIR) spectrophotometer. Developed models were compared with the currently available fruitlet growth model (FGM). 'Honeycrisp' fruitlet diameter and reflectance were measured on dates around a chemical thinner application across a 2-year period. After June drop, measured fruitlets were determined to have either persisted or abscised. Random forest, partial least squares regression, and XGBoost classification models were used to predict fruitlet abscission from reflectance data. Each classification model was developed with 2021, 2022, and combined 2021 + 2022 data. For each dataset, 5-fold cross validation was used to assess three model performance metrics: 1) overall accuracy, 2) recall, and 3) specificity. Datasets tested were either unbalanced, majority class down-sampled, or minority class up-sampled with synthetic minority oversampling technique. In both years, the FGM reliably estimated chemical thinner efficacy 9 days after application. Before this time point, the FGM had low prediction accuracy of the minority class in both years—persisting fruitlets in 2021 and abscising fruitlets in 2022. For reflectance spectroscopy, the developed random forest models that were balanced with synthetic minority over-sampling technique were found to be the best combination in predicting chemical thinner efficacy. The combined 2021 + 2022 dataset overall model accuracy ranged from 84% the day before to 93% at 9 days after thinner application. These results show that Vis/NIR is a promising tool to predict chemical thinner efficacy. This technology had high prediction accuracies over a range of fruitlet abscission potential and two growing seasons. Further development and testing of the model over cultivars, chemical thinner timings, and growing regions would facilitate commercialization of the technology.**

Crop load management (thinning; the intentional removal of flowers and/or fruitlets) is a critical annual management decision for apple growers. Apple trees produce an excessive number of fruit, and more than 70% must be removed (thinned) to optimize crop value, enhance fruit quality, and ensure consistent cropping (Lakso and Goffinet 2017). The application of plant bioregulators to induce fruitlet abscission (chemical thinning) is currently the most efficient and cost-effective method of apple crop load management. Apple trees are only susceptible to chemical thinners during a 3- to 4-week period (Byers et al. 1990). Environmental factors (temperature and solar radiation) greatly influence fruitlet abscission rates following a thinner application, leading to variable results (Lakso et al. 1999; Lordan et al. 2019). This variability can often necessitate multiple chemical thinner applications.

Ideally, the efficacy of a chemical thinner application should be determined before additional application(s) are made. Visible indicators of fruitlet abscission are not apparent for 10 to 14 d after a chemical thinner application, complicating management decisions. It is critical to provide apple growers with quick and accurate technologies to determine chemical thinner responses. Minimizing the time between chemical thinner application and efficacy determination provides the greatest flexibility for growers to make follow-up applications at favorable timing and environmental conditions.

Several physiological factors have been studied to find an early predictor of fruitlet abscission. Ward and Marini (1999) found that fruit stem water potential was less negative and starch concentration lower in fruitlets subjected to a high thinner rate compared with untreated fruitlets. These two parameters were hypothesized to be the cause of a cessation in growth of abscising fruitlets. Cell wall degradation due to cellulase was determined to be a secondary effect after fruitlets had stopped development (Ward and Marini 1999). The slowing of growth of fruitlets bound to abscise was observed in several studies (Byers et al. 1991; Marini 2003; McArtney and Obermiller 2012; Ward and Marini 1999). Greene et al. (2013) used this phenomenon to develop the FGM. The FGM requires repeated measures of fruitlet diameter to predict fruitlet persistence and abscission following a chemical thinner application. The FGM provided reliable results in 7 to 10 d after a chemical thinner application (Greene et al. 2013). While effective, use of the FGM is labor and time intensive and grower adoption of the FGM has been limited. To increase adoption, researchers and private industry have focused on the evaluation of modified approaches that use fruit weight (Hillmann et al. 2022) or vision systems to estimate fruit size and predict fruitlet abscission (Wallis et al. 2023). To our knowledge, the FGM and modified approaches have not been formally validated.

Vis/NIR spectroscopy measures the reflectance of light from ∼380 to 2500 nm. This portion encompasses Vis (∼380 to 700 nm) and NIR (∼800 to 2500 nm). Vis/NIR spectroscopy has been used to estimate a range of fruit characteristics, including soluble solids and dry matter content (Kumar et al. 2015), and pigments in the peel (Merzlyak 2006; Kumar et al. 2015). Most efforts with portable Vis/NIR spectrophotometers focused on nondestructive estimates of fruit quality parameters proximal to harvest. Recently, Vis/NIR spectroscopy was evaluated to predict apple fruitlet abscission in the field following a chemical thinner application (Orlova et al. 2020a, 2020b). Using partial least squares regression and light reflectance from 400 to 1000 nm, Orlova et al. (2020a) had greater than 80% accuracy to predict abscission as early as 6 d after thinner application.

The results of Orlova et al. (2020a) showed the potential of using Vis/NIR spectroscopy to distinguish between persisting and abscising fruitlets with greater than 80% prediction accuracy 6 d after application. This prediction date was a marginal increase from the FGM. The objectives of this study were to first develop machine learning classification models with Vis/NIR spectroscopy to determine how early differences between fruitlets that ultimately persisted or abscised could be detected. The second objective was to validate the FGM in the southeastern United States, comparing the performance of the FGM with developed Vis/NIR models.

Materials and Methods

Plant material and treatments. Experiments were conducted in mature commercial 'Honeycrisp' orchards in 2021 (Dana, NC, USA) and 2022 (Waynesville, NC, USA). In 2021, trees were 10 years old on 'M.26'

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rootstock and 6 years old on 'M.9' rootstock in 2022. In 2021, five single-tree replicates were selected based on uniformity of tree vigor and blossom cluster density. All trees received a thinner application of 600 $\mu L \cdot L^{-1}$ carbaryl + 5 $\mu L \cdot L^{-1}$ naphthalene acetic acid (NAA). In 2022, 10 uniform trees were selected, and treatments were randomly assigned to single-tree plots. Half of the trees received a thinner application of 600 $\mu L \cdot L^{-1}$ carbaryl + 5 $\mu L \cdot L^{-1}$ NAA, and the other half were untreated. In both years, treatments were applied when average fruitlet diameter was ~9 mm (2 May 2021 and 11 May 2022) with a CO_2 powered sprayer (Bellspray, Inc., Opelousas, LA, USA) calibrated to apply 935 L/hectare of water. No additional chemical thinners were applied.

