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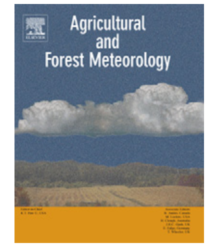

Suitability of relative humidity as an estimator of leaf wetness duration

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ABSTRACT

Leaf wetness duration (LWD) is a key parameter in agricultural meteorology since it is related to epidemiology of many important crops, controlling pathogen infection and development rates. Because LWD is not widely measured, several methods have been developed to estimate it from weather data. Among the models used to estimate LWD, those that use physical principles of dew formation and dew and/or rain evaporation have shown good portability and sufficiently accurate results, but their complexity is a disadvantage for operational use. Alternatively, empirical models have been used despite their limitations. The simplest empirical models use only relative humidity data. The objective of this study was to evaluate the performance of three RH-based empirical models to estimate LWD in four regions around the world that have different climate conditions. Hourly LWD, air temperature, and relative humidity data were obtained from Ames, IA (USA), Elora, Ontario (Canada), Florence, Toscany (Italy), and Piracicaba, São Paulo State (Brazil). These data were used to evaluate the performance of the following empirical LWD estimation models: constant RH threshold (RH $\geq$ 90%); dew point depression (DPD); and extended RH threshold (EXT_RH). Different performance of the models was observed in the four locations. In Ames, Elora and Piracicaba, the RH $\geq$ 90% and DPD models underestimated LWD, whereas in Florence these methods overestimated LWD, especially for shorter wet periods. When the EXT_RH model was used, LWD was overestimated for all locations, with a significant increase in the errors. In general, the RH $\geq$ 90% model performed best, presenting the highest general fraction of correct estimates (F_C), between 0.87 and 0.92, and the lowest false alarm ratio (F_{AR}), between 0.02 and 0.31. The use of specific thresholds for each location improved accuracy of the RH model substantially, even when independent data were used; MAE ranged from 1.23 to 1.89 h, which is very similar to errors obtained with published physical models for LWD estimation. Based on these results, we concluded that, if calibrated locally, LWD can be estimated with acceptable accuracy by RH above a specific threshold, and that the EXT_RH method was unsuitable for estimating LWD at the locations used in this study.

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1. Introduction

The presence of water on plant surfaces impacts in many biophysical processes, such as the spread of fungal and bacterial diseases, deposition of atmospheric pollutants, leaf gas exchange, and survival of some insects (Weiss, 1990; Huber and Gillespie, 1992; Brewer and Smith, 1997; Klemm et al., 2002). Concerning crop protection applications, leaf wetness duration (LWD) is a driving variable in epidemiological models for simulating risk of crop damage from many plant diseases. Grapevine downy mildew (*Plasmopara viticola*), apple scab (*Venturia inaequalis*), cercospora leaf spot (*Cercospora beticola*), wheat ear rot (*Fusarium graminearum*) and rice blast (*Pyricularia oryzae*) are examples of diseases for which simulation models based on LWD are used (Hoppmann, 1996; Luo and Goudriaan, 2000).

Leaf wetness may be caused by rain, fog, irrigation, dewfall from the atmosphere, or distillation from the soil. Dew, often the main contributor to leaf wetness, normally occurs by turbulent transfer during nighttime, when the surface on which deposition takes place is colder than the dew point of the surrounding air (Monteith, 1957). This process is the result of radiative loss of heat from plant surfaces to a clear sky during calm nights. Nocturnal radiative loss probably represents the most important factor involved in the condensation of dew, and for this reason it is an input for many physical models simulating leaf wetness occurrence and duration (Luo and Goudriaan, 2000).

Even though the dew condensation process can be easily described from a physical point of view, LWD is a difficult variable to measure since it is the result of interactions among leaf position and arrangement, canopy structure and the atmosphere. Depending on the physical properties of the leaf surface, such as concentration of stomata and trichome density, wettability characteristics can differ, allowing water to form in small individual droplets or as a continuous layer of variable thickness (Brewer and Smith, 1997). Leaf wetness duration within a canopy is also determined by plant structure, architecture and height (Huber and Gillespie, 1992; Dalla Marta et al., 2005a; Sentelhas et al., 2005). These complex interactions are not taken into account when LWD is measured by electronic sensors mounted in standard agrometeorological stations placed outside crop field. On the other hand, the measurement of crop LWD directly by installing sensors inside the crop field can be subject to uncertainties depending on sensor position in the canopy, angle of deployment and interaction with surrounding leaves (Lau et al., 2000; Dalla Marta et al., 2004; Sentelhas et al., 2004a).

Many efforts have been made to overcome the problem of LWD measurement. Since the 1980s simulation models have been developed following different approaches. Models can be divided into two broad categories – empirical (Gleason et al., 1994; Rao et al., 1998; Kim et al., 2002) and physical (Pedro and Gillespie, 1982; Bass et al., 1991; Luo and Goudriaan, 2000; Magarey et al., 2006; Sentelhas et al., 2006) – based on both agrometeorological and crop criteria. Further attempts have been made using mixed approaches such as Neural Networks, a distributed information processing system (Francl and Panigrahi, 1997; Chtioui et al., 1999; Dalla Marta et al., 2005b), and fuzzy logic, in which physical principles can be incorporated into empirical models (Kim et al., 2004, 2005).

Physical models are based on energy balance principles. Energy available for condensation and evaporation processes is calculated using net radiation or cloud cover data, to determine sensible and latent heat fluxes (Pedro and Gillespie, 1982; Weiss, 1990; Madeira et al., 2002; Magarey et al., 2006; Sentelhas et al., 2006). Models based on physical principles can be very accurate, as well as portable to different geographical and climatic areas. However, for some situations this kind of model is too complex, requiring inputs that are not always available. For example, instrumentation to measure net radiation can be expensive and difficult-to-maintain. Alternatively, net radiation may be estimated by complex methods which are not always accurate (Dalla Marta et al., 2005a; Sentelhas and Gillespie, 2008), since they have input variables such as cloud cover, which is based on visual observations and, consequently, affected by estimation errors. In addition, performance of physical LWD models is often degraded by insufficient accuracy of their inputs (Kim et al., 2005).

