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Spatial portability of numerical models of leaf wetness duration based on empirical approaches

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ABSTRACT

Leaf wetness duration (LWD) models based on empirical approaches offer practical advantages over physically based models in agricultural applications, but their spatial portability is questionable because they may be biased to the climatic conditions under which they were developed. In our study, spatial portability of three LWD models with empirical characteristics – a RH threshold model, a decision tree model with wind speed correction, and a fuzzy logic model – was evaluated using weather data collected in Brazil, Canada, Costa Rica, Italy and the USA. The fuzzy logic model was more accurate than the other models in estimating LWD measured by painted leaf wetness sensors. The fraction of correct estimates for the fuzzy logic model was greater (0.87) than for the other models (0.85–0.86) across 28 sites where painted sensors were installed, and the degree of agreement k statistic between the model and painted sensors was greater for the fuzzy logic model (0.71) than that for the other models (0.64–0.66). Values of the k statistic for the fuzzy logic model were also less variable across sites than those of the other models. When model estimates were compared with measurements from unpainted leaf wetness sensors, the fuzzy logic model had less mean absolute error (2.5 h day^{-1}) than other models (2.6–2.7 h day^{-1}) after the model was calibrated for the unpainted sensors. The results suggest that the fuzzy logic model has greater spatial portability than the other models evaluated and merits further validation in comparison with physical models under a wider range of climate conditions.

1. Introduction

Water plays an important role in many biological and physical processes which take place on plant surfaces. For example, it facilitates infection by many foliar pathogens (Huber and Gillespie, 1992). Surface wetness can also hamper satellite-based microwave remote sensing of crop canopy temperature and soil moisture (Basist et al., 1998; Hornbuckle et al., 2006) and affect the deposition of atmospheric pollutants on leaves (Klemm et al., 2002; Kruit et al., 2008).

No standard for calibration of leaf wetness duration (LWD) measurements has been accepted (Sentelhas et al., 2004a; Dalla Marta et al., 2005), which makes it difficult to compare and interpret these measurements. Occurrence of wetness is influenced by leaf position and arrangement as well as canopy structure (Sentelhas et al., 2005; Batzer et al., 2008). Measurements of LWD are also affected by height of sensor installation, angle of deployment, and orientation (Lau et al., 2000; Sentelhas et al., 2004a). It is recommended to coat the surface of sensors with latex-based paint to increase their precision and sensitivity (Davis and Hughes, 1970; Sentelhas et al., 2004b). To account for variability in wetness measurement and occurrence, multiple sensors can be installed at a single site (Francl and Panigrahi, 1997; Magarey et al., 2004), but monitoring and data handling costs rise proportionally as the number of sensors increases.

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Table 1
Average climate conditions at weather stations during the study period.

Site name	Periods (day/month/year)	N[a]	T[b] (°C)	RH[b] (%)	RD[b] (%)
Ames	6/5/1998–19/10/1998, 2/5/1999–3/10/1999	303	19.8	77.6	37.0
Ash Hollow Vineyard	1/5/2007–17/6/2007	48	17.5	53.6	10.4
Belleville	25/6/1998–17/8/1998, 2/5/1999–30/9/1999	196	23.8	82.8	24.5
Bondville	1/5/1998–17/8/1998, 3/6/1999–30/9/1999	204	21.9	79.8	29.9
Brookings	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	120	13.5	84.2	30.0
Ceiba	7/11/2000–12/12/2000, 19/1/2001–24/4/2001, 20/12/2002–1/4/2003	227	27.9	63.9	7.0
Corvallis	1/5/2000–12/8/2000, 1/5/2006–30/9/2006, 1/5/2007–21/7/2007	336	16.7	68.6	22.6
Crawfordsville	8/5/1998–19/10/1998, 2/5/1999–3/10/1999	303	20.3	77.4	36.0
Davis Gawith Gala	1/5/2007–17/6/2007	48	17.4	57.2	10.4
Dee Flat	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	92	15.1	60.6	10.9
Dixon Springs	23/4/1998–17/8/1998, 2/5/1999–30/9/1999	225	21.4	76.4	21.8
Elora	1/8/2003–22/9/2003	40	18	82.7	32.5
Garza	13/4/1999–22/9/1999, 7/11/2000–23/4/2001, 21/12/2002–1/4/2003	423	26.1	81.9	34.3
Geneva	1/5–30/9[c]	1389	18.8	74.1	37.0
Gordon	23/4/1998–19/10/1998, 2/5/1999–3/10/1999	322	18.2	67	26.4
Hood River	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	118	15.9	56.2	16.1
Junction City	1/5/2006–7/7/2006, 1/5/2007–8/7/2007	134	15.4	75.3	33.6
Lewis	6/5/1998–19/10/1998, 2/5/1999–3/10/1999	307	20.1	79.3	32.2
Liberia	14/4/1999–22/9/1999, 8/11/2000–23/4/2001, 14/12/2002–31/3/2003	425	27	66.3	27.1
Macleay	1/5/2006–17/7/2006	75	15.7	71	29.3
Medford	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	121	17.1	59.6	16.5
Mojica	6/5/1999–21/9/1999, 7/11/2000–19/4/2001, 19/12/2002–30/3/2003	369	27.5	67.5	26.6
Mondeggi Lappeggi	1/5–30/9[d]	1406	21.4	73.2	29.1
Monmouth	15/4/1998–17/8/1998, 2/5/1999–29/9/1999	231	19.7	77.9	24.7
Nashua	5/5/1998–19/10/1998, 2/5/1999–3/10/1999	301	19.1	79.4	34.2
Oliver Cherries	1/5/2007–17/6/2007	48	16.9	60.3	14.6
O'Neill	22/4/1998–18/10/1998, 2/5/1999–3/10/1999	270	18.2	75.9	30.4
Parkdale	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	115	13.9	64	22.6
Parma	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	121	18.6	47.5	86.8
Pinegrove	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	118	15.3	63	16.1
Piracicaba	15/7/2003–23/8/2003	29	19.4	77.4	27.6
Puntarenas	25/4/1999–21/9/1999	102	26.6	86.9	64.7
Red Cloud	25/4/1998–19/10/1998, 2/5/1999–3/10/1999	317	21.9	78.5	31.2
Rodigheiro	1/5/2007–17/6/2007	48	17.2	54.9	12.5
Santa Cruz	13/4/1999–18/8/1999, 8/11/2000–23/4/2001, 21/12/2002–31/3/2003	384	27.2	68.6	24.7
Seven Hills Vineyard	1/5/2007–17/6/2007	48	17.6	47.5	12.5
Shedd	1/5/2007–2/7/2007	62	13.7	77	27.4
Sidney	24/4/1998–19/10/1998, 2/5/1999–3/10/1999	322	17.5	63.3	26.1
Silverton	1/5/2007–15/7/2007	75	15	68.9	32.0
St. Charles	17/4/1998–17/8/1998, 14/5/1999–30/9/1999	218	18.8	75.8	26.1
Sutherland	6/5/1998–19/10/1998, 2/5/1999–3/10/1999	306	18.8	77.9	36.9
West Point	22/4/1998–19/10/1998	167	19.6	78.5	26.3
Worden	1/5/2006–30/6/2006, 1/5/2007–30/6/2007	117	13.6	60.7	76.9

[a] Number of 24-h periods.
[b] Daily averages of temperature (T) and relative humidity (RH); percentage of days with measurable rain (RD) during the study period.
[c] Measurements were taken from 1994 to 2005.
[d] Measurements were taken from 1998 to 2007. No measurement in 2002 was included in the present study.