On each tree, 20 spurs were selected and each fruitlet in the spur was uniquely labeled for repeated measurements. Fruitlet diameter and Vis/NIR spectra were measured on –4, –1, 3, 5, 7, 9, and 12 d after treatment (DAT) in 2021 and –1, 1, 3, 6, and 9 DAT in 2022. All persisting fruitlets within labeled spurs were measured on each date. Fruitlet diameter was measured at the widest point of the fruitlet with digital calipers. Vis/NIR spectra was captured with a portable Vis/NIR spectrophotometer (Felix F-750; Felix Instruments, Camas, WA, USA). All fruitlets were measured calyx end first, a cone was attached to isolate individual fruitlets in a cluster (Fig. 1). With each fruitlet was measured at a constant distance to the sensor with the calyx end on the surface of the spectrophotometer lens. The spectrophotometer had a range of 303 to 1200 nm and a resolution of 3 nm. A different portable Vis/NIR spectrophotometer unit was used in 2021 and 2022. Final fruitlet persistence/abscission was determined following the fruitlet abscission period [June drop (45 DAT and 29 DAT in 2021 and 2022, respectively)].

Carbon balance estimates. The Cornell apple carbohydrate thinning model was used to provide estimates of daily carbon balance –2 through 14 DAT (Lakso et al. 1999; https://www.newa.cornell.edu/apple-carbohydrate-thinning). A weather station in Edneyville, NC, USA, was used to input local weather data into the model for both years. The green tip and full bloom dates used for model output in 2021 were 14 Mar 2021 and 9 Apr 2021, respectively. In 2022, green tip was 20 Mar 2022 and full bloom was 14 Apr 2022.

Fruitlet growth model. The FGM was used following the methods of Greene et al. (2013). Specifically, growth rates were calculated for each fruitlet from the difference in diameter in successive measurement dates. The following predictions dates were made: –1, 3, 5, 7, 9, and 12 DAT (2021) and 1, 3, 6, and 9 DAT (2022). For each prediction date, all fruit were ordered from largest to smallest growth rates and the average growth rate of the 20 fastest growing fruitlets was calculated, 50% of this average was used as a cutoff to predict fruitlet persistence/abscission. A fruitlet growing at a rate greater than 50% of the 20 fastest growing fruitlets measured was predicted to persist, whereas a fruitlet growing less than 50% was predicted to abscise.

Reflectance model. Models to predict fruitlet abscission/persistence were developed with reflectance values at measured wavelengths as predictor variables. Models were developed with all measured wavelengths (303 to 1200 nm) and a trimmed dataset from 501 to 753 nm. The trimmed dataset eliminated wavelengths with reflectance greater than 1.0. Three different modeling techniques were used for fruitlet abscission classification: 1) partial least regression, 2) random forests, and 3) XGBoost. All models were built using 5-fold cross validation and model parameters chosen by highest area under the receiver operating characteristics curve. XGBoost models were developed with three boosting iterations and a max tree depth of four. Individual models were built for the following data sets: 1) 2021 data, 2) 2022 data, 3) 2021 + 2022 data. Models using the full dataset with unequal number of persisted/abscised fruitlets (unbalanced) were compared with balanced datasets through either down-sampling the majority class (Freeman et al. 2012) or up-sampling the minority class with synthetic minority over-sampling technique [SMOTE (Chawla et al. 2002)]. All data preparation and analysis were done in R (R Foundation for Statistical Computing, Vienna, Austria; R Core Team 2022). The caret package (version 6.0-92; R Foundation for Statistical Computing) was used for all model building and testing (Kuhn 2008). DMwR package (version 0.4.1; R Foundation for statistical computing) was used to balance the dataset with SMOTE (Torgo 2011).

Model performance metrics. FGM and reflectance models were evaluated on the following metrics: 1) overall accuracy (Eq. [1]), 2) predicting persisting fruitlets (recall, Eq. [2]), and 3) predicting abscising fruitlets (specificity, Eq. [3]). Presented metrics for reflectance models are the average of the test set on each one of the 5-folds.

$$\text{Overall Prediction Accuracy} = (\text{TP} + \text{TN}) \div (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad [1]$$

$$\text{Accuracy of Persisting (Recall)} = \text{TP} \div (\text{TP} + \text{FN}) \quad [2]$$

$$\text{Accuracy of Abscising (Specificity)} = \text{TN} \div (\text{TN} + \text{FP}) \quad [3]$$

In Eqs. [1] to [3], the positive (P) outcome is that the fruitlet persisted, and the negative (N) is that the fruitlet abscised following the drop period. Correct classification of fruitlet persistence/abscission is labeled "true" (T) and incorrect classification is labeled "false" (F).

Fig. 1. Capturing reflectance spectra of fruitlet with portable visible/near infrared spectrometer (Felix F-750; Felix Instruments, Camas, WA, USA). For each fruitlet, calyx end was held next to lens (left), a cone (right) was placed around the lens to limit sunlight entering the spectrometer and isolate the fruitlet being measured.

