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Dynamic Prediction of Preharvest Strawberry Quality Traits as a Function of Environmental Factors

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Abstract. **Fruit quality is of increasing importance for consumers but is a complex trait for growers, as it is affected by environment, genotype, and crop management interactions. Decision support tools, such as computer models that simulate crop growth and development can help optimize production but require further improvement to simulate quality aspects. The goal of this study was to apply the newly developed CROPGRO-Strawberry model in the Decision Support System for Agrotechnology Transfer (DSSAT) model framework and develop a module for the dynamic prediction of quality traits for strawberry. Experimental data from Florida with quality measurements from multiple harvests were correlated with indices based on preharvest weather conditions (temperature, radiation, rainfall) and simulated model parameters (evapotranspiration) during fruit development. Two quality relationships based on linear equations were identified and integrated into the model to simulate strawberry fruit soluble solids content (r^2 = 0.89, d = 0.97) and titratable acidity (r^2 = 0.55, d = 0.85) based on preharvest temperature. A strategic analysis with historical weather data for a subtropical growing region over a 10-year period showed the importance of seasonal climate variability for simulated strawberry yield and fruit quality across different harvest months. The improved CROPGRO-Strawberry model is the first process-based crop model to predict selected quality traits across multiple harvests throughout the season and can be extended to other crop models for which quality traits are important.**

Fruits and vegetables for global food and nutrition security

Modern agriculture has led to high yields for growers and producers, low prices for consumers, and year-around availability of agricultural products in vast parts of the world (Motes, 2010). Despite the successes in reducing hunger, issues of malnutrition and nutrition security continue and are receiving increased attention (Ingram, 2020). This highlights the role of fruits and vegetables as important sources for vitamins and micronutrients in the human diet (USDA, 2015) and underlines their role in overcoming malnutrition and hidden hunger (Lock et al., 2005). Nutritional guidelines are based on an average nutrient composition of the respective food group. However, both previous and more recent research has shown that fruits and vegetables, as well as agricultural commodities in general, vary in their nutritional and sensorial quality depending on genetics, preharvest conditions, maturity at harvest, and post-harvest treatments (Bertin et al., 2018; Davis et al., 1984; Howard et al., 1962; Roe et al., 2015; Shewfelt, 1990). In addition, the first studies about the potential impact of climate change on fruit and vegetable production and quality have begun to emerge (Cammarano et al., 2022; Dixon et al., 2014; Gustafson et al., 2021; Mattos et al., 2014). Whereas commercial quality initially focused more on size, visual appearance (color, shape), and suitability for processing and storage (shelf life), recent trends in fruit and vegetable quality have started to emphasize flavor and nutritional aspects (Fallik and Ilic, 2018; Shewfelt and Bruckner, 2000). Consumers are also showing an increased demand for high-quality fruits and vegetables (Acharya et al., 2014). Specific consumer preferences, however, are constantly shifting (Schreiner et al., 2013) and growers must adapt to these preferences to meet new quality demands.

Strawberry production and quality

Strawberry (*Fragaria ×ananassa*) is among the most consumed fruits worldwide and plays an important role in both the horticultural industry and global food supply (FAO, 2022). Although the leading producers are China, Mexico, and the United States, strawberry production occurs on all continents with regional cultivars and cultivation practices. Florida is the second largest producer of strawberries in the United States, with more than 3600 ha in production and a total production value of more than $300 million (USDA, 2022). Florida strawberries are typically grown in mild climates as a winter crop from September to April, and the state provides more than three-quarters of the winter strawberry production in the United States. Given the perishability of strawberries in general and variable growing conditions, strawberry is a high-input and high-value but also risky crop for growers. Besides pest and disease pressure, weather variability and extreme weather conditions are major concerns for commercial growers.

Strawberry and overall fruit quality is generally separated into external and internal quality, with the latter encompassing contents in nutrients, vitamins, and volatile compounds. External quality, such as fruit size, has been found to strongly depend on temperature preceding harvest (Miura et al., 1994; Menzel, 2021). Many strawberry taste and internal quality parameters can be rather complex to quantify, for example, volatile aromatic compounds influence sensory attributes and consumer preferences (Fan et al., 2021a, 2021b). However, other easy-to-measure quality attributes, such as dry matter content, soluble solids content (SSC), titratable acidity (TA), and fruit firmness are established as general proxies for overall strawberry fruit quality and commonly used by the strawberry industry (Jouquand et al., 2008; Mitcham, 1996; Plotto et al., 2013). Growers and breeders have observed large variability in strawberry quality depending on agronomic management, cultivar selection, and local weather conditions. The seasonal weather variability is of special importance because growers who produce in open fields can exert only limited control over growing conditions, compared with those grown in high tunnels, greenhouses, and other protected culture systems.

Seasonal mean SSC for strawberries of different cultivars grown in central Florida are reported to range from 5.1% to 10.6%. These values vary significantly throughout the growing season, with individual harvests as low as 5.3% SSC and as high as 14.5% SSC (Whitaker et al., 2011). Seasonal mean TA is reported to vary between 0.6% and 1.2% across cultivars and ±0.2% within a cultivar across individual harvests (Sahari et al., 2004; Whitaker et al., 2011). Previous research in Florida has found a significant decline in SSC and TA late during the growing season across all cultivars (Jouquand et al., 2008). The SSC and TA content of fruit tends to be lowest during periods of warm weather and higher yield, whereas they are highest during periods of colder weather with lower yield (Hoppula and Karhu, 2005; MacKenzie, 2011; Wang and Camp, 2000). This could be because of plant physiological processes and fruit biochemistry. During fruit development and maturation, carbohydrates are transported from the leaf photosynthetic tissue into fruit, where further biosynthetic processes take place (Fait et al., 2008). A higher temperature tends to increase the rate of fruit development, hence potentially shortening the time for carbohydrate accumulation in the fruit. Also, warm temperature enhances conversion of carbohydrates to other compounds (acids, volatiles) found in the fruit, as well as enhancing respiration. Hence, under warm conditions, a fruit is then likely lower in SSC and TA content and perceived of lower quality from a consumer perspective (Schwieterman et al., 2014). Considering this high degree of quality variability and general growing challenges, developing a model-based decision support system will be useful to better understand and potentially guide challenges of strawberry growers such as seasonal quality fluctuations. Potential adaptations by growers could be the variation of fertilizer and irrigation amount or frequency, as well as the choice of cultivars and overall timing of planting and harvest intervals. More immediate and realistic in terms of usability and application is the generation of a more systematic understanding of growth, development, yield, and quality of strawberry production for what-if analysis or to guide research questions. Mathematical modeling of the development and growth of plants based on biophysical mechanisms and plant-soil-environment interactions, is often referred to as "dynamic or process-based crop modeling." These model-based tools can, therefore, contribute to the decision support systems for growers, producers, and others involved in strawberry production.

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Quality modeling

The Cropping System Model (CSM) of the DSSAT crop modeling software package integrates weather, soil, genetic, and crop management information for the prediction of growth and development, and ultimately yield (Hoogenboom et al., 2019a, 2019b; Jones et al., 2003). DSSAT facilitates the development of alternative crop management practices and the optimal use of associated natural resources, helping reduce negative environmental impacts (Tsuji et al., 1998). It was initially developed for grain and legume crops, such as wheat, soybean, and maize, but it also has been expanded to horticultural crops such as tomatoes (Boote et al., 2012; Scholberg et al., 1997), green bean (Djidonou, 2008), and cabbage (Feike et al., 2010).

A new strawberry crop model was recently developed based on experimental data from multiple growing seasons in a subtropical production region (Hopf et al., 2022). This CSM-CROPGRO-Strawberry model can predict the growth and development of the plant and individual fruit cohorts (a set of fruit initiated on the same day) throughout the season as a function of genetic, crop management, and environmental factors, but the abilities of this and other crop models to predict fruit and yield quality are limited. Some cereal and legume crop models already include quality aspects in their modeling routine, such as the prediction of lipid and protein concentration of seed in the CROPGRO-Soybean model (Boote et al., 1998). The "Simulateur mulTIdisciplinaire pour les Cultures Standard" (STICS) crop model predicts carbohydrate and lipid as a fixed concentration proportional to dry matter content in plant organs for a number of different crops, whereas grain nitrogen content is proportional to the grain filling phase duration, and grain water content is dependent on hydration and dehydration dynamics (Brisson et al., 2003). Many of the wheat crop simulation models predict grain protein concentration (Asseng et al., 2018).

Some models that predict fruit development and the individual aspects of fruit quality have been developed, for example, peach fruit dry matter concentration and sweetness during the final stages of fruit growth (Lescourret and Genard, 2005), impact of genetic and physiological parameters on general peach fruit quality (Quilot et al., 2005), growth of individual apple fruits based on cumulative degree days (Chaves et al., 2017), or impact of early-season temperatures on potential growth and size of apple fruit (Austin et al., 1999). Other modeling efforts have focused on predicting quality during post-harvest and storage of fruits and vegetables, through the simulation of respiration rates (Fonseca et al., 2002), nonlinear statistical regression (Lukasse and Polderdijk, 2003; Tijskens and Polderdijk, 1996), or kinetics based on elementary chemical, microbial, and physical reactions within the fruit (van Boekel, 2008).

Strawberry quality model

The existing simulation of elemental components, such as lipids and carbohydrates, are notable for agricultural commodity products, but the internal quality for horticultural products tends to be determined by more complex compounds that reflect seasonal variation (Kyriacou and Rouphael, 2018). However, the current fruit quality models focus only on either fruit size or internal fruit quality. These models do not simulate the growth process of the crop within the complete agricultural system, including soil and plant water dynamics, interaction with weather conditions, and the growth and development of the entire crop including leaves, stems, roots, and fruits. The overarching difficulty remains in combining experimental data or sub-models and applying them at the field level (Bertin et al., 2006). With the increasing awareness of fruit and vegetable quality variability, it has become evident that specific models for horticultural crops must go beyond simulating bulk yield and will require the incorporation of quality aspects. Therefore, there is a need for a dynamic and model-based approach toward understanding and predicting the variability of quality of fruit and vegetable crops, throughout the entire growing season. A new generic sub-model for quality traits needs to be developed, adapted for specific crops, and coupled to existing crop models.

The goal of this research was, therefore, to develop a module for the prediction of quality traits for strawberries. The specific objectives were to 1) analyze the relationships between growing conditions and the variability in fruit SSC, TA, and firmness for strawberries; 2) implement these relationships in the existing CSM-CROPGRO-Strawberry crop model to simulate quality traits; and 3) apply the model to simulate and analyze seasonal and within-season variability of both yield and quality of strawberries over multiple years using long-term weather data.

Materials and Methods

Experimental data

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 (lat. 27.7611°N, long. 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. Contrary to other production regions, the production in

Florida starts in relatively warm environment, which then cools down and warms up again. 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 because of low market prices, although quality, disease pressure, and inclement weather also can have impacts.

Observations for the cultivar Florida Radiance (U.S. Plant Patent 20363, known as Florida Fortuna outside the United States) and Florida Brilliance (U.S. Plant Patent 30564) were collected during the 2014–15 (Florida Radiance only), 2016–17, and 2017–18 growing seasons. Released in 2019, 'Florida Brilliance' is a more recent variety with slightly earlier fruit production in the season and slightly smaller fruit (Whitaker et al., 2019) compared with 'Florida Radiance', which was released in 2009 (Chandler et al., 2009). Strawberry plants were grown in raised beds with a plastic film cover on the soil (plastic mulch). Typical raised beds were 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 Bluff, CA, USA) and planted in early October with typical air temperatures of 24 to 27 °C and soil temperatures of 25 to 28 °C. After planting, overhead irrigation was applied daily during daylight hours for 8 to 10 d to promote plant establishment, followed by irrigation and fertigation via drip tapes for the remainder of the season. Exact irrigation amounts are unknown but followed general statewide best practice recommendations to ensure optimal growth conditions with one or two irrigation sessions totaling up to 45 min per day. Fertilization was controlled to promote early-season plant growth with up to 2.24 to 3.36 kg/ha of nitrogen per day after transplanting, gradually decreasing to as low as 1.0 kg/ha of nitrogen per day.

