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ORIGINAL PAPER

Evaluation of leaf wetness duration models for operational use in strawberry disease-warning systems in four US states

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Abstract Leaf wetness duration (LWD) plays a key role in disease development and is often used as an input in disease-warning systems. LWD is often estimated using mathematical models, since measurement by sensors is rarely available and/or reliable. A strawberry disease-warning system called "Strawberry Advisory System" (SAS) is used by growers in Florida, USA, in deciding when to spray their strawberry fields to control anthracnose and Botrytis fruit rot. Currently, SAS is implemented at six locations, where reliable LWD sensors are deployed. A robust LWD model would facilitate SAS expansion from Florida to other regions where reliable LW sensors are not available. The objective of this study was to evaluate the use of mathematical models to estimate LWD and time of spray recommendations in comparison to on site LWD measurements. Specific objectives were to (i) compare model estimated and observed LWD and resulting differences in timing and number of fungicide spray recommendations, (ii) evaluate the effects of weather station sensors precision on LWD models performance, and (iii) compare LWD models performance across four states in the USA. The LWD models evaluated were the classification and regression tree (CART), dew point depression (DPD), number of hours with relative humidity equal or greater than 90 % (NHRH ≥90 %), and Penman-Monteith (P-M). P-M model was expected to have the lowest errors, since it is a physically based and thus portable model. Indeed, the P-M model estimated LWD most accurately (MAE <2 h) at a weather station with high precision sensors but was the least accurate when lower precision sensors of relative humidity and estimated net radiation (based on solar radiation and temperature) were used (MAE = 3.7 h). The CART model was the most robust for estimating LWD and for advising growers on fungicide-spray timing for anthracnose and Botrytis fruit rot control and is therefore the model we recommend for expanding the strawberry disease warning beyond Florida, to other locations where weather stations may be deployed with lower precision sensors, and net radiation observations are not available.

Keywords LWD sensors · Dew · Anthracnose · *Colletotrichum acutatum* · Botrytis · *Botrytis cinerea* · Disease control · Rational spray · Strawberry diseases

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Introduction

Disease-warning systems are decision tools used to optimize fungal and bacterial disease control. They can help improve disease management by recommending spray applications when environmental conditions are favorable for disease development, allowing producers to spray only when necessary rather than using conventional calendar-based spray schedules. Rational fungicide spraying, as guided by disease-warning systems, can provide benefits by reducing production costs, mitigating hazards to the health of farm workers and consumers, and lessening the negative impacts of pesticides on the environment (Gleason et al. 2008).

Temperature and leaf wetness duration (LWD) are widely used to predict the risk of crop disease development. Temperature influences all phases of pathogen development, whereas LWD, the period of time when free water is present on a crop canopy, influences the infection process (Huber and Gillespie 1992). Temperature is usually measured at weather stations, whereas LWD sensors are not commonly available and may not be reliable and therefore may act as a constraint on the use of disease-warning systems (Gleason et al. 2008). LWD is challenging to measure accurately and conveniently. A key problem is the lack of a standard protocol for its measurement (Sentelhas et al. 2004a; Sentelhas et al. 2004b). Commercially available LWD sensors vary widely in coating, color, and shape, and deployment protocols (for example, angle, orientation, and height) are not standardized (Sentelhas et al. 2004a; Gleason 2007).

An alternative to measuring LWD is to estimate it using mathematical models, which require input of meteorological variables such as relative humidity, temperature, rainfall, net radiation, and wind speed. LWD models are classified as empirical or physical. Physically based models use an energy balance approach, whereas empirical models are mostly based on regression analysis and other statistical techniques (Huber and Gillespie 1992). An advantage of empirical models is that they typically require fewer input variables, but they may need to be recalibrated when the model is applied in a region different from where it was developed (Gillespie and Sentelhas 2008).

The total value of strawberry production in the US is over $2 billion (USDA 2013a). Florida is the second-ranked state in the value of strawberry production, with a planted area of 3560 ha, producing 82,215 tons in 2012 (USDA 2013b). Anthracnose (caused by *Colletotrichum acutatum*) and Botrytis fruit rot (*Botrytis cinerea*) are the main diseases affecting strawberry production in Central Florida. Fungicide applications to control these diseases represent about 15 % of the total operating costs (Legard et al. 2005).

A disease-warning system, known as Strawberry Advisory System (SAS), was developed recently to help Florida strawberry growers make cost-efficient fungicide-spraying decisions to control anthracnose and Botrytis fruit rot. SAS uses hourly inputs of LWD and air temperature to determine when fungicides should be applied for control of anthracnose (Wilson et al. 1990; MacKenzie and Peres 2012a) and Botrytis fruit rot (Bulger et al. 1987; MacKenzie and Peres 2012b). The SAS warning system is available online (http://agroclimate.org/tools/strawberry/) and has reduced the number of fungicide applications by 50 % during seasons with conditions unfavorable for disease development (Pavan et al. 2011).

A key question in implementing disease-warning systems concerns their portability beyond the region where they were initially developed. Differences in climate, crop management practices, and disease complexes can all impact how a warning system will perform outside its zone of origin (Duttweiler et al. 2008). SAS gathers LWD data from sensors installed at six weather stations in Central Florida, but this configuration prevents the expansion of the system and its use by growers not located near existing stations. Using models to estimate LWD can therefore help to overcome system utilization constraints.

The main goal of this study was to evaluate the use of mathematical models to estimate LWD and their recommendations for disease control. Ultimately, we wanted to select a LWD model that would enable expansion of SAS. Specific objectives were to assess (i) differences in model estimated and measured LWD and resulting timing and number of spray recommendations, (ii) effects of weather station sensors precision on LWD models performance, and (iii) LWD models performance across four states in the USA.

Materials and methods

Study sites and data source

A weather station in Balm, Florida, USA (27.76° N, 82.22° W), designated as the reference station for the study with weather sensors of high precision, was installed adjacent to a station that is part of the statewide Florida Automated Weather Network (FAWN) network. In addition to the Balm site, weather data were collected from the Arcadia (27.22° N, 81.84° W), Dover (28.01° N, 82.23° W), and Lake Alfred (28.10 N, 81.71 W) stations. Data from FAWN stations is available at http://fawn.ifas.ufl.edu/data/. Weather data were also collected from research sites at Gilbert, Iowa (42.11° N, 93.58° W), Piketon, Ohio (39.07° N, 83.01° W), and Cooley (35.15° N, 81.95° W) and Keisler (33.97° N, 81.38° W), South Carolina.

Measurements of air temperature and relative humidity, wind speed, solar radiation, and rainfall were collected at 1.5- to 2.0-m height for at least two strawberry production seasons for each study site between 2011 and 2014. Table 1 summarizes the period of analysis and weather sensors of the study sites and Table 2 summarizes the weather conditions. Leaf wetness duration (LWD) was measured at each station using two adjacent flat plate sensors (Model 237, Campbell Scientific) deployed 30 cm above a turfgrass surface and facing north at an angle of 45° to the horizontal (Sentelhas et al. 2004b). The sensors were painted with two coats of white latex paint and heat-treated for 24 h at 70 °C after each coat (Sentelhas et al. 2004a). The threshold for wetness was calibrated for each pair of sensors based on visual observations of

Table 1 Weather variable sensors used at study sites in Arcadia, Balm, Dover, and Lake Alfred (Florida, FL), Gilbert (Iowa, IA), Ohio (OH), and South Carolina (SC).