In order to circumvent some of the limitations associated with measurement of LWD, wetness occurrence has been simulated using numerical models. LWD models are classified into three general categories: physically based (hereafter termed physical) (Pedro and Gillespie, 1982; Madeira et al., 2002; Magarey et al., 2006; Sentelhas et al., 2006), empirical (Gleason et al., 1994; Francl and Panigrahi, 1997), and physical–empirical hybrids (Kim et al., 2004).

Physical models, which simulate heat exchange processes between a plant surface and the atmosphere, have potential to be highly accurate in LWD estimation at any location, since these processes operate identically everywhere (Pedro and Gillespie, 1982; Madeira et al., 2002; Sentelhas and Gillespie, 2008). For example, Magarey (1999) developed the surface wetness energy balance (SWEB) model to estimate LWD on grapes. For agricultural decision support, however, physical models face practical limitations because some of their input variables are not widely available. For example, physical models depend on net radiation, but net radiation is seldom measured at standard automated weather stations (Sentelhas and Gillespie, 2008).

Empirical models are based on decision rules that are optimized by statistical best-fit procedures for specific locations and time periods. As a result, they often have relatively small errors in LWD estimation within a region where they were developed (Gleason et al., 1994). Because most empirical models do not explicitly incorporate physical processes influencing wetness occurrence, they would be expected to have limited spatial portability (Crowe et al., 1978; Francl and Panigrahi, 1997). For example, Sentelhas et al. (2008) found that it was necessary to obtain a site-specific correction parameter for an empirical model based on a relative humidity (RH) threshold in order to estimate LWD accurately. However, empirical models are readily adaptable to agricultural uses because they generally depend on input weather variables such as RH that are commonly measured at most automated weather stations (Sutton et al., 1984; Sentelhas et al., 2008).

Hybrid approaches that combine physical principles and empirical techniques have been developed in an attempt to overcome limitations of both approaches. For example, Kim et al. (2004) incorporated an energy balance equation within the framework of a fuzzy logic system, but optimized the fuzzy logic system using statistical analysis of training data. Hybrid models that are based on physical principles, yet use readily available weather variables, can potentially possess both portability and practical applicability.

Because climate conditions associated with wetness occurrence may differ by geographic region (Crowe et al., 1978; Duttweiler et

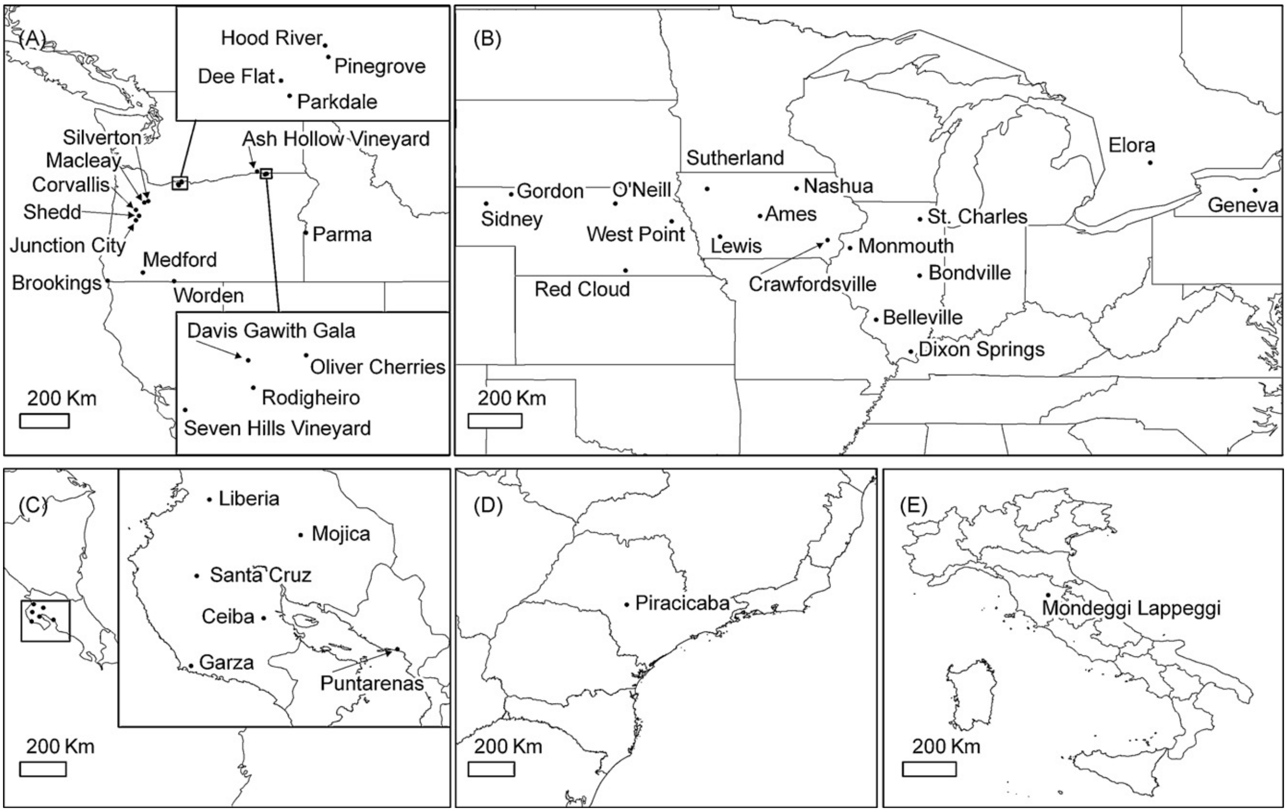

Fig. 1. Locations of weather station where measurements of leaf wetness duration were collected in: (A) Oregon and Idaho, USA; (B) Nebraska, Iowa, Illinois and New York, USA, and Ontario, Canada; (C) northwestern Costa Rica; (D) São Paulo, Brazil; and (E) Tuscany, Italy.

al., 2008), empirical approaches may require reassessment when they are transported from regions where they were developed to regions with different climates. However, comparative spatial portability of empirical and hybrid models has rarely been evaluated, in part because of difficulty in obtaining comparable wetness measurements under a diverse set of climate conditions. The objective of our study was to compare accuracy and spatial portability of hybrid and empirical LWD models using data sets collected from weather stations across a wide range of locations and climates. Physical models were not included because of limited availability of input data sets that included net radiation.

2. Materials and methods

2.1. Measurement of weather variables

Air temperature, RH, wind speed, and LWD were measured at 22 weather stations in Brazil, Canada, Italy, and the United States of America (USA) (Fig. 1). Except for Brazil, measurements between 1 May and 30 September were utilized to encompass most of the growing season of major crops at each site. In Brazil, data were measured from July to August, during a growing season in the subtropics. In addition to these data, previously published weather measurements at 21 sites in the midwestern USA and northwestern Costa Rica (Kim et al., 2004, 2005) were also included in our analysis (Table 1).