Fields were set up in a randomized complete block design with each measurement repetition coming from a different block, 10 plants per block. The harvests of ripe fruit occurred every 3 to 4 d with ripeness being determined by the extent and depth of fruit red color. For this study, only fruit harvested once per month were analyzed. For a given harvest day, a total of 40 ripe fruit from four repetitions (10 per repetition) were transported in clamshells in an air-conditioned vehicle to off-site laboratories for further processing to measure SSC, TA, and firmness. The 10 fruits of one repetition were measured individually for firmness, then combined and homogenized for SSC and TA measurements The measurement procedure was conducted two to four times per season per cultivar. Measurements from the four repetitions per measurement day were averaged to a single value for further analysis in this study. A combined total of 47 observations for quality are available, with 15 or 16 per quality trait. An overview of observed quality data are provided in Table 1. SSC (%) was measured from the supernatant of a homogenized fruit mass using a digital refractometer (RX5000α; Atago, Tokyo, Japan). TA (%) was measured by titrating 6 g of fruit supernatant with 0.1 N NaOH to pH 8.1 using a titrator equipped with a robotic autosampler (model 855; Metrohm, Herisau, Switzerland), a dosing interface (Dosino model 800; Metrohm) and controlling software (Tiamo v.2.5; Metrohm). Firmness (Newton or Newton*m^{-2}) measurements were taken for fresh fruit with a Firm-Tech 2 (Bioworks, Wamego, KS, USA) for all seasons except 2017–18, when firmness was measured with a Texture Analyzer XT2 (Texture Technologies Corp. Ltd., Hamilton, MA, USA).

The range of measured firmness values differed significantly between these two devices, because of the different probe sizes, penetration in the flesh or not, and speed of penetration or deformation of the fruit. Therefore, the measurements were considered as a separate group because no conversion factor between the two devices was available. Strawberry fruit firmness measurements with different devices are generally weakly correlated (Døving et al., 2005). A more detailed explanation of fruit quality measurements, including the devices, procedures, and reagents that were used, can be found in Whitaker et al. (2011). Further details about the experimental data, including field setup and measurement techniques, can be found in the variety release publications (Whitaker et al., 2015; 2017b; 2019).

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" (lat. 27.75998°N, long. 82.22410°W) was installed in 2006 and is located near the field trials. It provides daily minimum and maximum air temperature (2 m aboveground), precipitation, solar radiation, wind speed, and relative humidity, in addition to more detailed measurements.

Strawberry quality model. The crop simulations were performed in DSSAT Version 4.7.6 (Jones et al., 2003; Hoogenboom et al., 2019a, 2019b) with the recently developed CSM-CROPGRO-Strawberry model (Hopf et al., 2022), which simulates the continuous daily addition of flowers and subsequent development into fruits throughout the growing season of a strawberry plant. After flowering (BBCH 60–67), a fruit body (receptacle) and seeds are formed, which then grow in size, increase in weight, and ripen (BBCH 71–81) until fruit maturity (BBCH 85–89). A fruit cohort reaches maturity once it reaches a certain physiological age that depends on photothermal time. On each predefined harvest date, all fruit cohorts that had achieved simulated maturity are harvested and combined to account for the harvest of each individual harvest day. In addition to simulating soil-water-atmosphere processes and biomass development or partitioning of the strawberry plant, the model provides concrete dates for when specific growth stages as well as flower or fruit development phases are reached. The quality model is based on the modeling and tracking of the development phase of each individual fruit cohort and the conditions under which each cohort grows.

Crop model inputs. Based on the previous description of the 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 10 Oct of each growing season with a planting density of 4.3 plants/m^2 as transplants. The fertilizer and associated nitrogen, potassium, and phosphorus modules of the model were deactivated to simulate optimal conditions (i.e., no nitrogen or phosphorus stress). This assumption was deemed feasible because variety trials are generally conducted under optimal fertilization. Irrigation was based on the simulated soil water balance, with a set threshold of 80% available soil water in the top 30 cm soil to trigger automatic irrigation. Fruit harvesting was scheduled every 3 to 4 d and started between 22 and 24 Nov and continued until 14 to 16 Mar. The fruit harvest schedule is an important model setting because it drives several internal model processes and influences the simulated fruit growth period that is used to calculate weather indices.

Weather indices. The simulated dates for flowering, beginning of fruit development, and harvest date of each fruit cohort were used to calculate weather indices that occurred during the 15 to 22-d growth interval from flowering to maturity. They represent the growing conditions that are relevant for fruit quality. A total of 16 weather indices were computed for each cohort, based on observed weather data and simulated model parameters. For all weather variables, the timespan between start of fruit development (after flowering) for a given cohort until the date of harvest of that cohort is considered, representing the entire fruit development period. For this purpose, the daily minimum and maximum temperatures (2 m aboveground), as well as daily rainfall and solar radiation were obtained from the weather station. The average minimum temperature (Eq. [1], $Tmin_{avg}$] was calculated by taking sum of the minimum daily temperature for the days between the start of fruit growth and harvest for each individual fruit cohort and then dividing by timespan in days. The average maximum temperature (Eq. [2], $Tmax_{avg}$) was calculated by taking sum of the maximum daily temperature for the days between the start of fruit growth and harvest for each individual fruit cohort and then dividing by timespan in days.

The average temperature (Eq. [3], T_{avg}) was calculated by taking sum of the temperature readings available every 15 min divided by 96 (for 4*24 readings per day) for the days between the start of fruit growth and

Table 1. Simulated (Sim) and observed (Obs) soluble solids content (SSC) and titratable acidity (TA) and absolute difference (Bias) obtained from the quality model. Missing values indicated by "n/a" as respective data was not measured in this season.

			Fruit development		SSC (%)			TA (%)		
Cultivar	Season	Harvest (mm/dd)	Temp. (°C)	Duration (d)	Sim	Obs	Bias	Sim	Obs	Bias
Florida Radiance	2014–15	02/16	14.1	22	8.24	8.40	−0.16	0.78	0.80	−0.02
		03/16	22.3	18	5.50	5.40	0.10	n/a	n/a	n/a
	2016–17	01/30	16.9	16	7.30	7.10	0.20	0.74	0.77	−0.03
		02/20	18.6	16.5	6.73	6.20	0.53	0.71	0.67	0.04
		03/06	20.3	16	6.18	6.50	−0.32	0.68	0.72	−0.04
	2017–18	12/11	18.7	16.5	6.73	6.87	−0.14	0.71	0.74	−0.03
		01/29	15.1	19.5	7.93	7.97	−0.04	0.77	0.79	−0.02
		02/19	22.2	16.5	5.56	5.51	0.05	0.65	0.65	0.00
		03/05	21.0	17	5.96	5.53	0.43	0.67	0.63	0.04
Florida Brilliance	2016–17	01/30	16.9	16	7.30	7.13	0.17	0.74	0.72	0.02
		02/20	18.6	16.5	6.73	6.24	0.49	0.71	0.65	0.06
		03/06	20.3	16	6.18	6.64	−0.46	0.68	0.75	−0.07
	2017–18	12/11	18.7	16.5	6.73	6.86	−0.13	0.71	0.74	−0.03
		01/29	15.1	19.5	7.93	8.22	−0.29	0.77	0.73	0.03
		02/19	22.2	16.5	5.56	6.00	−0.44	0.65	0.68	0.03
		03/05	21.0	17	5.96	5.97	−0.01	0.67	0.63	0.04

Note: Results for two to three seasons with two to four harvests per cultivar-season. Simulated values based on average temperature during fruit growth. Fruit growth temperature and duration were obtained from crop model outputs from the start of growth until final harvest of each individual fruit cohort and averaged for the cohorts that were harvested on the same date.

harvest for each individual fruit cohort and then dividing by timespan in days:

$$Tmin_{avg} = \frac{\sum_{t_0}^{t_1} T_{min}}{t_1 - t_0} \quad [1]$$

$$Tmax_{avg} = \frac{\sum_{t_0}^{t_1} T_{max}}{t_1 - t_0} \quad [2]$$

$$T_{avg} = \frac{\sum_{t_0}^{t_1} \frac{T_{15min}}{96}}{t_1 - t_0}, \quad [3]$$

with T_{max} and T_{min}, the daily maximum and minimum temperature in °C; T_{15min}, the temperature reading of the weather station every 15 min in °C; t_0, the day of start of fruit development; t_1, the day of harvest; and $t_1 - t_0$ being the timespan in days between start of fruit growth and date of harvest.

The diurnal temperature variation (Eq. [4], *DTV*), also known as temperature differential, was calculated by taking the mean of the differences between the daily maximum and minimum temperature for the days between the start of fruit growth and harvest for each individual fruit cohort.

$$DTV = \frac{\sum_{t_0}^{t_1}(T_{max} - T_{min})}{t_1 - t_0}, \quad [4]$$

with T_{max} and T_{min}, the daily maximum and minimum temperature in °C; t_0, the day of start of fruit development; t_1, the day of harvest; and $t_1 - t_0$ being the timespan in days between start of fruit development and date of harvest.
Hypothetical growing degree days (Eq. [5], *GDD*) based on base temperatures of 0, 7.5, 10, 12.5, and 15.0 °C were calculated by subtracting the base temperature from the daily mean temperature and integrating on a daily basis, until harvest for each individual fruit cohort. The base temperature 0 °C was identified for basic growth and development processes in other cultivars in a similar subtropical environment (Rosa et al., 2011). Additional base temperatures were included in this analysis because other studies have shown a wide range of suitable base temperatures depending on cultivar and environment. This should be assessed to obtain a potential better correlation. The simple average method was chosen over other more complex methods, such as the Baskerville-Emin method (Baskerville and Emin, 1969), because the local minimum temperature is expected to be mostly above the base temperature.

$$GDD = \sum_{t_0}^{t_1}\left(\frac{T_{max} + T_{min}}{2} - T_{Base}\right) > 0 \quad [5]$$

with T_{base} the variable base temperatures of 0, 7.5, 10, 12.5, and 15.0 °C, the integration was performed when the mean of T_{min} and T_{max} was greater than T_{base}.

Average daily total rainfall (Eq. [6], *Rainfall*$_{avg}$) was calculated based on the daily total observed rainfall (mm^2/d) for the growth period of each individual fruit cohort.

$$Rainfall_{avg} = \frac{\sum_{t_0}^{t_1} H}{t_1 - t_0} \quad [6]$$

Average daily total solar radiation (Eq. [7], *Srad*$_{avg}$) and total solar radiation (Eq. [8], *Srad*$_{tot}$) were calculated based on the daily total observed solar radiation per horizontal surface area (H in MJ/m^2/d) for the individual fruit cohort growth periods.

$$Srad_{avg} = \frac{\sum_{t_0}^{t_1} H}{t_1 - t_0} \quad [7]$$

$$Srad_{tot} = \sum_{t_0}^{t_1} H \quad [8]$$

Average potential evapotranspiration (Eq. [9], PET_{avg}), total potential evapotranspiration (Eq. [10], PET_{tot}), average actual transpiration (Eq. [11], AT_{avg}), and total actual transpiration (Eq. [12], AT_{tot}) are based on simulated values from the soil-water-balance component of the crop model.

$$PET_{avg} = \frac{\sum_{t_0}^{t_1} PET}{t_1 - t_0} \quad [9]$$

$$PET_{tot} = \sum_{t_0}^{t_1} PET \quad [10]$$

$$AT_{avg} = \frac{\sum_{t_0}^{t_1} AT}{t_1 - t_0} \quad [11]$$

$$AT_{tot} = \sum_{t_0}^{t_1} AT, \quad [12]$$

with PET the potential evapotranspiration in mm/d and AT the actual transpiration in mm/d calculated by the crop model for every daily time step of the fruit cohort development periods.