In contrast, empirical models can simulate LWD by using simple relationships of this variable with parameters measured at standard agrometeorological stations. Their success depends on the accuracy of the weather data used as inputs and they are more site-specific than physical models (Huber and Gillespie, 1992; Kim et al., 2005).

Models based on the number of hours with relative humidity (RH) above a specific threshold are the most common empirical LWD estimation models. However, assessments of these models have yielded varying results. Gleason et al. (1994), comparing LWD measured by wetness sensors and estimated by RH $\geq$ 90%, found that the error associated with this empirical model was 40% greater than error obtained when they used the CART (classification and regression tree) model, which also uses dew point depression (DPD) and wind speed (U) data. Similar results were found by Francl and Panigrahi (1997) for a wheat crop. On the other hand, Rao et al. (1998), estimating LWD for corn ears in Canada, and Sentelhas et al. (2004b), estimating LWD for a cotton crop in Brazil, showed that wetness duration estimates from simple threshold models based on RH were as accurate as estimates from more complex physical models. Gillespie et al. (1993) also found good results when estimating LWD by a dew point depression model.

Kim et al. (2005) evaluated the portability of two LWD empirical models, based on CART (Gleason et al., 1994; Kim et al., 2002) and fuzzy logic (Kim et al., 2004) techniques, from a temperate (mid-western US) to a tropical (north-western Costa Rica) climate. The results demonstrated that the CART model was not exportable to the new sites whereas the fuzzy logic model underestimated LWD during the dry season, due mainly to errors in estimating net radiation. Sentelhas et al. (2004b), using the same CART model, found that it performed well during the wet season in southeastern Brazil.

Wichink Kruit et al. (2004) compared four LWD estimation models in the Netherlands. Two were based on physical models proposed by Garratt and Segal (1988) and Pedro and Gillespie (1982), whereas the other two were based on a simple RH threshold (87%) and an extended RH threshold, which uses a base threshold, 87%, that is extended according to the change in RH with time. The results demonstrated that, for their experimental conditions, the extended RH threshold model gave the best performance, increasing the proportion of correct estimates to almost 90% of hours assessed.

Results of these studies emphasized that performance of empirical models varies from place to place, and therefore that they require specific calibration according to the climate of the region. Consequently, it was hypothesized that a specific RH threshold, calibrated locally, could provide an accurate estimate of LWD when compared to observed data. To test our hypothesis, the following goals were set: (a) evaluate the ability of three simple RH-based empirical models to estimate LWD in four locations around the world, and (b) calibrate and test the best of them for each region.

2. Materials and methods

2.1. *Leaf wetness duration measurements*

Leaf wetness duration measurements over turfgrass were done with different sensors, according to the location. Flat plate sensors (Model 237, Campbell Scientific, Logan, UT (Gillespie and Kidd, 1978)) and electronic transducer sensors (S.W. and W.F. Burrage, Ashford Kent, UK (Dalla Marta et al., 2007)), were used. All sensors were previously tested and calibrated under laboratory and field conditions. These sensors were connected to dataloggers (Models CR10, 21X and CR23X, Campbell Scientific, Logan, UT; Delta-T Devices DL2, Burwell, Cambridge, UK) and programmed to measure the percentage of time in which the sensors were wet during each interval of time, which ranged from 10 to 60 min depending on the location. Flat plate sensors used in this study were painted with two or three coats of off-white latex paint to increase their ability to detect small amounts of wetness, and heat-treated (60–70 °C for 12 h) to remove or deactivate hygroscopic components of the paint. The electronic transducer sensor uses the same electrical resistance principle as the flat plate sensor, but has a different shape. This sensor has an active area of 450 cm^2, consisting of three graphite electrodes separated by a rough surface of waterproof resin. The threshold logger reading for each LWD sensor was determined in a laboratory; values smaller than or equal to this threshold were considered wet (1), whereas greater values were considered dry (0). Each LWD sensor was mounted on a section of PVC or metal tubing, with an inclination angle of 30–45°, and facing north in the Northern Hemisphere and south in the Southern Hemisphere.

Both kinds of LWD sensors were used as references for comparisons with models, since Pedro (1980), Lau et al. (2000), Sentelhas et al. (2004a) and Dalla Marta et al. (2004) showed that the differences between their measurements and visual observations of wetness duration were around 15–30 min, confirming their accuracy for measuring LWD in field conditions.

2.2. *Field experiments*

The field experiments were conducted over mowed turfgrass in the following locations where LWD was measured:

(a) Ames, IA, USA (42°01′N, 93°46′W) – flat plate LWD sensors were installed at 30-cm height facing north with an inclination angle of 45°, from 27 July to 7 October 2003, totaling 72 days of measurements.
(b) Elora, Ontario, Canada (43°49′N, 80°35′W) – flat plate LWD sensors were installed at 30-cm height facing north with a inclination angle of 30°, from 28 July to 7 October 2003, and from 24 July to 24 September 2004, totaling 118 days of measurements.
(c) Florence, Toscany, Italy (43°45′N, 11°21′E) – electronic transducer LWD sensors were installed at 120-cm height facing north with a inclination angle of 45°, from 16 May to 5 July 2003, and from 22 May to 20 August 2004, totaling 120 days of measurements.
(d) Piracicaba, São Paulo, Brazil (22°42′S, 47°30′W) – flat plate LWD sensors were installed at 30-cm height and deployed facing south at an inclination angle of 45°, from 12 July 2005 to 21 March 2006, totaling 183 days of measurements.