The occurrence of wetness was detected using electrical impedance sensors (Table 2) (Davis and Hughes, 1970). Voltage change was recorded and converted to the percentage of time wet during each recording interval. When occurrence of wetness was detected during >50% of a recording interval, the interval was classified as a wet period; when ≤50%, the interval was recorded as dry. At Geneva, however, wetness sensors were calibrated to indicate wetness for any hour during which wetness was detected for >20% of the recording interval. Thus, wetness measurement for >20% of the recording interval was used as a threshold to define a wet period. For sites with a single wetness sensor, a wet period was determined to begin when this sensor detected wetness occurrence in the given period. At sites where two or more sensors were installed, a given time period was classified as wet when wetness was detected for longer than the threshold of recording interval by at least two wetness sensors. Wetness sensors were installed over managed turfgrass except at Corvallis, Junction City, Macleay, Shedd and Silverton where sensors were installed over non-mowed grass seed crops whose canopy height ranged from 0.1 m to 0.6 m. At these sites, deployment height was adjusted to keep the sensor at the top of the canopy.

2.2. Leaf wetness duration models

Empirical models have depended on approaches based on a threshold (Sentelhas et al., 2008), a decision tree (Gleason et al., 1994), a fuzzy logic system (Kim et al., 2004) or artificial neural networks (Francl and Panigrahi, 1997). Among these models, the RH threshold model, the decision tree model and the fuzzy logic system model require small number of input variables, which would facilitate wide use of models. Thus, these models were used to analyze their spatial portability in the present study.

2.2.1. RH threshold model

The duration of periods with RH ≥ 90% has long been used to estimate LWD (Crowe et al., 1978; Sutton et al., 1984). Sentelhas et al. (2008) reported that this RH threshold model had greater accuracy in estimating LWD than a model that used dew point depression as the threshold. In our study, RH ≥ 90% was used as the threshold; this model was designated the RH model.

Table 2
Configuration of wetness sensors at weather stations.

Site	Type[a]	N[a]	Deployment[b]		Height (m)	
			Angle (°)	Orientation	Sensor	Model[c]
Ash Hollow Vineyard	UFC	1	45	E	1	1
Brookings	UFP	1	45	S	1.5	1.5
Corvallis[d]	PFP	4	45	W×4	0.1–0.6[e]	0.3
Davis Gawith Gala	UFC	1	45	E	1	1
Dee Flat	UFP	1	45	NW	1.25	1.25
Elora[d]	PFP	1	30	N	0.3	0.3
Geneva	UFP	4	45	S×2, N×2	0.2	0.2
Hood River	UFP	1	45	NW	1.25	1.25
Junction City[d]	PFP	2	45	W×2	0.1–0.6[e]	0.3
Macleay[d]	PFP	2	45	W×2	0.1–0.6[e]	0.3
Medford	UFP	1	45	S	1.25	1.25
Mondeggi Lappeggi	UET	1	45	N	1.6	1.6
Oliver Cherries	UFC	1	45	E	1	1
Parkdale	UFP	1	45	NW	1.25	1.25
Parma	UFP	1	45	S	1.25	1.25
Pinegrove	UFP	1	45	NW	0.6	0.6
Piracicaba[d]	PFP	1	45	S	0.3	0.3
Rodigheiro	UFC	1	45	SE	1	1
Seven Hills Vineyard	UFC	1	45	E	1	1
Shedd[d]	PFP	2	45	W×2	0.1–0.6[e]	0.3
Silverton[d]	PFP	2	45	W×2	0.1–0.6[e]	0.3
Worden	UFP	1	45	NW	0.6	0.6
IA, IL, NE, CR[f]	PFP	1	45	S	0.3	0.3

[a] UFP and PFP indicate unpainted and painted flat panel sensors (Model 237, Campbell Scientific, Logan, UT, USA), respectively. UFC represents Adcon unpainted sensors (Models A723 and A733, Adcon Telemetry GmbH, Klosterneuburg, Austria). UET indicates unpainted transducer sensor (S.W. and W.F. Burrage, Ashford, Kent, UK). N represents the number of sensors deployed at the weather stations.
[b] Deployment angle and orientation. E, W, N, and S indicate east, west, north, and south-facing, respectively. $\times N$ indicates N replicates.
[c] Height to which wind speed was adjusted to estimate leaf wetness duration using the Fuzzy and CART models.
[d] The time step of data recording was 15 min. At Corvallis in 2000, it was 30 min.
[e] The height of sensors ranged from 0.1 m to 0.6 m. Sensor height was adjusted to keep the sensor at the top of the crop canopy.
[f] Configuration of wetness sensor was the same for all sites in Iowa (IA), Illinois (IL), and Nebraska (NE) in the USA, and in northwestern Costa Rica (CR).

2.2.2. Decision tree model with wind speed correction

Gleason et al. (1994) suggested a model that combined classification and regression tree analysis with stepwise linear discriminant analysis, which was dependent on dew point depression (DPD), RH, and wind speed. High values of DPD, which is estimated using air temperature and RH, is used to identify when the difference between dew point temperature and surrounding air temperature is too large to allow wetness occurrence. High RH and low DPD identify conditions when leaf temperature is likely to be less than dew point temperature, drying is slow or precipitation is occurring. Thresholds of these variables are determined using climate conditions at the locality where wetness has been recorded.

The model consisted of a set of nodes that formed a decision tree. Each node contained if-then statements to determine whether or not input data exceeded a threshold associated with the node. The outcome of an if-then statement at a node determined which of two subsequent nodes was evaluated. Starting at the initial node of the tree, if-then statements were evaluated to reach an ultimate node that indicated wetness presence or absence.

This approach had greater accuracy in LWD estimation than the RH model and an artificial neural network model (Gleason et al., 1994; Francl and Panigrahi, 1997). Kim et al. (2002) reported that the accuracy of the model increased when wind speed inputs to the model were corrected to the height of wetness sensors. In the present study, the wind-corrected model, which was previously named CART/SLD/Wind (Kim et al., 2002), was designated the CART model.

2.2.3. Model using a fuzzy logic system

Kim et al. (2004) suggested a LWD model based on a fuzzy logic system, which was designated the Fuzzy model. In a fuzzy logic system, a set of rules is defined using current knowledge of a phenomenon of interest. These rules are defined in natural language to describe the reasoning, e.g., 'if net radiation is low, then wetness is likely to occur'. To evaluate these rules, membership functions of each input variable are defined to associate quantitative data with the corresponding natural language terms and predict whether leaves are 'wet' or 'dry'. For example, a rule statement is required to assign numerical values to the terms 'high' and 'low' for a variable such as net radiation. To evaluate phrases in the rule statements, e.g., 'if-then' or 'and', fuzzy operators are used. The outcomes of fuzzy operators are combined to determine the degree of truth of the rules. Further description of fuzzy logic systems can be found in Klir and Yuan (1995) and Nelles (2000).