Quality relationships. Observed quality and weather indices were analyzed to identify the best linear relationships. The linear regressions were created based on the combined data for all growing seasons that had observed quality measurements (i.e., 2014–15, 2016–17, and 2017–18), for both 'Florida Radiance' and 'Florida Brilliance'. The analysis of covariance test (ANCOVA) was used to determine if obtained regressions were dependent on the cultivar. Only regressions with a strong linear relationship were integrated into the process-based crop model for further testing. Because of the limited amount of data available, no separation of the dataset into a model development and evaluation dataset was performed. Therefore, the model needs to be evaluated for other and independent data sets.

Software, source code, and statistics

The crop simulations were performed with the CSM model (Jones et al., 2003) in the modeling software DSSAT (Hoogenboom et al., 2019a, 2019b) obtained from the DSSAT portal (www.dssat.net). To improve the model, code changes were made in the source code of the development version 4.7.6 available via the public GitHub Repository (www.github.com/DSSAT/dssat-csm-os). The code changes and improvements are further described in Hopf et al. (2022) and will be implemented in a future version of CSM and DSSAT for public release and will be available from the GitHub Repository.

Statistical analysis and visualization of the results were performed in RStudio 1.2.5033 (RStudio Team, 2015) with packages "ggplot2," "corrplot," and "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. [13]) also known as the d-statistic was used to assess general model performance (Willmott, 1981). It is a dimensionless index for model agreement related to the Nash-Sutcliffe index. The d-statistic value ranges between 0.0 and 1.0, with a value closer to 1 indicating a better model performance.

$$d - statistic \ = $$

$$1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}\left(|P_i - \bar{O}| + |O_i - \bar{O}|\right)^2}, \ 0 \le d \le 1, \quad [13]$$

with P_i the simulated value, O_i the observed value, and $\bar{O}$ the observed mean.

The Relative Root Mean Square Error (RRMSE) (Eq. [14]) was used to evaluate deviation between observed and simulated periodic harvests while accounting for the mean magnitude of observations. A lower RRMSE is considered better, with an 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.

$$\text{RRMSE} \ = \ \frac{\sqrt{\sum_{i=1}^{N}\left(P_i - O_i^2\right)^2 N}}{\bar{O}}, \quad [14]$$

with N the number of values, P_i the simulated value, O_i the observed value, and $\bar{O}$ the observed mean.

In addition, the Pearson correlation coefficient (R) (Eq. [15]) was used to evaluate the strength and direction of a linear relationship between a quality trait and the weather indices (Wilcox, 2016), as well as among weather indices or quality traits themselves. A 95% confidence interval was used to test for significance of the correlations. The coefficient R has a value between 1 and -1, with 1 indicating a strong positive, -1 a strong negative relationship, and 0 no relationship at all.

$$R \ = \ \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2}\sqrt{n(\sum y^2) - (\sum y)^2}}, \quad [15]$$

with n the number of pairs of data, and x and y are the values of respective pairs.

As part of the regression analysis, an ANCOVA test was applied in RStudio to test if quality regressions were dependent on the cultivar (Philippas, 2014). The null hypothesis was that the slope and the intercept of the two regression lines based on cultivar Florida Radiance or Florida Brilliance were not statistically different. For the general statistical analysis of model results, the recommendations provided by Yang et al. (2014) were followed.

Simulating long-term seasonal yield and quality distribution

A seasonal analysis (Thornton and Hoogenboom, 1994) was performed to demonstrate the capabilities of the quality module in assessing the variations in predicted quality due to seasonal climate variability under constant crop management. Simulations were conducted using historical weather data from 2010 through 2020, assuming identical crop management as in the previously described field experiments with optimal fertilization, irrigation, constant planting setup, and 3- to 4-d harvest intervals from 22 Nov to 15 Mar. The SSC and TA content for cultivar Florida Radiance were predicted based on the average temperature during the growth phases of harvested fruit cohorts at each single harvest date from 2010 to 2020. The typical strawberry growing season in Florida lasts from fall (October) through spring (March) in the following year. For example, the season of 2010–11 or 2010–2011 refers to the growing period from Oct 2010 to Mar 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. Additional quality data, not used in the model development or the related Hopf et al. (2022) study, were drawn in for a preliminary evaluation of the seasonal SSC and TA analysis. A total of 15 quality measurements for each SSC and TA comprising the seasons 2010–11, 2011–12, 2012–13, 2013–14, 2015–16, and 2018–19 were obtained from previous experimental records. The samples were obtained and analyzed using the same procedure previously described for the field experiments. The additional data do not include yield measurements and further parameters required to run the crop model. Hence, they were not suitable for the initial development or evaluation of the quality model and considered an independent dataset for a preliminary evaluation of the seasonal analysis only.

Results and Discussion

Weather data and indices

An overview of the monthly mean air temperature (October–March) from 2010 to 2020 in Balm, FL, confirms typical seasonal fluctuations with some variability from year to year (Fig. 1). 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 with 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), whereas the 2012–13 season (mean 18.2 °C) had a relatively cold month of March (15.0 °C). It is acknowledged that the measured temperature at 2 m height is only an approximation for actual temperature at the level of the strawberry plant, and future measurement should be taken closer to plant level if feasible. The correlation matrix (Fig. 2) shows positive correlations to varying degree among all weather indices except for average daily rainfall, which is negatively correlated to the remaining indices. This is because of the typical seasonal pattern in the growing season, where a decrease in rainfall coincides with the increase in temperature and vice versa. Most of the rainfall is concentrated during the hot and humid summer season (May to August), which is, however, outside the strawberry cultivation window and hence not considered in this analysis. Average temperatures as well as growing degree days on varying base

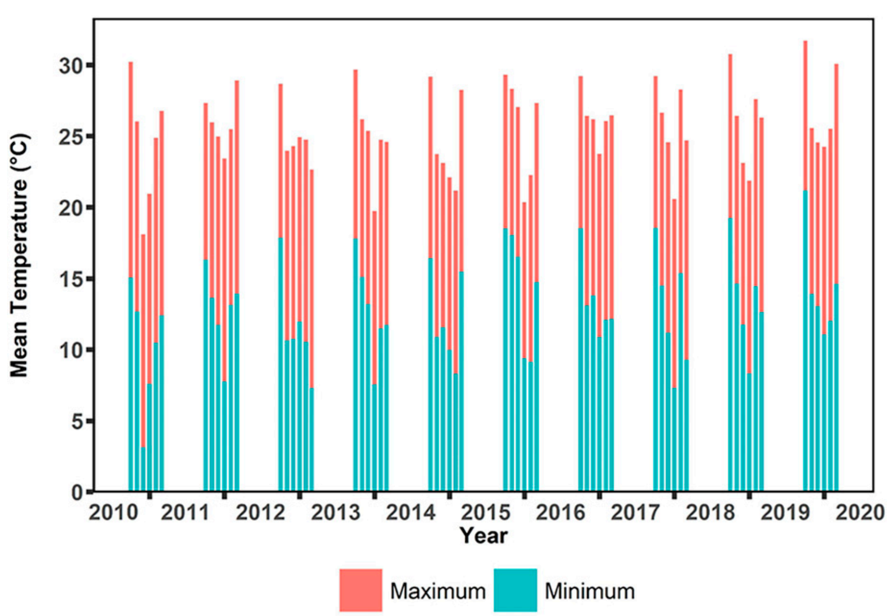

Fig. 1. Monthly average maximum and minimum temperature in Balm, FL, for the months of October through March for each growing season from 2010–11 to 2019–20. Year 2011 comprises the 6 months from Oct 2010 until Mar 2011, and equivalent timespans are used for the other years (from Hopf et al., 2022).

temperatures were strongly positively correlated (r = 0.79–0.99), which is expected because they rely on the same temperature patterns. Further strong positive correlations could be found for simulated evaporation and transpiration indices with radiation and to a slightly lesser extent temperature-based indices, which is expected because they are connected through common physical and physiological principles.

Quality data

A total of 47 quality measurement were available across 16 dates, with 16 for SSC, 15 for TA (one missing date), and 16 for firmness split into two sub-groups of eight for the two different measurement devices (Table 1). SSC ranged from 5.4% to 8.4%, with an average of 6.7%. TA ranged from 0.63% to 0.80%, with an average of 0.71%. Firmness measured with Firm Tech 2 varied from 176.9 to 250.6 $N \cdot m^{-2}$, with an average of 218.8 $N \cdot m^{-2}$. Firmness measured with Texture Analyzer XT2 ranged between 3.23 N and 4.35 N, with an average of 3.88 N. A strong positive correlation was observed between TA and SSC measurements in the whole dataset (r = 0.84–0.87), with a medium positive correlation among Firmness measured with the Firm Tech 2 device and SSC (r = 0.56) and TA (r = 0.57) and positive but weaker correlation for Firmness measured with the Texture Analyzer XT2 for SSC (r = 0.25) and TA (r = 0.22). All correlations were significant.

Quality correlations

The 16 weather indices, which represent the growing conditions of fruit cohorts from start of individual fruit growth until harvest, were subjected to a correlation analysis of the field measurements for SSC, TA, and firmness of the individual fruit cohorts.

Soluble solids content. All regressions showed a negative Pearson correlation coefficient, which means that SSC decreased with an increase in the value of the weather indices, except for average daily rainfall with a positive coefficient and reversed trend. The rainfall anomaly is likely due to its correlation to temperature driven by the general seasonal pattern of dry and relatively cooler winters and increasing rainfall with increasing temperatures in the spring and summer, and does not necessarily constitute a physiological relationship between SSC and rainfall. However, one plausible explanation could be that additional rainfall preceding harvest leads to uptake of excess water in the fruit and hence a dilution of SSC. The strongest and most significant regression was obtained for the average temperature from start of fruit development until the harvest of each individual cohort (Fig. 3A, $R = -0.94$, $P < 0.001$). The ANCOVA test confirmed that the regression line was not significantly different for each cultivar (P = 0.32) and that the same regression line could be used for both cultivars. Average minimum and maximum temperature during fruit development as well as