Study sites	Strawberry seasons	Period (strawberry season start date to end date)	Temperature/relative humidity	Wind speed	Solar radiation	Rainfall
Balm—FL (reference station)	2011/2012 2012/2013	November 1 to March 31 November 1 to March 23	Vaisala, HMP155A	Vaisala, WS425	[a]Kipp and Zone net radiometer, CNR4	from FAWN-Balm
Balm, Arcadia, Dover, Lake Alfred—FL	2011/2012 2012/2013	November 1 to March 31 November 1 to March 31	Campbell Scientific, CS215-L	Vaisala, 425A	Campbell Scientific pyranometer, LI200X	WaterLog, H-340
Gilbert—IA	2011 2012	July 1 to September 15 July 1 to September 13	Vaisala, HMP45	Campbell Scientific, 03002-L	Campbell Scientific pyranometer, LI200X	Texas Electronics, TE525
Piketon—OH	2011 2012 2013	May 4 to September 27 April 26 to September 30 May 14 to October 20	Vaisala, HMP155A	MetOne, 034B		Texas Electronics, TE525
Cooley—SC	2013 2014	February 7 to June 3 March 18 to June 16	Vaisala, HMP45C	RM Young, 05103	Apogee pyronometer, CS300-L	Hydrological Services, TB4-L25
Keisler—SC	2012 2013	February 7 to April 23 February 1 to March 19	Vaisala, HMP45C	RM Young, 05103	Apogee pyronometer, CS300-L	Hydrological Services, TB4-L25

[a]Net radiation was observed at this station based on incoming and outgoing radiation measurements

dew onset and dry-off over grass for 3 weeks prior to the experimental period (Rao et al. 1998) and was set between 200 and 500 kΩ. A pair of LW sensors was used to assure wetness and dryness conditions. Records of LW sensors were not included if there was a mismatch between the sensors (e.g., one sensor recorded "wetness" and the other "dryness"). Mismatched records were unusual, and seldom exceeded 45 min of difference when occurred. The weather stations with both sensors of weather variables and LW were located next to strawberry growing areas over turfgrass.

Leaf wetness duration models

Four LWD-estimating models were evaluated: (i) number of hours with relative humidity equal or greater than 90 % (NHRH ≥90 %) (Sentelhas et al. 2008); (ii) dew point depression (DPD) (Gillespie et al. 1993); (iii) classification and regression tree (CART) (Gleason et al. 1994); and (iv) Penman-Monteith (P-M) (Monteith 1990). The models and analysis were programmed using R programming language (http://www.r-project.org). Time intervals of 15 min to 1 h were classified as wet or dry according to each model. Daily LWD on day n was estimated by summing time intervals classified as wet between 12:01 pm of day $(n-1)$ and 12:00 pm of day n.

NHRH ≥90 %

NHRH is one of the most used and simplest models for LWD estimation. The only input variable is relative humidity, and a threshold that defines the transition from dry to wet periods is required. In this study, the threshold adopted was 90 % (Sentelhas et al. 2008).

DPD

DPD is calculated by the difference between air temperature and dew point temperature. The DPD model estimates LWD as the length of time in which DPD is within two thresholds, which indicates onset and offset of wetness. These thresholds were 2.0 and 3.8 °C, respectively, for wetness onset and offset (Lulu et al. 2008). The LWD starts when DPD is less than the onset threshold, and it ends when DPD is greater than the offset threshold (Gillespie et al. 1993).

CART

CART is a nonparametric procedure proposed by Gleason et al. (1994) based on relative humidity, dew point depression, and wind speed. The method classifies time intervals into four categories according to a binary tree. A time interval is classified as wet if it is within categories 3 or 4 and the results for Eq. 1 or 2 are above 14.4674 or 37.0, respectively.

Table 2 Median weather conditions in Arcadia, Balm, Dover, and Lake Alfred (Florida), Gilbert (Iowa), Ohio, and South Carolina during strawberry seasons

Location	Strawberry season	Number of days of data collection	T (°C)	RH (%)	U_{2m} (m s^{-1})	R_{total} (mm)
Florida						
Arcardia	2011/2012	132	19.2 (15.8–23.4)	84.7 (64.4–95.1)	2.1 (1.4–3.3)	83.3 (18 days)
Arcardia	2012/2013	151	17.9 (13.7–22.0)	85.0 (64.1–94.9)	2.0 (1.3–3.0)	124.3 (27 days)
Balm	2011/2012	150	18.7 (15.1–22.7)	83.6 (63.3–94.9)	2.3 (1.5–3.3)	76.0 (27 days)
Balm	2012/2013	151	17.2 (13.5–21.3)	83.1 (63.2–94.1)	2.0 (1.4–3.0)	124.3 (29 days)
Dover	2011/2012	152	18.5 (14.5–22.7)	84.8 (64.9–95.7)	0.9 (0.5–1.5)	103.8 (28 days)
Dover	2012/2013	151	17.4 (13.1–21.7)	84.2 (63.4–92.2)	0.9 (0.4–1.6)	194.3 (29 days)
Lake Alfred	2011/2012	152	18.9 (15.5–22.6)	82.1 (62.2–92.8)	1.2 (0.8–1.9)	107.5 (24 days)
Lake Alfred	2012/2013	151	17.2 (13.2–21.2)	80.6 (60.4–92.4)	1.2 (0.8–1.8)	78.2 (26 days)
Iowa						
Gilbert	2011	77	23.2 (19.3–26.8)	87.0 (71.9–95.6)	1.8 (1.1–2.5)	120.6 (23 days)
Gilbert	2012	61	23.7 (19.6–28.2)	77.8 (60.3–92.2)	1.6 (0.7–2.7)	90.9 (15 days)
Ohio						
Piketon	2011	147	20.7 (17.3–24.5)	80.1 (64.8–92.1)	1.7 (1.1–2.5)	468.9 (60 days)
Piketon	2012	158	20.2 (15.6–24.6)	74.8 (54.7–90.8)	1.7 (1.0–2.6)	606.3 (58 days)
Piketon	2013	160	19.5 (15.7–22.9)	84.9 (67.6–96.1)	1.7 (1.1–2.4)	581.7 (59 days)
South Carolina						
Cooley	2013	117	13.0 (6.4–18.7)	61.0 (42.0–86.5)	2.3 (1.3–3.7)	562.3 (50 days)
Cooley	2014	91	18.8 (13.0–23.6)	61.0 (43.9–82.0)	0.6 (0.0–2.4)	129.0 (23 days)
Keisler	2012	77	16.0 (10.7–19.8)	69.3 (49.3–87.2)	2.4 (1.5–3.4)	213.6 (23 days)
Keisler	2013	47	7.9 (4.5–12.4)	61.6 (45.1–81.8)	2.7 (1.7–3.8)	178.8 (14 days)

Numbers in parenthesis indicate the lower (first quartile) and upper (third quartile) limits containing 50 % of daily means (interquartile range)

T mean daily air temperature (°C), *RH* mean daily relative humidity (%), U_{2m} mean daily wind speed at 2 m (m s^{-1}), R_n mean daily net radiation (W m^{-2}), *R* total rainfall (mm)

$$1.6064T_{air}^{0.5} + 0.0036T_{air}^{2} + 0.1531RH - 0.4599UDPD - 0.0035T_{air}RH > 14.4674 \quad (1)$$

$$0.7921T_{air}^{0.5} + 0.0046RH^{2} - 2.3889U - 0.0390T_{air}U + 1.0613UDPD > 37.0000 \quad (2)$$

where T_{air} is the air temperature (°C); RH is the relative humidity (%); *U* is the wind speed (m s^{-1}); and DPD is the dew point depression (°C) in the time interval considered.