At each location LWD was measured by two sensors and the average of their output was used for analysis. At each site, a nearby standard automatic weather station was installed over turfgrass to measure air temperature (T) and relative humidity (RH) between 1.5 and 2.0 m above the ground, with a calibrated T and RH probe (model HMP35A, Vaisala). Time intervals for measuring these variables and LWD were: 60 min in Ames, 15 min in Elora and Piracicaba, and 10 min in Florence. The differences of periods of measurements, seasons, measurement intervals and LWD sensors among sites occurred because in this study we used the infrastructure and data available for each place. As our purpose was not to compare LWD between locations, these differences were not a problem for our analyses.

The climate conditions at each location during the monitoring periods are presented in Table 1.

2.3. *LWD models*

Temperature and RH data were used to estimate LWD according to the following empirical models:

2.3.1. *Constant RH threshold (RH ≥ 90%)*

This method assumes that LWD is equal to the number of hours with RH greater than or equal to a constant threshold. It was developed from observations that condensation on grass cover began before saturation in the air was reached, when relative humidity ranged from 91% to 99% (Monteith, 1957). This author implied that the leaves were colder than air and condensation began when leaf temperature reached the dew point of surrounding air. Different values of the threshold have subsequently been tried; for our study we initially chose a constant value of RH = 90% as the threshold for wetness presence at all sites.

2.3.2. *Dew point depression (DPD)*

The difference between T and dew point temperature (T_d) is the dew point depression (DPD) which has also been suggested as a LWD estimator by Huber and Gillespie (1992) and Gillespie et al. (1993), based on the same observations done by Monteith (1957) in relation to RH. Duration of wetness is estimated as the

Table 1 – Average climatic conditions during the field experiments in Ames (USA), Elora (Canada), Florence (Italy), and Piracicaba (Brazil)

Location	Year	Period (day/month)	T (°C)	RH (%)	R (mm)	RD (days)	U_{2m} (m s^{-1})
Ames	2003	23/07–07/10	20.5	75.1	197	18	3.0
Elora	2003	28/07–07/10	16.0	83.1	344	30	1.8
Elora	2004	24/07–24/09	17.8	80.3	133	21	0.8
Florence	2003	16/05–05/07	22.2	70.0	52	8	2.2
Florence	2004	22/05–20/08	23.9	64.4	65	10	1.3
Piracicaba	2005/2006	12/07–21/03	22.1	77.0	609	89	1.2

T, mean air temperature; RH, mean relative humidity; R, total rainfall; RD, rainy days; U_{2m}, mean wind speed.

length of time that DPD remains between two specific limits. The wetness criteria for this study were DPD $\leq$ 1.8 °C for wetness onset and DPD $\geq$ 2.2 °C for wetness dry-off (Rao et al., 1998).

2.3.3. *Extended RH threshold (EXT_RH)*

This method, proposed by Wichink Kruit et al. (2004), uses a base RH threshold of 87%, and wetness is extended to lower humidity ranges depending on the rate of change in RH. For periods with RH between 70% and 87%, leaves are assumed to be wet if average RH increases more than 3% in 30 min, and leaves are assumed to become dry if average RH decreases more than 2% in 30 min. During periods with average RH < 70% leaves are assumed to be dry, and during periods with average RH > 87% leaves are assumed to be wet.

2.4. *Data analysis*

Daily measured and estimated LWD data were created by considering 24-h periods that began at 12:01 and ended at noon (12:00) the next day.

To evaluate performance of the empirical methods in estimating daily LWD, observed and estimated LWD data were compared by regression analysis [linear (a) and angular (b) coefficients, and coefficient of determination (R^2)] and by the Willmott agreement index (D). Also, a confidence index (C) was calculated as the product of the root square of R^2, which expresses the precision of the estimates, and D, which expresses their accuracy (Camargo and Sentelhas, 1997). The estimation errors were also determined: mean error (ME), which describes the direction of the error bias, and mean absolute error (MAE), which indicates the magnitude of the average error.

LWD data were also analyzed considering each interval of time in order to quantify the proportion of intervals (10, 15, and 60 min) that were correctly classified as wet or dry, using a contingency table (Wilks, 1995), as presented below:

	Estimated—Yes	Estimated—No
Observed—Yes	Hits (X)	Misses (Y)
Observed—No	False alarms (W)	Correct negatives (Z)

If a method correctly estimated wetness presence in an interval of time, it was scored in box X. If a method failed to estimate wetness when it did occur, it was scored in box Y. If a method estimated wetness when it did not occur, it was scored in box W. Finally, if a method correctly estimated absence of wetness, it was scored in box Z. With the total of events in each box for a given model, the following statistical scores were obtained: fraction of correct estimates (F_C); correct success index (C_{SI}); false alarm ratio (F_{AR}); and bias (B_S).

$$F_C = \frac{X + Z}{X + Y + W + Z}$$

$$C_{SI} = \frac{X}{X + Y + W}$$

$$F_{AR} = \frac{W}{X + W}$$

$$B_S = \frac{X + W}{X + Y}$$

F_C varies from 0 to 1, and for the most accurate model it should be as high as possible. C_{SI} also varies from 0 to 1, but does not consider the correct negatives (Z), focusing instead on discriminating between event and non-event. F_{AR} varies from 0 to 1, and should be as small as possible. Finally, $B_S < 1$ indicates underestimation, $B_S > 1$ overestimation, and $B_S = 1$ no tendency (LW hours estimated = LW hours measured).

The model that provided the best general performance was then calibrated locally by selecting a specific threshold that gave the best results at each site. The statistical analyses previously described were applied to evaluate its performance for each location. The process of calibration to find the best RH threshold for each location was performed iteratively, considering R^2, D and C indices, and mean absolute error (MAE) as parameters.