Results and Discussion

Fruitlet abscission rates. Fruitlet abscission rates varied between years and treatments. In 2021, where all trees received a single thinner application, 85% of all fruitlets measured abscised by the end of the drop period. In 2022, there was 25% fruitlet abscission from untreated trees, whereas chemical thinning resulted in 46% fruitlet abscission. Because the same rate of thinner was used in both years, the differences in abscission rates are likely due to weather conditions around the time of application that led to greater carbon stress in 2021 than 2022 (Lordan et al. 2019). Estimates of daily carbon balance from the Cornell apple carbohydrate thinning model were higher in 2022 than 2021 for the 2 d before and after the chemical thinner application (Fig. 2). Notably, a carbohydrate deficit was estimated at 1 and 2 DAT in 2021. The lower estimates of carbon balance before the thinner application are likely due to lower solar radiation 0 to 2 DAT. During this time span, average daily solar radiation in 2021 was ∼19 (0 DAT), 9 (1 DAT), and 8 $MJ \cdot m^{-2}$ (2 DAT); in 2022, it was ∼29 (0 DAT), 26 (1 DAT), and 16 $MJ \cdot m^{-2}$ [2 DAT (Fig. 2)]. This variation in environmental conditions and thinning responses across years provided a robust range of fruitlet abscission rates to build and test prediction models.

Fruitlet growth model. In both years, the FGM reliably predicted fruit set 9 DAT (Table 1). In 2021, overall accuracy was >0.8 on 5 and 7 DAT; however, recall was low: 0.32 (5 DAT) and 0.57 (7 DAT). Conversely, in 2022, specificity was low for the control (0.59) and thinned (0.32) treatments 6 DAT (Table 1). These results show that one-dimensional growth rates of fruitlet diameter assessed at a 50% cutoff are not a reliable indicator of fruitlet abscission/persistence less than 9 DAT. In both years, the minority class outcome was not accurately predicted until 9 DAT. In 2021, where a relatively high rate of fruitlet abscission was observed, model specificity (accuracy of predicting abscising fruitlets) was high as

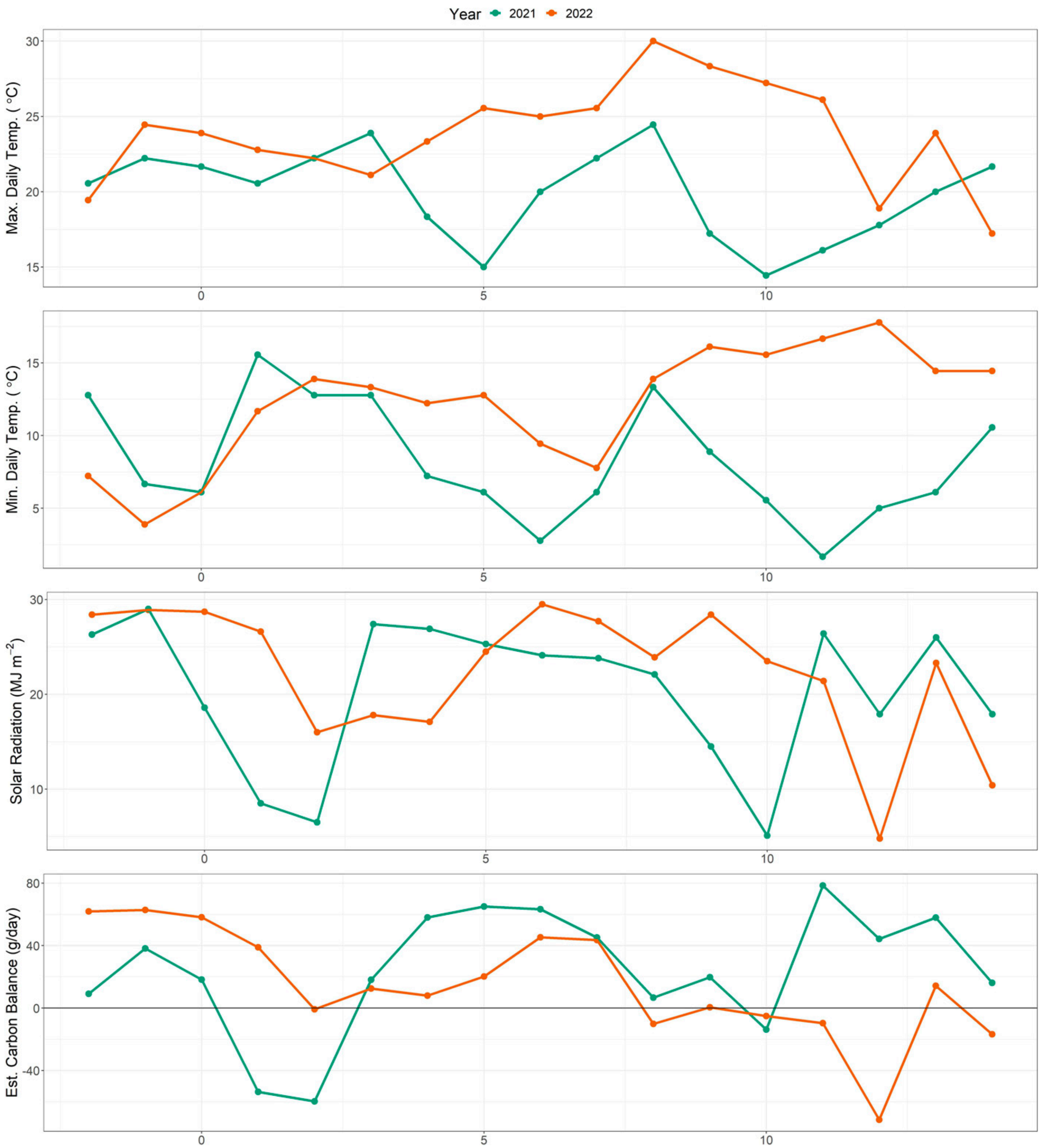

Fig. 2. Daily estimate of carbon balance ($g \cdot d^{-1}$), solar radiation ($MJ \cdot m^{-2}$), minimum and maximum temperature (°C). Daily data are relative to days after chemical thinner application 2 May 2021 and 11 May 2022. Weather conditions obtained in both years from Network for Environmental and Weather Applications (https://www.newa.cornell.edu/) from weather station in Edneyville, NC, USA. Estimated carbon balance calculated through Cornell apple carbohydrate thinning model (https://www.newa.cornell.edu/apple-carbohydrate-thinning), the following green tip and full bloom dates were input to obtain estimates: 14 Mar 2021 and 9 Apr 2021; 20 Mar 2022 and 14 Apr 2022.

