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Development and improvement of the CROPGRO-Strawberry model

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ABSTRACT

Strawberry is a high-value horticultural crop with a global market and it has a strong regional importance in production areas such as Florida. Strawberry growers face many challenges related to weather, cultivation, and markets. Decision support tools can help optimize strawberry production but require sound models or other predictive tools as a foundation. The goal of this study was to improve a new CROPGRO-Strawberry model in the Decision Support System for Agrotechnology Transfer (DSSAT) using experimental data with observations from different seasons and multiple cultivars. Model improvements were made in three primary areas: 1) cardinal temperatures for different development processes, 2) a module for the dynamic assimilate partitioning based on photothermal age, and 3) improvement of the cultivar and ecotype coefficients. The model predicts the growth, development, and fruit production of strawberry over time using weather, soil, management and physiological parameters as inputs. Overall, the results show a good simulation of development and growth ($d = 0.77$ to 0.99, $RRMSE = 0.26$ to 0.68), but an overestimation of vegetative growth during the early season. Periodic and cumulative fruit harvests were well-simulated ($d = 0.91$, RRMSE 0.47), capturing the seasonal dynamics and representing differences among cultivars and harvest intervals. A strategic analysis showed the applicability of the crop model to understand and manage the impact of seasonal climate variability on total strawberry yield as well as the distribution of fruit production across different harvest months. Future work should include improvements in the simulation of vegetative growth and evaluation against new datasets representing different production environments and cultivars. The improved CROPGRO-Strawberry model will enable future work on applications to other specialty crops where modeling of continuous fruiting and multiple harvests of individual fruit instead of one end-of-season harvest is desired.

1. Introduction

Strawberry *(Fragaria × Ananassa)* is among the most consumed fruits worldwide and plays an important role in both the horticultural industry and global food supply. Although the leading producers are China, Mexico, and the USA, strawberry production occurs on all continents with regional cultivars and cultivation practices. Florida is the second largest producer of strawberries in the USA, with over 3,600 ha in production and a total production value of over $300 million (USDA, 2021). Strawberry is typically grown as a winter crop from September to April, and Florida provides more than three quarters of the winter strawberry production in the USA. Given the perishability of strawberries in general and variable growing conditions, strawberry is a high-input and high-value, but also a risky crop for growers. Besides pest and disease pressure, weather variability and extreme weather conditions are major concerns for commercial growers.

In this context, developing a model-based decision support system could be beneficial to address some of the challenges faced by strawberry growers and other stakeholders. Previous strawberry modeling approaches focused on modeling the water-balance for irrigation

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scheduling (Kruger et al., 1999), statistical yield forecasting via direct correlation of weather parameters (Lobell et al., 2006; Pathak et al., 2016), machine learning (Khoshnevisan et al., 2014; Maskey et al., 2019; Misaghi et al., 2004) and prediction of phenological stages based on regressions or degree days (Døving and Måge, 2001; Labadie et al., 2019). The Decision Support System for Agrotechnology Transfer (DSSAT) is a crop modeling software platform that integrates weather, soil, plant genetics and management information for the prediction of crop development and yield (Hoogenboom et al., 2019a; Hoogenboom et al., 2019b; Jones et al., 2003). It supports the development of alternative management practices for optimal use of associated natural resources and for reducing negative environmental impacts (Tsuji et al., 1998). DSSAT was initially developed for major row crops such as wheat, soybean and maize, but it was later expanded to horticultural crops such as tomato (Boote, 2012; Scholberg et al., 1997), green bean (Djidonou, 2008) and cabbage (Feike et al., 2010). In 2016, an initial version of a strawberry crop model was developed for economic analysis (Boote et al., 2016; Oh, 2016). The initial CSM-CROPGRO-based model for strawberry production was built on one dataset that was collected in Balm, Florida (Oh, 2016) and data from the literature. The model uses the CROPGRO template within the Cropping System Model (CSM) of DSSAT and will hereafter be referred to as “CROPGRO-Strawberry”. The model has not been used, maintained, published, or released since the initial development in 2016. It, therefore, needed to be improved to better address the seasonality of production and growth and development response to temperature. Building on the tomato model, it allows the simulation of continuous addition and development of flowers and fruit, which are then harvested periodically. The initial strawberry model performed well for simulating cumulative end-of-season fruit yield, but further analysis revealed opportunities for improvement. Strawberry is harvested every three to four days compared to once at the end of the season for most row crops and other vegetable crops. Capturing this periodicity of strawberry production, is a particular challenge for strawberry modeling compared to modeling the traditional end-of-season harvest of agronomic crops.

Commercial strawberry cultivars in Florida typically produce a low number of fruits at the beginning of the season, followed by a peak in harvest production between January and March. Strawberries are one of most labor-intensive crops and the market price is sensitive to supply (Wu et al., 2015; Suh et al., 2017). Knowing the amount of early and late production is crucial for farm labor management (Biswas et al., 2018; Roka and Guan, 2018) and business planning and optimization due to seasonal variability in strawberry prices (Wu et al., 2018; USDA, 2020). Further improvement stemmed from the need to parameterize a new cultivar that has recently become the new dominant commercial cultivar in Florida.

The overall goal of this research project was to improve the CROPGRO-Strawberry model for field applications. The specific objectives were to 1) obtain additional experimental data from field trials and the literature for model evaluation, 2) improve the genetic parameters of the model and underlying physiological equations, as well as approaches to harvesting and their implementation, and 3) demonstrate the potential application of the model through seasonal analysis for time-of-season yield distribution.

2. Materials and methods

2.1. Experimental data

2.1.1. Field experiments

The experimental data for this study were obtained from field trials conducted at the Gulf Coast Research and Education Center (GCREC, www.gcrec.ifas.ufl.edu) in west-central Florida (27.7611° N, 82.2277°W) under common practices for commercial winter strawberry production in Florida. Winter strawberry fruit production generally takes place from November to April, starting with the planting of bare-root transplants in late-September to mid-October. A few early fruits are produced in late November and December, but most of the fruit production occurs from January to March, after which commercial harvesting declines rapidly primarily due to low market prices, though quality, disease pressure and inclement weather can also have impacts.

Strawberry plants were grown in raised beds with a plastic film cover on the soil (plastic mulching). Typical raised beds are 90 m long, 70 cm wide, 18 cm high in the center and 15 cm high at the edges and spaced 1.2 m between centers of two adjacent beds. Two rows of strawberry plants were planted per bed, with 28 cm between rows and 38 cm between plants within a row. Bare-root leaf-on transplants were obtained from Crown Nursery (Red Cluff, California, USA). After planting, overhead irrigation was applied daily during daylight hours for 8-10 days to promote plant establishment, followed by irrigation and fertigation via drip tapes for the remainder of the season. The harvests of ripe fruit occurred every three to four days with ripeness being determined by the extent and depth of red color of the fruit. Data were collected over multiple growing seasons from 2014 to 2018 as part of two similar, but independent field experiments later referred to as “plant growth analysis” and “variety yield trial”.

Plant growth analysis data were collected from 2014 to 2015 for the cultivars Florida Radiance (known as Florida Fortuna outside the USA) and Sensation® Florida127 (hereafter referred to as Florida127). In addition to biweekly measurements for weight and number of harvested ripe fruit, phenology and vegetative measurements were also taken at two-week intervals during the growing season. Further details about the experimental design can be found in Oh (2016). Growth analysis through destructive measurements were conducted at biweekly intervals; leaf, crown, flower number, fruit number and leaf area were determined and the dry weight of all plant organs, including fruit, were obtained. Non-destructive measurements were taken twice per week from first to final harvest, including fruit number and the fresh and dry weight of the harvested fruit. In addition, phenological observations were recorded for first flower, first fruit formation, first mature fruit and duration of flowering and fruit production.

The variety yield trial data were collected from 2014 to 2018. The biweekly observations of harvested marketable fruit for two cultivars, including ‘Florida Radiance’ and ‘Florida Brilliance’, collected during the 2014-15, 2015-16, and 2017-18 seasons were used in this study. Further details about the experimental data, including field setup and measurement techniques, can be found in the variety release publications (Whitaker et al., 2015; 2017; 2019).

2.1.2. Dataset adjustments

Due to the different nature and intended use of the two datasets, fruit were harvested and measured differently. The 2014-15 growth analysis dataset for cultivar Florida Radiance had an 8-10 day longer growing season with three additional harvests compared to the variety trial dataset. Harvests included all fruits, whereas the variety trial dataset only included fruit weight for “marketable” fruits, which are generally defined by regular shape, size and absence of blemishes or any sign of pest or disease on the fruits. For the variety trial, non-marketable fruit were counted and discarded, but not weighed. They accounted for 43.5% of total fruit number. This practice of “culling” is common in variety trials and other practical applications, since a grower is less interested in the weight of non-marketable fruit and measuring it would require additional labor.

A simple comparison revealed that the average number of fruits per plant was much larger and that the average weight per fruit was much smaller for the growth analysis dataset compared to variety trial dataset because of inclusion of smaller non-marketable fruit (Table 1).

Since both experiments were conducted in proximity and at the same time of year, the difference is most likely due to the inclusion of some smaller non-marketable fruit in the growth analysis dataset and the slightly longer harvest period. Non-marketable fruit can be caused by several biotic and abiotic factors and were difficult to include in an

Table 1
Comparison of fruit measurements from the 2014-15 variety trial and the 2014-15 growth analysis experiment for cultivar Florida Radiance, before and after normalization. Mean values for six (growth analysis) and two (variety trial) repetitions.

Average value per plant	Growth analysis		Variety trial
	Total yield	Marketable yield (normalized)	
Number of fruits	55.8	33.5 (-40%)	30.7
Cumulative fruit Weight (g)	1181 g	886 g (-25%)	759 g
Weight per fruit (g)	21.2 g	26.4 g	24.7 g

initial model version. To simplify model development, it was decided to standardize both datasets by reducing total fruit number by 40% and total fruit weight by 25% across the whole range of observations for the 2014-15 growth analysis dataset. The resulting fruit weight was reduced less than fruit number because it was assumed that non-marketable fruit are generally smaller and thus lighter than marketable fruit. This normalization brought the number and weight of fruit for both datasets into proximity (Fig. 1), which we assumed to be adequate since the datasets stem from two nearly identical trials. The final cumulative number of fruit and fruit weight was still higher in the growth analysis dataset, which is expected due to the slightly longer harvest season. We recognize that this normalization of datasets is very simplified but was deemed appropriate given the availability of data and importance of working with marketable instead of non-marketable harvests for practical application. A more precise observation of both marketable and non-marketable fruit is recommended for further experiments with an intended use for crop modeling where market production is the goal.