To validate the RH thresholds, independent LWD and RH data were used. These data were obtained with the same sensors described previously in experiments carried out at the same sites: Ames (1998/1999 – totaling 218 days); Elora and Ridgetown (2006 – totaling 101 days); Florence (2005 – totaling 73 days); and Piracicaba (2002/2003 – totaling 108 days). For the validation process, measured and estimated LWD data were compared by regression analysis, considering the same statistical indices and errors described earlier: R^2, D, C, ME, and MAE.

3. Results

3.1. *Daily comparisons*

The empirical models performed differently in each location. In Ames, all three models performed unsatisfactorily. There

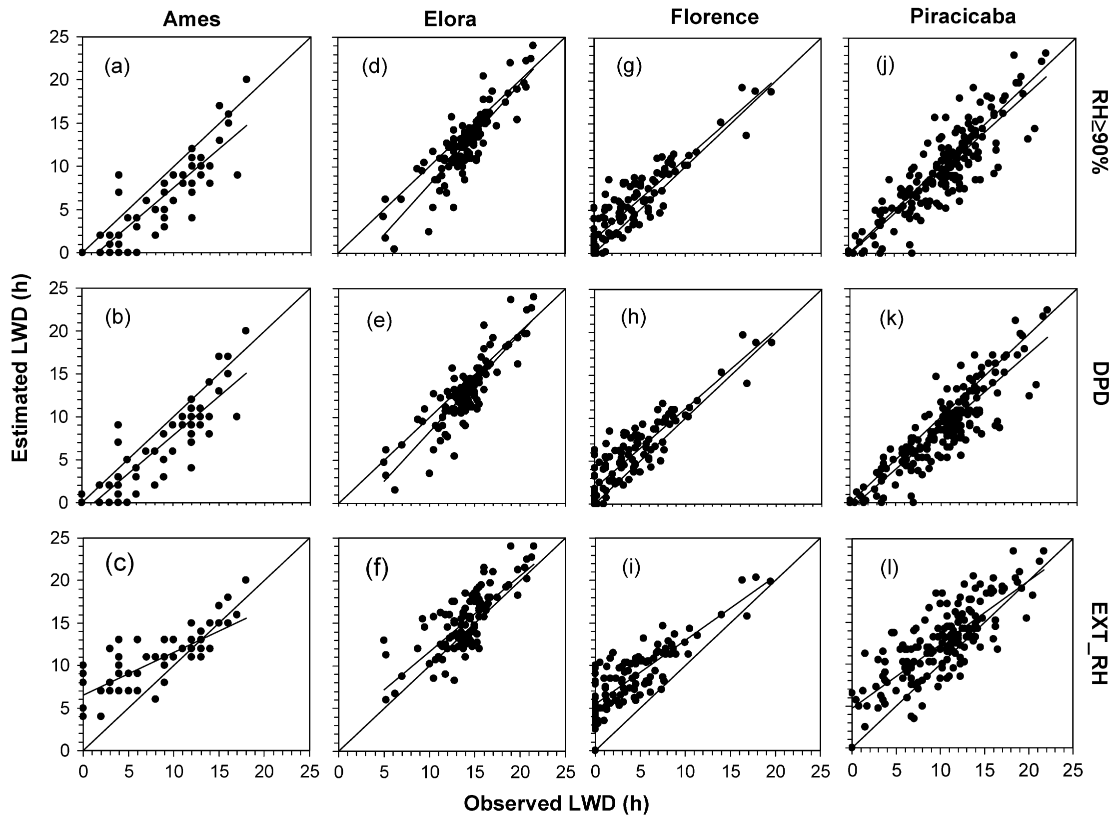

Fig. 1 – Relationship between LWD measured and estimated by empirical models in Ames, USA (a)–(c), Elora, Canada (d)–(f), Florence, Italy (g)–(i) and Piracicaba, Brazil (j)–(l). Letters (a), (d), (g), and (j) refer to RH model, letters (b), (e), (h), (k) to DPD model, and letters (c), (f), (i), (l) to EXT_RH model.

was a systematic LWD underestimation for the RH ≥ 90% and DPD models (Fig. 1a and b). The EXT_RH overestimated by up to 13 h for shorter LWD periods, but underestimated for longer LWD periods (Fig. 1c). In Elora, performance of RH ≥ 90% (Fig. 1d) and DPD (Fig. 1e) models was very similar, mainly underestimates, especially for shorter LWD periods. When EXT_RH was used to estimate LWD at Elora (Fig. 1f), however, the opposite trend was observed; a predominance of overestimates with a higher dispersion of data. In Florence, all three LWD models overestimated LWD, with

Table 2 – Regression analysis and errors related to the estimation of LWD by different models: constant RH threshold (RH ≥ 90%); dew point depression (DPD); extended RH threshold (EXT_RH)

Place	*a*	*b* (h)	R^2	*D*	*C*	ME (h)	MAE (h)
Constant RH threshold							
Ames	0.90	−1.42	0.81	0.90	0.81	−2.28	2.61
Elora	1.16	−3.68	0.76	0.88	0.77	−1.41	1.93
Florence	0.93	1.63	0.81	0.92	0.83	1.36	1.74
Piracicaba	0.95	−0.12	0.75	0.92	0.80	−0.67	1.89
Dew point depression							
Ames	0.91	−1.24	0.82	0.91	0.82	−2.04	2.43
Elora	1.14	−3.12	0.77	0.90	0.79	−1.06	1.74
Florence	0.93	1.84	0.81	0.91	0.82	1.55	1.84
Piracicaba	0.92	−0.76	0.78	0.91	0.80	−1.56	2.09
Extended RH threshold							
Ames	0.50	6.55	0.64	0.79	0.63	2.13	2.90
Elora	0.89	2.77	0.61	0.85	0.66	1.21	2.33
Florence	0.75	5.48	0.71	0.76	0.64	4.42	4.44
Piracicaba	0.76	4.72	0.62	0.83	0.65	2.35	2.89

Locations were: Ames (USA); Elora (Canada); Florence (Italy); and Piracicaba (Brazil). *a* is the slope (dimensionless), *b* is the intercept, R^2 is the determination coefficient, *D* is the Willmott agreement index; *C* is the confidence index, ME is the mean error, MAE is the mean absolute error.