P-M

P-M model is a physical model, also known as aerodynamic resistance model (Rao et al. 1998). The model's principle is to estimate latent heat flux (LE) as shown in Eq. 3 (Monteith 1990).

$$\mathrm{LE} = -\frac{s\,R_n + \left[\frac{1200(e_s - e_a)}{r_a + r_b}\right]}{s + \gamma^*} \tag{3}$$

where s is the slope of the saturation vapor pressure curve (hPa°.C^{-1}), R_n is the net radiation (W.m^{-2}), e_s is the saturated vapor pressure at the weather station air temperature (hPa), e_a is the actual air vapor pressure (hPa), r_a is the additional aerodynamic resistance (s.m^{-1}), r_b is the boundary layer resistance for heat transfer (s.m^{-1}), and γ^* is the modified psychrometer constant (assumed to be 0.64 kPa.K^{-1} with moisture and heat transfer to both sides of sensor during dew and 1.28 kPa.K^{-1} for evaporation from one side of a sensor after rain) (Sentelhas et al. 2006). A time interval is considered wet when LE is greater than zero or rain begins. R_n was derived from incoming solar radiation and air temperature using the model proposed by Iziomon et al. (2000) with the exception of the reference weather station in Balm, which has a net radiometer.

SAS

The four LWD models were used to determine the number of fungicide sprays recommended for anthracnose and Botrytis fruit rot using the SAS advisory system (Pavan et al. 2011). LWD and temperature during the wetness period are inputs required by SAS for predicting the proportion of infected strawberry fruit, called an infection index (INF). INF varies from 0 to 1, indicating, respectively, zero and 100 % of predicted infected strawberry fruits, and is calculated separately for anthracnose ($\mathrm{INF_{Ant}}$) and Botrytis fruit rot ($\mathrm{INF_{Bot}}$). A spray recommendation occurs when $\mathrm{INF_{Ant}} \geq 0.15$ and/or $\mathrm{INF_{Bot}} \geq 0.5$. These thresholds were calibrated for Florida weather conditions (MacKenzie and Peres 2012a; MacKenzie and Peres 2012b), but, in this study, the same thresholds were assumed for other locations as a case study.

$$\ln(\mathrm{INF_{Ant}}/1-\mathrm{INF_{Ant}}) = -3.70 + 0.33*\mathrm{LWD} - 0.069*\mathrm{LWD}*\mathrm{T_{air}} + 0.0050*\mathrm{LWD}*\mathrm{T_{air}}^2 - 0.000093*\mathrm{LWD}*\mathrm{T_{air}}^3$$

$$\ln(\mathrm{INF_{Bot}}/1-\mathrm{INF_{Bot}}) = -4.268 - 0.0901*\mathrm{LWD} + 0.0294*\mathrm{LWD}*\mathrm{T_{air}} - 0.0000235*\mathrm{LWD}*\mathrm{T_{air}}^2$$

where $\mathrm{INF_{Ant}}$ and $\mathrm{INF_{Bot}}$ are the infection indexes for anthracnose and Botrytis fruit rot, respectively; LWD in hours; and T_{air} is the average air temperature during the wetness period (°C).

Data analysis

Evaluation of LWD models estimates

Daily measured and simulated LWD obtained from the reference station in Balm was compared to evaluate performance of the LWD models. The following indexes were used to evaluate the models performance: mean error (ME), the model bias; mean absolute error (MAE), the magnitude of the average error; efficiency (EF), the model performance in comparison with observed data; and mean square error (MSE), the mean square of the deviations around the 1:1 line. MSE was decomposed into three components of source of error according to the method of Gauch et al. (2003): squared bias (SB), the model error from bias; nonunity slope (NU), the capability of the model to mimic the fluctuation of the measurements; and lack of correlation (LC), the observed values. The MSE components are given by:

$$\mathrm{MSE} = \mathrm{SB} + \mathrm{NU} + \mathrm{LC}$$
$$\mathrm{SB} = \left(\overline{X} - \overline{Y}\right)^2$$
$$\mathrm{NU} = (1 - b_{\mathrm{LWD\ models}})^2\,\sigma_Y^2$$
$$\mathrm{LC} = \left(1 - r^2\right)\,\sigma_X^2$$
$$b_{XY} = \frac{\sigma_{XY}^2}{\sigma_Y^2}$$

where $\overline{X}$ and $\overline{Y}$ are the estimated and measured LWD means, b_{XY} is the slope of the least-squares regression of X on Y, r^2 is the square of this correlation, σ_{XY}^2 is the covariance of X and Y, and σ_X^2 and σ_Y^2 are the variance of X and Y, respectively.

Bonferroni's (1936) comparison test was used to determine significant differences between MSE across LWD models.

Influence of LWD models on disease control recommendations

The methodology used in this section was adapted from Kim et al. (2004), originally used to evaluate LWD model performance in order to correct estimate wetness intervals. Fungicide spray recommendations for anthracnose and Botrytis fruit rot control based on measured and estimated LWD were compared using data from the reference station in Balm. A four-cell contingency table was used to evaluate LWD models performance to recommend disease control, which shows the distribution of recommendations of correct sprays (H), correct no sprays (N), incorrect sprays (F), and incorrect no sprays (M) (Table 3). The fraction of correct estimates (θ_1) for a LWD model is given by:

$$\theta_1 = \frac{\mathrm{H} + \mathrm{N}}{(\mathrm{H} + \mathrm{N} + \mathrm{F} + \mathrm{M})}$$

Table 3 Four-cell contingency table used to classify LWD model's spray recommendations into the number of correct spray (H) and no spray (N) recommendations and incorrect spray (F) and no spray (M) recommendations in comparison with recommendations based on measured LWD

	Model: spray	Model: no spray
Observed: spray	Hits (H)	Misses (M)
Observed: no spray	False alarms (F)	Correct negatives (N)

To weight the occurrence of H and N events, assuring the LWD models recommend both spray and no-spray events correctly, a k agreement index (Dietterich 2000) was calculated for each of the LWD models evaluated for both diseases:

$$k = \frac{\theta_1 - \theta_2}{1 - \theta_2}$$

$$\theta_2 = \frac{(\mathrm{H} + \mathrm{M}) \cdot (\mathrm{H} + \mathrm{F})}{(\mathrm{H} + \mathrm{M} + \mathrm{F} + \mathrm{N})^2} + \frac{(\mathrm{F} + \mathrm{N}) \cdot (\mathrm{M} + \mathrm{N})}{(\mathrm{H} + \mathrm{M} + \mathrm{F} + \mathrm{N})^2}$$

where θ_2 is an estimate of the probability that disease control recommendation based on measured and the estimated LWD agree by chance, given the observed counts in the contingency table.