2.1.3. Weather data

The weather data for the GCREC field location were obtained from the Florida Automated Weather Network (FAWN; www.fawn.ifas.ufl.edu; Lusher et al., 2008). The FAWN weather station "Balm" (N 27.75998, W 82.22410) was installed in 2006 and is located near the field trials. It provides daily minimum and maximum air temperature (2 m above ground), daily total precipitation and solar radiation, wind speed, and relative humidity, in addition to more detailed measurements.

2.2. Software, source code and statistics

The crop simulations were performed with the Cropping System Model (CSM) (Jones et al., 2003) in the modeling software DSSAT (Hoogenboom et al., 2019a) obtained from the DSSAT portal (www.dssat.net). To improve the model, code changes were made based on the source code of the current development version 4.7.6 available via the public GitHub Repository (www.github.com/DSSAT/dssat-csm-os). The code changes and improvement will be implemented in a future version of CSM for public release and will be available from the GitHub repository. Statistical analysis and visualization were performed in R-Studio 1.2.5033 (RStudio Team, 2015) with packages "ggplot2" and

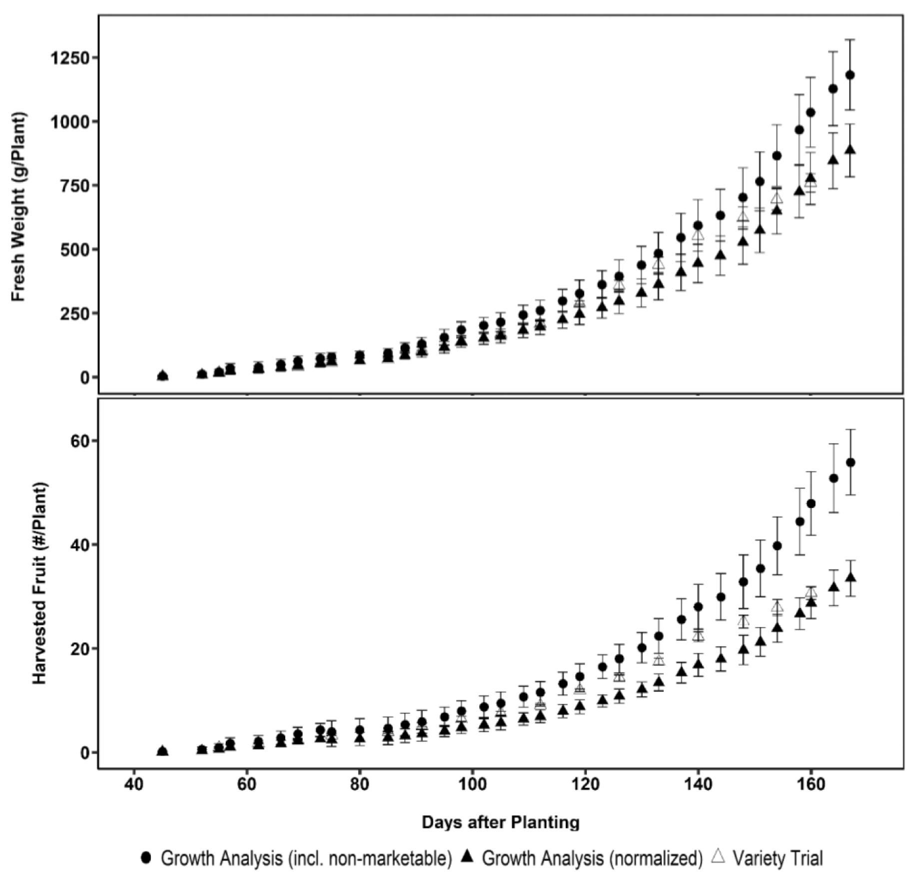

Fig. 1. Data normalization to remove estimated amount of non-marketable fruit from the growth analysis. Cumulative fruit weight (top) and cumulative harvested fruit number (bottom) for 'Florida Radiance' 2014-15 variety trial and the growth analysis analysis, before (incl. non-marketable) and after normalization. Error bars represent standard deviation of observations.

"gridExtra" for graphing, "tidyverse", "dplyr", "readr" and "reshape2" for data processing and "hydroGOF" and "Wilcox" for statistical analysis. The Wilmott Index of Model Agreement (Eq. (1)) was used to assess general model performance (Willmott, 1981). The Wilmott Index of Model Agreement is also known as d-statistics and it is a dimensionless index for model agreement related to the Nash-Sutcliffe index. The test d-statistics range in value between 0.0 and 1.0, with a value closer to 1 indicating a better model performance.

$$d - statistics = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}\left(\left|P_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^2}, \ 0 \le d \le 1 \tag{1}$$

With P_i the simulated value, O_i the observed value and $\overline{O}$ the observed mean.

The Relative Root Mean Square Error (RRMSE, Eq. (2)) was used to evaluate deviation between simulated and observed periodic harvests while accounting for the mean magnitude of observations. A lower RRMSE is considered better with a RRMSE of 0 indicating perfect agreement between model and observation. RRMSE is calculated by dividing the Root Mean Square Error (RMSE) by the mean of all observations.

$$\mathrm{RRMSE} = \frac{\sqrt{\sum_{i=1}^{N}(P_i - O_i)^2/N}}{\overline{O}} \tag{2}$$

With N the number of values, P_i the simulated value, O_i the observed value and $\overline{O}$ the observed mean. In general, the recommendations provided by Yang et al. (2014) were followed.

2.3. Crop model inputs

Based on the previous description of field trial site and data collection methods, the crop model simulation was set up to resemble the field trials. Separate crop model input files were created for each individual experiment, growing season, and cultivar. The standard soil profile from the Candler series was used, representing a hyperthermic sandy, well drained and permeable soil typically found in southern Florida (USDA, 2013). Planting occurred on the same date on October 10 every year with a planting density of 4.3 plants/m^2 as transplants. Variety trials are generally optimally fertilized, hence the fertilizer and associated nitrogen and phosphorus modules were deactivated to simulate optimal conditions. Irrigation was based on the simulated soil water balance, with a set threshold of 80% available soil water in the top 30 cm soil level to trigger automatic irrigation. Harvests took place every seven days for the variety trial experiment with cultivar Florida Radiance in 2014-15, and every three to four days for all remaining variety trials and the growth analysis experiment. Harvesting started between November 22 and 24 and continued until March 26 for the growth analysis experiment with 'Florida Radiance' and 'Florida127' in 2014-15 and March 14 to 16 for all other experiments (Table 8).

2.4. Original model and improvement process

The initial version of the strawberry model was developed by Boote et al. (2016) and Oh (2016) based on experimental data collected during the 2014-15 growing season at the GCREC in Balm, Florida. Key characteristics of the improved model will be described as this is the first formal publication of the strawberry model. For initial model development, the CROPGRO-Tomato template was used as it is a transplanted crop with fruit fresh weight harvest that most closely resembled strawberry within the family of DSSAT crop models (Boote, 2012; Rybak, 2009; Scholberg et al., 1997). CROPGRO is a generic modeling template within DSSAT, initially developed for grain legumes with hourly leaf-level photosynthesis calculations, soil-plant-N balance as well as photosynthetic, vegetative and reproductive growth and development processes (Boote et al., 1998). Multiple genetic parameters for the species, ecotype and cultivar files were changed to resemble growth and development of strawberry plants. For example, the genetic coefficients for canopy height, width and growth are important factors for simulating the overall growth and hedgerow canopy structure of a strawberry plant. Compared to the initial CROPGRO-Tomato model (Boote, 2012; Rybak, 2009), coefficients were reduced to simulate a less wide, shorter, and denser canopy of strawberry in open-field crops with plastic mulching compared to tomato (Table 2).

The model code had been modified to handle multiple harvests at three- to four-day intervals and to only remove fruit that are ripe, while simulating continuous flowering, fruit set, and growth of individual fruit. The model achieves this by simulating fruit growth and development for successive fruit cohorts that can be each tracked individually. For each day of the simulation, fruit cohorts that reach the predefined harvest criterium (photothermal age) are assigned to a fictional "harvest basket". Fruit growth, as other crop physiological processes, require a certain amount of "photothermal time" to be completed, which accumulates at a rate of 1 or lower depending on the difference between optimal (cardinal) and actual temperature. The photothermal time age of fruit (PHTIM) accumulates from day to day (Eq. (3)).

$$PHTIM_i = PHTIM_{\,i-1} + TDUMX_i \tag{3}$$

With TDUMX being the photo-thermal time that occurs in a real day based on thermal time (TNTFAC) and photoperiod time (DRPP) on a real day (Eq. (4)).

$$TDUMX_i = TNTFAC * DRPP \tag{4}$$

DRPP is determined by a genetic coefficient (FUDAY, range 0-1) which describes the effect of daylength on development progress, depending on the growth phase and crop specifics. For this production environment and cultivars, daylength was not considered to have an effect on strawberry growth and development.

All fruit cohorts keep growing until a predefined harvest day is reached when the fruit cohorts within the harvest basket are removed from the plant and become classified as a periodic harvest for a given harvest day. The remaining fruit cohorts, and continuously new appearing cohorts, remain on the plant to grow until they eventually reach the harvest criterium. This is fundamentally different from the

Table 2
Species parameters for canopy height and width per internode growth of CROPGRO-Strawberry model. The original values from the CROPGRO-Tomato model are provided in the second line in italics for comparison.