Table 3 – Statistical scores calculated by comparing LWD measured by the sensors and estimated by different models: constant RH threshold (RH ≥ 90%); dew point depression (DPD); extended RH threshold (EXT_RH)

Place	F_C	C_{SI}	F_{AR}	B_S
Constant RH threshold				
Ames	0.87	0.66	0.06	0.74
Elora	0.92	0.86	0.02	0.90
Florence	0.92	0.65	0.31	1.34
Piracicaba	0.90	0.79	0.09	0.93
Dew point depression				
Ames	0.88	0.67	0.07	0.76
Elora	0.92	0.87	0.03	0.92
Florence	0.91	0.65	0.32	1.38
Piracicaba	0.87	0.62	0.09	0.85
Extended RH threshold				
Ames	0.83	0.65	0.29	1.26
Elora	0.89	0.83	0.13	1.09
Florence	0.80	0.46	0.54	2.10
Piracicaba	0.85	0.73	0.23	1.22

Locations were: Ames (USA), Elora (Canada), Florence (Italy), and Piracicaba (Brazil). F_C is the fraction of correct estimates; C_{SI} is the correct success index; F_{AR} is the false alarm ratio; B_S is the bias.

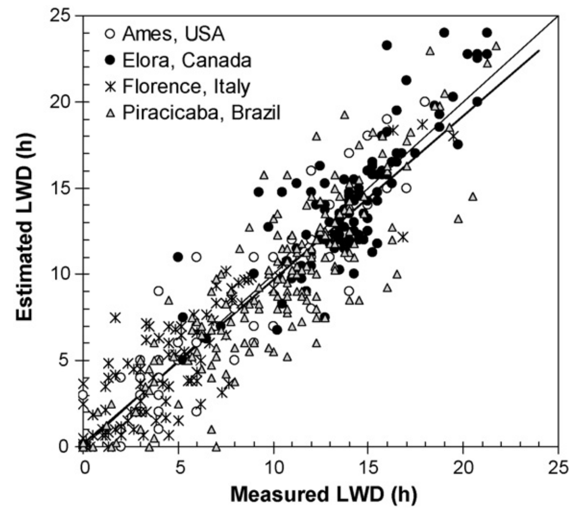

Fig. 2 – Relationship between LWD measured and estimated by the RH model, using a calibrated threshold for each location: 83% for Ames (USA); 85% for Elora (Canada); 92% for Florence (Italy); and 90% for Piracicaba (Brazil).

very similar results for RH ≥ 90% (Fig. 1g) and DPD (Fig. 1h). For EXT_RH model, LWD overestimation was greater and precision of the estimates decreased (Fig. 1i). In Piracicaba the RH ≥ 90% model resulted in relatively accurate LWD estimates with very small underestimates (Fig. 1j). Precision of the estimates increased slightly when the DPD model was used, but the magnitude of underestimation increased (Fig. 1k). As at the other locations, using the EXT_RH method in Piracicaba resulted in LWD overestimation and in an increase of data dispersion (Fig. 1l).

Performance of all models at the four locations is summarized in Table 2. In general, accuracy differed little between RH ≥ 90% and DPD models (Table 2). Results of regression analysis were very similar for accuracy and precision of the estimates, with R^2 ranging from 0.75 to 0.82, D ranging from 0.88 to 0.92, C ranging from 0.77 to 0.83, and MAE ≤ 2.61 h. The DPD model performed best at Elora, likely because the threshold values used in this model were chosen for southern Ontario. The EXT_RH model had the worst performance, with the lowest precision (R^2 from 0.61 to 0.71), accuracy (D from 0.76 to 0.85) and confidence (C from 0.63 to 0.66), and the highest MAE (from 2.3 to 4.4 h).

3.2. *Hourly comparisons*

Analyzing the statistical scores from the contingency table (Table 3), it is possible to evaluate the performance of the models further, since this analysis shows how accurately each model estimated wet and dry periods. By this analysis, RH ≥ 90% and DPD models performed similarly with F_C ranging from 0.87 to 0.92, and C_{SI} from 0.66 to 0.87, across the four locations. F_C and C_{SI} values decreased to less than 0.89 and 0.83, respectively, for most locations when the EXT_RH model was used. F_{AR} increased substantially, explaining the general LWD overestimation by the EXT_RH model, as shown by the fact that the Bias index was always greater than 1, which is also shown by positive values of ME.

3.3. *Calibration, test and validation*

Because the RH and DPD models performed best at all locations and no significant differences were observed between them, the RH model was selected for calibration, since it is the simplest model. The process of calibration

Table 4 – Regression analysis, errors and statistical scores calculated comparing LWD measured by sensors and estimated by RH model when calibrated locally for Ames (USA), Elora (Canada), Florence (Italy), and Piracicaba (Brazil)

Place	RH threshold (%)	a	b (h)	R^2	D	C	ME (h)	MAE (h)	F_C	C_{SI}	F_{AR}	B_S
Ames	83	0.92	0.63	0.84	0.96	0.87	−0.10	1.54	0.91	0.77	0.13	0.99
Elora	85	1.01	−0.12	0.68	0.93	0.77	0.01	1.55	0.92	0.87	0.07	1.00
Florence	92	0.93	0.41	0.83	0.98	0.89	0.14	1.23	0.94	0.71	0.18	1.04
Piracicaba	90	0.95	−0.12	0.75	0.92	0.80	−0.67	1.89	0.90	0.78	0.09	0.93
General	–	0.96	0.19	0.85	0.96	0.82	−0.23	1.60	0.92	0.78	0.12	0.99

a is the slope (dimensionless), b is the intercept, R^2 is the determination coefficient, D is the Willmott agreement index, C is the confidence index, ME is the mean error, MAE is the mean absolute error, F_C is the fraction of correct estimates, C_{SI} is the correct success index, F_{AR} is the false alarm ratio, B_S is the bias.