The Fuzzy model inferred wetness occurrence based on energy balance principles, although the reasoning was stated in natural language. The Fuzzy model depends on air temperature, RH, and wind speed measurements to derive its input variables – net radiation, vapor pressure deficit and wind speed – at a sensor surface (Kim et al., 2004). The value of net radiation was calculated, based on the method proposed by Idso and Jackson (1969), under the assumption of a clear sky condition, which required no cloud cover data as inputs but would underestimate incoming long wave radiation if cloud cover was present. The membership functions were defined through training processes. Fuzzy operators were used to determine a set L that represented the outcome of the reasoning. Because the Fuzzy model depends on multiple rule statements, multiple sets of L were obtained as a result of the reasoning. To determine the final outcome of fuzzy logic reasoning, the set of L was combined into a single set O in a process called aggregation. Subsequently, a defuzzification process was performed to convert O into a numeric value $o \in [0,1]$. Absence of wetness was predicted when the value of o was <0.5; otherwise, the model predicted occurrence of wetness.

2.3. Calibration of the Fuzzy model for unpainted sensors

The Fuzzy model was developed and validated using painted electrical impedance LWD sensors (Kim et al., 2004). However, unpainted electrical impedance sensors are often deployed to measure LWD (Francl and Panigrahi, 1997), principally because almost all suppliers sell them in this condition. Unpainted sensors may fail to detect wetness occurrence under marginal conditions because unpainted sensors are less sensitive to small water droplets than are painted sensors (Sentelhas et al., 2004b). Therefore, bias can arise when measurements from unpainted sensors are compared with estimates using the Fuzzy model.

In the present study, a version of the Fuzzy model was calibrated to estimate LWD measurements made by unpainted LWD sensors, since these sensors were used exclusively at some of the study sites (Table 2). Kim et al. (2005) reported that the Fuzzy model estimated LWD accurately under semi-arid climate conditions after applying an empirical correction factor that increased the output of the Fuzzy model by 5%. Because unpainted sensors are less sensitive to small amounts of water than painted sensors, especially under marginal conditions for leaf wetness detection, the Fuzzy model would be expected to overestimate LWD measured by unpainted sensors, since the model was built with reference to painted sensors. Therefore, the Fuzzy model needed a correction factor to *decrease* the output of the model. Thus, the output of the Fuzzy model was decremented using a correction factor to emulate unpainted sensors.

Our correction factor for unpainted sensors was derived using a simple parameterization of cloud cover for a numerical weather model (Slingo, 1987):

$$C_{RH} = \left[\mathrm{Max}\left\{0.0, \frac{\mathrm{RH}-80}{20}\right\}\right]^2 \quad (1)$$

where C_{RH} is the coefficient of humidity effect on an unpainted sensor. This function increases in value as the RH increases above 80%, which fits the assumption that unpainted sensors approach the performance of painted sensors at very high humidity. A correction factor f for the Fuzzy model was defined as follows:

$$f = 0.95 + C_{RH} \times 0.05 \quad (2)$$

The output o_c of the adjusted Fuzzy model was the product of o and f at a given time period. When RH was <80% at a period, the value of C_{RH} and f became 0 and 0.95, respectively. Thus, the value of o_c became equivalent to 95% of o, to simulate the weaker sensitivity of unpainted sensors at lower humidity. When RH was 100%, the values of CC and f became 1, resulting in no difference between outputs of the adjusted and original Fuzzy models, which simulated equal performance of painted and unpainted sensors at very high humidity. When the value of o_c was <0.5, it was predicted that no wetness was present; otherwise, wetness was assumed to be present.

2.4. Implementation of LWD models

Spatial portability of RH, CART, Fuzzy and adjusted Fuzzy models was assessed using weather data collected across 43 sites. A computer program module was created to implement the LWD models using Microsoft® Visual Studio 6 C++ (Microsoft, Richmond, WA, USA). The module was embedded in Microsoft® Excel files that contained weather measurements at each site in a given year. A script was written to run the LWD models in each Excel file.

2.5. Analysis of estimates

Estimates of LWD were analyzed at intervals of 15, 30, or 60 min depending on the time step of data recorded at each site (Table 2). The interval was classified as wet or dry using measurements by on-site sensors as inputs to the LWD models. A four-cell contingency table was used to calculate a degree of agreement statistic for the LWD models as follows:

	Estimated-Wet	Estimated-Dry
Observed-Wet	Hits (H)	Misses (M)
Observed-Dry	False alarms (F)	Correct negatives (N)

H and F denote the number of positive, i.e., 'wet', estimates that correspond to observed occurrence and absence of wetness, respectively. M and N represent the number of negative, i.e., 'dry', estimates that were accompanied by occurrence and absence of wetness, respectively.

The probability that an LWD model and electronic sensor agree can be estimated using the fraction of correct estimates (Θ_1) as follows:

$$\Theta_1 = \frac{H+N}{H+M+F+N}. \quad (3)$$

However, leaf wetness data may contain one class, e.g., 'dry', more frequently than the other class, e.g., 'wet', since in most temperate environments the dry hours far outnumber the wet hours. As a result, it is possible for an LWD model to predict sensor behavior with a high degree of accuracy simply by predicting the preponderance of hours in which wetness was absent. Dietterich (2000)

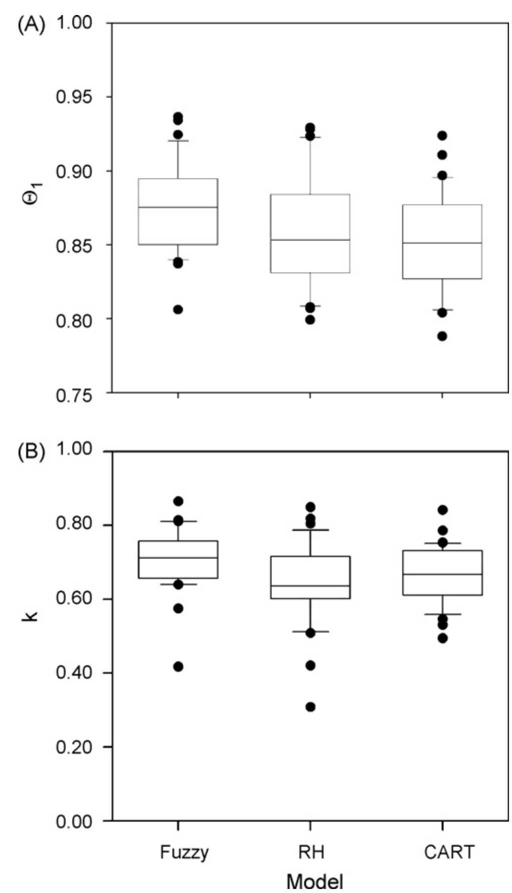

Fig. 2. Boxplot of the statistics for the leaf wetness duration models, using data obtained at 28 sites where painted sensors were installed: (A) fraction of correct estimates (Θ_1); (B) a degree of agreement statistic (k). Fuzzy, RH and CART indicate the Fuzzy model, the RH model and the CART model, respectively. Top and bottom of box and the whiskers indicate upper quartile, lower quartile, and the 10th and 90th percentiles of the box plot, respectively. Dots represent data above the 90th and below 10th percentiles.

used a k statistic to correct for this artifact as follows:

$$k = \frac{\Theta_1 - \Theta_2}{1 - \Theta_2}, \quad (4)$$

where Θ_2 is an estimate of the probability that the two classifiers, e.g., LWD model and sensor, agree by chance, given the observed counts in the contingency table. The term Θ_2 is defined as follows:

$$\Theta_2 = \frac{(H+M)\cdot(H+F)}{(H+M+F+N)^2} + \frac{(F+N)\cdot(M+N)}{(H+M+F+N)^2} \quad (5)$$

Θ_1 and k were calculated using all recording intervals over the study period at each site. The coefficient of variation of the k value, CV_k (%), was calculated for the LWD models to quantify spatial portability of the models across our study sites as follows:

$$CV_k = \frac{\sigma}{\mu} \times 100, \quad (6)$$

where σ and μ were standard deviation and average, respectively, of the k values for an LWD model across all sites.