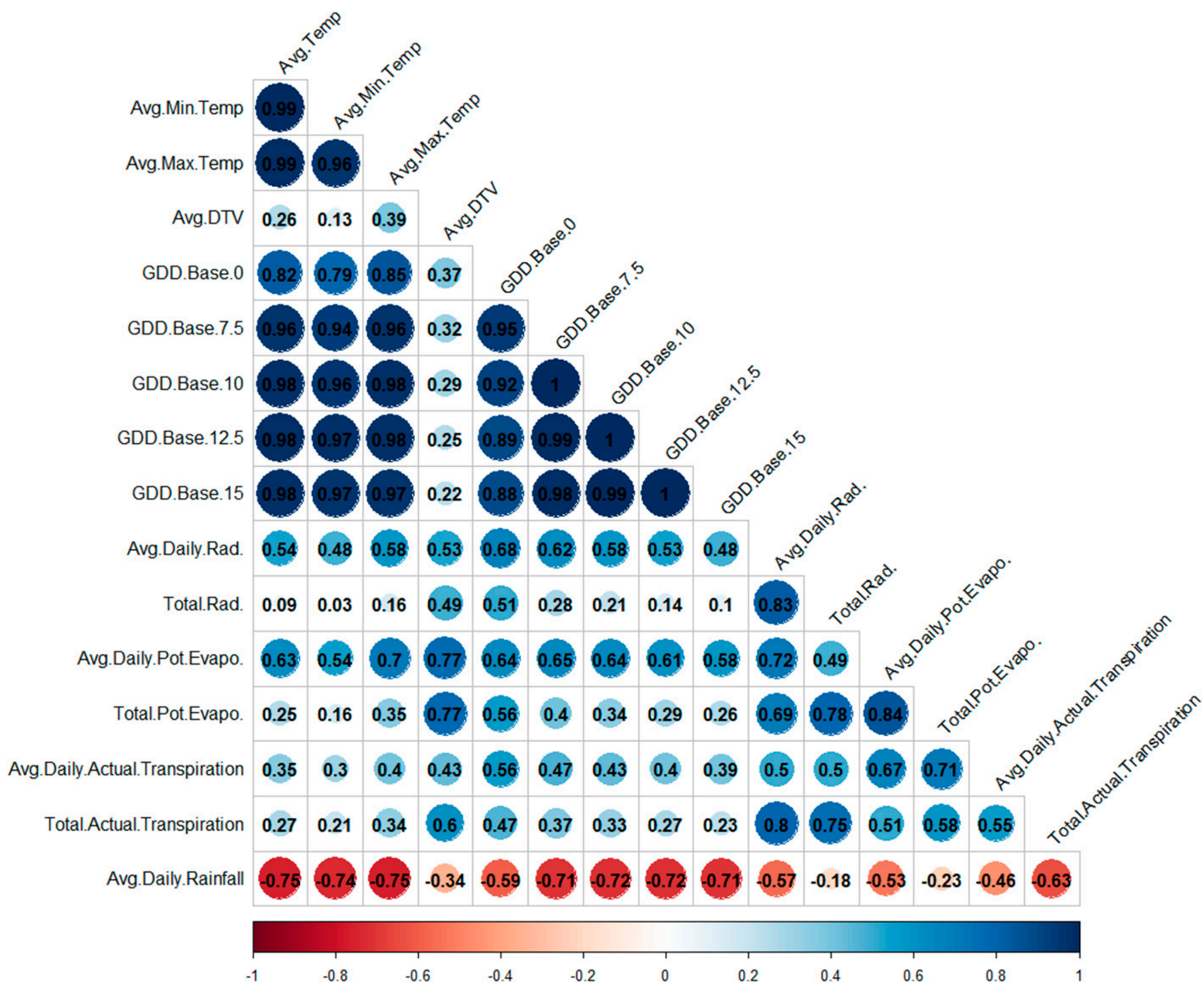

Fig. 2. Pearson correlation matrix among weather indices in Balm, FL, for the weather conditions preceding each harvest for both cultivar Florida Radiance and Florida Brilliance and all seasons that have quality measurements (2014–15, 2016–17, 2017–18). Weather indices are based on observed weather conditions during the dynamic timespan from flowering to individual fruit maturity, which lasts ≈2 to 3 weeks. Strong positive correlations are shown in blue and strong negative correlations are shown as red. Correlations are significant at the 0.05 P value.

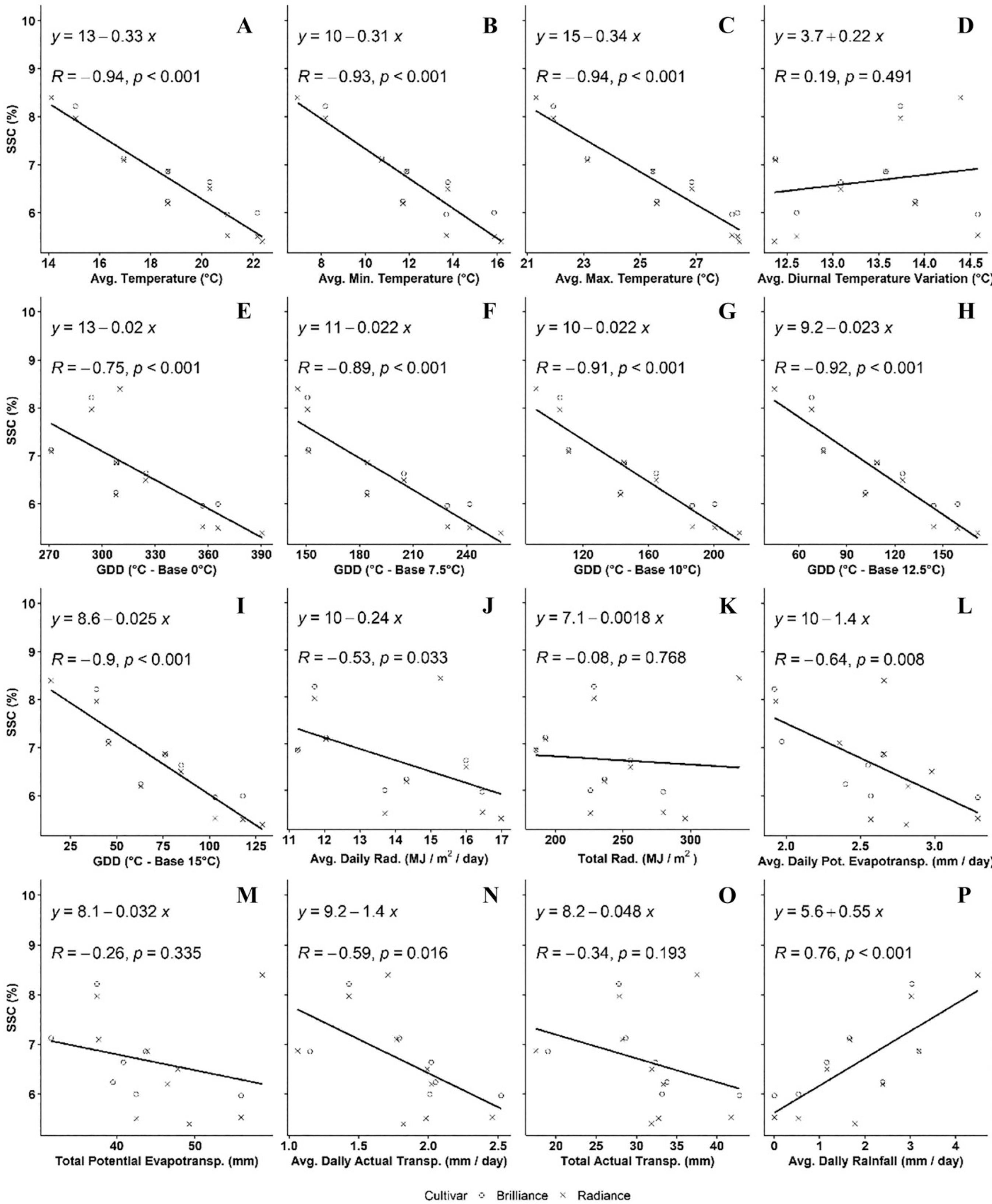

Fig. 3. Quality correlations for observed soluble solid content (SSC) of strawberry fruit and weather indices for average temperature and growing degree days (**A–I**), average and total radiation (**J** and **K**), potential evapotranspiration (**L** and **M**), actual transpiration (**N** and **O**) and average rainfall (**P**). The linear regression is based on observations (n = 16) for both cultivar Florida Radiance and Florida Brilliance, and all seasons that have quality measurements (2014–15, 2016–17, 2017–18). The *R* value indicates the correlation coefficient and *P* the significance.

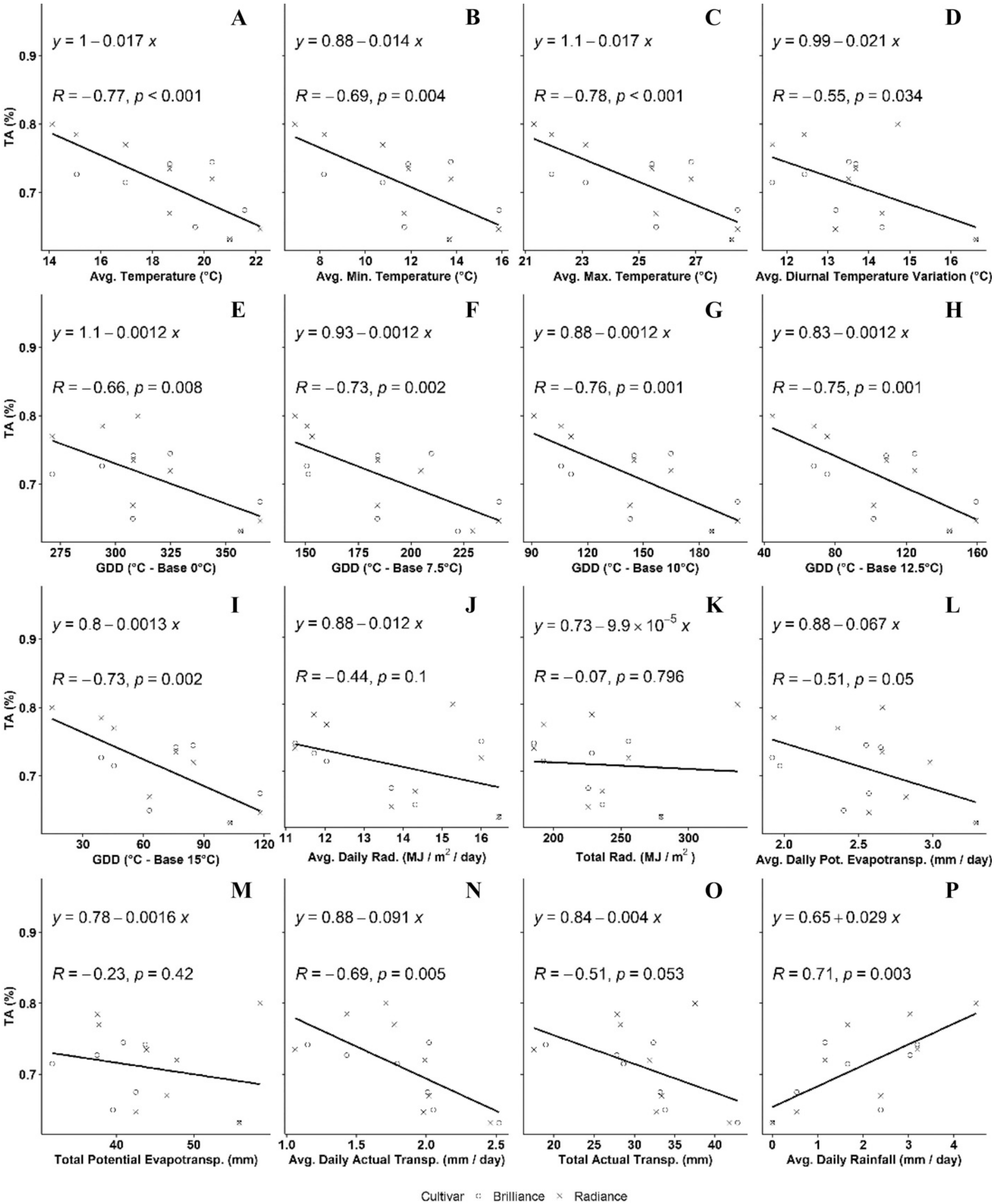

Fig. 4. Quality correlations for observed titratable acidity content of strawberry fruit and weather indices for average temperature and growing degree days (**A–I**), average and total radiation (**J** and **K**), potential evapotranspiration (**L** and **M**), actual transpiration (**N** and **O**), and average rainfall (**P**). The linear regression is based on observations (n = 15) for both cultivar Florida Radiance and Florida Brilliance and all seasons with quality measurements (2014–15, 2016–17, 2017–18). The *R* value indicates the correlation coefficient and *P* the significance.