Table 5 – Regression analysis, statistical indices and errors for the comparison between LWD measured by sensors and estimated by RH model when calibrated locally (data independent from the calibration process) for Ames (USA), Elora and Ridgetwon (Canada), Florence (Italy), and Piracicaba (Brazil)

Place	*a*	*b* (h)	R^2	*D*	*C*	ME (h)	MAE (h)
Ames	1.06	0.17	0.85	0.95	0.88	0.75	1.78
Elora–Ridgetwon	0.96	0.04	0.80	0.94	0.84	−0.53	1.60
Florence	0.75	2.95	0.87	0.92	0.86	0.92	1.71
Piracicaba	0.95	0.28	0.89	0.97	0.92	−0.25	1.29
General	0.92	1.20	0.86	0.96	0.89	0.36	1.63

a is the slope (dimensionless), *b* is the intercept, R^2 is the determination coefficient, *D* is the Willmott agreement index, *C* is the confidence index, ME is the mean error, MAE is the mean absolute error.

determined the following thresholds: 83% for Ames, 85% for Elora, 92% for Florence, and 90% for Piracicaba. These differences are related mainly to the macroclimate of each region, not only in relation to RH conditions but also to its relationship with temperature, rainfall and wind speed.

With these new RH thresholds, performance of the RH model improved substantially at all locations for both determination of wetness presence or absence, and daily LWD estimation (Table 4). The calibrated thresholds also improved the accuracy of the estimates, with the *D* index increasing to 0.92–0.98. Improvement in accuracy resulted in a reduction of error, particularly MAE, which varied between 1.2 and 1.9 h. The error reductions can also be evaluated by noting that the B_S is now very close to 1.

The general performance of the RH model is presented in Fig. 2, where the results of all locations are plotted together. With this analysis it is possible to see how accurately the RH model estimated daily LWD when locally calibrated. Overall average MAE was only 1.6 h and B_s was 0.99, indicating almost no bias (Table 4).

The new RH thresholds were also validated with independent data for all sites. Results from this analysis are presented in Table 5 and Fig. 3, for LWD. The performance of the RH model with independent data was very similar to that with data used for calibration of the model, with good precision (R^2 ranging from 0.80 to 0.89) and high accuracy (*D* ranging from 0.92 to 0.97), resulting in a *C* index ranging from 0.84 to 0.92. The same was observed for MAE, which was always smaller than 1.8 h.

4. Discussion

Our results confirmed that empirical models for LWD estimation, when not calibrated locally, can perform quite differently depending on the climate of the region for which

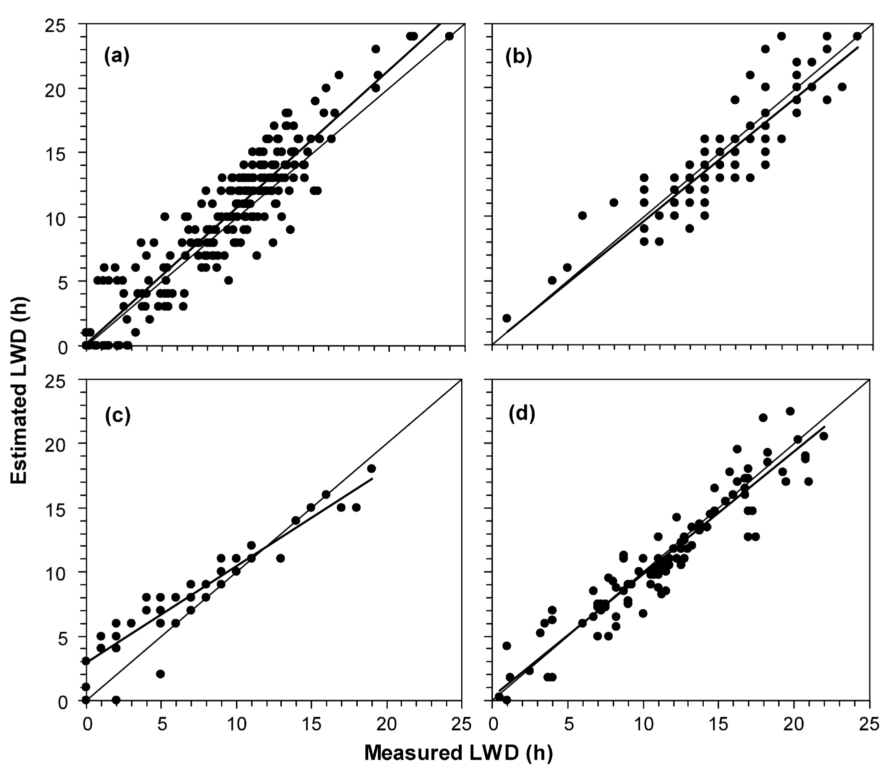

Fig. 3 – Relationship between LWD measured and estimated by the RH model with calibrated thresholds, using independent data from Ames, USA (a), Elora and Ridgetown, Canada (b), Florence, Italy (c), and Piracicaba, Brazil (d).

estimations are done. These results agree with Huber and Gillespie's (1992) assertion that LWD empirical models might be satisfactory for some applications but not as general predictors of the complex micrometeorological processes involved in LWD. Even considering the limitations of the empirical RH-based models, however, there was reasonable agreement between measured and estimated LWD for the evaluated locations (Fig. 1), and errors obtained by RH and DPD models (Table 2) were very similar to those obtained with more complex physical models. The most successful physical models for LWD estimation, such as Pedro and Gillespie (1982), Francl and Panigrahi (1997) and Sentelhas et al. (2006), found mean absolute errors of around 1 h. Other studies like Rao et al. (1998), Luo and Goudriaan (2000), Madeira et al. (2002), Sentelhas et al. (2004b), and Dalla Marta et al. (2005) found errors between 1.5 and 2.3 h. Our results also agree with those of Gillespie et al. (1993), estimating LWD for tomatoes in southern Canada, Rao et al. (1998), estimating LWD for corn ears in Canada, and Sentelhas et al. (2004b), estimating LWD for a cotton crop in Brazil, which showed that LWD estimates from simple empirical models were sufficiently accurate to be used as inputs to disease-warning systems.