Vegetative and reproductive process	Growth stage 1-10 (VSTAGE)
Node number on main stem for use in computing height and width growth rates (XVSHT)	0.00 7.95 10.12 14.12 18.60 20.90 21.20 23.20 27.20 47.00
	0.00 3.95 6.12 10.12 14.60 16.90 17.20 19.20 23.20 43.00
Length of internode vs. node developed on the main stem defined by XVSHT (m/node) (YVSHT)	.0130 .0120 .0110 .0080 .0080 .0080 .0080 .0080 .0040 .0035
	.0250 .0250 .0280 .0410 .0760 .0770 .0770 .0720 .0480 .0150
Increase in canopy width per node developed on the main stem (m/node) (YVSWH)	.0195 .0190 .0190 .0190 .0190 .0190 .0190 .0180 .0170 .0150
	.0250 .0250 .0350 .0500 .0590 .0590 .0560 .0350 .0220 .0100

Note: The remaining species parameters of the CROPGRO-Strawberry model that are not discussed in this table or Table 3 were not changed and are listed in the Supplementary Material A.

typical end-of-season harvest for most cereal and legume crops, as well as for most vegetables. As common in crop modeling, the model simulation and calibration are based on the dry weight of organs and fruit. Since strawberry fruits are typically measured in fresh weight, fruit dry weight is converted to fresh weight in the simulation using an empirically determined average dry matter concentration of 16%. The value for dry matter concentration was obtained by drying fruits in a convective oven at 70 °C for over 48 h.

For an initial assessment of the model, simulated results were compared with observed experimental data. It was deemed necessary to improve the simulation of vegetative growth as well as seasonal and overall fruit production. Although total final fruit yield production was accurate, the simulated distribution of fruit production within the season was not matching the observed data. Therefore, further improvement of the original CROPGRO-Strawberry model was required. Based on additional data from literature and new experimental data, the model code and parameters were stepwise changed and improved. Besides focusing on quantitative improvements in model evaluation statistics, observed patterns of fruit yield and vegetative growth were also considered. The individual steps of model improvement were separated into "Original Version", "Version 1", "Version 2", "Version 3" and "Version 4" to delineate the approach and to allow for a comparison between the original model and successive steps of model improvement. Fig. 2 provides a general overview of the improvement process and the specific model processes that were improved or added at each step of the model development.

2.5. Simulating long-term seasonal yield distribution

To demonstrate the potential of the new strawberry model, a seasonal analysis (Thornton and Hoogenboom, 1994) was conducted using 10 years of historical weather data and keeping all crop management the same. The daily weather data from the FAWN weather station at Balm, Florida were used to simulate the growing seasons between 2010 and 2020. Crop management was assumed to be identical to the previously described field experiments, with automatic irrigation, optimal fertilization and same planting setup and harvest dates at three to four-day intervals from November 22 to March 15. Periodic harvests were summarized by their respective harvest month from November to March to analyze the monthly distribution of the seasonal production. The typical

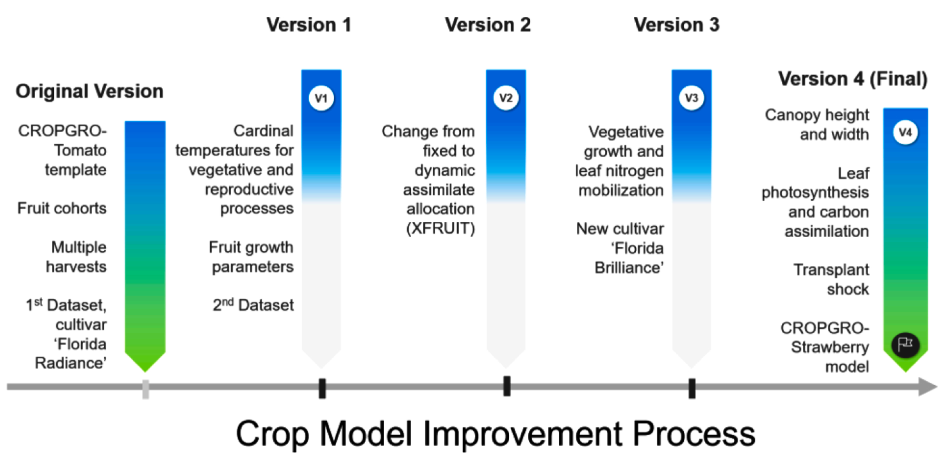

Fig. 2. Schematic representation of the CROPGRO-Strawberry model improvement process. The labels "Original Version" to "Version 4" refer to the individual steps of model improvement. Each version implements changes to parameters, physiological processes, or includes additional data.

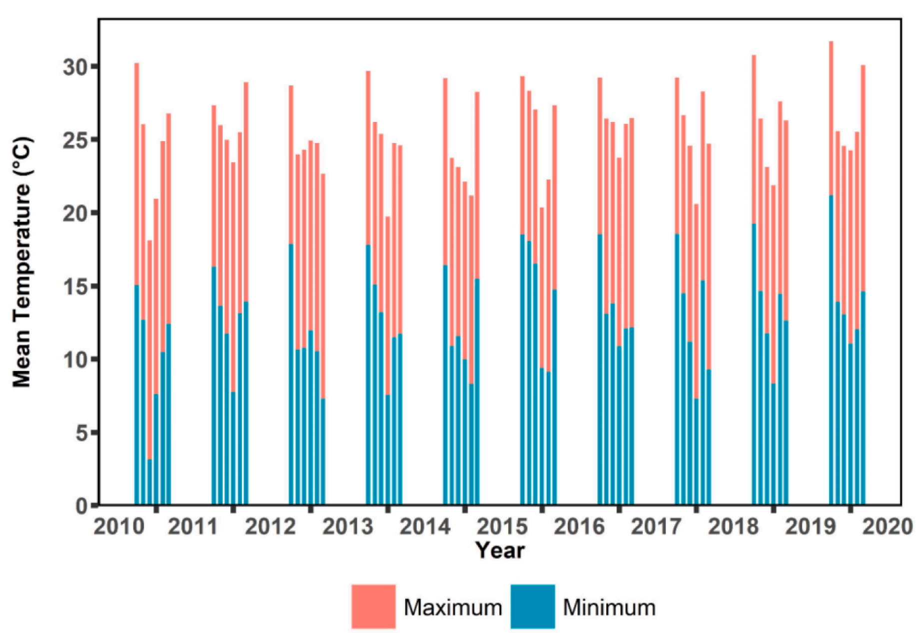

Fig. 3. Monthly mean maximum and minimum temperature in Balm, Florida for the months of October through March for each growing season from 2010-11 to 2019-20.

strawberry growing season in Florida lasts from Fall (October) through Spring (March) in the following year. For example, the season of 2010-11 refers to the growing period from October 2010 to March 2011. Annual production refers to the cumulative fruit harvested throughout the entire growing season, whereas monthly production refers to the sum of fruit harvested during a specific month.

3. Results

3.1. Weather data

An overview of the monthly mean temperature from 2010 to 2020 in Balm confirms typical seasonal fluctuations with some variability from year to year (Fig. 3). The seasonal mean temperature ranged between 17.4 and 20.6 °C. The 2010-11 season was a relatively cold season with particularly low temperatures during December and January compared to the other years. Seasons with similar seasonal averages can vary significantly on a month-by-month basis. For example, the 2014-15 season (mean 18.3 °C) had a very warm month of March (21.9 °C), while the 2012-13 season (mean 18.2 °C) had a relatively cold month of March (15.0 °C).

3.2. Model improvement process

3.2.1. Cardinal temperatures

Cardinal temperatures define the temperature-dependency of both the vegetative and reproductive processes of all cultivars within a species in the model.

The temperature range for two critical reproductive processes was changed based on new findings from the literature (Table 3). The optimal temperature range for flower/fruit addition was shifted downward, promoting fruit addition at lower temperatures that become harvestable a month or more later, and the optimal range for fruit growth was shifted downward to promote fruit growth and to better simulate the considerable increase in harvestable fruit once the temperature starts to increase in January. The remaining coefficients are based on values from the literature or the CROPGRO-Tomato model.

3.2.2. Fruit growth duration and size

The growth of an individual strawberry fruit is characterized by a

Table 3
Species parameters for temperature sensitivities of the CROPGRO-Strawberry model. Original and improved cardinal temperatures for vegetative and reproductive processes. Values in **bold** are modifications as part of model improvement. Values in italics in second row are values from original model version. Remaining values are from the original model version and were adapted from the CROPGRO-Tomato model.

Vegetative or reproductive process	Tb (°C)	Topt1 (°C)	Topt2 (°C)	Tmax (°C)	Literature source
Fruit addition (Pod Addition)*	**7.5** *7.5*	**12.0** *17.4*	**16.0** *24.0*	**30.0** *33.0*	(Le Mière et al., 1996; Ledesma et al., 2008; Sønsteby and Heide, 2008)
Fruit growth rate (and Seed Growth)*	**8.5** *9.2*	**20.0** *21.6*	**25.0** *27.2*	**32.0** *32.2*	(Kumakura et al., 1994; Wang and Camp, 2000)
Rate of leaf appearance	2	20	24	40	(Chabot and Chabot, 1977; Galletta and Himmelrick, 1990; Rosa et al., 2011)
Early reproductive development	7	15	18	40	(Durner and Poling, 1988; Heide, 1977)
Late reproductive development	7	17	18	48	(Strik, 1984; Wang and Camp, 2000)
Leaf photosynthesis (instantaneous)	4.2	28.1	30	42	Set from growth during cold weather
Leaf photosynthesis (prior night Tmin)	-2.0	13.4			Set from growth during cold weather
Temperature below which plant loses all leaves, but development continues (FREEZ1)	**-6.5** *-2.0*				Set from growth during cold weather
Temperature below which plant growth stops completely (FREEZ2)	**-9.0** *-5.0*				Set from growth during cold weather
Leaf area expansion	0.48 at 14.0	19.1	24.0	0.1 at 50.4	Set from growth during cold weather

Note: The four columns indicate base (Tb), first optimum (Topt1), second optimum (Topt2), and maximum (Tmax) temperatures.
* The four cardinal temperatures for fruit addition and fruit growth rate only are converted to process value through a four-sided parabolic (QDR) function using hourly air temperature in DSSAT. All other functions compute rate with a linear interpolation between cardinal temperatures using hourly air temperature.

Table 4
Ecotype coefficients of the CROPGRO-Strawberry model. The original values based on the CROPGRO-Tomato model are shown in the first column. The original values for the cultivar Florida Radiance are shown in the second column, while the calibrated values are shown in **bold**.