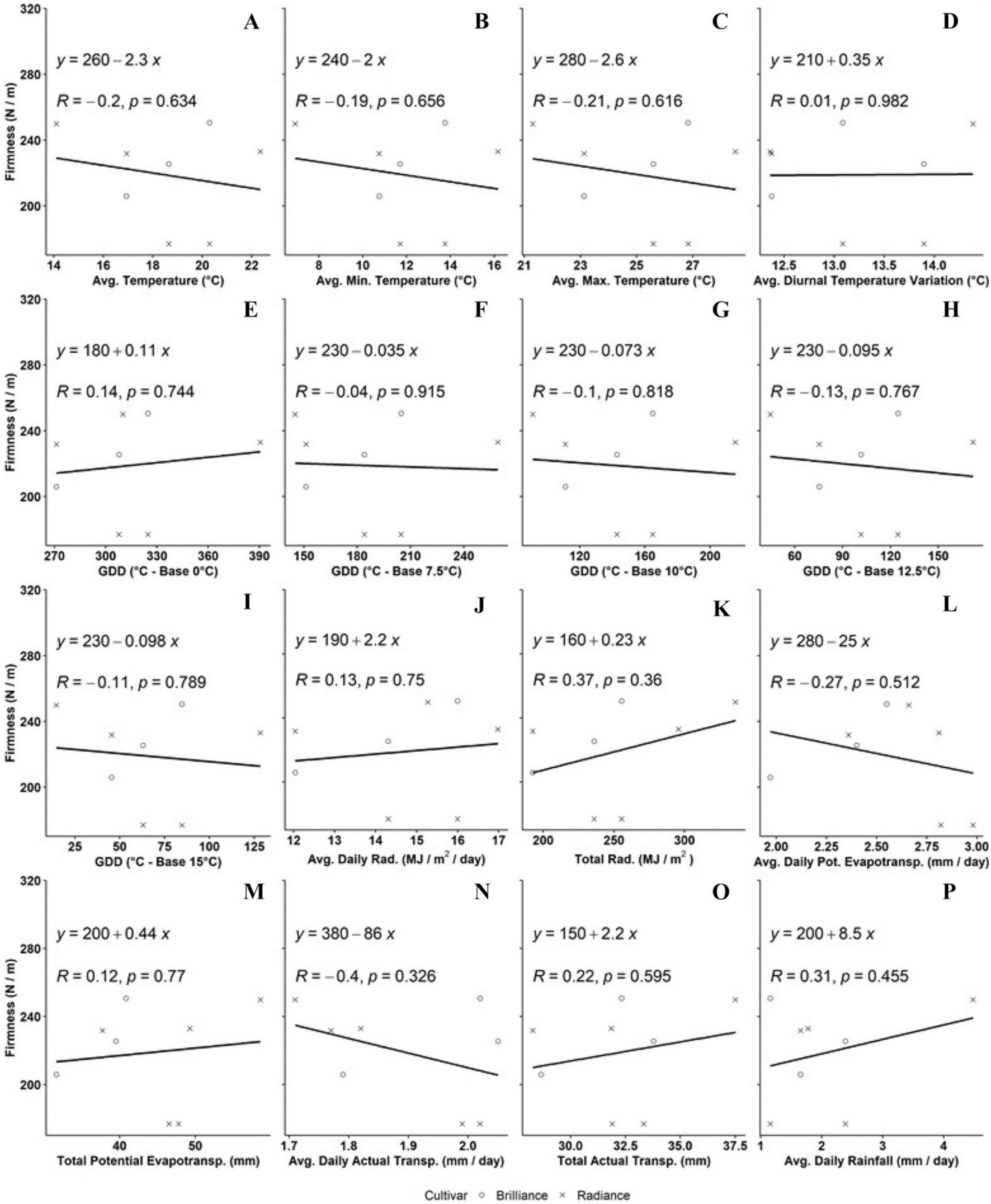

Fig. 5. Quality correlations for observed firmness of strawberry fruit measured with FirmTech 2 and weather indices for average temperature and growing degree days (**A–I**), average and total radiation (**J** and **K**), potential evapotranspiration (**L** and **M**), actual transpiration (**N** and **O**), and average rainfall (**P**). The linear regression is based on observations (n = 8) for both cultivar Florida Radiance and Florida Brilliance and seasons 2014–15 and 2016–17. The *R* value indicates the correlation coefficient and *P* the significance.

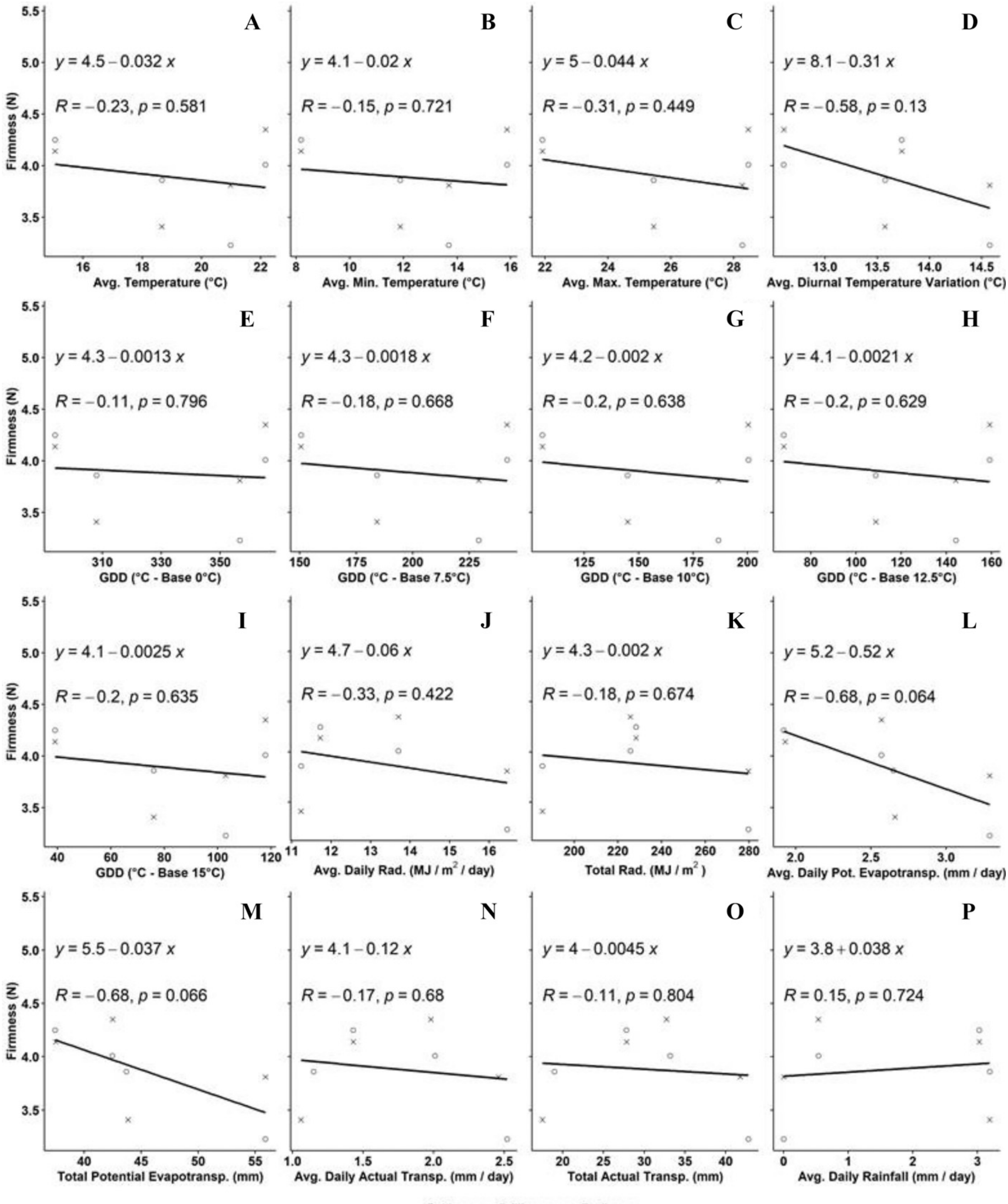

Fig. 6. Quality correlations for observed firmness of strawberry fruit measured with Texture Analyzer XT2 and weather indices for average temperature and growing degree days (**A–I**), average and total radiation (**J** and **K**), potential evapotranspiration (**L** and **M**), actual transpiration (**N** and **O**), and average rainfall (**P**). The linear regression is based on combined observations (n = 8) for both cultivar Florida Radiance and Florida Brilliance and season 2017–18. The *R* value indicates the Pearson correlation coefficient and *P* the significance.

GDD using a base temperature of 0, 7.5, 10, 12.5, or 15 °C had a similar but slightly weaker and less significant correlation than average temperature (Fig. 3B, C, and E–I, $R = -0.94$ to -0.75, $P < 0.001$ to 0.008). Average daily rainfall showed a positive and significant but slightly weaker correlation (Fig. 3P, $R = 0.76$, $P < 0.001$). All remaining indices for diurnal temperature difference, average daily and total radiation, potential evapotranspiration, and actual transpiration showed very low to fair level of correlation and low significance with R ranging from -0.64 to 0.18 and P ranging from 0.008 to 0.77 (Fig. 3D and J–O).

The strongest and most significant regression was found for the average temperature during cohort growth in this analysis. Within the range of temperatures that we observed (daily average 14.1 to 22.3 °C during fruit growth), SSC decreased as temperature increased, resulting in less sweet fruit. This is similar to the observed decrease in SSC due to a late-season increase in average temperature found in field experiments (Jouquand et al., 2008; MacKenzie, 2011) and controlled growth chamber studies (Wang and Camp, 2000). A similar pattern has been observed for post-harvest storage of strawberries, in which an increase in average temperature causes an increase in the respiration rate and, hence, a reduced SSC (Barrios et al., 2014; Shin et al., 2007).

Titratable acidity. All regressions showed a negative Pearson correlation coefficient, which means that TA decreased with an increase in the value of the weather index, except for average daily rainfall, which showed a positive coefficient and reverse trend. Like for SSC, the rainfall anomaly is likely due to its correlation to temperature and general seasonal patterns and does not necessarily constitute a physiological relationship between TA and rainfall. The strongest and most significant correlation was obtained for the average temperature from the start of individual fruit development until harvest of each cohort (Fig. 4A, $R = -0.77$, $P < 0.001$). The ANCOVA test confirmed that the regression line was not significantly different for each cultivar ($P = 0.54$) and that the same linear relation can be used for both cultivars. Average minimum, maximum, and diurnal temperature as well as GDD based on different base temperatures showed a very similar but slightly weaker and less significant regression (Fig. 4B–I, $R = -0.78$ to -0.55, $P = 0.034$ to < 0.001) compared with the average temperature. Average daily rainfall showed a positive but slightly weaker correlation (Fig. 4P, $R = 0.71$, $P = 0.003$). Average daily potential evapotranspiration also showed a fair but less

Table 2. Statistical indices R^2, Wilmott Index (d-statistic), Root Mean Square Error (RMSE), and Relative RMSE (RRMSE) for prediction accuracy (observed versus simulated) of soluble solids content (SSC) and titratable acidity (TA) for each cultivar and season based on the average air temperature during fruit growth.

		SSC (%)				TA (%)			
Cultivar	Season	R^2	Wilmott index	RMSE	RRMSE	R^2	Wilmott index	RMSE	RRMSE
Florida Radiance	2014–15	1.0	1.0	0.13	0.02	n/a	n/a	0.02	0.02
	2016–17	0.44	0.79	0.37	0.06	0.26	0.57	0.04	0.05
	2017–18	0.97	0.99	0.23	0.35	0.90	0.94	0.03	0.04
	All	0.94	0.98	0.27	0.04	0.80	0.91	0.03	0.04
Florida Brilliance	2016–17	0.31	0.72	0.40	0.06	0.09	0.16	0.05	0.07
	2017–18	0.97	0.98	0.27	0.40	0.49	0.82	0.03	0.05
	All	0.83	0.95	0.33	0.05	0.19	0.65	0.04	0.06
All	**All**	**0.89**	**0.97**	**0.3**	**0.05**	**0.55**	**0.84**	**0.04**	**0.05**

Note: There is no value for R^2 and Wilmott Index for 'Florida Radiance' for the 2014–15 growing season (indicated as n/a) because only one pair of simulated and observed data was available.