Effects of weather sensor precision on the performance of LWD models

To quantify the influence of weather sensor precision in LWD estimation and SAS performance, data from the reference and FAWN stations in Balm (Florida) were compared. Mean error (ME), mean absolute error (MAE), and the k agreement index for both diseases were used to evaluate the differences in LWD and recommendations for disease control. In addition, the ratio between the number of recommended sprays by each model for both diseases was calculated using data from the FAWN station in comparison with the reference station. For instance, a ratio of 0.8 between the number of sprays recommended by the DPD model using FAWN data in comparison with the reference data means that using the input data from FAWN to estimate LWD reduced the number of sprays by 20 % in comparison with LWD measurements at the reference station.

LWD model performance across four states in the USA

To assess model performance in LWD estimation and SAS performance across different locations, data from Arcadia, Dover, and Lake Alfred (Florida), Gilbert (Iowa), Piketon (Ohio), and Cooley and Keisler (South Carolina) were used as inputs. The statistical indexes ME and MAE and k agreement index for both diseases and the k coefficient of variation (CV_k) were used to evaluate differences between measured and the estimated LWD and disease control recommendations.

$$\mathrm{CV}_k = \frac{\sigma}{\mu}(100)$$

where σ is the standard deviation and μ is the average of the k agreement indexes of LWD models across all study sites.

Results

LWD model performance

The P-M model was the most efficient at estimating LWD, followed by CART, DPD, and NHRH ≥90 %; average EF during the strawberry seasons was 80, 65, 50, and 30 %, respectively (Table 4). All LWD models errors were within an acceptable range of MAE of 2 h for operational use in warning systems (Gleason et al. 1994; Sentelhas et al. 2008) with the exception of the NHRH ≥90 % model. CART, NHRH ≥90 %, and P-M had a negative bias when estimating LWD, with ME varying between −0.3 h and −2.5 h. The DPD model had no bias (ME≈0 h) due to the model's compensatory overestimation of lower values of LWD (<10 h) and underestimation of higher values (>10 h) (Fig. 1c, d).

Table 4 Statistical indexes and errors comparing measured and estimated LWD using the CART, DPD, NHRH ≥90 %, and P-M models during the 2011/2012 and 2012/2013 strawberry seasons in Balm, Florida, USA

Models/season	ME (h)	MAE (h)	EF (%)	k_{ant}	k_{bot}
CART					
2011/2012	−1.13	1.54	70.4	0.807	0.831
2012/2013	−1.46	2.05	59.7	0.701	0.740
DPD					
2011/2012	0.11	1.76	50.0	0.749	0.748
2012/2013	−0.25	2.12	48.5	0.732	0.651
NHRH ≥90 %					
2011/2012	−2.13	2.38	42.8	0.795	0.831
2012/2013	−2.54	3.02	23.3	0.682	0.570
P-M					
2011/2012	−0.25	0.98	83.3	0.834	0.882
2012/2013	−0.71	1.34	79.0	0.673	0.597

k agreement index of anthracnose and Botrytis recommendations based measured and estimated LWD

ME mean error in hours, *MAE* mean absolute error in hour, *EF* efficiency in percentage

Analysis of MSE showed that the main source of error for all LWD models was from lack of correlation (LC) related to unexplained variability in LWD estimates by the models (Fig. 2). CART and NHRH ≥90 % models had higher bias (SB), since they systematically underestimated LWD. The nonunity slope (NU) partition of source of error for the P-M model was negligible in comparison with the other models, meaning that the P-M model better mimicked onset and dry-off processes of leaf wetness in comparison with CART, DPD, and NHRH ≥90 % and achieved the highest accurate LWD estimates. However, even if the CART, DPD, and NHRH ≥90 % models were calibrated, and NU and SB were minimized, their LC error would still be greater than the total MSE of the P-M model. According to Bonferroni's comparison test,