Genetic coefficient	Tomato	Strawberry 'Florida Radiance'	
		Original	Calibrated
Time (PD) between planting and emergence (PL-EM)*	6.0	6.0	6.0
Time (PD) required from emergence to first true leaf (EM-V1)*	22.0	22.0	22.0
Time (PD) required from first true leaf to end of juvenile phase (V1-JU)*	0	0	0
Time (PD) required for floral induction, equal to minimum number of days for floral induction under optimal temperature and daylengths (JU-R0)*	5.0	5.0	5.0
If 0.0, there is no slow fruit growth phase; if greater than 0.0, there is slow growth phase (PM06)	0.55	0.55	**0.99**
Fraction (%) of time from first seed to maturity during which fruits can be added (PM09)	0.75	0.99	0.99
Time (PD) required for growth of individual fruit (LNGSH)	39.0	8.1	**12.0**
Time (PD) between physiological (R7) and harvest maturity (R8) (R7-R8)	0.0	0.0	0.0
Time (PD) from first flower to last leaf on main stem (FL-VS)	24.5	70.0	70.0
Rate of leaf appearance on main stem (leaves / PD) (TRIFL)	0.45	0.40	0.40

Note: coefficients related to daylength sensitivity and photoperiod effect (THVAR, R1PPO, OPTBI, SLOBI) are not applicable and set to 0. Coefficients related to width and height of this ecotype to standard width and height (RWDTH, RHGHT), maturity group (MG) and temperature adaptation (TM) are not applicable and set to 1.
* Coefficient from the CROPGRO-Tomato model, which is required for internal model functioning but has no practical relation to growth of Strawberry transplant. PD = photothermal days.

Table 5
Cultivar coefficients of the CROPGRO-Strawberry model. The original values based on the CROPGRO-Tomato model are shown in the first column. The original values for the cultivar Florida Radiance are shown in the second column, while the calibrated values are shown in **bold**.

Genetic coefficients	Tomato	'Florida Radiance' (Original)	**'Florida Radiance' (Calibrated)**
Time (PD) between plant emergence and first flower appearance (EM-FL)	24.2	27	**26**
Time (PD) from flowering to begin fruit growth (FL-SH)	2.2	6.9	**4.0**
Time (PD) between first flower and first seed (FL-SD)	19	8.2	8.2
Time (PD) between first seed and physiological maturity (SD-PM)	45.2	91.5	**110**
Time (PD) between first flower and end of leaf growth (FL-LF)	52	400	400
Maximum leaf photosynthesis rate at 30 °C, 350 vpm CO_2 and high light ([mg CO_2/m^2]/s) (LFMAX)	1.36	1.07	**1.35**
Specific leaf area (cm^2/g) of cultivar under standard growth conditions (SLAVR)	300	200	200
Maximum size (cm^2) of full leaf (all leaflets, SIZLF)	300	150	150
Maximum fraction (%) of daily growth partitioned to fruit growth (XFRUIT)	0.78	0.96	**0.2-0.96 (dynamic)**
Maximum weight (g) per seed (WTPSD)	0.004	0.005	0.005
Seed filling duration (PD) for fruit cohort at standard growth conditions (SFDUR)	26	11.7	11.7
Average number of seed (seeds / pod) per fruit under standard growing conditions (SDPDV)	300	130	**185**
Time (PD) required for cultivar to reach final fruit load under optimal conditions (PODUR)	55	41.8	**45**
Threshing percentage (%), maximum ratio (%) of seed to (seed+shell) at maturity (THRSH)	8.5	20	20
Fraction of protein in seeds (g (protein)/g (seed)) (SDPRO)	0.30	0.30	0.30
Fraction (%) of oil in seed (g (oil)/g (seed)) (SDLIP)	0.05	0.05	0.05

Note: coefficients related to daylength sensitivity and photoperiod effect (CSDL,PPSEN) are not applicable and set to 0, under assumption of no photoperiod sensitivity. PD = photothermal days.

slow growth phase immediately following flowering, followed by a rapid growth phase and ultimately flattening growth curve when approaching the final size and maturity. This sigmoid growth curve occurs during a time span of circa two weeks in photothermal time after flowering. This results in a total fruit development time of three to four calendar weeks from flowering to harvestable fruit, with possible variation for special cultivars (Luo et al., 2019; Miura et al., 1994; Poling, 2012). Two of the ecotype coefficients shown in Table 4 were adjusted to implement a sigmoidal growth curve: PM06 defines the proportion of time between first flower and first fruit shell, with higher values lengthening the time. PM06 was increased to 0.99 to have the slow growth phase last for three to four days after flowering. LNGSH sets the required photothermal time for the fruit shell to reach its maximum size (mass); it was increased so the fruit reaches its maximum size on the day of or a few days prior to harvest.

Connected to the slow individual fruit growth phase, the species coefficient SHLAG was increased to 0.2 to increase the relative rate of fruit growth in the slow growth phase. Furthermore, several cultivar coefficients were adjusted to improve fruit growth duration and size (Table 5). The cultivar coefficient FL-SH determines the required photothermal time between flower opening and beginning of the fruit (shell) growth, applied to each fruit cohort, and was decreased from 6.9 to 4.0 photothermal days to shorten the development time between flower and harvestable fruit and enable a more direct response to weather conditions between flowering and harvest. The cultivar coefficient SDPDV defines the number of seeds per fruit and thereby determines the size of an average fruit; SDPDV was increased from 130 to 185 to increase the average simulated fruit size closer to the observed 26 g/fruit. The cultivar coefficient PODUR defines the required photothermal time for the crop to reach final fruit load and was increased from 41.8 to 45.0 photothermal days to extend a portion of the excessive early harvests into a later part of the season. The large values for PODUR, SD-PM, and FL-FL are all designed to create a long fruiting period (SD-PM), extended fruit addition (PODUR), and continued leaf area expansion after first flower (FL-LF). The adjustment of cardinal temperatures, fruit size and fruit duration time resulted in limited improvements by shifting some of the fruit production towards the later parts of the season and reducing excessive early production. However, the seasonal distribution of harvests was not sufficient, so further improvements remained necessary.

3.2.3. Seasonality of production and dynamic assimilate allocation

A key issue of the original model version was the relatively inaccurate simulation of the seasonal yield distribution in Florida. Winter strawberry production occurs from October to March but most fruit are produced from mid-January to March, with very few fruits reaching harvest in early January or December. This process is presumable driven by phenology and temperature (Fernandez et al., 2001), as the mean temperature generally decreases until December/January and then increases again after mid-January.

The CROPGRO-Strawberry model distributes available assimilates between reproductive (fruit) and vegetative (leaf, stem, root) growth based on phenology and various parameters such as the partitioning coefficient "XFRUIT". In the original model, XFRUIT is set as a constant partitioning parameter between 0 and 1, with 1 indicating that all assimilates can be allocated to reproductive growth, once a full-carrying capacity (maximum number of fruit) is reached. The previously described long fruit adding period delays the time of reaching that full-carrying capacity for a month or longer, but that by itself was insufficient to mimic the greater production after mid-January. For the initial CROPGRO-Strawberry version, the value for XFRUIT was set to 0.96, which caused excessive fruit production during the first half of the season, followed by a shortage of production during the second half of the growing season due to insufficient leaf area and flowers to enable increased fruit production with an increase in temperature during the second half of the growing season.

Our solution to this situation was to change XFRUIT from a static to a dynamic parameter (Eq. (5)). XFRUIT is initialized to a low value of 0.2 at the time of first flowering, which reduces fruit addition and increases vegetative growth during the early part of the fruit production cycle, and increases progressively to a value of 0.96 as a linear function of cumulative photothermal time (Fig. 4a). The required photothermal time is set empirically to 60 photothermal days after the initiation of the first fruit to sufficiently delay early fruit production but enable sufficient fruit production during the second half of the growing season (Eq. (5)). The accumulation of photothermal days is dependent on the temperature; in the experiments the threshold of 60 photothermal days is reached at approximately 105 to 115 days after transplanting. This is a parameter that should be considered as a genetic trait, as it may vary among cultivars.

$$XFRUIT(Dynamic) = \frac{XFRUIT(Static)}{60} * \ PHTIM * \ 0.8 + 0.2 * XFRUIT(Static) \qquad (5)$$

PHTIM is the photothermal time in days after the initiation of the first fruit. The value 60 is the empirically set required photothermal time to reach the maximum value for *XFRUIT(Dynamic)*.