LWD estimates, which were the number of wet hours per 24-h period, were calculated from sub-hourly and hourly data for periods that began at 12:00 pm and ended at 11:59 am the next day. Mean error (ME) and mean absolute error (MAE) were calculated for the LWD models. ME was the 24-h average of differences between measured and estimated LWD, whereas MAE was obtained by averaging absolute values of 24-h differences between LWD measurements and estimates. Because it was uncertain whether MAE would have a normal distribution, which would limit use of parametric statistical tests such as Least Significant Difference test, Wilcoxon's signed rank test was performed to examine differences in MAE among LWD models using the JMP statistical package ver. 6.0 (SAS Institute Inc., Cary, NC, USA).

2.6. Analysis of temporal variability of leaf wetness duration models

LWD data were obtained for one or two seasons at most sites. However, these data were collected for more than 10 years at two sites, Mondeggi Lappeggi, Italy and Geneva, NY. At these sites, where unpainted sensors were installed, temporal variability of LWD models was analyzed in addition to spatial portability. At Mondeggi Lappeggi, Dalla Marta et al. (2005) determined statistics for accuracy of the SWEB model in comparison with unpainted wetness sensors. The Θ_1 values for the SWEB model were derived from their statistics and compared with those for the numerical models used in this study.

3. Results

3.1. Sites where painted LWD sensors were deployed

The Fuzzy model had the highest value of Θ_1 at more sites than the other models. The values of Θ_1 for the Fuzzy model ranged from 0.84 to 0.93, higher than for the CART and RH models (Fig. 2A). For example, the median of Θ_1 values for the CART and RH models was similar to the first quartile value of Θ_1 for the Fuzzy model.

Overall, the k value for the Fuzzy model (0.71) was greater than that for the CART (0.66) and RH models (0.64). The k value for the

Table 3
Comparison between measurements and estimates of leaf wetness duration for 24-h periods among sites where painted wetness sensors were installed in Iowa (IA), Illinois (IL), Nebraska (NE) and Oregon (OR), USA, northwestern Costa Rica (CR), Ontario (ON), Canada, and Sao Paulo (SP), Brazil.

Site	N[a]	D[b]	ME[b]			MAE[b]		
			Fuzzy[c]	RH[c]	CART[c]	Fuzzy	RH	CART
Ames, IA	303	8.7	−0.2	−0.9	0.3	2.7 b	3.2 a	2.8 b
Belleville, IL	196	7.6	2.2	3.8	2.9	2.6 c	4.2 a	3.4 b
Bondville, IL	204	10	−1.4	0.1	−1.6	2.7 b	3.9 a	3.0 b
Ceiba, CR	227	2.1	−0.8	−0.7	1.1	1.7 a	1.8 a	2.0 a
Corvallis, OR	336	9.7	−1.5	−4.9	−1.6	2.0 c	4.9 a	2.2 b
Crawfordsville, IA	303	8.1	0.9	−0.1	1.9	2.0 c	2.3 b	2.7 a
Dixon Springs, IL	225	9.2	−1.3	−1.1	0.4	2.4 b	2.9 a	2.4 b
Elora, ON	40	14.1	−0.7	−1.9	0.1	1.4 b	2.2 a	1.3 b
Garza, CR	423	9.3	2.3	2.8	6.5	2.5 c	2.9 b	6.5 a
Gordon, NE	322	8.5	−1.3	−3.1	−2.1	3.0 b	4.0 a	3.1 b
Junction City, OR	134	12.8	−2.1	−5.2	−2.3	2.5 c	5.3 a	2.7 b
Lewis, IA	307	7.6	1.4	1.3	1.2	3.1 b	3.4 a	3.4 ab
Liberia, CR	425	7	−1.6	−1.4	1.4	2.5 c	2.7 b	3.3 a
Macleay, OR	75	9.2	−1.0	−3.6	−1.8	1.9 c	3.7 a	2.3 b
Mojica, CR	369	4.6	−0.9	−0.7	1.4	1.8 b	1.8 b	3.0 a
Monmouth, IL	231	7.5	−0.8	1.2	−0.8	2.5 c	3.6 a	3.0 b
Nashua, IA	301	8	2.7	2.0	3.3	3.4 b	3.4 b	3.9 a
O'Neill, NE	270	6.9	2.7	1.6	2.4	4.0 b	4.4 a	4.1 ab
Piracicaba, SP	29	10.8	0.6	−1.3	1.4	2.6 b	3.2 ab	3.1 a
Puntarenas, CR	102	12.7	−1.5	−0.8	3.5	1.8 b	1.4 c	3.5 a
Red Cloud, NE	317	7.8	1.6	1.8	1.9	3.1 b	3.7 a	3.5 a
Santa Cruz, CR	384	5.6	−0.5	−0.4	2.0	1.1 c	1.2 b	2.3 a
Shedd, OR	62	13	−1.6	−4.9	−2.3	1.7 c	4.9 a	2.3 b
Sidney, NE	322	6.5	0.2	−1.8	−1.0	2.3 b	2.7 a	2.5 ab
Silverton, OR	75	8.7	−1.1	−6.2	−2.6	2.8 c	6.2 a	3.4 b
St. Charles, IL	218	8.6	0.0	0.1	−0.6	2.1 b	2.7 a	2.5 a
Sutherland, IA	306	8	1.8	0.7	1.4	3.3 a	3.3 a	3.2 a
West Point, NE	167	10.5	−1.1	−1.7	−1.0	2.6 a	2.8 a	2.3 b
μ[d]	–	8.7	−0.1	−0.9	0.5	2.4	3.3	3.0
σ[d]	–	2.5	1.5	2.4	2.1	0.64	1.17	0.92
CV[d]	–	–	–	–	–	26.3	35.5	30.9

[a] N is total number of 24-h periods in the data set.
[b] Average leaf wetness duration (D), mean error (ME), and mean absolute error (MAE) per 24-h period. Within each row, MAE values sharing a letter are not significantly different at $p = 0.05$ from Wilcoxon's signed rank test.
[c] Fuzzy, RH and CART indicate the Fuzzy model, the RH model and the CART model, respectively.
[d] μ, σ and CV represent mean, standard deviation and coefficient of variation (%), respectively.

Fuzzy model was highest at more sites than for either of the other models, and the CART and RH models tended to have lower k values than the Fuzzy model (Fig. 2B). Variation of k values across sites was lower for the Fuzzy and CART models than the RH model. At 28 sites in Brazil, Costa Rica, Canada, and the USA, the CV_k value was 12%, 12%, and 18% for the Fuzzy, CART, and RH models, respectively.