Table 1. Fruitlet growth model results in 2021 and 2022. All trees treated with a single application of a chemical thinner in 2021. An untreated control and a single chemical thinner application were compared in 2022.

	2021[i]			2022[i]					
	Thinner			Control			Thinner		
DAT[ii]	Acc.[iii,v]	Recall[v]	Spec.[iv,v]	Acc.	Recall	Spec.	Acc.	Recall	Spec.
−1	0.30	0.89	0.19	—	—	—	—	—	—
1	—	—	—	0.71	0.86	0.23	0.55	0.82	0.22
3	0.48	1.00	0.36	0.82	0.94	0.44	0.61	0.93	0.21
5	0.81	0.32	0.91	—	—	—	—	—	—
6	—	—	—	0.89	0.98	0.59	0.71	1.00	0.32
7	0.89	0.57	0.97	—	—	—	—	—	—
9	0.95	0.88	0.97	0.94	0.95	0.91	0.91	0.95	0.86
12	0.92	0.75	0.98	—	—	—	—	—	—

[i] Study conducted in Dana, NC, USA, in 2021 and Waynesville, NC, USA, in 2022.

[ii] DAT = days after treatment of chemical thinner application: 600 ppm carbaryl + 5 ppm naphthalene acetic acid applied ∼9 mm on 2 May 2021 and 11 May 2022.

[iii] Acc. = overall accuracy of model.

[iv] Spec. = specificity of model.

[v] Equations to calculate model performance metrics are presented in Materials and Methods: Model Performance Metrics.

early as 5 DAT, but model recall (the accuracy of predicting persisting fruitlets) was low. In 2022, where most fruitlets persisted, model specificity was 0.59 for the control and 0.32 for thinner treatments (Table 1).

Reliable fruit set predictions with the FGM 9 DAT accords with previous work, where accurate predictions were observed 7 to 10 DAT (Greene et al. 2013). It is evident that the FGM cannot reliably detect differences between persisting and abscising fruitlets until 7 to 10 DAT. Prediction accuracy with the FGM is likely limited by the loss of precision with a one-dimensional measure of fruitlet size and setting a cutoff for persist/abscise at 50% growth rate when fruitlet abscission potential is a gradient along growth rate. Given the results of this study, 9 DAT was then the benchmark to compare reflectance models to determine if earlier prediction of fruitlet set was possible.

Reflectance models. Across both years, the greatest differences between fruitlets that ultimately persisted/abscised were seen in the visible portion of the spectra (Figs. 3 and 4). When compared with abscising fruitlets, reflectance values were lower for persisting fruitlets

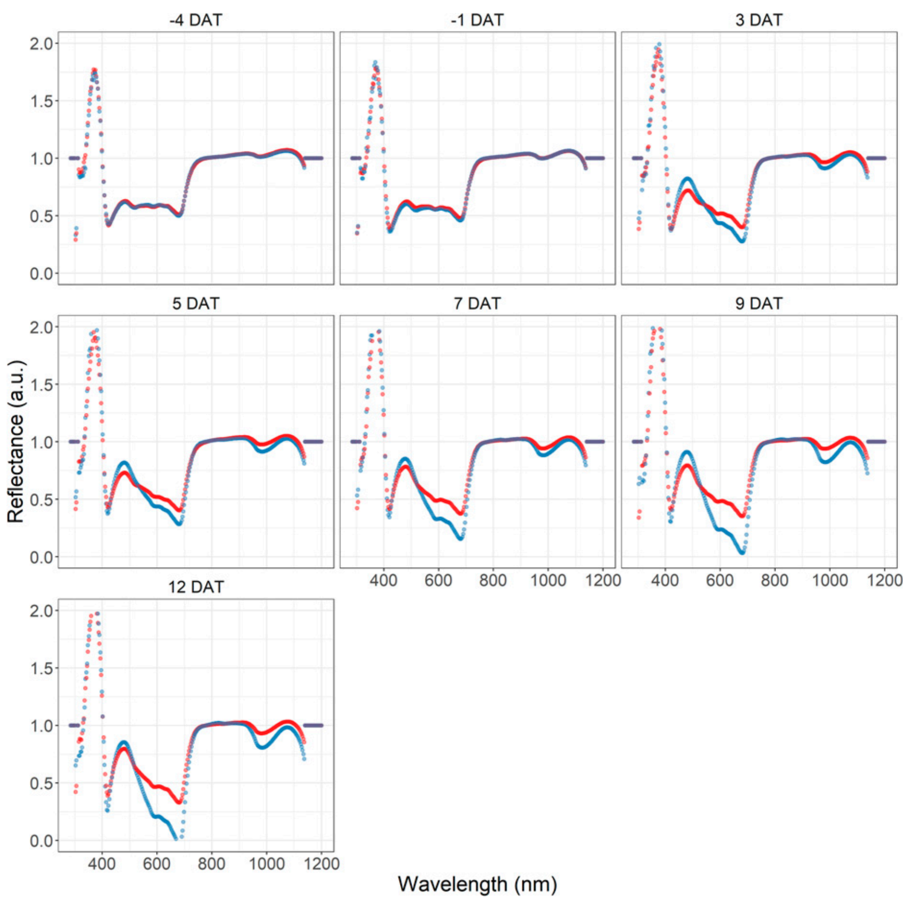

Fig. 3. Mean reflectance spectra of 'Honeycrisp' fruitlets (n = 424) that ultimately abscised (red points) or persisted (blue points) at the end of the fruitlet abscission period in 2021 in Dana, NC, USA. The seven measurement dates are in respect to a single chemical thinner application on 2 May 2021 of 600 ppm carbaryl plus 5 ppm naphthalene acetic acid applied to all trees: –4, –1, 3, 5, 7, 9, and 12 d after treatment (DAT). Fruitlet persistence determined 45 DAT. Reflectance values measured with portable spectrophotometer (Felix F-750; Felix Instruments, Camas, WA, USA) every 3 nm from 303 to 1200 nm. a.u. = arbitrary units.