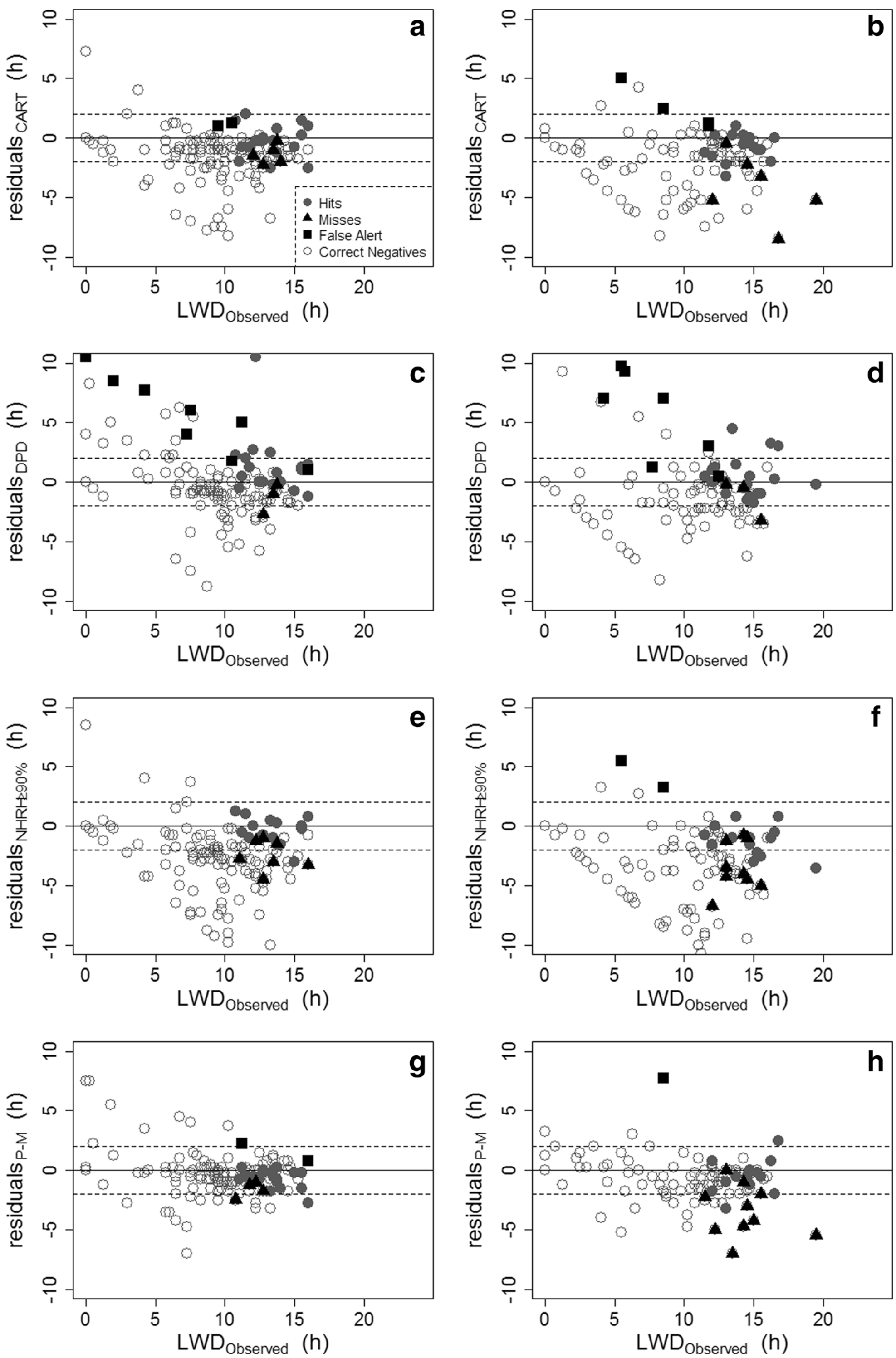

Fig. 1 LWD model residuals (LWD_{Model}–$LWD_{Observed}$) for CART (**a**, **b**), DPD (**c**, **d**), NHRH ≥90 % (**e**, **f**), and P-M (**g**, **h**) models versus measured LWD. Symbols represent hits (sensor = spray, model = spray—*filled circle*), misses (sensor = spray, model = no spray—triangle), false alerts (sensor = no spray, model = spray), and correct negatives (sensor = no spray, model = no spray—*nonfilled circle*) events for anthracnose monitoring during 2011/2012 (*left column*) and 2012/2013 (*right column*) strawberry seasons in Balm (reference station), Florida, USA. *Dashed line* represents acceptable errors of LWD estimation: ±2 h of model error in comparison with observed LWD

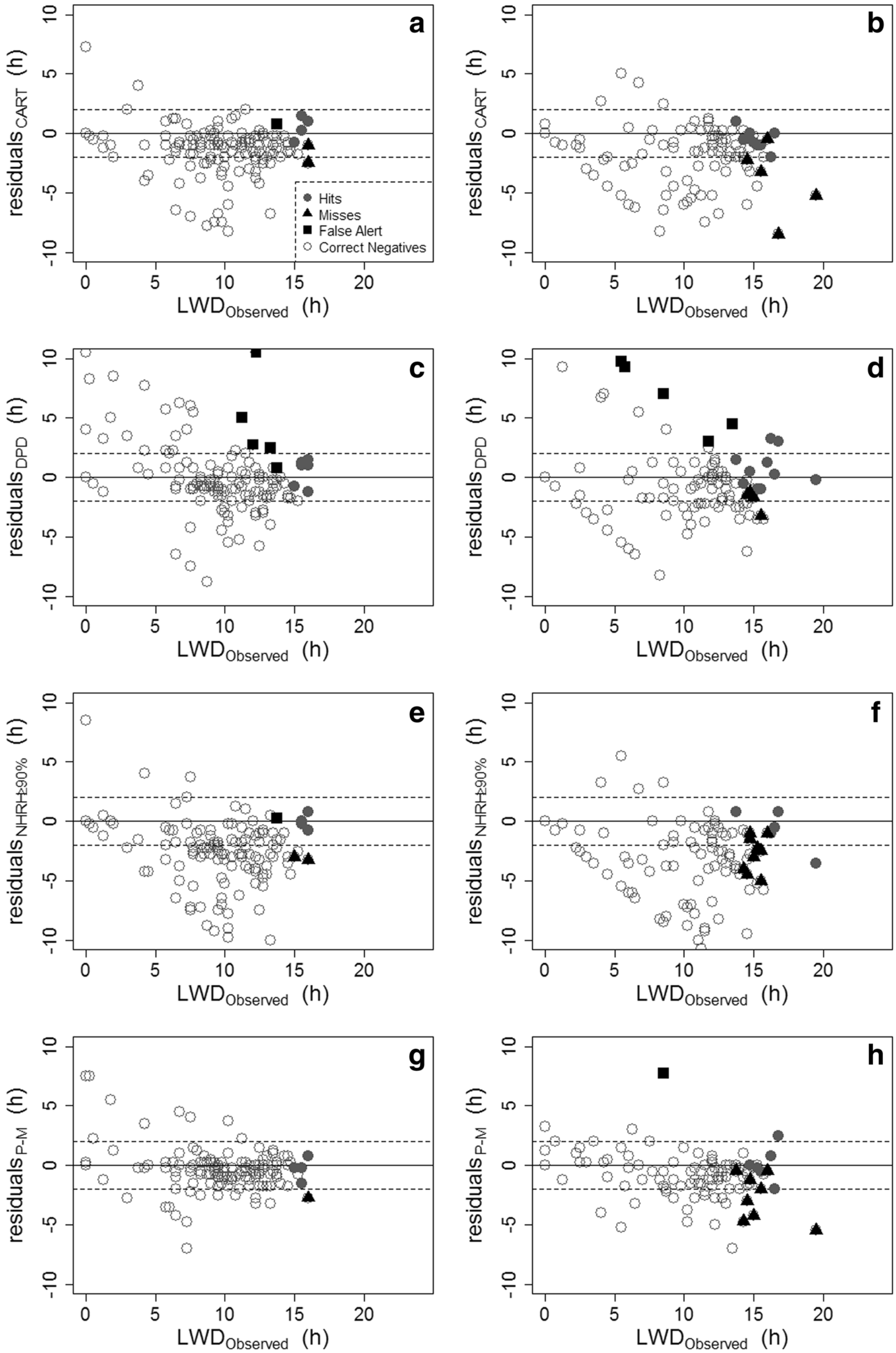

Fig. 2 LWD model residuals (LWD_{Model}–LWD*Observed*) for CART (**a**, **b**), DPD (**c**, **d**), NHRH ≥90 % (**e**, **f**), and P-M (**g**, **h**) models versus observed LWD. Symbols represent hits (sensor = spray, model = spray—*filled circle*), misses (sensor = spray, model = no spray—triangle), false alerts (sensor = no spray, model = spray), and correct negatives (sensor = no spray, model = no spray—*nonfilled circle*) events for Botrytis monitoring during 2011/2012 (*left column*) and 2012/2013 (*right column*) strawberry seasons in Balm (reference station), Florida, USA. Dashed line represents acceptable errors of LWD estimation: ±2 h of model error in comparison with observed LWD

P-M and NHRH ≥90 % were the only models that differed significantly with regard to their MSE ($P < 0.05$), whereas CART and DPD were not significantly different from either P-M or NHRH ≥90 %.