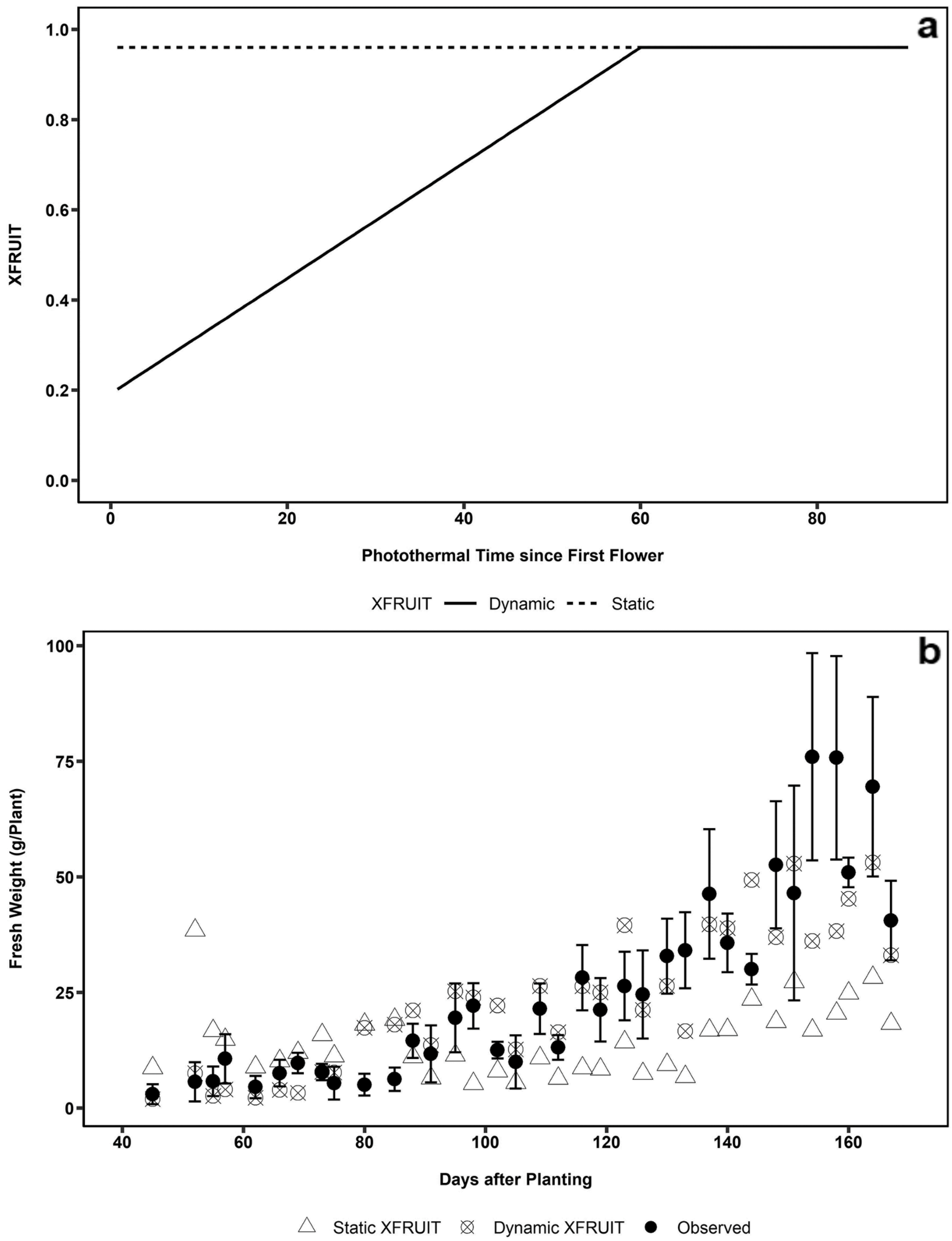

Fig. 4. Comparison of Static and Dynamic XFRUIT as a function of photothermal time since first flower (a) and respective simulated periodic harvests to observed values over time with for 'Florida Radiance' 2014-15 growth analysis (b). Error bars represent standard deviation from the growth analysis dataset with six repetitions.

The dynamic adjustment of XFRUIT (Fig. 4,a) significantly reduced simulated fruit production during the first month of harvests (45 to 75 days after planting) and increased fruit production (Fig. 4,b) during the second half of the growing season, compared to the static XFRUIT. The simulation based on a dynamic XFRUIT now more closely resembles the observed patterns. However, the adjustment of XFRUIT to reduce early fruit production resulted in concomitant sharp increases in simulated leaf and stem growth, which were higher than the observations and thus required further adjustment of the model.

3.2.4. *Vegetative growth and leaf nitrogen*

The vegetative leaf weight was overpredicted. To address this, parameters for leaf senescence and leaf nitrogen mobilization were modified, resulting in decreased leaf weight. These changes mimic the practice of continuous removal of dying or diseased leaves practiced during the season in Florida (Chandler et al., 2017). The species coefficients for nitrogen mobilization, nitrogen mining, and leaf senescence were increased significantly compared to the original version (Table 6).

The modifications produced a pattern of simulated leaf nitrogen concentration that started at 4.2% at transplanting in October, then decreased during the season until reaching a value of 3.2% at the end of the growing season at the end of March. Reasonably comparable values were found in the literature, which reported leaf N% ranging from 3.5 to 3.9% for early (November) and from 2.5 to 2.8% for late (March) season for strawberries in Florida (Hochmuth et al., 1996). A different

Table 6
Parameters affecting N balance, leaf nitrogen concentration and leaf senescence in the species file for CROPGRO-Strawberry model. Default values from original version and modified values for improved version in bold.

Species (genetic) parameter	Original	Final
Rate (fraction) of nitrogen mobilization per day (NMOBMX)	0.015	**0.061**
Relative rate (fraction) of nitrogen mining during vegetative phase (NVSMOB)	0.38	**1.00**
Factor by which protein mined from leaves each day is multiplied to determine leaf senescence (g (leaf)/g (protein loss)) (SENRTE)	1.5	**2.75**

Table 7
Cultivar coefficients for new cultivar Florida Brilliance compared to Florida Radiance for CROPGRO-Strawberry model. Default values from original cultivar Florida Radiance and calibrated values for Florida Radiance and Florida Brilliance in **bold**.

Parameter	'Florida Radiance' (original)	'Florida Radiance' (calibrated)	'Florida Brilliance' (calibrated)
Maximum leaf photosynthetic rate ([mg CO_2/m^2]/s) (LFMAX)	1.07	**1.35**	**1.75**
Number of seeds per fruit (number / fruit) (SDPDV)	130	**185**	**150**
Time (PD) to final fruit load (PODUR)	41.8	**45.0**	**33.0**

Note: PD = photothermal days.

experiment with another cultivar and location reported lower leaf nitrogen concentration between 3 and 2% (Menzel, 2018), so these parameters might be specific to cultivar, region and growing system. The initial value of NMOBMX of 0.015 is much lower than the typical CROPGRO models and had been created to sustain leaf N concentration and function through a very long fruiting phase. The value of 0.061 is more reasonable and mimics the case of more reasonable shorter leaf longevity, with replacement of new leaves allowed by the new XFRUIT function because (1-XFRUIT) of assimilate is reserved for vegetative growth.

3.2.5. Parameterization of the new cultivar Florida brilliance

At the beginning of the development of the strawberry model, 'Florida Radiance' was the dominant cultivar in Florida, but new cultivars are continuously being released. Therefore, the CROPGRO-Strawberry model must be able to include new cultivars such as 'Florida Brilliance' which is like 'Florida Radiance' but with a smaller fruit size and improved fruit quality (Whitaker et al., 2019). Using additional data from the variety trials conducted during the 2016-17 and 2017-18 growing seasons, the cultivar parameters related to phenology and leaf photosynthesis were adapted to resemble the described traits of the new cultivar. The maximum leaf photosynthetic rate was increased significantly to achieve a higher level of production with the same leaf area. The number of seeds per fruit was decreased to simulate a slightly smaller fruit and the photothermal days required for final fruit load was decreased slightly to promote a higher early harvest (Table 7). It was assumed that the remaining genetic coefficients that define the species and ecotype characteristics were the same for both cultivars Florida Radiance and Florida Brilliance. An overview of the final and complete model parameters, including parameters that were not changed during the model improvement process, are available in the Supplementary Material A (Species), B (Ecotype) and C (Cultivar).

3.2.6. Final version

Final revisions to canopy height and width coefficients were made to create compact architecture that further reduced excessive canopy width and height as well as vegetative growth for growth phase from 40 to 120 days after planting (Table 2). Parameters related to the simulation of leaf photosynthesis and carbon assimilation, namely specific leaf weight (SLWREF) and area (FINREF and SLAVR) were modified. In addition, a temporary reduction of photosynthesis for 40 days after transplanting was implemented for all cultivars to simulate the observed transplant shock under field conditions. During the phase of transplant shock, the photosynthetic rate increases linearly from 1/40th of the regular rate on day 1 back to the full rate on day 40. At this point, the model functions correctly, and represented the most important physiological and growth characteristics of the strawberry crop and the model was deemed sufficiently improved for application.

3.3. Analysis of model performance

The detailed analysis of model performance is based on Version 4 of the model that includes all previously described improvements presented under Version 1, 2, 3 and Version 4 (Fig. 2). A detailed analysis of time-series organ growth performance was only conducted for the growth analysis experiment with 'Florida Radiance' in the 2014-15 growing season. Analysis of periodic and total fruit production was performed for all experiments. A summary of model performance and comparison between model versions is provided in Tables 8 and 9.

3.3.1. Growth analysis

Simulations for the Leaf Area Index (LAI, d = 0.9, RRMSE = 0.48), leaf mass (d = 0.89, RRMSE = 0.40), vegetative mass (d = 0.77, RRMSE = 0.68) and total aboveground biomass (d = 0.99, RRMSE = 0.26) were good to satisfactory (Fig. 5). Leaf and vegetative mass and LAI were over-simulated during the first half of the growing season but approached observed values during the second part of the growing season. This trend is likely due to the use of the dynamic partitioning factor XFRUIT, leading to excessive vegetative growth during the first half of the season before fruit growth becomes dominant during

Table 8
Comparison of simulated to observed periodic fruit harvests for different model versions. d-statistics (d) and Root Relative Mean Square Error (RR.) were used to evaluate model performance. No data exist for cultivar Florida Brilliance 2016-17 and 2017-18 for the Original Version and Version 1 and 2 because the new cultivar was not included in these versions.

		Orig. Version		Version 1		Version 2		Version 3		Version 4	
Cultivar	Season	d	RR.	d	RR.	d	RR.	d	RR.	d	RR.
Radiance*	2014-15	0.69	0.77	0.71	0.76	0.86	0.62	0.89	0.55	0.92	0.5
Radiance†	2014-15	0.60	0.68	0.65	0.64	0.91	0.41	0.87	0.51	0.93	0.36
	2016-17	0.55	0.84	0.60	0.76	0.89	0.60	0.93	0.57	0.89	0.52
	2017-18	0.74	0.92	0.75	0.85	0.94	0.52	0.96	0.44	0.88	0.56
Brilliance†	2016-17							0.92	0.41	0.96	0.47
	2017-18							0.85	0.41	0.88	0.43
Average		0.65	0.80	0.68	0.75	0.90	0.53	0.90	0.48	0.91	0.47

* Growth analysis dataset.
† Variety trial dataset.

Table 9
Comparison of simulated (Sim.) and observed cumulative harvest with successive model versions. Percentage sign (%) indicates percentage over- or underestimation (bias) compared to the observed value. All values in gram fresh weight per plant. Italic values are the number and the range of the observations.

