Citrus Section

Proc. Fla. State Hort. Soc. 133:55–58. 2020.

Performance of Leaf Wetness Sensors for Applicability In Decision-support Systems for Management of Citrus, Blueberry, and Strawberry Diseases

Andre B. Gama[1], Megan M. Dewdney[1], Clyde Fraisse[2], and Natalia A. Peres[3]*

[1]*Citrus Research and Education Center, University of Florida IFAS, 700 Experiment Station Rd., Lake Alfred, FL 33850*

[2]*Agricultural and Biological Engineering, University of Florida IFAS, 1741 Museum Rd., Gainesville, FL 32603*

[3]*Gulf Coast Research and Education Center, University of Florida IFAS, 14625 County Rd. 672, Wimauma, FL 33598*

Additional index words. disease alert systems, disease management, disease risk assessment, leaf wetness duration sensors, disease alert systems, disease management, weather stations

Disease Alert Systems (DAS) in the Agroclimate decision-support system provide site-specific information to aid citrus, blueberry, and strawberry growers to decide when a fungicide application would be required. All of these DAS use disease models based on temperature and leaf wetness (LW) duration data to predict when weather conditions are favorable for disease development and control measures are needed. Daily environmental data are obtained from the weather stations of the Florida Agricultural Weather Network (FAWN). Previous research has shown that the electrical resistance-based Campbell 237-L leaf wetness (LW) sensors provide reliable data. However, they require painting and in-situ calibration, which is not easily done by growers. Conversely, Decagon LW dielectric sensors come ready to use by the manufacturer, with pre-established thresholds for wet and dry conditions. However, their performance in the field is uncertain. We compared the LW estimations provided by Campbell 237-L and Decagon dielectric sensors installed in the same station in Plant City, Florida. We performed comparisons of every sensor combination using 15-minute observations and maximum daily LW duration. The sensors of the same manufacturer had high (> 0.90) Pearson's correlation coefficient (Pc), low (< 1.0) mean absolute error (MAE), and high *k* agreement indices (> 0.9), which indicate a strong correlation. However, when comparing Campbell and Decagon sensors, the precision was lower as indicated by Pc of approximately 0.8, MAE around 2.0 hours, and k-indices around 0.8. Nevertheless, the estimations MAE were within the acceptable range for DAS applicability. Decagon dielectric sensors could be used in the FAWN weather stations to provide reliable LW estimations.

Disease Alert Systems (DAS) intended for plant disease management routinely use leaf wetness (LW) as input for disease risk calculations. LW can be estimated by sensors specifically built for that purpose or by mathematical models that use commonly observed weather variables, most often relative humidity. There is a wide array of different LW sensors available in the market and no standardized way to measure LW in the field (Rowlandson et al. 2015). Two types of LW sensors are used in weather stations in the Florida Automated Weather Network (FAWN) that provide information to DAS—the Decagon LW dielectric sensor (Decagon Devices Inc., Pullman, WA) and the electrical resistance-based Campbell 237-L sensors (Campbell Scientific, Logan, UT). Each sensor has benefits and drawbacks in comparison to the other. For instance, the Decagon LW dielectric sensors have the advantage of being calibrated and painted by the manufacturer. The electrical resistance-based Campbell 237-L sensors provide reliable LW estimations (Sentelhas et al. 2004a) and have been functional for more than ten years after installation (Peres, personal observation). The drawback of Decagon dielectric sensors was their low durability. In previous trials, it was observed that older models were functional for approximately one to two years in Florida fields (Peres and Fraisse, personal observation). However, it is our understanding that Decagon has since made improvements to its sensors. The Campbell 237-L leaf wetness sensors have the disadvantage of not being painted by the manufacturer and requiring an in-situ calibration that cannot be easily performed by growers. Painting provides more precise wetness estimations by responding better to the onset and offset of wetness, and thus, it is recommended when integrating LW sensors into a DAS (Gillespie and Kidd 1978; Sentelhas et al. 2004b; Sentelhas et al. 2008). Calibration of these sensors can be performed in the field or the laboratory. Briefly, laboratory calibration is done by applying droplets of water to the sensor and registering the electric resistance values provided by the sensor (Sentelhas et al. 2004a). Field calibration requires on-site observations of dew onset and offset so a resistance threshold that distinguishes wet and dry is established (Rao et al. 1998). The establishment of resistance thresholds is essential for the use of Campbell 237-L

We thank Juliana S. Baggio for valuable suggestions for this manuscript.