∼500 to 725 nm. For example, at 660 nm, in 2021, this decrease in reflectance ranged from 0.739% –4 DAT to 147% 9 DAT. This difference was less pronounced in 2022, where persisting fruitlets had 23% to 56% decrease in reflectance at 660 nm than abscising fruitlets across all measurement dates. Differences in reflectance between 550 to 700 nm suggests that chlorophyll contents differ between persisting and abscising fruitlets. In fact, the ratio in reflectance of 520 to 580 nm from 640 to 700 nm has been used to estimate chlorophyll content (Gitelson et al. 2003; Merzlyak et al. 2002).

The tissue(s) of the fruitlet that contribute to differences in chlorophyll content is uncertain. Given the fruit positioning used in this study, the pistil, stamens, sepals, and hypanthium tissues are likely among the first tissues that light from the spectrophotometer reaches. The proportion of light that is intercepted by each respective tissue will vary based on multiple factors, including the developmental stage of the fruitlet. The dynamics of light movement is further complicated by use the reflectance cone. Additional study is required to understand the relationship between tissue type and estimated chlorophyll content with this instrument. Larson et al. (2021) examined differences in plant pigment and dry matter content of fruitlets that were predicted to persist/abscise with these reflectance models.

Reflectance values were commonly greater than 1.0 at wavelengths 303 to 400 nm throughout measurement dates in 2021 and 2022 and at ∼1050 to 1100 nm in 2021 (Figs. 3 and 4). In the NIR range, reflectance values were greater than 1.0 at wavelengths ∼1050 to 1100 nm in 2021 and greater than 700 nm on –1 and 1 DAT (Fig. 4). These reflectance values out of the theoretical range (0 to 1) signal that the internal calibration with the portable spectrophotometer used in the current study was insufficient. For each measurement, the Felix F-750 takes a separate reading with the shutter "open" and "closed." The difference between the "open" and "closed" readings account for incident light traveling to the spectrophotometer (Felix Instruments, personal communication). The measured spectra are only "dark" calibrated, not calibrated to a known reference that would further correct spectra to "true reflectance" (Shaikh et al. 2021).

Models with predictor variables of reflectance from 501 to 753 nm were developed along with models with all measured wavelengths (303 to 1200 nm) to determine if elimination of out-of-theoretical-range wave lengths decreased reflectance model performance. Trimming the predictor wavelengths to 501 to 753 nm slightly decreased model performance compared with using the full measured spectra (303 to 1200 nm). For example, with the combined 2021 + 2022 dataset that was balanced with SMOTE the overall accuracy of the 303 to 1200 nm model ranged from 0.88 (–1 DAT) to 0.95 [9 DAT (Supplemental Table 1)]. Trimming the predictive wavelengths of this dataset to 501 to 753 resulted in overall accuracy of 0.84 (–1 DAT) to 0.93 [9 DAT (Table 2)]. Due to the small decrease in accuracy from trimming the dataset, all further discussion of the developed reflectance models details the predictor wavelengths from 501 to 753 nm.

Balancing the dataset with SMOTE yielded the highest accuracy, recall, and specificity compared with the unbalanced and down sampled datasets (Tables 2–4). Unbalanced data set models underperformed in predicting the minority class. For example, overall accuracy of 2021 random forest model for the unbalanced dataset ranged from 0.79 to 0.86 for all measurement dates. Abscising fruitlets were the majority class in 2021 and accordingly the recall ranged from 0.90 to 0.99, but the specificity ranged from 0.01 to 0.60. Balancing the dataset with SMOTE yielded overall accuracy, recall, and specificity ranges between 0.87 to 0.94, 0.82 to 0.90, and 0.89 to 0.97, respectively