Cultivar and Season	Observed (g / plant)	Orig. Version Sim.	%	Version 1 Sim.	%	Version 2 Sim.	%	Version 3 Sim.	%	Version 4 Sim.	%
Radiance 2014-15 *	886 (*n = 6,736-1008)*	779	-14%	788	-12%	890	0%	961	8%	892	1%
Radiance 2014-15 †	759 *(n = 2, 733-795)*	621	-22%	642	-18%	704	-8%	655	-16%	712	-6%
Radiance 2016-17 †	854 *(n = 5, 789-954)*	873	2%	859	1%	963	11%	872	2%	940	10%
Radiance 2017-18 †	722 *(n = 5, 604-764)*	729	1%	721	0%	661	-9%	731	1%	701	-3%
Brilliance 2016-17 †	1018 *(n = 5, 951-1087)*							1054	4%	1099	8%
Brilliance 2017-18 †	909 *(n = 5, 806-1013)*							784	-16%	855	-6%
	Average		**-8%**		**-8%**		**-1%**		**-3%**		**1%**

* Growth analysis dataset.
† Variety trial dataset.

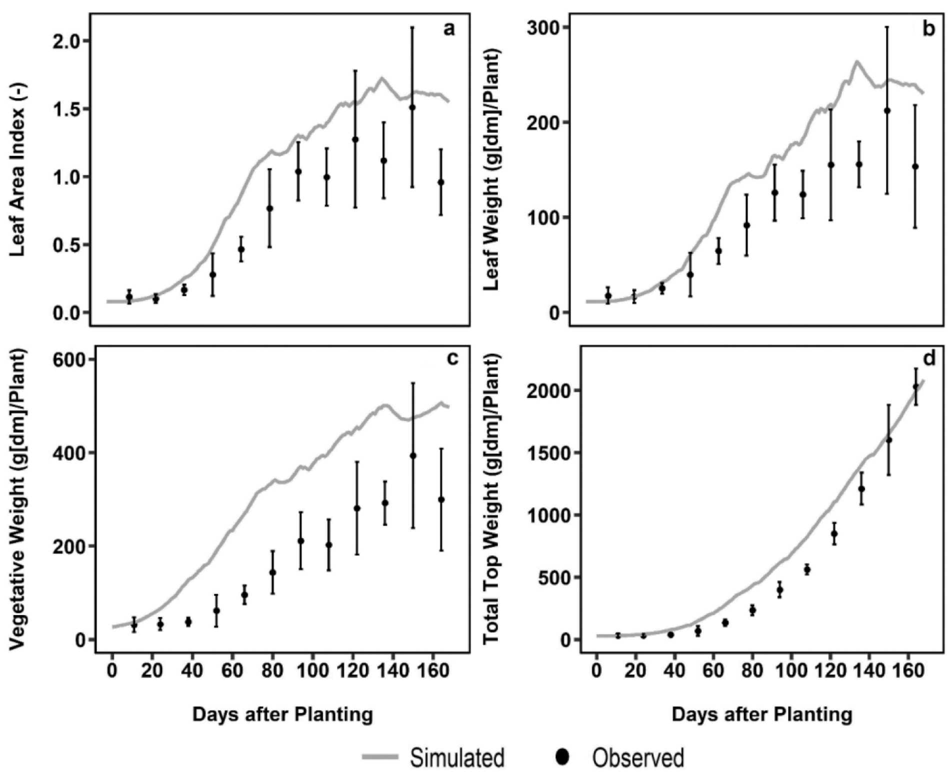

Fig. 5. Model performance for simulation of growth dynamics compared to observed for 'Florida Radiance' 2014-15 growth analysis for (a) Leaf Area Index, (b) leaf weight, (c) vegetative weight and (d) total aboveground biomass. Error bars represent standard deviation from the growth analysis dataset with six repetitions (n = 6). Total aboveground biomass consists of combined leaf, stem, and cumulative fruit weight.

the second half of the growing season. Simulated total aboveground biomass (including all periodic cumulative fruit) over time shows a pattern of being higher than observed during the middle of the growing season but simulates closer later in the growing season, resulting in final simulated values slightly below the observed values. The variability among the six repetitions was high, which indicates typical high variability among individual plants in the field or difficulty in obtaining precise measurements.

3.3.2. *Periodic harvests*

Periodic harvests are well simulated and capture the general fluctuations in the observed periodic yields during the first half of the season, with larger deviations from the observed values during the second half of the growing season (Fig. 6). Several peak harvests at circa 120 to 140 days after planting are significantly over- or undersimulated by the model, resulting in either an overall lower or higher yield. The cultivar Florida Radiance for the 2014-15 variety trial had higher periodic harvests, up to 115 g/plant, due to longer accumulation of fruit during the seven-day harvest interval compared to three to four-day intervals in all other experiments.

3.3.3. *Cumulative fruit number*

Final simulated and observed harvested fruit numbers are very close for the cumulative number of fruits during the growing season. These are well simulated based on the statistical indices that range from 0.95 to 0.99 for the d-statistics and 0.13 to 0.33 for RRMSE for all seasons and cultivars. The simulated cumulative fruit number for cultivar Florida Radiance 2014-15 followed the observed values for the 2014-15 growth

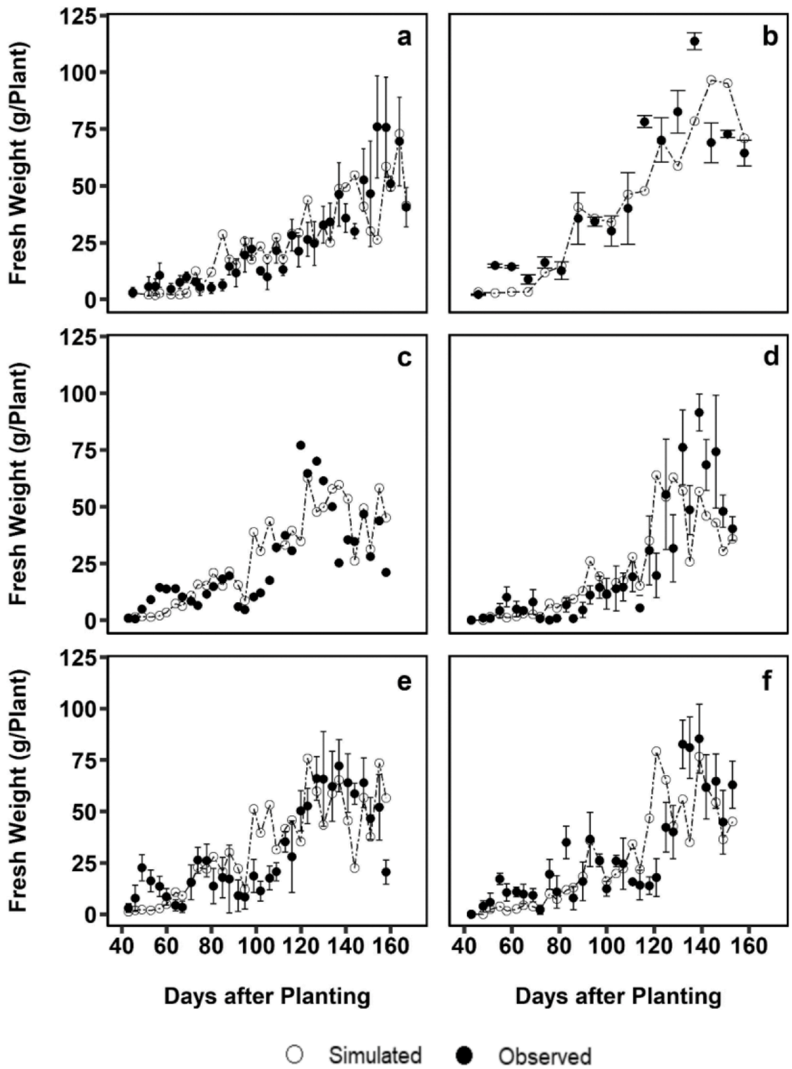

Fig. 6. Model performance for simulated and observed periodic harvests for (a) 'Florida Radiance' 2014-15 growth analysis, (b) 'Florida Radiance' 2014-15 variety trial, (c) 'Florida Radiance' 2016-17, (d) 'Florida Radiance' 2017-18, (e) 'Florida Brilliance' 2016-17, (f) 'Florida Brilliance' 2017-18. Observations are means of two to six repetitions depending on dataset (n = 2 to 6). Each datapoint shows fresh weight of mature fruit which were harvested at each harvest date. Error bars represent standard deviation of observed data.

analysis experiment very closely except for an underestimation during the final month of the growing season (Fig. 7a). Overestimation of fruit numbers occurs to a varying extent during the middle part of the season for all variety trials with 'Florida Radiance' (Fig. 7b-d). The fruit number for both growing seasons of 'Florida Brilliance' are undersimulated during the first half of the growing season but follow the observed values more closely during the second part of the growing season (Fig. 7e-f).

3.3.4. Cumulative fruit mass harvest

Cumulative harvests are generally well simulated and capture the trend of increasing harvests in the second half of the season as visualized by increasing slopes (Fig. 8). Over- and underestimation of harvests occurs in line with the previously described model performance for periodic harvests but show some time delay due the cumulative nature of the graph. The variability in observed yield increases significantly towards the end of the growing season. The cumulative fresh weight for the cultivars Florida Radiance for the 2016-17 and 2017-18 variety trials (Fig. 8c,d) and Florida Brilliance for the 2016-17 variety trial (Fig. 8e) are well simulated with periodic under- and overestimation. However, the end-of-season cumulative harvests are within the observed range. Higher deviations can be found for 'Florida Brilliance' for the 2017-18 variety trial (Fig. 8f), which is simulated too low during the first half of the growing season, then only temporarily "catches up" to the observed cumulative values, but then due to periodic underestimation still has a simulated cumulative harvest that is below the observed cumulative harvest at the end of the growing season. There are also some significant deviations in cumulative yield when comparing the cultivar Florida Radiance for the 2014-15 growth analysis with the 2014-15 variety trial (Fig. 8a,b). The growth analysis trial is overestimated, and the variety trial underestimated during the second half of the same harvest season.