*Corresponding author. Email: nperes@ufl.edu

sensors since we have observed a significant variation in the values below which a sensor considers a resistance observation as wet (Montone 2013). Given the advantages and disadvantages of each sensor and the importance of LW for DAS, the objective of this study was to compare the LW estimations of the recently improved Decagon dielectric sensors to those of Campbell 237-L sensors over three years in Florida.

Materials and Methods

Weather stations and data acquisition. All the sensors were located in the same weather station installed in Plant City, Fla. This weather station is maintained by FAWN, and data were retrieved from its database. The weather station was equipped with four LW sensors, two Decagon dielectric, and two Campbell 237-L sensors. The sensors were placed approximately 10 cm from each other at 30 cm over turfgrass and installed at a 45º angle. The two sets of Campbell and Decagon sensors were positioned adjacent to each other and installed on a PVC pipe bar centered at the base of the automated weather station. One set of sensors was placed equidistantly to the left and the other one to the right of the weather station. Leaf wetness (LW) data were acquired every 15 min. from 26 July 2017 to 29 Jan. 2020. A total of 88,096 observations for each of the four sensors was recorded for the analysis.

The comparison between sensors was performed based on a methodology adapted from Montone et al. (2016) and Kim et al. (2004). Comparisons were performed in pairs for every possible combination: Campbell sensor 1 vs. Campbell sensor 2; Decagon sensor 1 vs. Decagon sensor 2; Decagon sensor 1 vs. Campbell sensor 1; Decagon sensor 2 vs. Campbell sensor 1; Decagon sensor 1 vs. Campbell sensor 2; and Decagon sensor 2 vs. Campbell sensor 2.

Linear regression analysis, determination of Pearson's correlation coefficients, mean square error (MSE), and mean absolute error (MAE). Pairwise linear regression analyses were performed for every combination of sensors. When comparing different sensors, data from Campbell 237-L sensors were considered the standard and plotted on the x-axis of the regression. Maximum daily LW duration data for each sensor were considered for this analysis, which totaled 931 data points (days) for each sensor. The slope, intercept, coefficient of determination (R^2), and statistical significance level (*P*-value) were calculated for each combination of sensors. Pearson's correlation coefficients were also calculated for data obtained for each of the combinations of sensors described previously. The significance level for the correlation was also calculated. Daily LW duration values were also used to calculate the mean square error (MSE) and mean absolute error (MAE) of the relationship as done previously in a similar study (Montone et al. 2016). The errors were calculated in the unit of hours and hours^2 for MAE and MSE, respectively.

Contingency table and k agreement indices calculations. Every observation acquired at 15-min intervals was used for this step of the comparison. The data obtained by the Campbell 237-L sensors were considered the standard for this analysis when they were compared to Decagon dielectric sensors, as Campbell 237-L sensors were calibrated based on visual observations in a site-specific manner and were known to provide good LW estimations from previous research (Montone et al. 2016). Six four-cell contingency tables were designed, one for every pairwise comparison of the combinations previously described. The tables had true positives for wetness (W), true negative for wetness (i.e., dry – D), false positive (i.e., false wet – FW), and false negative (i.e., false dry – FD). The number of W, D, FD, and FW events was calculated in the unit of hours, as done for MAE. After the tables were designed, a *k* agreement index (Dietterich 2000) was calculated for each comparison of sensors. The equations below (Eq. 1, Eq. 2, and Eq. 3) describe how the *k* agreement index and its components were calculated.

$$\theta_1 = \frac{W + D}{W + D + FW + FD} \qquad \text{[Eq. 1]}$$

$$\theta_2 = \frac{(W + FD) * (W + FW)}{(W + FD + FW + D)^2} + \frac{(FW + D) * (FD + D)}{(W + FD + FW + D)^2} \qquad \text{[Eq. 2]}$$

$$k = \frac{\theta_1 - \theta_2}{1 - \theta_2} \qquad \text{[Eq. 3]}$$

In which:

θ_1 = fraction of correct estimations,
W = true positives for wetness,
D = true negative for wetness, i.e., dry events,
FW = positive (i.e., false wet—FW),
FD = false negative (i.e., false—FD),
θ_2 = estimate of the probability that the LW estimations agree by chance, based on the contingency table counts,
k = *k* agreement index.