In contrast, the EXT_RH model performed poorly at all locations, generally overestimating LWD (Fig. 1, and Tables 2 and 3), especially for short wetting periods. Use of this model reduced both precision (R^2) and accuracy (D) of the estimates (Table 2), and increased the errors to more than 2.3 h. Our results contradicted those of Wichink Kruit et al. (2004), for whom this model performed well when compared with LWD measured by flat plate sensors and estimated by other empirical and physical models. A possible explanation for these divergent outcomes is the relatively small number of days used by Wichink Kruit et al. (2004) to evaluate his model in the Netherlands in comparison with the much larger data set used in our study. Another possibility is climatic differences among the Netherlands and the four locations used in this study. Errors of the EXT_RH model were not systematic, which prevented adoption of a simple calibration for each place.

The RH and DPD models did show systematic errors which allowed us to calibrate them for different locations and climates. This was done for the RH model, finding a new threshold for each place; smaller for Ames and Elora, and greater for Florence and Piracicaba. With these new thresholds, the RH model was able to estimate LWD with similar precision to the uncalibrated version, but with higher accuracy (Fig. 2). Also, a general improvement in F_C, C_{SI} and B_S indices was observed, whereas F_{AR} decreased for all places (Table 4).

The data show that all models gave the worst performance when applied in Florence, even when the RH threshold was calibrated (Tables 3 and 4). In almost all cases in Florence, C_{SI} presented the lowest values, F_{AR} values were higher than for other places, and the bias showed a clear tendency toward overestimation, which is demonstrated by the high number of cases in which LW was not observed but a variable amount of wet hours was estimated by the models (Fig. 1g–i). This problem is probably related to the difference in the height of LWD sensor installation, which was around 120 cm in Florence compared to 30 cm for the other places. During dew deposition conditions, wind speed at 30-cm height is expected to be considerably slower than at 120 cm. This means that a simple LWD estimation scheme which ignores wind speed is expected to be more successful at 30 cm. Sentelhas et al. (2004a) showed that a LWD sensor exposed at 30 cm over turfgrass was a better mimic of wetness on nearby crops than a sensor at screen height. Consequently, availability of measured wetness data at 30 cm in Florence might have resulted in a more successful and practical result at that location.

Despite the differences mentioned above, our results obtained in different regions and climatic conditions show that even the very simple RH model to estimate LWD can be practical and useful, especially when solar radiation and wind speed data are not available. Even where solar radiation data are available, additional net radiation simulation is required, which makes processing of data more complex and may result in estimation errors since physical models are very sensitive to the radiation input data. With a locally calibrated threshold, errors with the RH model can be as small as those obtained by more complex models. In our study, MAE obtained with the calibrated RH model was between 1.2 and 1.9 h (Tables 4 and 5), small enough (<2 h) to be used to run weather-based plant-disease management schemes in places where only a modest weather data set is available.

The results presented in this study are a comprehensive analysis of RH-based empirical models to estimate daily LWD in different climates around the world. This fact makes our findings robust and broadly adaptable to many climates. Our purpose in this study was not to asset that RH-based empirical models are better than more complex models to estimate LWD, since the latter ones can produce highly accurate results (Pedro and Gillespie, 1982; Francl and Panigrahi, 1997; Sentelhas et al., 2006), but to show how useful these simple models can be to estimate LWD when only RH data are available.

Even considering the good results obtained with RH data from a nearby weather station at the standard height, a better performance of RH-based empirical model could be achieved if measurements were taken at the crop height. However, under this condition the advantage of having just standard measurements would be lost and new thresholds should be determined.

5. Conclusions

RH-based empirical models for LWD estimation, when not calibrated locally, performed differently at four locations with contrasting climate. Both RH $\geq$ 90% and DPD models consistently underestimated LWD in Ames, Elora and Piracicaba, and overestimated it in Florence. The EXT_RH model was least able to estimate LWD, resulting in much lower precision and accuracy than the RH and DPD models. When the RH model was locally calibrated, the accuracy of LWD estimates improved substantially, and resulting errors were small enough (<2 h) to provide inputs for plant disease-warning systems. Therefore, these results indicate that the RH model could be a practical and useful tool for estimating LWD, especially when solar radiation and wind speed data are not available. For best success, use of the empirical RH model requires a first phase of calibration, but then its application can be very fast, with simple computational procedures and acceptable errors which are comparable to those obtained by more complicated empirical and physically based models. Ease of use probably represents their most important advantage as potential tools for operational application.

REFERENCES

Bass, B., Savdie, I., Gillespie, T.J., 1991. Simulation of leaf wetness duration for field corn. Agric. Forest Meteorol. 57, 69–84.

Brewer, C.A., Smith, W.K., 1997. Patterns of leaf surface wetness for montane and subalpine plants. Plant, Cell Environ. 20, 1–11.

Camargo, A.P., Sentelhas, P.C., 1997. Performance evaluation of different potential evapotranspiration estimating methods in the State of São Paulo. Brazil. Rev. Bras. Agrometeorol. 5, 89–97.

Chtioui, Y., Panigrahi, S., Francl, L., 1999. A generalized regression neural network and its application for leaf wetness prediction to forecast plant disease. Chemometr. Intell. Lab. 48, 47–58.