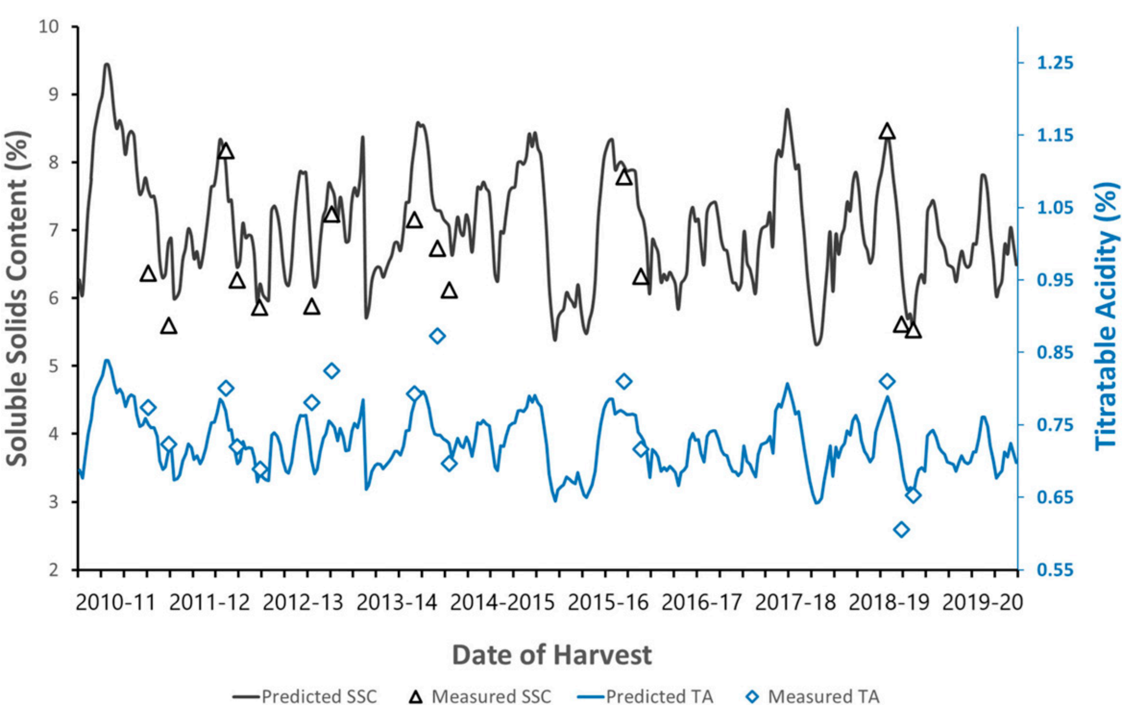

Fig. 7. Long-term seasonal distribution of simulated soluble solids content and titratable acidity for each harvest every 3 to 4 d for cultivar Florida Radiance for 10 growing seasons (2010–20) in Balm, FL, with observed data in selected seasons. The y-axis is not continuous and only includes dates from the harvest period (November to March) of each growing season. The black line and triangle show predicted and measured soluble solids content, respectively. The blue line and rhombus show predicted and measured titratable acidity, respectively.

significant correlation (Fig. 4L, $R = -0.51$, $P = 0.05$), whereas average daily radiation, total radiation, total potential evapotranspiration, total actual transpiration, and average daily actual transpiration showed only a weak or no correlation with a low level of significance (Fig. 4J, K, and M–O, $R = -0.69$ to -0.07, $P = 0.80$–0.005).

This analysis found that the strongest and most significant regression of TA was for the average temperature. Within the range of temperatures that we observed (daily average 14.1–22.3 °C during fruit growth), TA decreased as temperature increased, resulting in less acidic or tart fruit. This is similar to field experiments (McKean, 2019) and a controlled growth chamber study (Wang and Camp, 2000), in which an increase in average temperature resulted in a reduction in TA, but to a lesser extent than the reduction in SSC. A decrease in TA due to an increase in temperatures has also been found for blackberries (Naumann and Wittenburg, 1990) and grapevine (Sadras et al., 2013).

Firmness. Measurements taken with FirmTech 2 and Texture Analyer XT2 were analyzed as different datasets, as no conversion coefficient was available. Total solar radiation had a weak positive but not significant ($R = 0.37$, $P = 0.36$) and daily actual transpiration a weak negative but not significant ($R = -0.4$, $P = 0.33$) correlation for the firmness measurements taken with FirmTech 2 (Fig. 5K and N). Measurements with Texture Analyzer XT2 had a medium negative, but not a significant correlation with average daily potential evapotranspiration and total potential evapotranspiration (Fig. 6L and M, $R = -0.68$, $P = 0.064$–0.066). Regardless of the measurement device, firmness showed no strong or significant correlation to any of the remaining weather indices, as indicated by low R values that ranged from -0.33 to 0.14 and high P values that ranged from 0.42 to 0.92. Overall, no clear pattern could be found, with some regressions being positive for FirmTech 2 but negative for Texture Analyzer XT2, which is in line with the observed lack of correlation between firmness measurements of different devices (Døving et al., 2005).

Other studies confirm the complexity of fruit firmness due to interactions of genetics, fruit shape and size, maturity stage, and environment (Agüero et al., 2015; Alavoine and Crochon, 1989; Capocasa et al., 2008; Døving and Måge, 2001; Hietaranta and Linna, 1999; Salentijn et al., 2003). The tested weather indices alone did not have a sufficient direct relationship with these processes.

Integration of quality variables into the strawberry model

To verify the functioning of promising quality-weather-relations, the derived linear equations for the impact of average temperature during fruit cohort growth on SSC (Eq. [16]) and TA (Eq. [17]) were integrated into the process-based crop model.

$$SSC = a - b^{*}T_{avg}, \qquad [16]$$

where a is the reference SSC value of 13%, b the slope of -0.33 (%/°C), and T_{avg} the average Temperature (°C) during fruit cohort growth.

$$TA = a - b^{*}T_{avg}, \qquad [17]$$

where a is the reference TA value of 1%, b is the slope of -0.017 (%/°C), and T_{avg} is the average Temperature (°C) during fruit cohort growth.

The quality model is currently independent from the existing simulation of plant growth and development and is applied after the simulation has been completed; however, it uses detailed outputs of the simulation for each individual cohort. The quality model can be added as a new subroutine to the CSM-CROPGRO-Strawberry model at a later stage. For each simulation, the quality model tracks the days on which a fruit cohort is initiated, starting with flowering, when initial growth starts, and when the individual fruits of the cohort are mature for each periodic harvest. The quality model then calculates the average air temperature and other weather indices for the period during which each fruit cohort developed. Based on the average air temperature of a fruit cohort, a quality trait such as SSC and TA for a specific harvest is then calculated. The average value for a single harvest date is obtained by averaging across all cohorts that are harvested on a single harvest date, because some older mature fruit may be 2 to 3 d older than later maturing fruit if the harvest interval is 4 d. The quality trait equations are constrained by a lower and upper bound, representing the range slightly above and below the observed data and biological limits above or below which a quality trait is not expected to change. In this analysis, a common equation was established for two similar cultivars, but

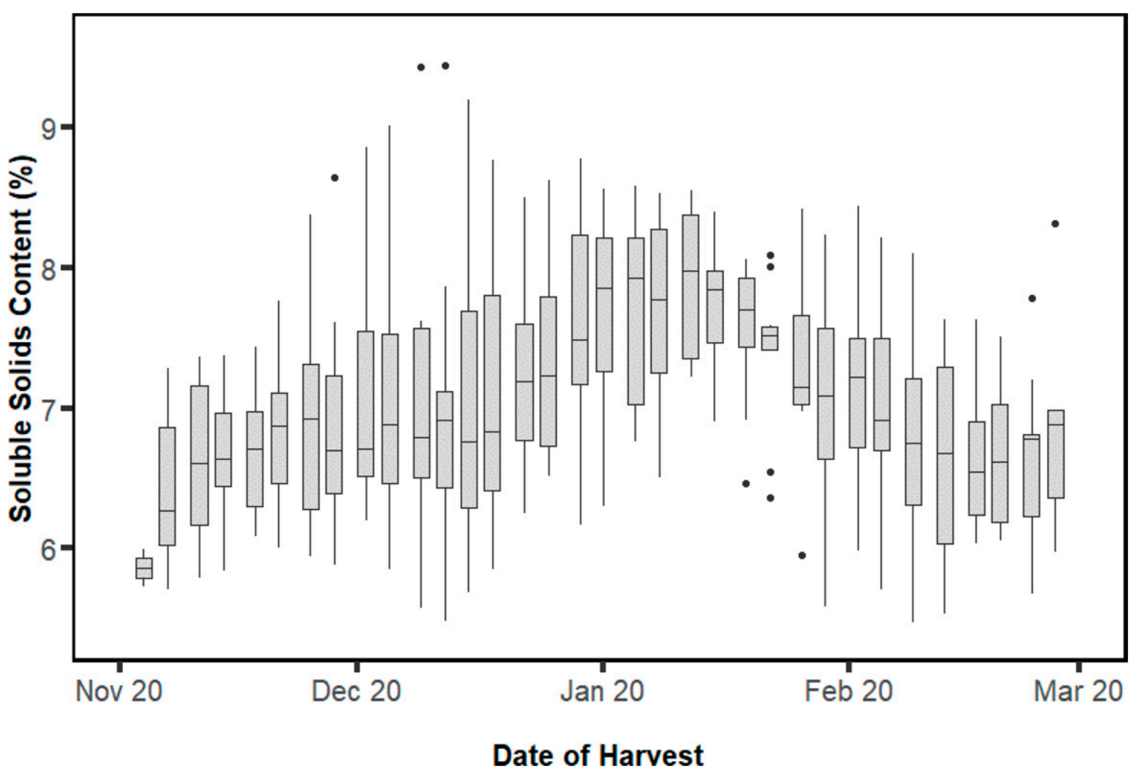

Fig. 8. Simulated soluble solids content with average distribution boxplot of each harvest every 3 to 4 d for cultivar Florida Radiance for 10 growing seasons (2010–20) in Balm, FL. The horizontal line is the mean, the box extent represents the first and third quartiles, the whiskers the minimum and maximum quartiles, and the points the outlier values.

this might not be the case for other cultivars that may have a different observed range and variability in the quality trait's values (Hasing et al., 2013). Therefore, the linear equations and upper or lower quality trait bounds are assumed to be cultivar specific. They will be implemented in a future model version as cultivar (ecotype) coefficients and may need to be adjusted depending on available data or general knowledge when expanding the quality model for new strawberry cultivars.

Quality model performance

The quality model performance was evaluated by running the crop model with the two new quality variables and comparing simulated values for each individual harvest of each growing season to the observed values for SSC and TA from the same respective month and day of each growing season. Observed SSC values ranged between 5.4% and 8.4% and simulated between 5.5% and 8.2% (Table 1). The simulated SSC fits well with the observed SSC, with the highest prediction bias being +0.5% and −0.5%. All statistical indices indicate a good to very good model agreement for prediction of SSC across all seasons and for both cultivars with an r^2 of 0.89, a Wilmott Index of 0.97, and a RRMSE of 0.05. When considering individual seasons and cultivars, the model performance for SSC was somewhat more variable for both cultivars in the 2016–17 season, with a low prediction accuracy (r^2 of 0.31–0.44, Wilmott Index of 0.72–0.79, and RRMSE of 0.06) (Table 2). The average r^2 across all seasons was less for cultivar Florida Brilliance (0.83) than for cultivar Florida Radiance (0.94).