Results

The agreement between sensors of the same manufacturer (Campbell 1 vs. Campbell 2 and Decagon 1 vs. Decagon 2) was very good (Fig 1A and B, Table 1). The coefficient of determination (R^2) was 0.96 and 0.83 for the comparisons between Campbell and Decagon sensors, respectively (Fig 1-A, 1-B, Table 1). When comparing Decagon and Campbell sensors, however, the agreement was not as good (Fig. 1, Table 1). The R^2 of the relationships between Campbell and Decagon sensors ranged from 0.60–0.64 (Fig. 1C–F, Table 1). When comparing the regression line between the data points obtained from Campbell and Decagon sensors, an overestimation of LW duration by Decagon sensors in relation to the Campbell ones was revealed, especially at maximum daily LW duration lower than 20h (Fig. 1C–F). At approximately 30 h of LW duration, a slight shift towards underestimation was observed (Fig. 1C–F). Pearson's correlation coefficients for the sensor comparisons from the same manufacturer were high, both above 0.9 (Table 1). When comparing sensors from different manufacturers, the correlation coefficients were all approximately 0.8 (Table 1). Similarly, MAE estimations were low when comparing sensors from the same manufacturer, all below 1 h (Table 1). However, MAE increased to about 2.2 h when compared the different sensors (Table 1). The same pattern was observed for *k* agreement indices. Comparisons between Campbell sensors and Decagon sensors had very high *k* agreement indices of 0.96 and 0.92,