3.3.5. Summary of model performance

The stepwise approach for the development of the strawberry model showed significant improvements in the estimation of the periodic harvests as measured by RRMSE and d-statistics across all experiments (Table 8). The number of model version refers to the step of model improvement previously described. The average d-statistics increased from 0.65 to 0.91 and RRMSE decreased from 0.80 to 0.47, when comparing the Original Version and Version 4 of the model. The most significant improvements were achieved by Version 2, which implemented the photothermal-age dependent partitioning factor XFRUIT to determine allocation to reproductive growth versus vegetative growth. The change from Version 2 to Version 3 improved the average model performance only slightly but it is important because of the improvements in vegetative growth and the inclusion of the new strawberry cultivar Florida Brilliance in the analysis. Additional changes from Version 3 to Version 4 improved the nitrogen balance and leaf senescence, refined the physiological processes, and slightly improved the accuracy of the simulations.

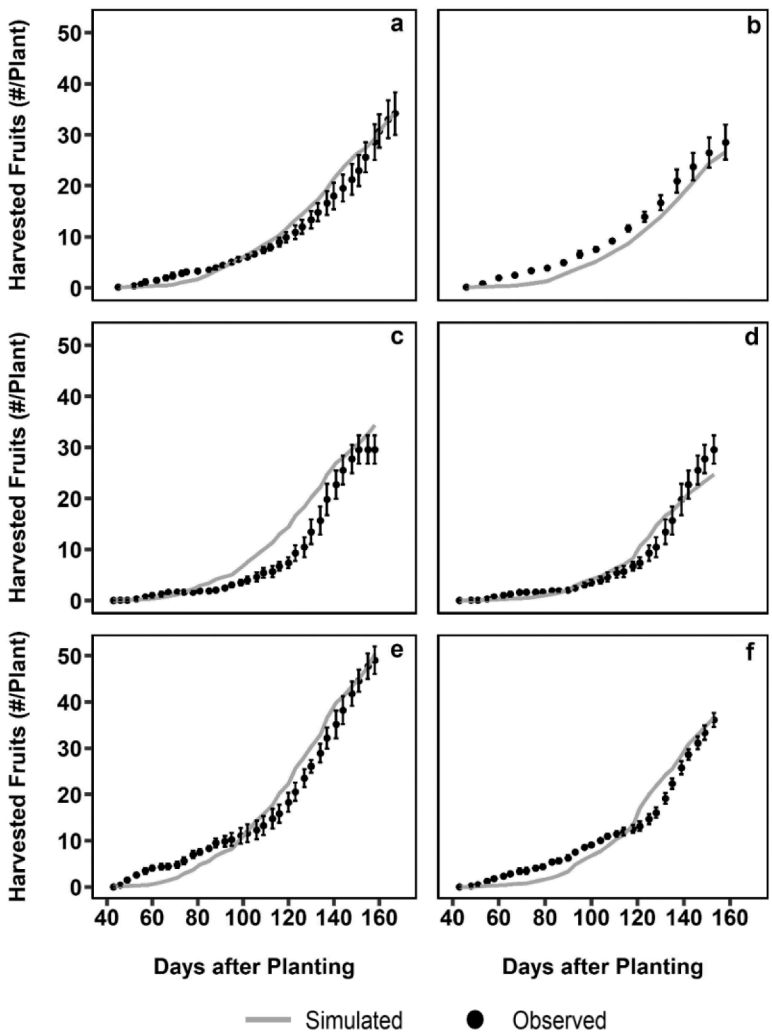

Fig. 7. Model performance for simulated and observed cumulative fruit number for (a) 'Florida Radiance' 2014-15 growth analysis, (b) 'Florida Radiance' 2014-15 variety trial, (c) 'Florida Radiance' 2016-17, (d) 'Florida Radiance' 2017-18, (e) 'Florida Brilliance' 2016-17, (f) 'Florida Brilliance' 2017-18. Observations are means of two to six repetitions depending on dataset (n = 2 to 6). Each datapoint shows cumulative number of fruit harvested until that point of time. Error bars represent standard deviation of observed data.

Total cumulative harvests are reasonably well simulated with an average overestimation of 1%, but deviation up to +10% or -6% in single experiments compared to observed harvests (Table 9). Observed cumulative harvests have a large range of variability, and simulated final cumulative harvests are within the range of observed values for all experiments except for the variety trial 'Florida Radiance' in 2014-15 and variety trial 'Florida Brilliance' in 2017-18. Given the economic importance of early strawberry yields for growers, simulating the seasonality of production is an important model capability and should be further evaluated in a seasonal analysis.

3.4. Model application

The long-term seasonal yield distributions in Balm, Florida were simulated using historical weather data from 2010 through 2020 for cultivar Florida Radiance. The simulated periodic harvests showed a significant variability ranging from 0 to 80 g of fresh weight per harvest per plant (Fig. 9) across all seasons from 2010 to 2020. The typical seasonal pattern shows small harvests in November and December, then gradually increasing until the beginning of March, followed by a slight decline until the end of the growing season in mid-March. Later harvests are larger but also more variable. The simulated "final" cumulative yield from 2010 to 2020 (Fig. 10) ranges between 529 to 879 g/plant and the inset of monthly harvest within each annual production bar shows the same previously described production pattern with a low yield in December followed by a strong increase from January to late February (Fig. 9). For all seasons, both the overall amount and relative share of fruit during the main production period from January to March varied significantly from season to season.

4. Discussion

4.1. Model improvement

Overall results are satisfying for this initial and novel modeling of a new crop with multiple fruit harvests. Each step of the model improvement process refined the simulation of physiological processes, added desired complexity of capability into the model and ultimately improved model performance (Tables 8 and 9). The cumulative changes and improvements made the model suitable for further application. Particularly the changes toward creating a dynamic XFRUIT enabled an important improvement regarding simulation of individual fruit growth and seasonality of strawberry harvests, with small harvests occurring during the first half of the season followed by a considerable increase in early January (Fig. 4b). The possibility of simulating a more dynamic allocation to fruit growth through adjustment of XFRUIT depending on physiological age, or the temporary reduction of photosynthesis after a transplant shock will be useful to modeling further fruit and vegetable crops where seasonality in production plays an important role. Previous work on modeling multiple harvests of strawberry were limited to nonlinear (Sari et al., 2018) or multivariate (Diel et al., 2020) statistical approaches, without simulation of crop physiological processes or

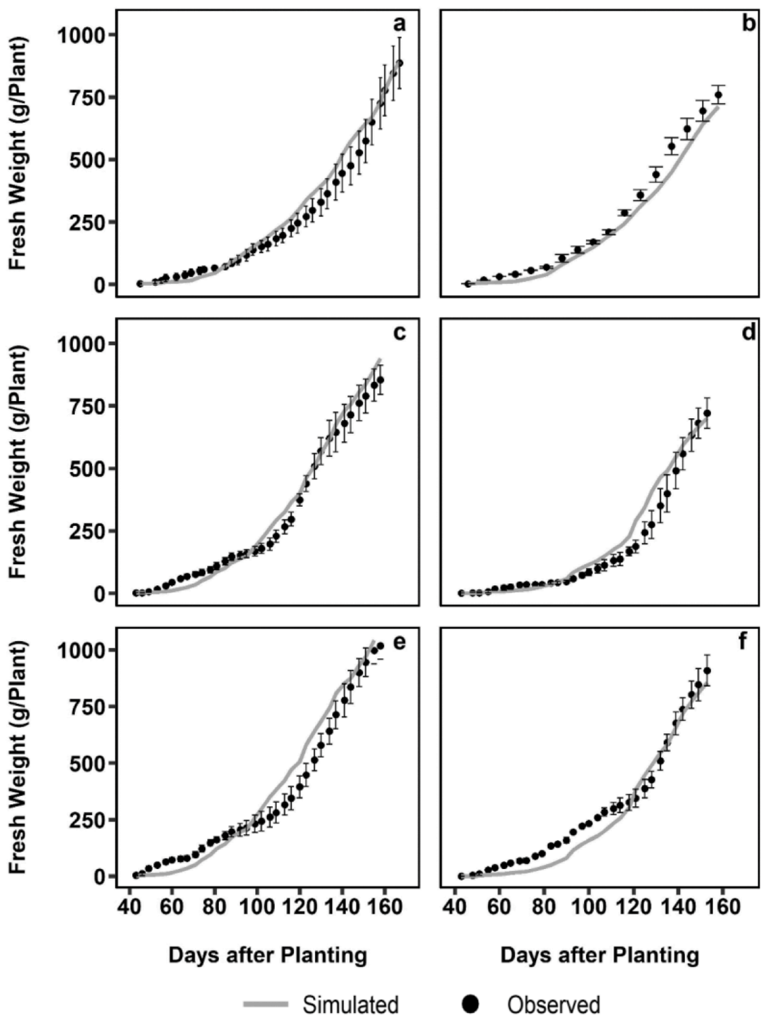

Fig. 8. Model performance for simulated and observed cumulative harvests for (a) 'Florida Radiance' 2014-15 growth analysis, (b) 'Florida Radiance' 2014-15 variety trial, (c) 'Florida Radiance' 2016-17, (d) 'Florida Radiance' 2017-18, (e) 'Florida Brilliance' 2016-17, (f) 'Florida Brilliance' 2017-18. Observations are means of two to six repetitions depending on dataset (n = 2 to 6). Each datapoint shows cumulative sum of fresh weight of mature fruit which were harvested until that point of time. Error bars represent standard deviation of observed data.

individual fruit growth. The proposed addition of multiple harvests into the process-based CROPGRO-Strawberry model will lead the way for modeling other crops with continuous harvests from the same plant such as tomato, cucumber, pepper, or green bean.

Another strength of this model is the inclusion of vegetative processes into the simulation, contrary to previously described statistical strawberry models, which focus solely on yield (Lobell et al., 2006; Pathak et al., 2016). Although the in-season simulations for the leaf and vegetative mass did not follow the observed seasonal patterns very well, the final simulated values were relatively close to the observed values. The overestimation of vegetative biomass during the early growing season might be addressed through further analysis of the previously adjusted coefficients for leaf senescence, leaf photosynthesis and specific leaf area parameters as well as the dynamic adjustment of XFRUIT and partitioning to root mass. Further adjustments to the partitioning among leaf, stem, and root mass, as well as improving the transplant stress effect that reduces early growth may also be needed. The current simulation of vegetative growth and development was deemed acceptable for the intended purpose of the model toward simulation of periodic fruit harvests over time but could be further improved in the future through additional vegetative growth analysis data.