Overall, the Fuzzy and RH models underestimated LWD at most sites (Table 3). On average, ME for the Fuzzy model was closer to zero than that of other models, and mean MAE values were lower for the Fuzzy model than for other models. The Fuzzy model had the lowest MAE at 22 of 28 sites, and the value of MAE for the Fuzzy model showed relatively small variation (1.1–4.0 h day^{-1}) compared with 1.2–6.2 and 1.3–6.5 h day^{-1} for the CART and RH models, respectively. There were four and two sites where the CART and RH models, respectively, had the smallest MAE values. However, there was only one site where MAE for these models was significantly smaller than that for the Fuzzy model.

3.2. Sites where unpainted LWD sensors were deployed

Values of Θ_1 for the Fuzzy model averaged about 0.87 at sites where unpainted sensors were installed, which was smaller than that at sites where painted sensors were deployed (0.88) (Fig. 3A). On average, the adjusted Fuzzy model had a higher Θ_1 value (0.89) than other models. Values for the adjusted Fuzzy model were greater than for the original Fuzzy model at 73% of unpainted-sensor sites. The RH model had the highest Θ_1 value at more unpainted-sensor sites than the other models, but values for the RH model were similar to those for the adjusted Fuzzy model.

The k values for the LWD models were considerably lower at sites where unpainted sensors were installed than at sites where painted sensors were deployed. The Fuzzy model had the highest k value at more sites than did other models. For example, the k values for the Fuzzy and RH models were greatest at six of 15 sites. On average, the k value for the Fuzzy model was greater (0.52) than that for the RH model (0.44). The adjusted Fuzzy model had lower k values (0.50) than the original Fuzzy model, but the median for the adjusted Fuzzy model (0.54) was similar to that for the original Fuzzy model (0.54). CV_k values for LWD models ranged from 30% to 35% across sites where unpainted sensors were installed, and were similar among the models. For example, CV_k values for the Fuzzy and RH models were 30% and 33%, respectively.

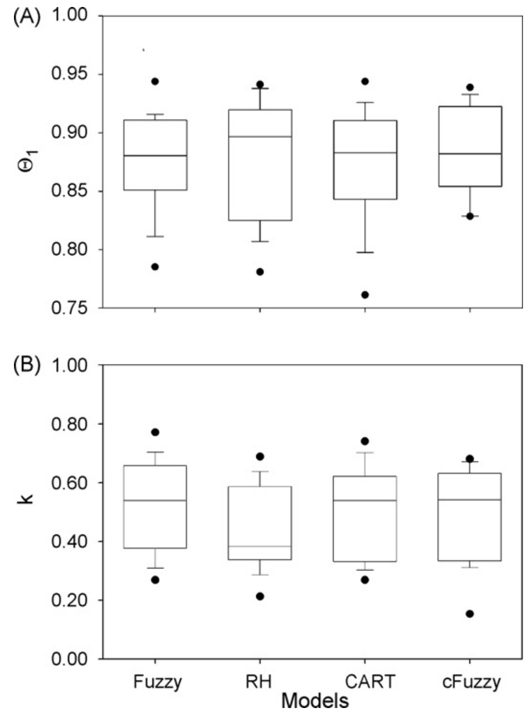

Fig. 3. Boxplot of the statistics for the leaf wetness duration models, using data obtained at 15 sites where unpainted sensors were installed: (A) fraction of correct estimates (Θ_1); (B) a degree of agreement statistic (k). Fuzzy, RH, CART, cFuzzy indicate the Fuzzy model, the RH model, the CART model and the adjusted Fuzzy model for unpainted leaf wetness sensors, respectively. Top and bottom of box and the whiskers indicate upper quartile, lower quartile, and the 10th and 90th percentiles of the box plot, respectively. Dots represent data above the 90th and below 10th percentiles.

Table 4
Comparison between measurements and estimates of leaf wetness duration for 24-h period among sites where unpainted sensors were installed in the state of Oregon (OR), Idaho (ID), and New York (NY) in the USA, and the province of Tuscany (TU) in Italy.

Site	N[a]	D[b]	ME[b]				MAE[b]			
			Fuzzy[c]	cFuzzy[c]	RH[c]	CART[c]	Fuzzy	cFuzzy	RH	CART
Ash Hollow Vineyard, OR	48	1.9	−0.1	−1.0	−0.6	−1.0	1.8 a	1.6 a	1.6 a	1.5 a
Brookings, OR	120	11.2	4.4	1.9	1.5	3.8	4.7 a	3.5 c	3.9 b	4.4 a
Davis Gawith Gala, OR	48	4	−1.3	−2.4	−2.9	−1.4	3.1 a	3.2 a	3.1 a	3.2 a
Dee Flat, OR	92	3.6	1.5	−0.7	−1.7	0.3	2.1 a	1.4 c	1.8 ab	1.5 bc
Geneva, NY	1389	6.1	1.6	−1.1	−0.7	2.9	2.7 b	2.2 c	2.2 c	3.6 a
Hood River, OR	118	2.9	0.7	−1.3	−2.0	0.0	2.2 a	1.8 b	2.1 a	2.0 ab
Medford, OR	121	3.4	2.2	−0.5	−1.4	1.4	2.8 a	1.8 c	1.7 c	2.3 b
Mondeggi Lappeggi, TU	1406	5.6	3.8	2.6	2.5	5.1	4.1 b	3.3 c	3.2 d	5.4 a
Oliver Cherries, OR	48	2	2.4	0.6	−0.3	2.0	3.5 a	2.8 b	2.2 c	3.2 ab
Parkdale, OR	115	7.2	−0.5	−3.1	−4.6	−1.6	2.4 c	3.3 b	4.6 a	2.5 c
Parma, ID	121	2.2	−0.6	−1.7	−1.8	−1.0	1.7 ab	1.7 b	1.8 a	1.6 ab
Pinegrove, OR	118	7.9	−1.1	−3.4	−4.3	−1.8	1.7 d	3.4 b	4.3 a	2.2 c
Rodigheiro, OR	48	1.8	−0.1	−1.0	−1.2	−0.2	2.0 a	1.6 a	1.5 a	1.9 a
Seven Hills Vineyard, OR	48	1.6	−1.4	−1.5	−1.4	−1.4	1.4 a	1.5 a	1.4 a	1.4 a
Worden, OR	117	7.5	−0.6	−3.7	−5.2	−2.9	2.7 c	3.9 b	5.2 a	3.1 c
μ[d]	–	4.6	0.7	−1.1	−1.6	0.3	2.6	2.5	2.7	2.6
σ[d]	–	2.9	1.9	1.8	2.1	2.3	1.0	0.9	1.2	1.2
CV[d]	–	–	–	–	–	–	36.7	36.0	45.9	43.9

[a] Total number of 24-h periods.
[b] Average leaf wetness duration (D), mean error (ME), and mean absolute error (MAE) per 24-h period. Within each row, MAE values sharing a letter are not significantly different at $p = 0.05$ from Wilcoxon's signed rank test.
[c] Fuzzy, RH, CART, cFuzzy indicate the Fuzzy model, the RH model, the CART model and the adjusted Fuzzy model for unpainted leaf wetness sensors, respectively.
[d] μ, σ and CV represent mean, standard deviation and coefficient of variation (%), respectively.