Dalla Marta, A., Orlandini, S., Ghironi, M., Sabatini, F., 2004. Influence of different sensor positions on leaf wetness duration measurements and their effect on the simulation of grapevine downy mildew (*Plasmopara viticola*). Idojaras 108, 253–263.

Dalla Marta, A., Magarey, R., Orlandini, S., 2005a. Modelling leaf wetness duration and downy mildew simulation on grapevine in Italy. Agric. Forest Meteorol. 132, 84–95.

Dalla Marta, A., De Vincenzi, M., Dietrich, S., Orlandini, S., 2005b. Neural network for the estimation of leaf wetness duration: application to a *Plasmopara viticola* infection forecasting. Phys. Chem. Earth 30, 91–96.

Dalla Marta, A., Magarey, R.D., Martinelli, L., Orlandini, S., 2007. Leaf wetness duration in sunflower (*Helianthus annuus*): analysis of observations, measurements and simulations. Eur. J. Agron. 26, 310–316.

Francl, L.J., Panigrahi, S., 1997. Artificial neural network models of wheat leaf wetness. Agric. Forest Meteorol. 88, 57–65.

Garratt, J.R., Segal, M., 1988. On the contribution of atmospheric moisture to dew formation. Boundary-Lay. Meteorol. 45, 209–236.

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

Gillespie, T.J., Srivastava, B., Pitblado, R.E., 1993. Using operational weather data to schedule fungicide sprays on tomatoes in Southern Ontario. Can. J. Appl. Meteorol. 32, 567–573.

Gleason, M.L., Taylor, S.E., Loughin, T.M., Koehler, K.J., 1994. Development and validation of an empirical model to estimate the duration of dew periods. Plant Dis. 78, 1011–1016.

Hoppmann, D., 1996. Agrarmeteorologische Entscheidungsmodelle im Weinbau am Beispiel der Prognose der Rebenperonospora (Plasmopara viticola). Abschlußbericht AM 37, Deutscher Wetterdienst, Geisenheim, 1996, p. 75.

Huber, L., Gillespie, T.J., 1992. Modeling leaf wetness in relation to plant disease epidemiology. Ann. Rev. Phytopathol. 30, 553–577.

Kim, K.S., Taylor, S.E., Gleason, M.L., Koehler, K.J., 2002. Model to enhance site-specific estimation of leaf wetness duration. Plant Dis. 86, 179–185.

Kim, K.S., Taylor, S.E., Gleason, M.L., 2004. Development of a leaf wetness model using a fuzzy logic system. Agric. Forest Meteorol. 127, 53–64.

Kim, K.S., Taylor, S.E., Gleason, M.L., Villalobos, R., Arauz, L.F., 2005. Estimation of leaf wetness duration using empirical models in northwestern Costa Rica. Agric. Forest Meteorol. 129, 53–67.

Klemm, O., Milford, C., Sutton, M.A., Spindler, G., van Putten, E., 2002. A climatology of leaf surface wetness. Theor. Appl. Climatol. 71, 107–117.

Lau, Y.F., Gleason, M.L., Zriba, N., Taylor, S.E., Hinz, P.N., 2000. Effects of coating, deployment angle, and compass orientation on performance of electronic wetness sensors during dew periods. Plant Dis. 84, 192–197.

Luo, W.H., Goudriaan, J., 2000. Dew formation on rice under varying durations of nocturnal radiative loss. Agric. Forest Meteorol. 104, 303–313.

Madeira, A.C., Kim, K.S., Taylor, S.E., Gleason, M.L., 2002. A simple cloud-based energy balance model to estimate dew. Agric. Forest Meteorol. 111, 55–63.

Magarey, R.D., Russo, J.M., Seem, R.C., 2006. Simulation of surface wetness with a water-budget and energy balance approach. Agric. Forest Meteorol. 139, 373–381.

Monteith, J.L., 1957. Dew. J. R. Meteorol. Soc. 83, 322–341.

Pedro, M.J., 1980. Relation of leaf surface wetness duration to meteorological parameters. Ph.D. Dissertation. University of Guelph, Guelph, ON, Canada.

Pedro, M.J., Gillespie, T.J., 1982. Estimating dew duration. I. Utilizing micrometeorological data. Agric. Meteorol. 25, 283–296.

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

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

Sentelhas, P.C., Gillespie, T.J., Monteiro, J.E.B.A., Rowlandson, T., 2004b. Estimating leaf wetness duration on a cotton crop from meteorological data. Rev. Bras. Agrometeorol. 12, 235–245.

Sentelhas, P.C., Gillespie, T.J., Batzer, J.C., Gleason, M.L., Monteiro, J.E., Pezzopane, J.R.M., Pedro, M.J., 2005. Spatial variability of leaf wetness duration in different crop canopies. Int. J. Biometeorol. 49, 363–370.

Sentelhas, P.C., Gillespie, T.J., Gleason, M.L., Monteiro, J.E.B.A., Pezzopane, J.R.M., Pedro, M.J., 2006. Evaluation of a Penman–Monteith approach to provide "reference" and crop canopy leaf wetness duration estimates. Agric. Forest Meteorol. 141, 105–117.

Sentelhas, P.C., Gillespie, T.J., 2008. Estimating hourly net radiation for leaf wetness duration modelling using the Penman–Monteith equation. Theor. Appl. Climatol. 91, 205–215.

Weiss, A., 1990. Leaf wetness: measurements and models. Rem. Sens. Rev. 5, 215–224.

Wichink Kruit, R.J.W., van Pul, A.J., Jacobs, A.F.G., Heusinkveld, B.G., 2004. Comparison between four methods to estimate leaf wetness duration caused by dew on grassland. In: Conference on Agricultural and Forest Meteorology, 2004. American Meteorological Society, Vancouver.

Wilks, D.S., 1995. Statistical Methods in Atmospheric Sciences. Academic Press, San Diego, CA.