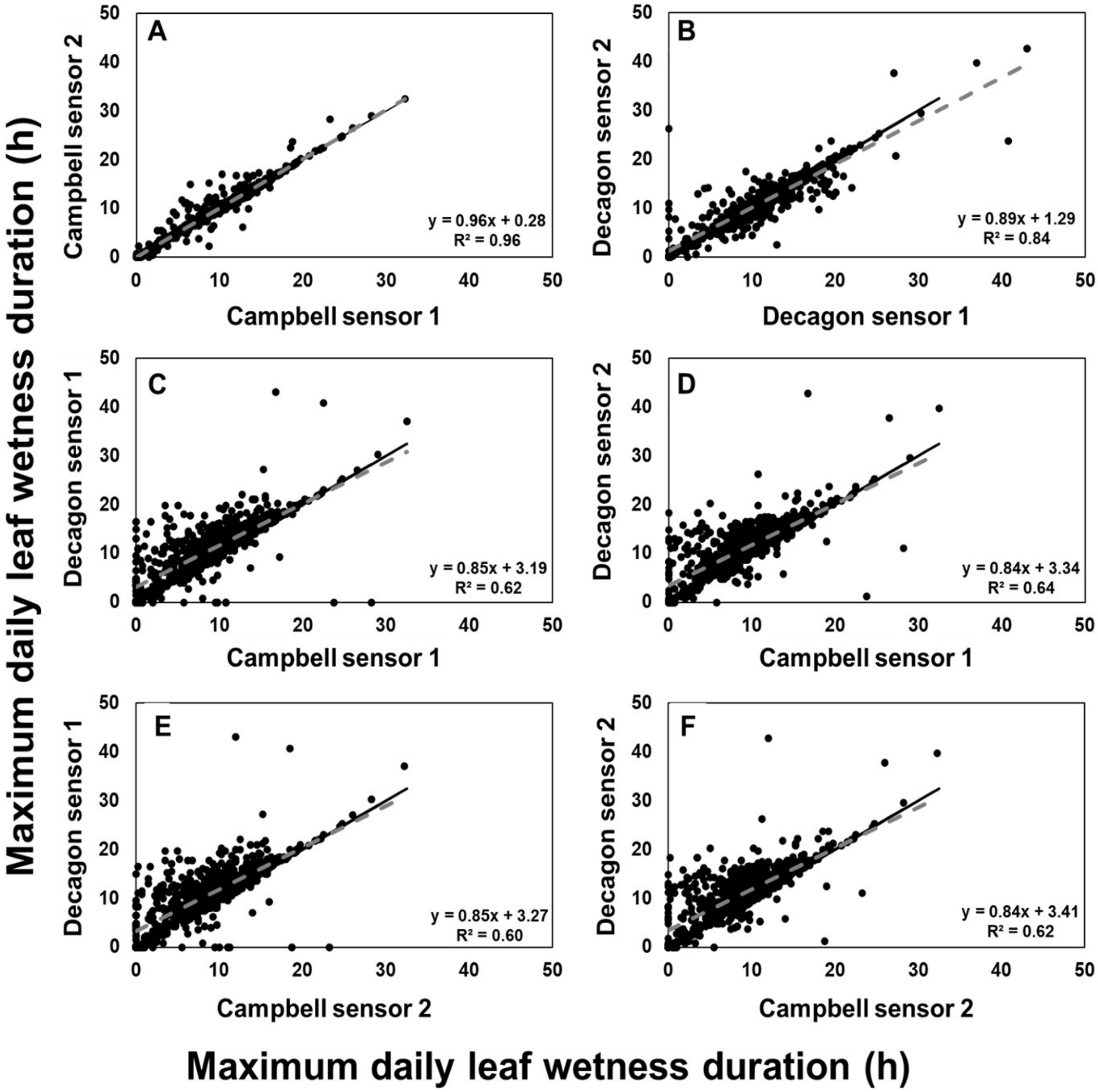

Fig. 1. Linear regression (gray dashed line) analysis between maximum daily leaf wetness duration (in hours) estimated by Campbell 237-L sensor 1 and Campbell 237-L sensor 2 (**A**), Decagon dielectric sensor 1 and Decagon dielectric sensor 2 (**B**), Campbell 237-L sensor 1 and Decagon dielectric sensor 1 (**C**), Campbell 237-L sensor 2 and Decagon dielectric sensor 1 (**D**), Campbell 237-L sensor 1 and Decagon dielectric sensor 2 (**E**), and Campbell 237-L sensor 2 and Decagon dielectric sensor 2 (**F**). The continuous black line represents the perfect agreement line (i.e., a R^2 of 1.0).

Table 1. Pearson's correlation coefficient (Pc), coefficient of determination of the linear regression (R^2), intercept and slope of the linear regression, and their respective estimation significance levels (*P* value) related to the comparison between Campbell 237-L and Decagon dielectric leaf wetness sensors. Mean square error (MSE), mean absolute error (MAE), and *k* agreement index of leaf wetness data acquired at 15-minute intervals by different sensors, specified in the comparison column.

	Correlation		Linear regression							*k* agreement
Comparison	Pc	*P* value	R^2	Intercept	*P* value	Slope	*P* value	MSE[z]	MAE[z]	index[y]
Campbell 1 vs. Campbell 2	0.98	< 0.0001	0.96	0.28	< 0.0001	0.96	< 0.0001	0.91	0.42	0.96
Decagon 1 vs. Decagon 2	0.92	< 0.0001	0.84	1.29	< 0.0001	0.89	< 0.0001	4.19	0.96	0.92
Campbell 1 vs. Decagon 1	0.80	< 0.0001	0.62	3.19	< 0.0001	0.85	< 0.0001	13.46	2.20	0.81
Campbell 1 vs. Decagon 2	0.80	< 0.0001	0.64	3.34	< 0.0001	0.84	< 0.0001	12.53	2.12	0.80
Campbell 2 vs. Decagon 1	0.77	< 0.0001	0.60	3.27	< 0.0001	0.85	< 0.0001	14.54	2.35	0.80
Campbell 2 vs. Decagon 2	0.79	< 0.0001	0.62	3.41	< 0.0001	0.84	< 0.0001	13.52	2.26	0.80

[z]Calculated based on the difference between daily maximum wetness duration estimated by each combination of sensors

[y]Calculated according to the methodology developed by Dietterich (2000).

respectively (Table 1). The *k* agreement indices of comparisons made between Campbell and Decagon sensors were all approximately 0.8 (Table 1). Our results do not indicate any loss in precision for the two types of sensors over the course of the three years of data analyzed in this study.

Discussion

While the Campbell 237-L sensors are the gold standard, the Decagon sensors can be viable options for weather stations used for plant disease risk calculation based on our results. These sensors provide LWD estimation within the acceptable MAE margin for application in DAS of approximately 2 h (Sentelhas et al. 2008) compared to in-situ calibrated Campbell 237-L sensors. The convenience of being painted and calibrated with a pre-established LW threshold makes the Decagon dielectric sensors suitable options to be installed in FAWN or grower-owned weather stations. The comparisons of the four sensors yielded very similar regression equations and results. The analysis of three-years of data was important to verify the durability of the sensors, i.e., to confirm if the measurements would lose accuracy over time. Growers and researchers should keep monitoring the data from weather stations to identify erroneous data in DAS, especially during critical periods for plant disease management in Florida.