The observed values for TA ranged between 0.63% and 0.80%, and simulated TA values ranged between 0.65% and 0.78% (Table 1). The simulated TA fit the observed TA well, with the highest prediction bias being +0.06 and −0.07%. All statistical indices indicate a fair to good model agreement for TA across all seasons and cultivars (r^2 of 0.55, Wilmott Index of 0.84, and RRMSE of 0.05). When considering individual seasons and cultivars, the model performance for TA was somewhat more variable for both cultivars for the 2016–17 growing season with a lower prediction accuracy (r^2 0.09–0.29, Wilmott Index 0.16–0.26, RRMSE 0.05–0.07) (Table 2). The average r^2 and Wilmott Index across all

Fig. 9. Distribution patterns of simulated soluble solids content (SSC) for cultivar Florida Radiance in 10 growing seasons (2010–20) in Balm, FL, for 2010–15 (top rows) and 2016–20 (bottom rows) growing seasons. Pie charts represent the % distribution of cumulative fruit weight (first and third row) and seasonal harvest number (second and fourth row). Periodic harvests were summarized into brackets from 5% to 10% depending on their simulated soluble solids content. White space indicates lower numbers of harvests in the respective season due to a shorter season.

seasons was also significantly lower for the cultivar Florida Brilliance (0.19, 0.65) compared with the cultivar Florida Radiance (0.80, 0.91).

One of the reasons for the better performance for the prediction of SSC and TA for the cultivar Florida Radiance could be because of the larger number of observations that provided a wider range for statistical evaluation. In total, data from the 2014–15, 2016–17, and 2017–18 growing seasons were used to define the quality correlations with the cultivar Florida Radiance grown in all three seasons, whereas the cultivar Florida Brilliance was only grown during the 2016–17 and 2017–18 seasons.

The feasibility of using the same linear equations for both cultivar Florida Radiance and Florida Brilliance, although confirmed by the ANCOVA test, might have to be reconsidered in future analysis. The lower model performance in predicting both observed SSC and TA for the 2016–17 compared with the 2017–18 growing season could be because of the lower number and more narrow range of observations for the 2016–17 growing season. For the 2016–17 growing season, six observations with a relatively narrow spread of 6.2% to 7.1% SSC were available, compared with the 2017–18 growing season with eight observations with a wider spread of 5.5% to 8.2% SSC. Furthermore, it is also plausible that other environmental conditions besides average air temperature had a significant effect on SSC and TA, but are not reflected in the linear quality variables for the 2016–17 growing season.

The overall results confirm the correct implementation and functioning of the fruit SSC and TA state variables in the strawberry quality model, although there was relatively high variability in model performance. Wilmott Index and r^2 values above 0.7 are generally considered very good to good and within acceptable ranges for initial model development with limited data. Values below 0.5 indicate the need for further analysis and model refinement in these areas.

Model application

Long-term seasonal distribution of quality traits' values. The model application for the seasonal analysis presented in this section is limited to the cultivar Florida Radiance, in which the quality model performance for both SSC and TA were better than for the cultivar Florida Brilliance. Because of the high impact of weather variability on strawberry quality, we analyzed the influence of seasonal weather variability on SSC, TA, and SSC/TA ratio for the cultivar Florida Radiance with the new strawberry quality model for the Balm, FL, location using 10 years of historical weather data. The preliminary evaluation shows good performance for predicting SSC (Fig. 7, $r^2 = 0.76$) and acceptable performance for predicting TA (Fig. 7, $r^2 = 0.53$) in seasons that were not already used for model development. Larger discrepancies between individual predicted and measured quality values would require additional analysis. They could be related to growing conditions outside the range of observed data in the model development dataset (e.g., particularly warm, or cold growing periods). Although further validation is recommended, it shows that the model can predict with reasonable accuracy and be used for a more in-depth seasonal analysis of fruit quality.

Soluble solids content. Simulated SSC values showed significant variability among years and throughout the growing season, ranging from 5.3% to 9.4%. The typical seasonal pattern (Fig. 8) showed a low SSC (5.5% to 7%) during November and December (with very few harvestable fruit), then a gradual increase from 7.5% to 8.5% in January and February, followed by a decline to 5.5% to 7% in March. The seasons varied in the number of harvests, having either a lower or higher SSC content (Fig. 9, top). The 2010–11 growing season was the coldest and showed the highest number of harvests with a high SSC (>8%), whereas the particularly warm season of 2016–17 had the most harvests with a low SSC (<6%). On the other hand, the large number of "high SSC" harvests is less relevant when the weight of respective harvests and their share of the total harvest weight per season were considered (Fig. 9, bottom). The fruit growth period for harvests that had a high predicted SSC in 2010–11 mainly occurred during the months of December and early January, when the fruit production was low due to the low temperature. Therefore, the harvests with a high predicted SSC had very little fruit weight and did not significantly contribute to cumulative fruit weight of this season. The opposite is shown in 2017–18, where the number of harvests with 5% to 6% SSC harvest was low, but the harvests and respective fruit development occured during the warmer production time from February to early March. These harvests contain a larger number and weight of fruit and the resulting share of low (5% to 6%) SSC fruits of cumulative fruit weight was almost 50%.

Titratable acidity. Simulated TA showed a significant variability among years and throughout the season, ranging from 0.64% to 0.84% and followed a similar pattern as SSC. The typical seasonal pattern (Fig. 10) had a low TA (<0.7%) during November and December, then gradually increased to 0.75% to 0.84% in January and February, followed by a decline to 0.64% to 0.75% in March.

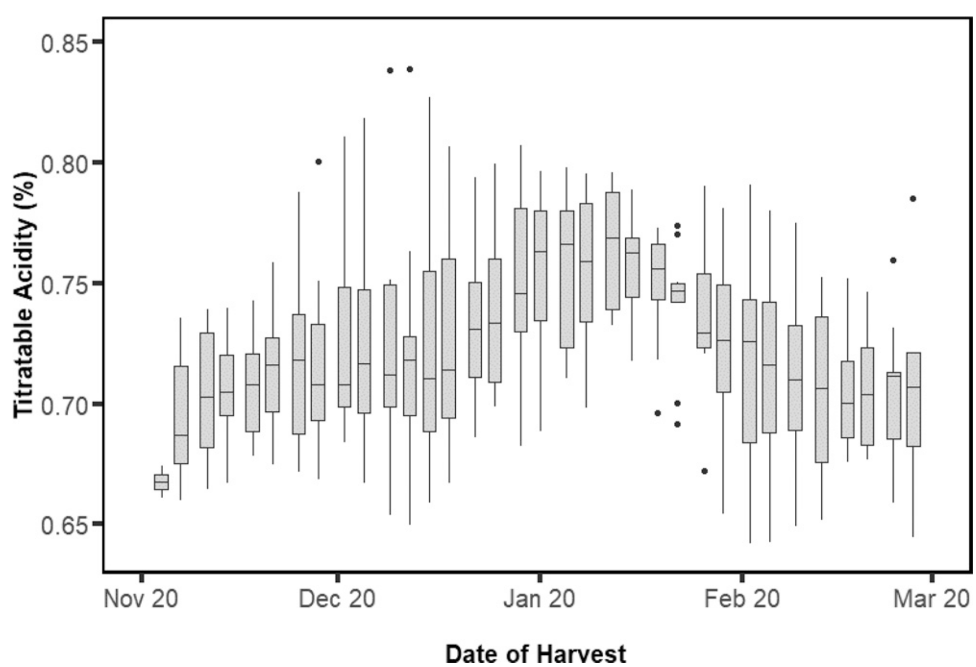

Fig. 10. Simulated titratable acidity with average distribution boxplot of each harvest every 3 to 4 d for cultivar Florida Radiance and 10 growing seasons (2010–20) in Balm, FL. The horizontal line is the mean, the box extent represents the maximum first and minimum third quartiles, the whiskers the minimum and maximum quartiles, and the points the outlier values.

Similar to SSC, the distribution of harvest numbers and fruit weight for TA was variable. Almost two-thirds of harvests were classified with a TA >0.75% in 2010–11 (Fig. 11, top), but their fruit development occurred during the relatively cold months of December and early January. Thus, they only carried ≈25% of the cumulative fruit weight (Fig. 11, bottom). Fewer than a third of the number of harvests in 2018–19 had a low TA (<0.70%) but their fruit grew mainly during the high-yielding harvest period in February and March. Hence, these harvests contributed to more than 50% of total fruit weight.

SSC/TA ratio. The SSC/TA ratio was calculated by dividing the simulated SSC by the simulated TA. Simulated SSC/TA showed a significant variability among years and throughout the season, ranging from 8.3 to 11.2 and followed a similar pattern as SSC and TA. The typical seasonal pattern (Fig. 12) showed a low SSC/TA (<9.5) during November and December, then gradually increased to 10.0 to 10.5 in January and February, followed by a decline to 9.0 to 9.5 in March. The increase in SSC/TA is caused by SSC increasing more than TA with decreasing temperatures (or stronger decreasing with rising temperatures), as observed by Wang and Camp (2000). Like SSC and TA, the distribution of harvest numbers and fruit weight was variable. Almost half of harvests were classified with a SSC/TA >10.5 in 2010–11 (Fig. 13, top), but their fruit growth occurred during the relatively cold months of December and early January and they only carried ≈15% of the cumulative fruit weight (Fig. 13, bottom). Fewer than 25% of the harvests in 2016–17 and 2017–18 had a low SSC/TA (<9) but their fruit grew mainly during the high-yielding harvest period in February and March and contributed to more than 40% of total fruit weight in each year.

The 10-year simulations confirmed the initial observation that fruits that grow during periods of lower temperature have a higher SSC (>8.0%) and TA (>0.8%), compared with fruit that develop during periods of a higher temperature and have a lower SSC (<6%) and TA (<0.70%). The SSC/TA ratio follows this trend. Changes in seasonal weather patterns have a significant impact on the seasonal distribution of harvested fruit weight with either a lower or higher SSC and TA. Particularly low and high simulated