Regarding the influence of estimated LWD on the estimation of anthracnose and Botrytis fruit rot risk, the number of spray recommendations based on the different LWD models varied by one to two per ten recommendations for each disease (k values between 0.6 and 0.8). The k agreement index of correct recommendations (k_{ant} and k_{bot}) based on measured and estimated LWD were alike among LWD models but diverged with regard to the type of events that caused erroneous recommendations (Fig. 1). The divergence is related to biases of the LWD models. Both diseases, anthracnose and Botrytis fruit rot, need at least 10 to 12 h of LWD with adequate temperature to trigger a spray recommendation. The DPD model overestimated by 5 h or more observed LWD values lower than 10 h, causing false alerts. There were also a few misses of spray recommendations, but within an acceptable range of error for operational use in warning systems (Gleason et al. 1994; Sentelhas et al. 2008) less than 2 h. On the other hand, CART and NHRH ≥90 % tended to underestimate LWD observations, causing erroneous recommendations for no spray, especially during the 2012/2013 strawberry season. CART and NHRH ≥90 % underestimated LWD values lower than 15 h, which did not result in erroneous recommendations due to lack of disease risk within this range. P-M performed similarly to the other models when estimating risk of anthracnose and Botrytis. However, most of the erroneous recommendations, missed and false alerts events, were within the acceptable 2-h range of LWD error. During the 2011/2012 strawberry season, P-M had only one erroneous recommendation when monitoring Botrytis fruit rot, when it missed one spray (Fig. 1g). P-M's worst performance was during 2012/2013 strawberry season, underestimating LWD values greater than 15 h—a critical range for disease risk.

Influence of weather sensor precision on LWD model performance

Comparison of measurements of temperature, relative humidity, and wind speed from the reference and FAWN stations in Balm are shown in Fig. 3. Net radiation was measured at the reference station, whereas it was derived from temperature and solar radiation at the FAWN station (Fig. 3). Relative humidity and net radiation had the greatest differences between weather stations. Relative humidity from the FAWN station was systematically 3.8 % higher than values from the reference station (Fig. 3). Net radiation derived from FAWN data was systematically 42.7 W m^{-2} lower than measured values at the reference station—the higher the net radiation value, the greater the difference between stations (Fig. 3). Temperature and wind speed were in good agreement between stations, with MAE equal to 0.2 °C and 0.3 m s^{-1}, respectively.

When data from the reference and FAWN stations were used as inputs in LWD models, the difference between weather variables from the stations resulted in a systematic positive bias of LWD with ME >0 and similar magnitude of MAE, especially for LWD values lower than 10 h (Fig. 4). The model most affected by the differences in input was P-M (ME = 3.7, MAE = 3.5 h), followed by NHRH ≥90 % (ME = 1.7 h, MAE = 2 h), DPD (ME = 1.5, MAE = 1.9), and CART (ME = 0.9 h, MAE = 1.2 h) (Table 5).

The number of sprays recommended for anthracnose and Botrytis fruit rot increased in comparison with the reference station as a result of the positive bias in estimated LWD. Spray recommendations based on LWD estimated by P-M increased substantially (155 % for anthracnose and 382 % for Botrytis), followed by NHRH ≥90 % (41 % for anthracnose and 56 % for Botrytis), DPD (33 % for anthracnose and 59 % for Botrytis), and CART (20 % for anthracnose and 37 % for Botrytis) (Table 5). The k agreement indexes between recommendations based on measured and the estimated LWD by CART and NHRH ≥90 % were similar when using FAWN station data. For anthracnose control recommendations, CART and NHRH ≥90 % models resulted in k_{ant} about 0.8 and 0.7, respectively, independent of the data source, whereas for Botrytis, k_{bot} was 0.78 and 0.74 for CART and 0.69 and 0.63 for NHRH ≥90 % when using

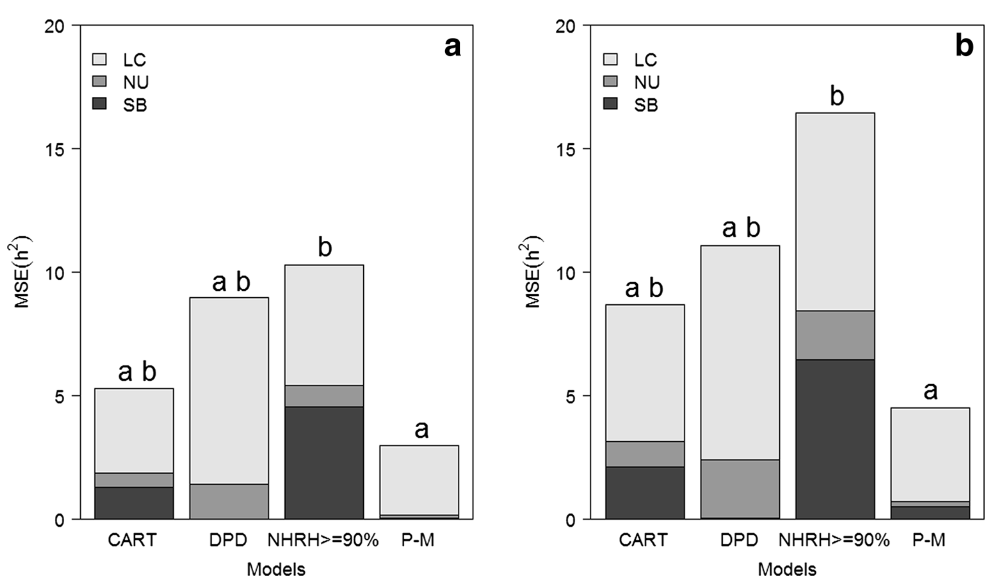

Fig. 3 Components of mean square error (MSE) in lack of correlation (LC), nonunity slope (NU), and squared bias (SB) for CART, DPD, NHRH ≥90 %, and P-M LWD models during the 2011/2012 and 2012/2013 strawberry seasons Balm (reference station), Florida, USA

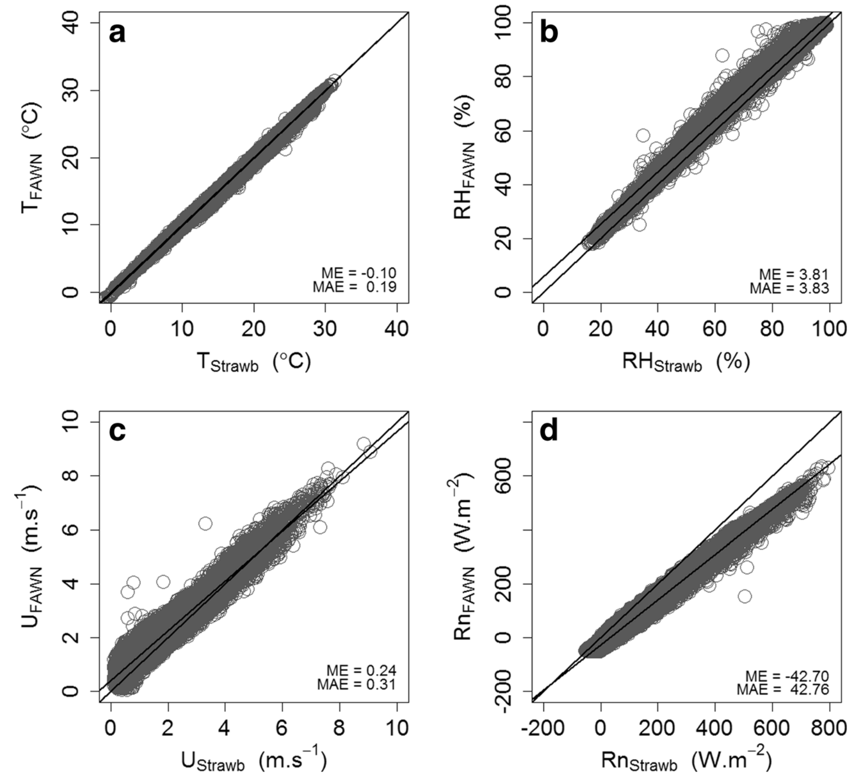

Fig. 4 Relationship between LWD estimated by CART (**a**), DPD (**b**), NHRH ≥90 % (**c**), and P-M (**d**) models using data from the reference and FAWN weather stations in Balm, Florida

data from the reference and FAWN stations, respectively. The *k* agreement indexes for recommendations based on P-M for both diseases decreased when using FAWN data as input. For anthracnose, k_{ant} decreased from 0.76 to 0.55, whereas for Botrytis, k_{bot} decreased from 0.72 to 0.39. The *k* agreement indexes based on DPD model also decreased when using FAWN data as input, k_{ant} from 0.74 to 0.61 and k_{bot} from 0.69 to 0.63.