In Florida, the Agroclimate decision-support system contains three DAS, intended for strawberry, citrus, and blueberry growers (Fraisse et al. 2016; Gama et al. 2021; Pavan et al. 2011; Perondi et al. 2020). They all rely on LW data to calculate and provide daily disease risk assessments to growers. LW sensors must be reliable when feeding information to the DAS once the implementation of disease management practices must be deployed as promptly as possible to maximize efficacy. It is also desirable for sensors to be durable to provide results for more than one season. Our results could be used by growers, extension specialists, and stakeholders when deciding which LW sensor to install in weather stations used for DAS application in Florida.

Literature Cited

Dietterich T.G. 2000. An experimental comparison of three methods for constructing ensembles of decision trees: Bagging, boosting, and randomization. Mach Learn 40:139–157.

Fraisse, C., J.H. Andreis, T. Borba, V. Cerbaro, E. Gelcer, W. Pavan, D. Pequeno, D. Perondi, X. Shen, C. Staub, O. Uryasev, and A.P. Wagner. 2016. AgroClimate—tools for managing climate risk in agriculture. Agrometeoros 24:121–129.

Gama, A.B., L.G., Cordova, C.S. Rebello, and N.A. Peres. 2021. Validation of a decision-support system for blueberry anthracnose and fungicide sensitivity of Colletotrichum gloeosporioides isolates. Plant Dis. https://doi.org/10.1094/PDIS-09-20-1961-RE.

Gillespie, T.J. and G.E. Kidd. 1978. Sensing duration of leaf moisture retention using electrical impedance grids. Can. J. Plant Sci. 58:179–187.

Kim, K.S., S.E. Taylor, and M.L. Gleason. 2004. Development and validation of a leaf wetness duration model using a fuzzy logic system. Agric. For. Meteoro. 127:53–64.

Montone, V.O. 2013. Leaf wetness duration modeling and spatialization to optimize fungicide application in strawberry production systems. M.S. Thesis, Univ. of Florida, Gainesville.

Montone, V.O., C.W. Fraisse, N.A. Peres, P.C. Sentelhas, M. Gleason, M. Ellis, and G. Schnabel. 2016. Evaluation of leaf wetness duration models for operational use in strawberry disease-warning systems in four US states. Int. J. Biometeorol. 60: 1761–1774.

Pavan, W., C.W. Fraisse, and N.A. Peres. 2011. Development of a web-based disease forecast system for strawberries. Comput. Electron. Agric. 75:169-175.

Perondi, D., C.W. Fraisse, M.M. Dewdney, V.A. Cerbaro, J.H.D. Andreis, A.B. Gama, G.J. Silva Jr., L. Amorim, W. Pavan, and N.A. Peres. 2020. Citrus advisory system: A web-based postbloom fruit drop disease alert system. Comput. Electron. Agric. https://doi.org/10.1016/j.compag.2020.105781.

Rao, P.S., T.J. Gillespie, and A.W. Schaafsma. 1998. Estimating wetness duration on maize ears from meteorological observations. Can. J. Soil Sci. 78:149–154.

Rowlandson, T., M. Gleason, P. Sentelhas, T. Gillespie, C. Thomas, and B. Hornbuckle. 2015. Reconsidering leaf wetness duration determination for plant disease management. Plant Dis. 99:310–319.

Sentelhas, P.C., T.J. Gillespie, M.L. Gleason, J.E.B.A. Monteiro, and S.T. Helland. 2004a. Operational exposure of leaf wetness sensors. Agric. For. Meteorol. 126:59–72.

Sentelhas, P.C., J.E.B.A. Monteiro, and T.J. Gillespie. 2004b. Electronic leaf wetness duration sensor: Why it should be painted. Int. J. Biometeorol. 48:202–205.

Sentelhas, P.C., A. Dalla Marta, S. Orlandini, E.A., Santos, T. J. Gillespie, and M.L. Gleason. 2008. Suitability of relative humidity as an estimator of leaf wetness duration. Agric. For. Meteorol. 148:392–400.