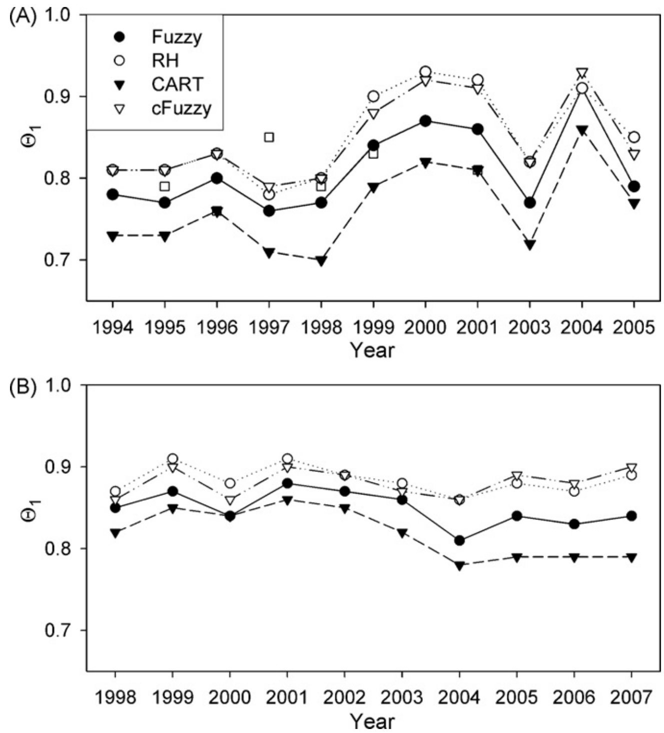

Fig. 4. Fraction of correct estimates (Θ_1) at sites where unpainted wetness sensors were deployed for ≥10 years: (A) Mondeggi Lappeggi, Tuscany, Italy; (B) Geneva, New York, USA. In 2002, no measurement was available for analysis at Mondeggi Lappeggi. Fuzzy, RH, CART, cFuzzy indicate the Fuzzy model, the RH model, the CART model and the adjusted Fuzzy model for unpainted leaf wetness sensors, respectively. The square symbol indicates Θ_1 values for the SWEB model, which were derived from Dalla Marta et al. (2005).

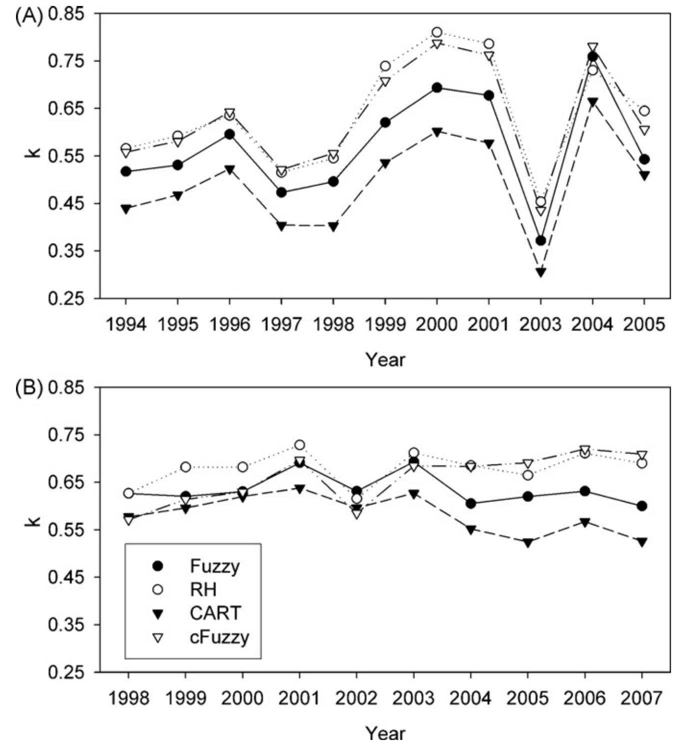

Fig. 5. A degree of agreement statistic (k) at sites where unpainted wetness sensors were deployed for ≥10 years: (A) Mondeggi Lappeggi, Tuscany, Italy; (B) Geneva, New York, USA. In 2002, no measurement was available for analysis at Mondeggi Lappeggi. Fuzzy, RH, CART, cFuzzy indicate the Fuzzy model, the RH model, the CART model and the adjusted Fuzzy model for unpainted leaf wetness sensors, respectively.

The Fuzzy and CART models tended to overestimate LWD whereas the RH model underestimated LWD at most of the unpainted-sensor sites (Table 4). For example, the Fuzzy and CART models overestimated LWD at seven sites whereas the adjusted Fuzzy and RH models did so at three and two sites, respectively. The MAE for the Fuzzy model, which ranged from 1.4 to 4.7 h day^{-1}, was greater than values for other models at seven sites. However, application of the correction factor to the Fuzzy model reduced the magnitude of MAE by about 4% on average. The MAE values for the adjusted Fuzzy model ranged from 1.4 to 3.9 h day^{-1}. In contrast, values of MAE ranged from 1.4 to 5.4 h day^{-1} and from 1.4 to 5.2 h day^{-1} for the CART and RH models, respectively (Table 4).

3.3. Sites where unpainted LWD sensors were deployed for more than 10 years

Accuracy of the LWD models varied similarly at Mondeggi Lappeggi and Geneva (Fig. 4). For example, Θ_1 values for the LWD models increased at Mondeggi Lappeggi from 1998 to 2000. At Geneva, the Θ_1 values for the LWD models decreased from 2001 to 2004. The RH model tended to have the greatest value of Θ_1 at both sites in a given year. The Θ_1 values for the adjusted Fuzzy model were similar to those for the RH model, whereas the Fuzzy and CART models had lower Θ_1 values than the adjusted Fuzzy and RH models.

It appeared that the RH and adjusted Fuzzy models were more accurate in LWD estimation than the SWEB model at Mondeggi Lappeggi (Fig. 4A). For example, the Θ_1 values for the SWEB model ranged between 0.76 and 0.85 from 1995 to 1999 at the Mondeggi Lappeggi site. In 2001, the SWEB model had a Θ_1 value of 0.81. For the period, the RH and adjusted Fuzzy models had greater Θ_1 values than the SWEB model except in 1997.

During the 10-year period, variability of the k values for the LWD models was greater at Mondeggi Lappeggi than at Geneva (Fig. 5). For example, the CV_k value for the RH model was 18% and 5% at Mondeggi Lappeggi and Geneva sites, respectively. The CV_k value for the adjusted Fuzzy model was similar to that for the RH model, which was 18% and 8% at Mondeggi Lappeggi and Geneva sites, respectively.

4. Discussion

Our results suggested that the Fuzzy model was more accurate than the empirical models included in our study across a wide range of geographic locations and climates. Firstly, the Θ_1 and k values for the Fuzzy model were greater than those for other models at sites where painted sensors were installed. Secondly, the value of CV_k for the Fuzzy model was lower than for other models, indicating it was more consistent in accuracy across locations. Thirdly, the MAE values for the adjusted Fuzzy model tended to be lower than those for other models at sites where unpainted sensors were installed. These findings support our hypothesis that the Fuzzy model has greater spatial portability than the other empirical models.