LWD model performance across four states in the USA

Comparisons between measured and estimated LWD across locations are shown in Table 6. The CART model estimated LWD most accurately across locations, with average MAE of 2.0 h, ranging between 1.4 and 3.1 h, followed by DPD (MAE between 2.0 and 2.7 h), NHRH ≥90 % (MAE between 1.9 and 3.1 h), and P-M (MAE between 2.6 and 4.9 h). NHRH ≥90 % underestimated LWD at all sites (ME varied between −0.6 and −2.7 h), whereas P-M systematically overestimated LWD at all sites (ME varied between 2.0 and 4.7 h) with ME quite similar to MAE. CART mostly underestimated LWD, with ME between −2.6 and 0.5 h, while DPD had almost no bias or a positive bias with a ME between −0.6 and 1.6 h.

Figure 5 shows *k* agreement indexes for anthracnose and Botrytis recommendations based on measured and estimated LWD. For anthracnose recommendations (Fig. 5a), CART had the highest median k_{ant} of 0.76 and 11 % of variation

Table 5 Statistical indexes and errors comparing measured and estimated LWD using the CART, DPD, NHRH ≥90 %, and P-M models during the 2011/2012 and 2012/2013 strawberry seasons in Balm, Florida, USA

Models	ME (h) ($Model_{FAWN}$–$Model_{Ref.}$)	MAE (h) ($Model_{FAWN}$–$Model_{Ref.}$)	$\frac{\text{FAWN Ant}_{sprays}}{\text{Ref. Ant}_{sprays}}$	k_{ant} FAWN	k_{ant} Ref.	$\frac{\text{FAWN Bot}_{sprays}}{\text{Ref. Bot}_{sprays}}$	k_{bot} FAWN	k_{bot} Ref.
CART	0.88	1.22	1.20	0.78	0.76	1.37	0.74	0.78
DPD	1.51	1.94	1.33	0.61	0.74	1.59	0.53	0.70
NHRH ≥90 %	1.72	1.95	1.41	0.73	0.74	1.56	0.63	0.69
P-M	3.48	3.66	2.55	0.55	0.76	4.82	0.39	0.72

k agreement index of anthracnose and Botrytis recommendations based measured and estimated LWD

ME mean error in hours, *MAE* mean absolute error in hour, *EF* efficiency in percentage

Table 6 Statistical indexes and k agreement indexes of recommendations for anthracnose (k_{ant}) and Botrytis (k_{bot}) comparing measured and estimated LWD using the CART, DPD, NHRH ≥90 %, and P-M models across locations in Florida, Iowa, Ohio, and South Carolina

Models/ locations	ME (h) (LWD_{Model}–LWD_{Sensor})	MAE (h) (LWD_{Model}–LWD_{Sensor})	$\frac{\text{Model Ant}_{sprays}}{\text{Sensor Ant}_{sprays}}$	k_{ant}	$\frac{\text{Model Bot}_{sprays}}{\text{Sensor Bot}_{sprays}}$	k_{bot}
CART						
Arcadia, FL	−0.41	1.56	1.11	0.82	0.97	0.64
Dover, FL	−0.09	1.45	1.17	0.76	1.09	0.80
Lake Alfred, FL	0.48	1.53	1.31	0.77	1.71	0.64
Gilbert, IA	0.40	1.39	1.03	0.76	2.13	0.52
Piketon, OH	−1.08	2.06	0.96	0.78	1.24	0.65
Cooley, SC	−0.58	2.82	0.82	0.66	0.69	0.62
Keisler, SC	−2.55	3.10	0.45	0.60	1.00	0.74
DPD						
Arcadia, FL	1.22	2.25	1.49	0.66	2.20	0.54
Dover, FL	−0.22	2.00	1.15	0.76	1.09	0.71
Lake Alfred, FL	0.77	2.07	1.40	0.71	2.00	0.50
Gilbert, IA	1.57	2.32	1.22	0.78	3.62	0.37
Piketon, OH	0.33	2.43	1.17	0.73	1.98	0.57
Cooley, SC	0.20	2.66	0.75	0.61	0.92	0.70
Keisler, SC	−0.61	2.67	1.09	0.66	2.50	0.55
NHRH ≥90 %						
Arcadia, FL	−0.91	1.87	1.00	0.78	1.07	0.64
Dover, FL	−2.65	3.06	0.70	0.74	0.73	0.71
Lake Alfred, FL	−1.55	2.27	0.75	0.75	0.92	0.76
Gilbert, IA	−0.60	1.88	0.90	0.63	1.25	0.76
Piketon, OH	−2.17	2.80	0.78	0.70	1.05	0.69
Cooley, SC	−1.37	2.91	0.43	0.46	0.76	0.68
Keisler, SC	−2.31	2.82	0.36	0.51	0.75	0.56
P-M						
Arcadia, FL	2.81	2.87	1.71	0.63	3.03	0.40
Dover, FL	3.95	3.95	2.00	0.48	2.93	0.33
Lake Alfred, FL	4.69	4.69	2.55	0.41	5.33	0.21
Gilbert, IA	3.27	3.33	1.66	0.47	4.13	0.33
Piketon, OH	2.39	2.57	1.78	0.58	2.69	0.47
Cooley, SC	4.40	4.94	2.29	0.49	3.62	0.33
Keisler, SC	1.97	2.98	2.09	0.46	2.75	0.51

k agreement index of anthracnose and Botrytis recommendations based measured and estimated LWD

ME mean error in hours, *MAE* mean absolute error in hour, *EF* efficiency in percentage

across locations (CVk_{ant}, Table 7), followed by DPD (median k_{ant} of 0.71 and CVk_{ant} = 9 %), NHRH ≥90 % (median k_{ant} of 0.70 and CVk_{ant} = 19.1 %), and P-M (median k_{ant} of 0.48 and CVk_{ant} = 15.1 %). For Botrytis recommendations (Fig. 5b), NHRH ≥90 % had the highest median value of k_{bot} of 0.69 across locations and CVk_{bot} = 10 % variation across locations, followed by CART (median k_{bot} of 0.64 and CVk_{bot} = 14 %), DPD (median k_{bot} of 0.55 and CVk_{bot} = 21 %), and P-M (median k_{bot} of 0.33 and CVk_{bot} = 27 %). Divergences between recommendations based on measured and estimated LWD were associated mainly with LWD model bias (Table 6). For instance, P-M had the highest LWD overestimates, which resulted in the highest number of sprays recommended in comparison with those recommended when measured LWD was used. The opposite occurred for NHRH ≥90 %.