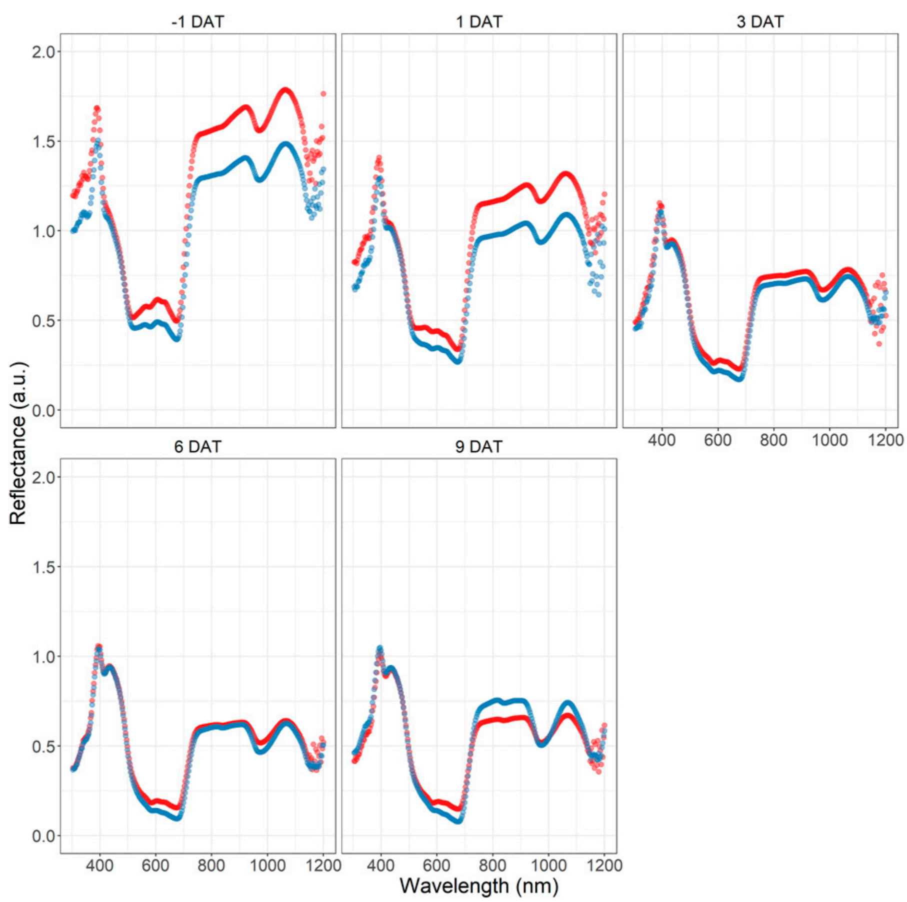

Fig. 4. Mean reflectance spectra of 'Honeycrisp' fruitlets (n = 644) that ultimately abscised (red dots) or persisted (blue dots) at the end of the fruitlet abscission period in 2022 in Dana, NC, USA. The five measurement dates are in respect to a single chemical thinner application on 11 May 2022 of 600 ppm carbaryl plus 5 ppm naphthalene acetic acid: –1, 1, 3, 6, and 9 d after thinner (DAT). Fruitlet spectra are averaged over fruitlets that received a chemical thinner application and an untreated control. Reflectance values measured with portable spectrophotometer (Felix F-750; Felix Instruments, Camas, WA, USA) every 3 nm from 303 to 1200 nm. a.u. = arbitrary units.

Table 2. Performance metrics of partial least squares regression, random forest, and XGBoost classification models. Fruitlet persistence/abscission response predicted with reflectance values from 501 to 753 nm measured with a portable visible/near infrared spectrophotometer (Felix F-750; Felix Instruments, Camas, WA, USA). Model includes measurements collected during the chemical thinning period in 2021 (Dana, NC, USA) and 2022 (Waynesville, NC, USA).

	Accuracy[i]			Recall[i]			Specificity[i]		
DAT[ii]	Unbal.[iii]	Down samp.[iv]	SMOTE[v]	Unbal.	Down samp.	SMOTE	Unbal.	Down samp.	SMOTE
Partial least squares regression									
−1	0.60	0.63	0.60	0.46	0.52	0.46	0.73	0.73	0.73
3	0.72	0.71	0.72	0.62	0.59	0.62	0.81	0.82	0.81
7/6[vi]	0.75	0.74	0.75	0.58	0.56	0.58	0.89	0.88	0.89
9	0.77	0.77	0.77	0.55	0.53	0.55	0.93	0.93	0.93
Random forest									
−1	0.68	0.69	0.84	0.70	0.66	0.87	0.66	0.71	0.81
3	0.70	0.72	0.90	0.67	0.63	0.90	0.72	0.79	0.90
7/6	0.70	0.73	0.90	0.64	0.64	0.88	0.76	0.79	0.91
9	0.81	0.82	0.93	0.76	0.73	0.92	0.85	0.88	0.94
XGBoost									
−1	0.68	0.69	0.75	0.63	0.60	0.74	0.73	0.77	0.76
3	0.69	0.71	0.77	0.66	0.61	0.69	0.73	0.79	0.85
7/6	0.73	0.72	0.77	0.65	0.61	0.64	0.81	0.81	0.88
9	0.79	0.78	0.83	0.67	0.59	0.69	0.89	0.91	0.93

[i] Equations to calculate model performance metrics are presented in Materials and Methods: Model Performance Metrics.
[ii] DAT = days after chemical thinner application. 600 ppm carbaryl + 5 ppm NAA applied ∼9 mm on 2 May 2021 and 11 May 2022. 2021: all trees treated with chemical thinner; 2022: treatments were either untreated or treated with chemical thinner.
[iii] Unbal. = unbalanced dataset. n = 1068 (persist = 481, abscise = 587).
[iv] Down samp. = down sampled dataset. n = 962 (persist = 481, abscise = 481).
[v] SMOTE = Synthetic Minority Oversampling Technique. n = 1924 (persist = 962, abscise = 962).
[vi] Dataset from 7 DAT in 2021 combined with 6 DAT in 2022.

(Table 3). Under-predicting the minority class was particularly pronounced with the two machine learning models—random forest and XGBoost—compared with partial least squares regression (Tables 2–4). Random forest and XGBoost are both tree-based models that iteratively select parameters based on minimizing error. When the dataset is unbalanced, the models overfit toward the majority class to minimize error.

Balancing the dataset with SMOTE consistently outperformed down sampling. This difference in performance is likely due to a greater number of observations to train models with SMOTE than down sampling. For example, the 2022 down-sampled dataset had 454 observations whereas SMOTE balanced had 908 observations. The relatively small

Table 3. Performance metrics of partial least squares regression, random forest, and XGBoost classification models. Fruitlet persistence/abscission response predicted with reflectance values from 501–753nm measured with a portable visible/near infrared spectrophotometer (Felix F-750; Felix Instruments, Camas, WA, USA). Model includes measurements collected during the chemical thinning period in 2021 in Dana, NC, USA.