Where LWD measurements from painted sensors were available, the Fuzzy model estimated wetness occurrence more reliably than other models. It is preferable to use painted sensors for agricultural decision support systems in situations when all wetting events, including light dew, fog or rain, need to be accounted for, because their sensitivity is substantially greater than that of unpainted sensors (Lau et al., 2000; Sentelhas et al., 2004b). Unpainted sensors often record shorter wet periods than painted sensors, except during conditions of rapid condensation due to rapid cooling or under very humid conditions (Lau et al., 2000). Breuer et al. (2008) reported that a weather forecast would be considered reliable when it was accurate 80–85% of the time. Under the assumption that Θ_1 values > 0.8 indicate acceptably accurate LWD estimation at a site, the Fuzzy model was accurate at all 28 sites in the USA, Canada, Brazil, and Costa Rica where painted sensors were present (Fig. 2). Furthermore, the Fuzzy model had Θ_1 values of >0.85 at 75% of those sites whereas Θ_1 values for the CART and RH models were >0.85 at about 54% of sites.

In the present study, the values of the k statistic for the Fuzzy model were higher and more consistent than for the other models across sites with painted sensors. This indicated that the Fuzzy model corresponded with painted sensors more reliably than other models. The CART model had a relatively similar CV_k value to that of the Fuzzy model, implying that empirical models like CART could possess spatial portability even if they only implicitly represented physical principles of wetness occurrence. However, the median and inner quartile range of the k statistic distribution was higher for the Fuzzy model than the CART model (Fig. 2B), indicating a more reliable prediction of painted sensor behavior.

The application of a correction factor allowed acceptable calibration of the Fuzzy model to unpainted sensors. For example, the MAE value for the Fuzzy model was significantly lower at seven sites after the correction factor was applied. The Fuzzy model was developed to simulate wetness occurrence on a painted sensor surface (Kim et al., 2004). Thus, it is expected to raise false alarms when unpainted sensor data are utilized for model validation. Although the Fuzzy model tended to overestimate LWD at sites where unpainted sensors were deployed (Table 4), the adjusted Fuzzy model reduced the MAE values considerably.

It was challenging to determine spatial portability of the LWD models among sites where a single unpainted LWD sensor was installed, because the LWD models had considerably greater variability across these sites than across those where painted sensors were installed. The variability in performance of unpainted LWD sensors considerably exceeds that of painted sensors (Sentelhas et al., 2004b). The accuracy of LWD estimates also varied considerably over time at sites where a single unpainted sensor was installed compared with estimates at sites where multiple unpainted sensors were deployed (Figs. 4 and 5). This variability could introduce considerable spatial and temporal error in LWD models, which makes it difficult to assess spatial portability of LWD models. Therefore, it would be preferable to use painted sensors for further validation studies on spatial portability of LWD models.

The accuracy of the Fuzzy model appeared to be similar to that of physical models when painted LWD sensors were the standard of comparison. For example, Sentelhas et al. (2006) reported that a physical model using measurements of net radiation as input data had MAE of 1.1 and 1.9 h day^{-1} at Elora and Piracicaba, respectively. In our study, these values for the Fuzzy model were 1.4 and 2.6 h day^{-1}, respectively, at the same sites in the same year (Table 3). This suggested that MAE for the Fuzzy model could be comparable to that for a physical model at sites where painted sensors were installed. However, this preliminary conclusion needs further validation in field studies at sites where input data for physical models are available.

Although the Fuzzy model had greater accuracy than other models at sites where painted sensors were used to measure LWD, it had relatively large errors in LWD estimation at some of those sites, e.g., O'Neill (Table 3). Because the Fuzzy model depended on net radiation estimated under the assumption of clear sky conditions, it sometimes underestimated incoming long wave radiation when cloud cover was present. Thus, the accuracy of the Fuzzy model would be proportional to the frequency of events in which net radiation estimates were accurate. For example, the Fuzzy model had relatively large errors in LWD estimation under semi-arid climate conditions in Costa Rica due to errors in estimating incoming long wave radiation (Kim et al., 2005). The effect of clouds on LWD estimation during dew periods prompted the development of a cloudiness modelling function (Madeira et al., 2002; Sentelhas and Gillespie, 2008). Evaluation of a model to estimate the sky radiation was not within the scope of the present study.

Our results confirmed that the Fuzzy model would be preferable to the CART model in terms of accuracy and portability. Both Fuzzy and CART models require air temperature, RH, and wind speed as inputs. However, estimation error for the CART model was greater over space and time than for the Fuzzy model in previous studies (Kim et al., 2004, 2005). The CART model resulted in greater errors in LWD estimation than the Fuzzy model (Table 3). In the present study, the CART model had greater MAE than the Fuzzy model at all sites where painted sensors were installed except at Elora.

Sentelhas et al. (2008) showed that the optimum threshold for the RH model differed among sites. Our results supported the view that, for acceptable accuracy, the RH model would need a site-specific threshold. For example, Θ_1 values for the RH model were relatively low at sites where painted wetness sensors were installed. Furthermore, CV_k values for the RH model were considerably higher than those from other models across sites where painted sensors were installed, which indicated that the RH model had relatively low spatial portability.

It may be challenging to determine a site-specific threshold for the RH model in practice. For example, Sentelhas et al. (2008) found that the optimal threshold for the RH model was 83% at Ames. When this threshold was applied to estimate LWD at Ames using the data set included in our study, the Θ_1 value for the RH model with the site-specific threshold was similar, i.e., 0.82, to that for the original RH model using a 90% threshold (0.83). At Macleay, the k value increased from 0.61 to 0.83 when the threshold was replaced with 82%. However, the application of the same threshold at Corvallis, which is about 50 km distant from Macleay, reduced the k value from 0.51 to 0.35. These results suggest that the benefit of the site-specific threshold could be marginal or negative, depending on weather conditions at a given site in a given year. It would be necessary to collect LWD measurements for multiple sites over several years in order to determine the site-specific threshold in a region for the RH model. However, a potent advantage of the RH model – simplicity in estimating LWD – could outweigh such shortcomings at sites for which wind speed and/or solar radiation data are not available. Further study to optimize methods for determining the RH threshold is therefore merited.

Our study demonstrated that it was useful to determine values of the k statistic in order to quantify compatibility of LWD models with LWD sensors. Several indices, including critical success index and false alarm rate (Schaefer, 1990), have been used to quantify the accuracy of LWD models (Sentelhas et al., 2008). However, these indices focus on one class of wetness occurrence, i.e., wet or dry. Sentelhas et al. (2008) also used the Willmott agreement index, which assumes that observations are free of errors (Willmott et al., 1985). However, discrepancy between wetness measurements and actual wetness occurrence has been reported even when painted sensors were used (Lau et al., 2000). Alternatively, the k statistic was useful to quantify the degree of agreement between wetness sensors and LWD models for both wet and dry events without depending on any assumptions. At Silverton, for example, the Θ_1 values for the Fuzzy and RH models were 0.84 and 0.80 whereas the k values for these models were 0.64 and 0.31, respectively. These results suggested that high level of accuracy for the RH model was achieved by chance rather than assessment of weather conditions. Thus, the k statistic could be used as an alternative measure to determine performance of LWD models in further validation studies.

Our results showed that accuracy of the Fuzzy model could be comparable to that of physical models. Major advantages of the Fuzzy model over physical models are the small number of input variables and simplicity in calculation (Kim et al., 2004). Further field validation is needed to assess use of the Fuzzy model to replace physical models at sites where input data for physical models are rarely available.

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