Discussion

Several interesting findings were obtained, helping us to better understand how LWD models can be used in disease-warning systems. In the first phase of our study, we used data from a

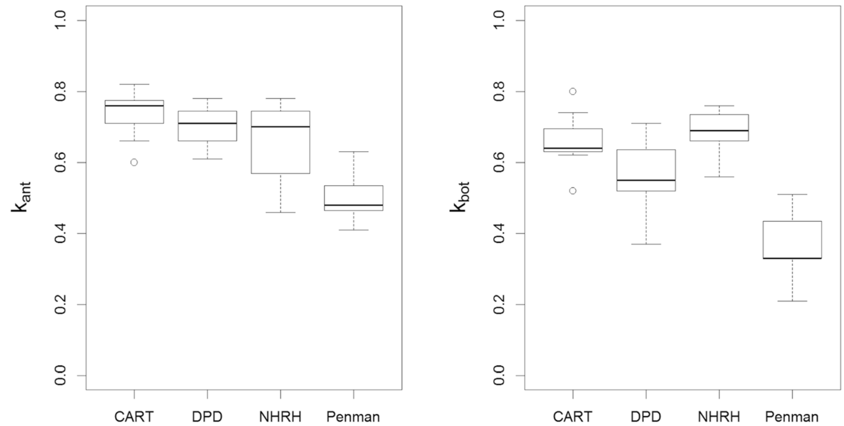

Fig. 5 Average correct recommendation index when the sprays were advised based on LWD models in comparison with those based on LWD sensors for anthracnose (k_{ant}) and Botrytis (k_{bot}) in Florida, Iowa, Ohio, and South Carolina

reference station with high-precision weather sensors as input in LWD models to minimize the influence of sensors precision on the LWD models performance. The rank of the models efficiency to estimate LWD, from the highest to the least efficient, was as follows: P-M, CART, DPD, and NHRH ≥90 % (Table 4); but significantly, difference at 5 % level was only observed for the LWD estimated by P-M and NHRH ≥90 % (Fig. 2). Errors smaller than 2.0 h are considered acceptable for operational use (Gleason et al. 1994; Sentelhas et al. 2008); by this criterion, only NHRH ≥90 % performed unacceptably, an indicative of need of threshold adjustment (Rowlandson et al. 2015). P-M model better mimicked onset and dry-off processes of leaf wetness, and its source of error in estimating LWD comes from uncontrollable errors whereas the other three models could be improved after local calibration to minimize bias (Fig. 2).

For anthracnose and Botrytis fruit rot monitoring, all four LWD models performed similarly in recommending timing for control of each disease, differing by the type of incorrect recommendations that degraded their performance (Fig. 1). For example, incorrect DPD recommendations were related to false-positive alerts, whereas NHRH ≥90 % resulted in false-negative outcomes (missed spray recommendations).

When using data from a weather station with different weather sensors, located no more than 10 m from the reference station, results were different (Table 1). P-M was the most affected by differences in the input data, greatly overestimating the number of spray recommended in comparison with the reference data (Table 5). P-M model sensitivity to data imprecision, resulting in a systematic bias in LWD estimation, with ME of 3.5 h and MAE of 3.7 h, possibly due to the discrepancies between relative humidity and net radiation between the stations and thus error propagation in estimating LWD. Relative humidity values from FAWN station averaged 3.8 % higher than the reference station. FAWN relative humidity sensor accuracy at 25 °C was ±4 %, whereas the reference relative humidity sensor accuracy at 25 °C was ±1.7 %. According to the manufacturers, relative humidity sensors may drift out of calibration by 1 % per year. Trained staff periodically maintain the weather stations used in this study, more often than once a year, which allow us to conclude that the difference found between sensor performance was acceptable. Net radiation estimated with temperature and solar radiation data from FAWN, using the Iziomon et al. (2000) approach, systematically underestimated measured values at the reference station by −42.7 W m^{-2}. Gillespie and Sentelhas (2008) compared estimated and measured net radiation using the same method in Elora, Canada, and obtained a bias of −38.8 W m^{-2} under overcast conditions, which are frequent during the Florida strawberry season, compared to 0.5 W m^{-2} bias under clear sky conditions. These authors found almost no systematic error when estimated net radiation was used as input in the P-M model (ME of −0.6 h) but found MAE of 1.5 h and maximum errors up to 4 h. The CART model was the least influenced by variation in weather variables, possibly because it is a classification tree method with no direct propagation error, since the last time interval estimated does not influence the next LWD estimate.

In the third phase of our study, LWD models performance in Florida, Iowa, Ohio, and South Carolina study sites varied in comparison with results obtained from the reference station. The rank of LWD models performance to estimate LWD was, on average from the smallest to the largest MAE: CART,

Table 7 Coefficient of variation (CV) of *k* agreement indexes for anthracnose (k_{ant}) and Botrytis fruit rot (k_{bot}) between measured and estimated LWD using the CART, DPD, NHRH ≥90 %, and P-M models across locations in Florida, Iowa, Ohio, and South Carolina

Models	CVk_{ant} (%)	CVk_{bot} (%)
CART	10.5	13.6
DPD	8.7	20.8
NHRH ≥90 %	19.1	10.2
P-M	15.1	27.3

DPD, NHRH ≥90 %, and P-M, which agrees with the results obtained in Balm with data from the FAWN station. This result indicates that estimated net radiation and differences on precision of relative humidity sensors have a substantial impact on P-M performance. In Piketon, Ohio, where the relative humidity sensor is the same model as the one deployed at the reference station in Balm, Florida, P-M had the smallest MAE.

CART was the most robust model to estimate LWD and the risk of anthracnose and Botrytis control, whereas P-M was the worst, which is partially associated to the errors in net radiation when estimated by an empirical model. According to Gillespie and Sentelhas (2008), the Iziomon et al.'s (2000) approach to estimate net radiation might need local adjustments for latitudes lower than 40°.

Weather data reliability is crucial for LWD estimation and for disease-warning systems operation (Gleason et al. 2008). Our study shows that if the weather station data is imprecise, a more robust LWD model such as CART should be used, since P-M was highly sensitive to data uncertainty, leading to error propagation. DPD also had robust performance to estimate LWD across locations but, in general, had large number of false-positive alerts, which decreased its potential for application with disease-warning systems rationale. A final consideration is that LWD measurements were used as the gold standard in our evaluations, because LW sensors were treated, calibrated in field conditions, and correctly deployed. These conditions are unusual, and thus, LWD models can be a preferred alternative to substitute for LWD measurements, as shown in this study.

Conclusions

The P-M model is the best option to estimate LWD when a weather station is assembled with high precision sensors, mimicking the processes of wetness onset and dry-off and allowing precise recommendation of anthracnose and Botrytis fruit rot control. However, P-M is highly sensitive to weather data quality, making its use restricted, mainly where net radiation data is not available and relative humidity sensors are not highly precise, with precision greater than ±2 %. In this case, the CART model showed to be the best option to estimate LWD and also to recommend anthracnose and Botrytis control across different sites in the USA.

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