	Accuracy[i]			Recall[i]			Specificity[i]		
DAT[ii]	Unbal.[iii]	Down samp.[iv]	SMOTE[v]	Unbal.	Down samp.	SMOTE	Unbal.	Down samp.	SMOTE
Partial least squares regression									
−4	0.56	0.55	0.56	0.53	0.55	0.53	0.58	0.55	0.58
−1	0.60	0.49	0.60	0.36	0.21	0.36	0.80	0.74	0.80
3	0.63	0.59	0.63	0.63	0.54	0.63	0.64	0.64	0.64
5	0.64	0.68	0.64	0.53	0.65	0.53	0.73	0.71	0.73
7	0.68	0.70	0.68	0.58	0.64	0.58	0.75	0.75	0.75
9	0.81	0.78	0.81	0.69	0.64	0.69	0.88	0.86	0.88
12	0.84	0.84	0.84	0.69	0.72	0.69	0.91	0.90	0.91
Random forest									
−4	0.85	0.53	0.87	0.99	0.48	0.84	0.06	0.58	0.89
−1	0.82	0.51	0.88	0.99	0.45	0.82	0.01	0.56	0.94
3	0.82	0.59	0.88	0.96	0.57	0.84	0.16	0.60	0.92
5	0.79	0.70	0.91	0.93	0.70	0.86	0.15	0.70	0.94
7	0.79	0.62	0.90	0.91	0.47	0.83	0.32	0.74	0.95
9	0.86	0.78	0.93	0.94	0.68	0.90	0.60	0.84	0.95
12	0.81	0.84	0.94	0.90	0.69	0.86	0.56	0.92	0.97
XGBoost									
−4	0.84	0.48	0.70	0.98	0.44	0.66	0.03	0.53	0.73
−1	0.80	0.47	0.72	0.96	0.39	0.65	0.00	0.53	0.78
3	0.82	0.58	0.75	0.97	0.56	0.70	0.14	0.61	0.79
5	0.78	0.58	0.75	0.93	0.57	0.61	0.13	0.59	0.85
7	0.79	0.63	0.82	0.93	0.45	0.76	0.25	0.77	0.86
9	0.86	0.77	0.87	0.93	0.73	0.77	0.59	0.80	0.93
12	0.82	0.80	0.90	0.88	0.66	0.79	0.64	0.88	0.95

[i] Equations to calculate model performance metrics are presented in Materials and Methods: Model Performance Metrics.
[ii] DAT = days after chemical thinner application. 600 ppm carbaryl + 5 ppm NAA applied ∼9 mm on 2 May 2021. All 5 trees in study treated with chemical thinner.
[iii] Unbal. = unbalanced dataset. n = 424 (persist = 360, abscise = 64).
[iv] Down samp. = down sampled dataset. n = 128 (persist = 64, abscise = 64).
[v] SMOTE = synthetic minority oversampling technique. n = 640 (persist = 320, abscise = 320).

Table 4. Performance metrics of partial least squares regression, random forest, and XGBoost classification models. Fruitlet persistence/abscission response predicted with reflectance values from 501 to 753nm measured with a portable visible/near infrared spectrophotometer (Felix F-750; Felix Instruments, Camas, WA, USA). Model includes measurements collected during the chemical thinning period in 2022 in Waynesville, NC, USA.

	Accuracy[i]			Recall[i]			Specificity[i]		
DAT[ii]	Unbal.[iii]	Down samp.[iv]	SMOTE[v]	Unbal.	Down samp.	SMOTE	Unbal.	Down samp.	SMOTE
Partial least squares regression									
−1	0.55	0.53	0.55	0.44	0.43	0.44	0.66	0.63	0.66
1	0.61	0.55	0.61	0.45	0.37	0.45	0.75	0.74	0.75
3	0.54	0.56	0.54	0.35	0.37	0.35	0.73	0.75	0.73
6	0.65	0.60	0.65	0.42	0.43	0.42	0.83	0.75	0.83
9	0.74	0.73	0.74	0.36	0.53	0.36	0.95	0.89	0.95
Random forest									
−1	0.59	0.53	0.81	0.28	0.52	0.81	0.77	0.53	0.81
1	0.60	0.54	0.76	0.20	0.52	0.71	0.82	0.56	0.81
3	0.65	0.55	0.72	0.25	0.55	0.67	0.85	0.54	0.77
6	0.67	0.59	0.79	0.34	0.58	0.66	0.83	0.61	0.89
9	0.81	0.76	0.86	0.61	0.68	0.74	0.90	0.83	0.94
XGBoost									
−1	0.62	0.53	0.59	0.15	0.60	0.56	0.88	0.45	0.61
1	0.63	0.54	0.65	0.14	0.45	0.54	0.89	0.62	0.77
3	0.61	0.53	0.59	0.22	0.52	0.54	0.82	0.54	0.65
6	0.69	0.59	0.70	0.31	0.52	0.61	0.88	0.66	0.76
9	0.79	0.73	0.77	0.45	0.70	0.55	0.94	0.75	0.89

[i] Equations to calculate model performance metrics are presented in Materials and Methods: Model Performance Metrics.

[ii] DAT = days after chemical thinner application. 600 ppm carbaryl + 5 ppm NAA applied ~9 mm on 11 May 2022. five trees treated with a chemical thinner, five trees were untreated.

[iii] Unbal. = unbalanced dataset. n = 644 (persist = 417, abscise = 227).

[iv] Down samp. = down-sampled dataset. n = 454 (persist = 227, abscise = 227).

[v] SMOTE = synthetic minority oversampling technique. n = 908 (persist = 454, abscise = 454).

dataset that was created with this study was sensitive to decreasing sample size to train the model. Balancing the dataset with SMOTE will likely yield the best results until the dataset is large enough to withstand down sampling.

Machine learning models—random forest and XGBoost—outperformed partial least squares regression (Tables 2–4). In this study, prediction accuracy with partial least squares regression was < 0.80 earlier than 9 DAT. Orlova et al. (2020a) found ~80% accuracy in predicting fruitlet persistence/abscission as early as 6 DAT with partial least squares regression. Between the two machine learning models, random forest had higher accuracy, recall, and specificity than XGBoost. Random forest and XGBoost are both tree-based ensemble models that use decision trees for predictor variables to distinguish between response classes from a collection of models. Random forest is a bootstrapping aggregate model that builds many decision trees with a random sample with replacement of observations independently in parallel. XGBoost is a gradient boosting ensemble model that iteratively builds decision trees and trains the following tree to improve predictions of misclassified observations. The combination of predictor variables of reflectance from 501 to 753 nm, balancing the dataset with SMOTE using a random forest algorithm was found to have the highest overall accuracy and distinguish between persisting and abscising fruitlets in this study.