Differences in season-to-season periodic harvests over time can be explained by the observed temperature trends. The 2016-17 growing season was slightly warmer than the 2017-18 growing season (Fig. 3), particularly during the month of January. As this marks the beginning of a highly desirable production period, this might explain both the observed and simulated higher yields in 2016-17 compared to 2017-18. The model captures this trend well for both cultivars, although the simulated cumulative yield for 'Florida Brilliance' 2017-18 is undersimulated and requires further investigation. A slightly larger cumulative production in the 'Florida Radiance' 2014-15 growth analysis trial compared to the 'Florida Radiance' 2014-15 variety trial is expected due to the longer harvesting season for the growth analysis experiment, but the alternative over- and underestimation reinforces the gap in simulated production between the growth analysis and variety trial. This could be caused by the longer seven-day harvest interval for the variety trial compared to three to four days in the growth analysis study. This might be more challenging for the model to simulate due to the longer accumulation of ripe but not yet harvested fruit in the model and requires further analysis.

4.2. Model application

The 10-year analysis highlights the general importance of temperature for overall production as well as temperature during key production periods. The 2010-11 season had a much lower simulated yield due to lower average temperatures in December and January (Fig. 3) leading to lower production in these and following months. The seasons with highest overall simulated production are the seasons with highest seasonal mean temperature, e.g., 2015-16, 2016-17 and 2019-20. Particularly large harvests in February, the key production month besides late January and early March, were driven by above average temperatures during the same month of the seasons 2011-12 and 2016-17. Further evidence for the importance of seasonality can be seen in the 2012-13

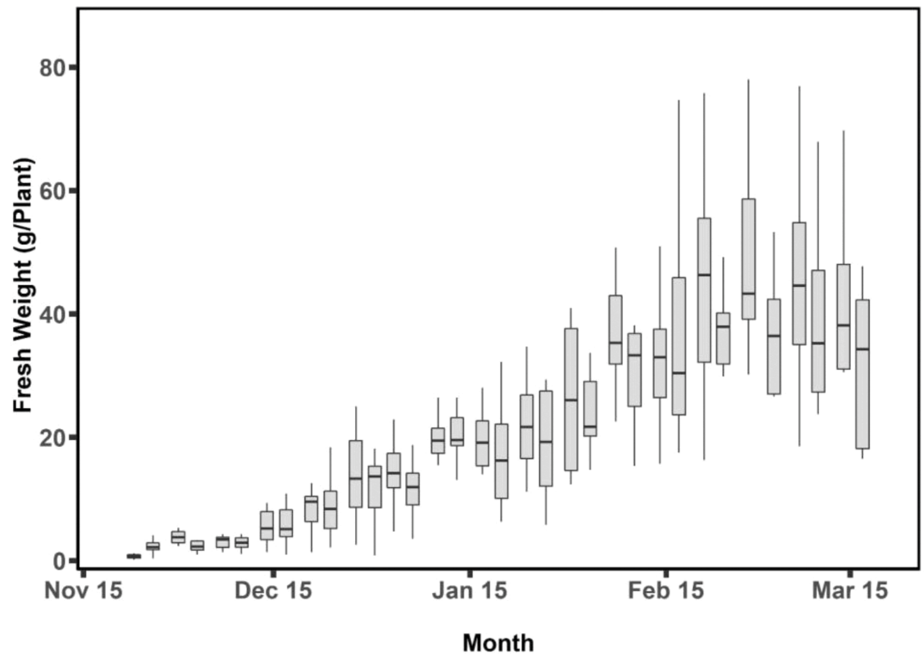

Fig. 9. Simulated periodic harvests of cultivar Florida Radiance, average distribution boxplot for 10 growing seasons (2010-2020) in Balm, Florida. The box indicates upper and lower quartiles, the vertical bar in the center of the box represents the median and the whiskers indicate maximum to minimum periodic harvests for each harvest date.

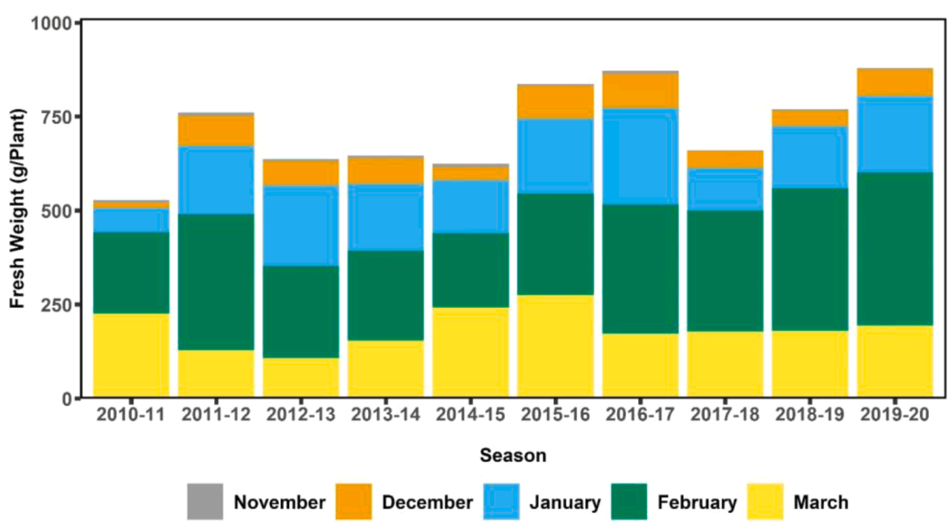

Fig. 10. Simulated 10-year monthly yield distribution of cultivar Florida Radiance for 10 growing seasons (2010-2020) in Balm, Florida. Periodic harvests were summarized into brackets from November to March depending on their harvest date.

and 2014-15 seasons which have a similar yield of 637 and 626 g/plant and almost identical whole season mean temperature of 18.2 and 18.3 °C, respectively. Due to higher temperatures in December and January of 2012-13, the simulated harvests for these two months were circa 30% larger compared to the 2014-15 season. Since strawberries generally achieve much higher market prices in the early season (Wu et al., 2015; USDA, 2020), the 2012-13 season might have been much more profitable despite almost an identical simulated yield over the whole season.

Although still based on simulated results and in need of further evaluation with observed yield data, the seasonal analysis application highlights the importance of sub-seasonal weather patterns for the production of strawberries and other fruits that are grown and harvested continuously. In combination with seasonal weather forecasts, this may have application for agronomic and farm management planning to respond to market competition or labor shortages (Suh et al., 2017; Beal Cohen et al., 2020) or change seasonal production patterns (Wu et al., 2015). This is an important step towards making crop models more user-relevant and increasing model adoption by considering potential end-uses (Prost et al., 2011). The capability of the model to predict individual harvests might add complexity and requires additional parameters compared to a simpler simulation approach that predicts only final yield. However, it adds value through refined simulation outputs and potential analysis of the impact of growing conditions on specific developmental processes.

4.3. Future work

Further evaluation and improvement of the CROPGRO-Strawberry model should entail additional datasets that represent different weather conditions and cultivars to make the model more robust and versatile. In addition to the plasticulture production of short-day cultivars typical for Florida, everbearing strawberry varieties are common in other locations and climates and those cultivars may have important physiological differences regarding flowering and fruit production (Nishiyama and Kanahama, 2002; Soønsteby and Heide, 2007). Data sets on leaf, stem, and root growth relative to fruit growth over time are needed to improve parameterization of model growth dynamics. Strawberry production in high-tunnels, greenhouses or soilless systems in hydroponic or aquaponic facilities is prevalent in some production areas (Carey et al., 2009; Mattner et al., 2017) and simulating these production environments may require model adjustments to account for altered aerial and soil-media environments. Photoperiod and chilling requirements (Tanino and Wang, 2008) or other potential mechanisms that control the observed shift from vegetative to reproductive growth during the second part of the growing season should be investigated and if important, implemented in the model. Further studies with more precise monitoring of individual fruit and individual growth rate and duration would allow for a more precise model evaluation and adjustment. More detailed observations of marketable and non-marketable fruit, including the weight of each type of fruit, could replace the simplified data normalization performed in this study, which would allow modeling potential relationships between unmarketable fruit due to adverse growing conditions. Linked to this, pest and diseases can drastically reduce yield, but these aspects are currently not simulated in this version of the strawberry model. Even the well-maintained variety trials reported some level of disease and pest pressure for each growing season, which may have reduced the observed marketable yield due to overall lower fruit production and a larger share of non-marketable fruit. Strawberry disease models (Pavan et al., 2011; Xu et al., 2000) could be logically integrated with this model, which is an advantage of this modeling approach compared to previously discussed simpler yield forecasting tools.

5. Conclusion

This study finalized a new CROPGRO-Strawberry crop model through improvement of the model, its source code, and parameters and resulted in accurate simulation of weekly fruit harvest periodicity. A first application shows the applicability of the model to demonstrate variability of simulated seasonal production due to temperature variability over ten growing seasons in a subtropical region. Commercial growers might use the model for yield prediction, comparison of management options and harvest planning relative to past, current, and forecast weather. Further studies and adjustment of model parameters will be valuable to improve simulation of vegetative growth and to verify the model for other varieties and growing locations. The implementation of multiple continuous harvests and monitoring of individual fruit cohorts throughout the growing period is a valuable addition to the field of crop modeling and might be applicable to other crops in the future.

CRediT authorship contribution statement

Alwin Hopf: Conceptualization, Methodology, Visualization, Writing – original draft. **Kenneth J. Boote:** Conceptualization, Data curation, Methodology, Resources, Supervision, Writing – review & editing. **Juhyun Oh:** Data curation, Resources. **Zhengfei Guan:** Data curation, Resources. **Shinsuke Agehara:** Data curation, Resources, Writing – review & editing. **Vakhtang Shelia:** Resources. **Vance M. Whitaker:** Data curation, Resources, Writing – review & editing. **Senthold Asseng:** Supervision. **Xin Zhao:** Supervision, Writing – review & editing. **Gerrit Hoogenboom:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors report no declarations of interest.

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Supplementary materials

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