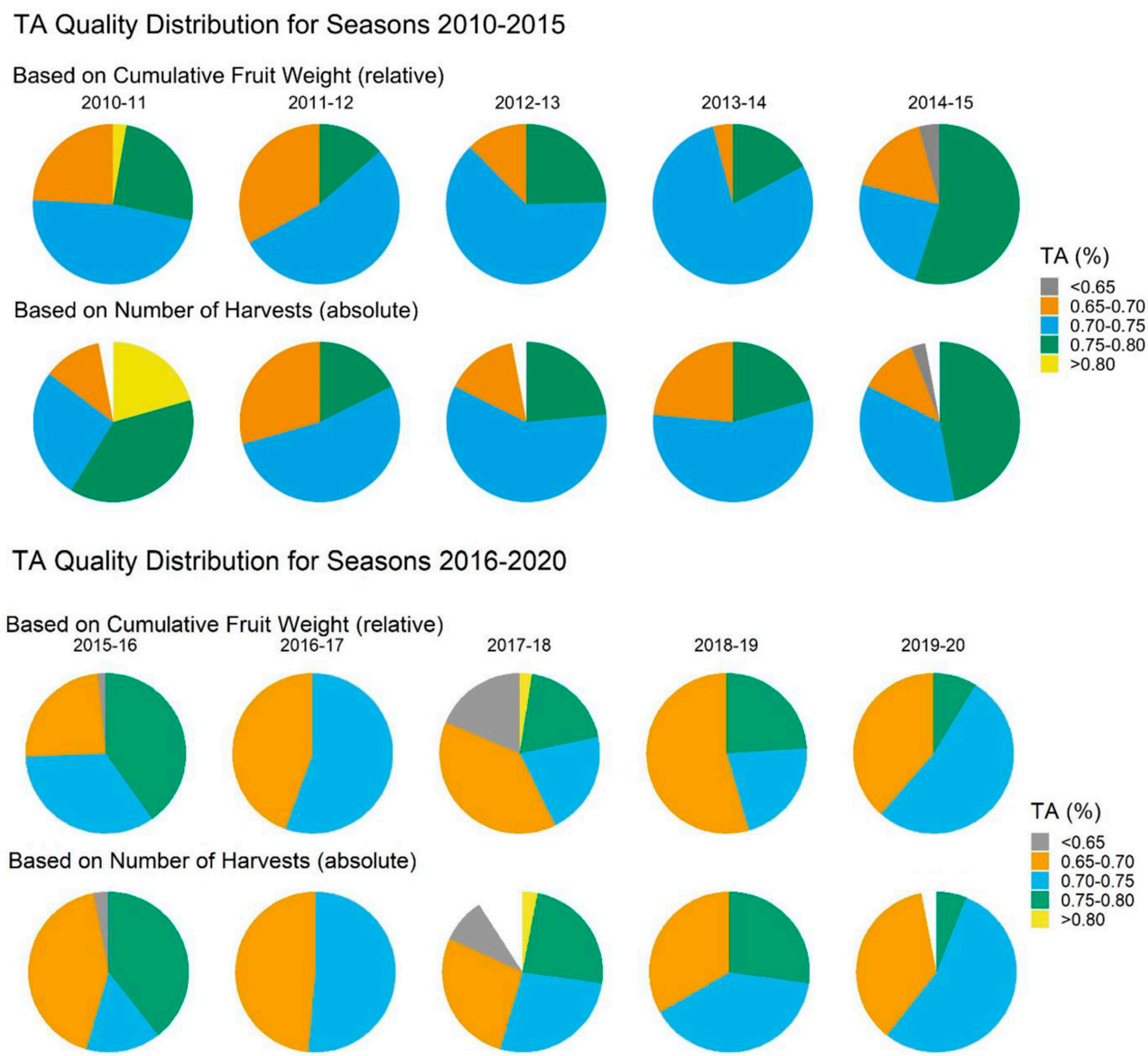

Fig. 11. Distribution patterns of simulated titratable acidity (TA) for cultivar Florida Radiance during 10 growing seasons (2010–20) in Balm, FL, for 2010–15 (top rows) and 2016–20 (bottom rows). Pie charts represent the % distribution of cumulative fruit weight (first and third row) and seasonal harvest number (second and fourth row). Periodic harvests were summarized into multiple brackets ranging from <0.65 to >0.8% depending on their simulated titratable acidity. White space indicates lower numbers of harvests in the respective season due to a shorter season.

quality traits are associated with high or low temperatures, respectively, in the month before harvest, representing the temperatures during fruit growth. Based on the simulation results and within the range of temperatures observed (daily average 14.1–22.3 °C during fruit growth), SSC/TA increased with decreasing temperature resulting in more sweet and tart fruit. For instance, for the same harvest date on 28 Dec,. the simulated SSC (9.4%) and TA (0.84%) were high in 2010–11 and the simulated SSC (5.5%) and TA (0.65%) were low for the 2015–16 growing season. The difference can be explained by a low temperature for December, with a mean temperature of 10.6 °C in 2010 compared with a mean temperature of 21.6 °C in 2015. Fruit harvested on 28 Dec in each season had been continuously exposed to a lower or higher temperature. This is also reflected in simulated fruit growth duration, with the respective fruit cohorts taking up to 25 d to reach harvest maturity in 2010 compared with only 15 d in 2015. Despite the higher content in SSC and TA, quantitative fruit harvests are much lower for the entire month of December in 2010–11 (14 g/plant) compared with 2015–16 (86 g/plant).

The application of the model for simulating quality from a consumer perspective is limited, as the current literature or grower practices lack a clear threshold for a "good" SSC or TA in strawberry production. Mitcham et al. (1996) stated that a minimum of 7% SSC and a maximum of 0.8 TA, equivalent to an SSC/TA Ratio of 8.75, are acceptable strawberry quality, but this depends on consumer preferences. As a general rule, however, lower values for SSC and higher values for TA or a low ratio of SSC/TA are often related to inferior sensory quality and result in a lower rating in consumer taste panels (Alavoine and Crochon, 1989; Azodanlou et al., 2003; Carlen and Ancay, 2003; Giampieri et al., 2012; Jouquand et al., 2008). Optimizing production and breeding toward a higher SSC, SSC/TA ratio and other qualitative compounds should, therefore, be an important goal for growers, breeders, and other stakeholders (Vitten et al., 2009). The described fruit quality and yield dynamics are important, for instance when considering the ongoing breeding efforts to achieve overall higher quality especially when focused on early-yielding cultivars while also improving or maintaining fruit quality (Mezzetti et al., 2018; Whitaker et al., 2017a). Decision support systems based on crop models can help to inform and guide research though these challenges (Jones et al., 2017; Tsuji et al., 1998). The 10-year application shown here highlights the importance of seasonal and sub-seasonal weather patterns for both quality and quantity of strawberry production, although further evaluation of the model is needed with additional experimental data.

Future work

Future research should evaluate different strawberry cultivars and different environments that represent additional weather conditions to make the model more robust across a wider range of environments, genetics, and management options. Other strawberry cultivars were found to have both a different range and magnitude of variation in quality traits such as SSC (Whitaker et al., 2011) and, thus, would require adjustment of model parameters. The single-factor analysis could also be extended with a multilinear or nonlinear regression to analyze the combined impact of multiple weather and growth variables on quality traits to account for interdependences. The choice of weather indices, and particularly methods for calculation of GDDs, can be extended as other methods could be more suitable (Ruml et al., 2010). A differentiation between rainfall and irrigation could reveal different effects on quality (e.g., physical damages or excess water uptake from rainfall events) (Morton et al., 2017). Related to the dataset itself, going beyond a single location and selected seasons might uncover curvilinear or otherwise unexpected quality relationships outside the range of currently observed data. A more extensive dataset would allow for a split or independent dataset for model training and testing, which would improve assessment of performance and generalization of model results. Improvement to the quality simulation could be made by incorporating the current level of assimilate production and relating this to fruit load or number of "competing" fruits growing at the same time. Correia et al. (2011) observed a higher SSC in fruit grown under low crop load, but only for some genotypes. Source-sink relations are already modeled to determine fruit size, but the applicability to fruit quality remains to be explored (Grossman and Dejong, 1994; Heuvelink et al., 2004). The cohort tracking and continuous harvesting capabilities of the model

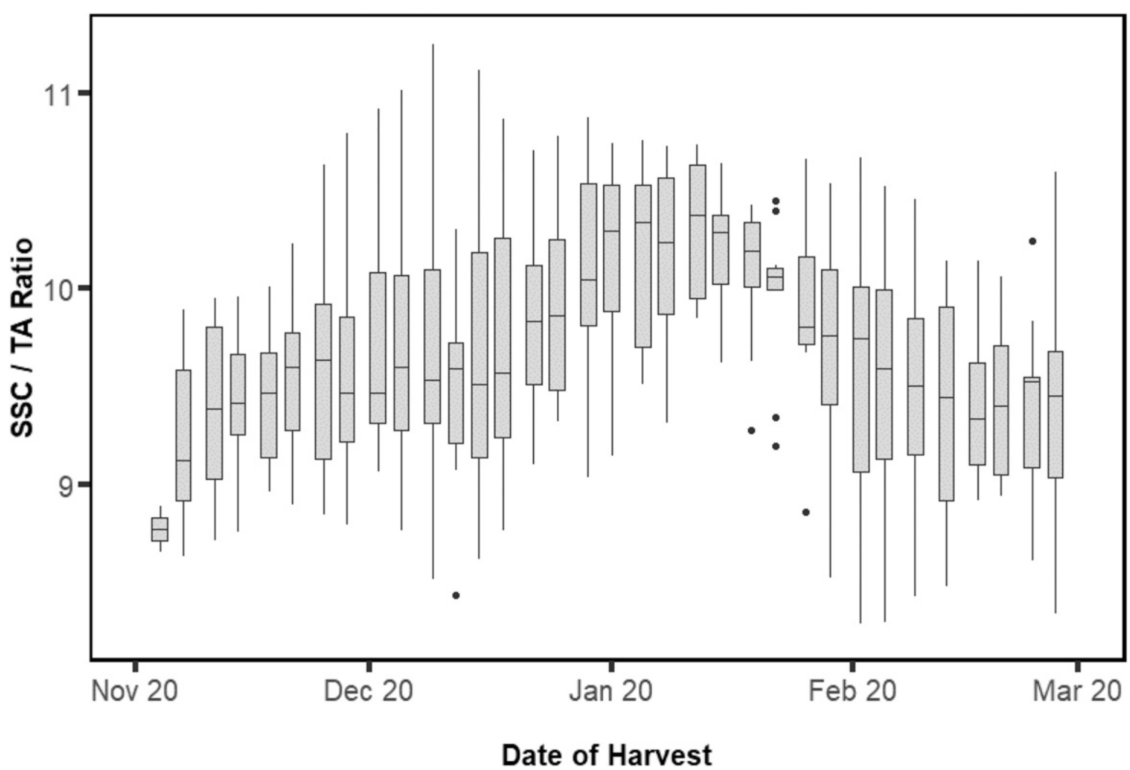

Fig. 12. SSC/TA ratio, calculated from simulated soluble solid content (SSC) and titratable acidity (TA), with average distribution boxplot of each harvest every 3 to 4 d for cultivar Florida Radiance and 10 growing seasons (2010–20) in Balm, FL. The horizontal line is the mean, the box extent represents the maximum first and minimum third quartiles, the whiskers the minimum and maximum quartiles, and the points the outlier values.

Fig. 13. Distribution patterns of SSC/TA ratio, calculated from simulated soluble solid content (SSC) and titratable acidity (TA), for cultivar Florida Radiance during 10 growing seasons (2010–20) in Balm, FL, for 2010–15 (top rows) and 2016–20 (bottom rows). Pie charts represent the % distribution of cumulative fruit weight (first and third row) and seasonal harvest number (second and fourth row). Periodic harvests were summarized into multiple brackets ranging from <9 and >10.5 depending on their simulated SSC/TA ratio. White space indicates lower numbers of harvests in the respective season due to a shorter season.

provide a suitable framework for further analysis in this direction. In general, future experimental studies should emphasize the more precise monitoring of individual fruits and their growth period and quality instead of seasonal or monthly averages. The adoption of the model by growers or strawberry industry for actual decision support or strategic planning would likely involve further work and participatory methods to refine the decision problem and improve the usability of the model (Jakku and Thorburn, 2010; Rose et al., 2016; Zhai et al., 2020).

The modeling approach for strawberries to enable the simulation of continuous harvesting and prediction of quality traits through tracking of individual fruit cohorts, can be applied to other crop models. For instance, a suitable next crop for quality parameterization may be the CROPGRO-Tomato model for the production of processing tomatoes, in which a minimum SSC of 4.0% or 4.5% is commonly required for processing and where payout prices vary by SSC content (Garcia and Barrett, 2006; North Italian Tomato Producer Organization, 2019).

Conclusion

This study expanded the existing CSM-CROPGRO-Strawberry crop model of DSSAT with the prediction of quality traits for individual harvests of two commercial strawberry cultivars: Florida Radiance and Florida Brilliance. A seasonal analysis over a 10-year period revealed a large variability in simulated SSC and TA over 10 growing seasons due to the variability in air temperature in a subtropical region. Further studies will be valuable to verify that the model simulates well for other environmental conditions, strawberry cultivars, and crop management scenarios and to extend the simulation to other quality traits and potentially other vegetable and fruit crops.

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