Reflectance models developed accurately predicted persisting/abscising fruitlet within and across study years for all measurement dates (Tables 2–4). With the 2021 + 2022 dataset, overall accuracy ranged from 0.84 (–1 DAT) to 0.93 [9 DAT (Table 2)]. Accuracy was only slightly improved within the 2021 dataset, ranging from 0.87 (–4 DAT) to 0.94 (12 DAT; Table 3). Performance was slightly decreased with 2022 data alone, where accuracy ranged from 0.72 (3 DAT) to 0.86 (9 DAT). The 2021 dataset was the most homogenous of the three, occurring all on the same trees, site, and thinning treatment, which likely led to the highest prediction accuracies. The 2022 dataset underperformed predicting persisting fruitlets 1 to 6 DAT as recall ranged from 0.66 to 0.71 on these dates. Accuracy of persisting fruitlets dropped in the days after a chemical thinner application due to misclassification of a portion of fruitlets in the control trees that would have abscised had the trees received a thinner. The combined 2021 + 2022 dataset had the full spectrum of fruitlet abscission rates, likely causing the combined year model to draw clearer distinctions between abscising and persisting fruitlets than the 2022 dataset that had lower thinning activity than in 2021.

Overall accuracy, recall, and specificity of the combined model on each measurement date of the combined year dataset showed that reflectance spectroscopy is a promising technology to predict fruitlet abscission before and after a chemical thinner application. The early prediction dates seen in this study has not been previously demonstrated, to the best of our knowledge. Orlova et al. (2020a) accurately predicted persistence/abscission as early as 6 DAT. The reflectance-based model developed in this study provided considerable improvement in determining chemical thinner efficacy than was seen with the FGM in the study and in previous studies (Greene et al. 2013). An earlier prediction time with reflectance model compared with the FGM would give growers more flexibility to determine efficacy of a thinner application and make a follow-up application, if needed. Chemical thinners are only effective for ~3 weeks during the spring. A reliable prediction of chemical thinner response at 3 DAT could aid in improved crop load management decisions. High prediction accuracy on the day before the thinner application of fruitlet abscission rates shows the potential of this technology to determine whether a chemical thinner needs to be applied.

Conclusions and Future Directions

The results of this study show that reflectance spectroscopy has the potential to be a valuable tool to inform chemical thinning decisions for apple growers. Machine learning algorithms, here random forest, provided considerable improvement in prediction accuracy than traditional models such as partial least squares regression. However, machine learning models overfit toward the majority class, necessitating balancing observation of persisting and abscising fruitlets. The single measurement date models with reflectance spectroscopy showed that earlier and more efficient prediction could be determined than with the currently available FGM that needs at least two measurement dates to calculate growth rates.

Although the current study shows the promise of reflectance to predict fruitlet abscission over multiple years, it is limited to only one cultivar and location. Further development is needed before commercialization. Specifically, multiple cultivars need to be tested to determine whether an omnibus model is adequate or cultivar specific models are needed. Thinner chemistry and rate is another input that may affect reflectance and should be incorporated into model development. Weather conditions can greatly affect fruitlet abscission rates in the spring (Lordan et al. 2019). Therefore, it will be important to include data from multiple growing regions. Collecting measurements over a wider range of fruitlet stages will also determine how applicable this technology is throughout the fruitlet thinning period because both years were centered around a thinner application at 9-mm fruitlet diameter. Beyond being a valuable decision-making aid for growers, development of reflectance models to distinguish between persisting and abscising fruitlets will be important for study of fruitlet abscission physiology and mechanisms

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Supplemental Table 1. Performance metrics for random forest classification model to predict fruitlet persistence/abscission from reflectance values from 303 to 1200 nm.

DAT[i]	Accuracy[ii]	Recall[ii]	Specificity[ii]
2021 dataset[iii]			
−4	0.89	0.91	0.87
−1	0.91	0.92	0.90
3	0.89	0.85	0.93
5	0.88	0.85	0.91
7	0.88	0.83	0.91
9	0.94	0.93	0.94
12	0.94	0.87	0.98
2022 dataset[iv]			
−1	0.84	0.84	0.84
1	0.77	0.70	0.84
3	0.78	0.73	0.82
6	0.81	0.69	0.90
9	0.88	0.76	0.95
2021 + 2022 dataset[v]			
−1	0.88	0.90	0.87
3	0.90	0.89	0.90
7/6[vi]	0.91	0.89	0.92
9	0.95	0.94	0.95

[i] DAT = days after treatment application. 600 ppm carbaryl + 5 ppm NAA applied ∼9 mm on 2 May 2021 and 11 May 2022.

[ii] Equations to calculate model performance metrics are presented in Materials and Methods: Model Performance Metrics.

[iii] Data collected with a portable visible/near infrared spectrophotometer (Felix F-750; Felix Instruments, Camas, WA, USA) from each fruitlet in 20 clusters on 5 trees used for model building. All trees treated with a chemical thinner. Study conducted in Dana, NC, USA. Dataset balanced with Synthetic Minority Oversampling Technique. n = 640 (persist = 320, abscise = 320).

[iv] Each fruitlet in 20 clusters on 10 trees used for model building. 5 trees treated with a chemical thinner and 5 trees were untreated. Study conducted in Waynesville, NC, USA. Dataset balanced with synthetic minority oversampling technique. n = 908 (persist = 454, abscise = 454).

[v] Each fruitlet in 20 clusters on 5 trees (2021) and 10 trees (2022) used for model building. In 2021, all trees were treated with a chemical thinner. In 2022, 5 trees were untreated and 5 were treated with a chemical thinner. Studies conducted in Dana, NC, USA (2021) and Waynesville, NC, USA (2022). Dataset balanced with Synthetic Minority Oversampling Technique. n = 1924 (persist = 962, abscise = 962).

[vi] Dataset from 7 DAT in 2021 combined with 6 DAT in 2022.