Development of A Leaf Wetness Duration Model Using a Fuzzy Logic System

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1. Introduction

Models have been developed to estimate leaf wetness duration (LWD) using conventional weather observations, e.g., air temperature, water vapor pressure, and wind speed, which are relatively invariant over space (Pedro and Gillespie, 1982; Gleason et al., 1994; Francl and Panigrahi, 1997). As an alternative method to estimate LWD, a fuzzy logic system (FLS) may provide a computational framework to develop an empirical model for estimating wetness duration that complies with energy balance principles. Existence of wetness, especially dew, is determined by calculating whether or not water vapor will condense on a surface. Thus, estimation of LWD does not require exact calculation of latent heat flux between a surface and its surroundings, but rather direction of the energy flux. FLS, therefore, can be utilized to infer occurrence of wetness on a surface with representation of physical processes since outcome of fuzzy logic need not to be precise and its conclusion tends to be dispositional. The objectives of this study were to develop and validate a LWD model using FLS in order to empirically estimate wetness duration based on energy balance principles.

2. Materials and methods

2.1. Weather data

Hourly measurement of air temperature, RH, and wind speed were obtained from 15 sites in Iowa (IA), Illinois (IL), and Nebraska (NE) during May to September of 1997, 1998, and 1999. . Electronic wetness sensors (Model 237, Campbell Scientific, Logan, UT) were coated with latex paint to enhance sensitivity to small water droplets and to approximate the emissivity of plant leaves (Davis and Hughes, 1970; Potratz et al., 1994; Lau et al., 2000). When electrical impedance <1000 kΩ was detected for ≥ 30 min in an hour, the hour was counted as wet (1); otherwise, the hour was scored as dry (0).

2.2. Development of a fuzzy logic system to estimate LWD

A LWD model based on fuzzy logic (Fuzzy LWD model) consisted of variables, membership functions of each variable, and rules to determine whether or not wetness existed on a surface (Table 1; Figure 1). Variables of the fuzzy LWD model were selected using the Penman equation:

$$LE = \frac{\rho C_p VPD / r_a + \Delta(R_n - G)}{\Delta + \gamma} \qquad \text{(eq. 1)}$$

where ρ = density of air (1.2 kg m^{-3}), C_p = specific heat of air at constant pressure (1004.7 J kg^{-1} K^{-1}), VPD = vapor pressure deficit (kPa), Δ = slope of the saturated vapor pressure versus temperature curve (kPa K^{-1}), R_n = net radiation (W m^{-2}), G = ground heat flux (W m^{-2}), γ = psychrometric constant (0.066 kPa K^{-1}), and r_a = aerodynamic resistance for heat and water vapor (s m^{-1}).

From the Penman equation, vapor pressure deficit (VPD), wind speed, and R_n were chosen as variables of the fuzzy LWD model since they play major parts in determining occurrence of wetness. Cloud condition influences incoming long wave radiation in the R_n term of the Penman equation. Since cloud cover data are rarely available, instead of using R_n, which requires use of cloud data, a para-R_n (pR_n) expression was devised for the fuzzy LWD model as follows:

$$pR_n = \varepsilon_a \cdot \sigma \cdot (T+273)^4 - [\varepsilon_s \cdot \sigma \cdot (T_{dew}+273)^4 + (1-\varepsilon_s)\varepsilon_a \cdot \sigma \cdot (T+273)^4] \quad \text{(eq. 2)}$$

where ε_a and ε_s = emissivity of atmosphere and sensor surface, respectively, σ = Stefan-Boltzmann constant (5.67×10^{-8} W m^{-2} K^{-4}), and T_{dew} = dew point temperature (°C). In order to calculate incoming radiation estimates, ε_a was calculated by using the Idso-Jackson formula as follows:

$$\varepsilon_a = 1 - 0.261 \cdot \exp(-7.77 \cdot 10^{-4} \cdot T^2) \quad \text{(eq. 3)}$$

and ε_s was assumed to be 0.98 (Idso and Jackson, 1969).

2.3. Analysis of LWD estimation

Accuracy of LWD estimation by the Fuzzy LWD model was compared to that of the CART/SLD/Wind model, in which the wind speed parameter of the original CART/SLD model was adjusted to the level of sensor height (Gleason et al., 1994; Kim et al., 2002). Mean error (ME) was calculated by averaging differences between measured and model-estimated LWD for 24-h periods that began at 12:00 and ended at 11:00 on the next day. Mean absolute error (MAE) was also computed by averaging the absolute values of hourly errors during each 24-h period. ME provided a measure of the tendency to over- or underestimate LWD, whereas MAE assessed overall accuracy.

Table 1. Fuzzy rules to infer occurrence of wetness

Antecedent[a]			Consequence[a]	Weight[c]
VPD[b]	Wind speed	pRn[b]	Wetness	
High			Absent	0.55
Moderate	Slow		Likely Absent	0.50
Moderate	**NOT** Slow		Likely Absent	0.95
Low	Slow		Likely Present	0.90
Low	Fast		Likely Absent	0.85
Low	Moderate		Likely Present	0.65
Low	Moderate		Likely Absent	0.30
		High	Absent	0.65
		Moderate	Likely Absent	0.60
		Moderate	Likely Present	0.20
		Low	Likely Present	0.30
		Very Low	Likely Present	0.45

a. A fuzzy statement includes antecedent, p, and consequence, q, in form of "If p, then q." p consists of combination of variables, which is both VPD and Wind speed or pRn.
b. VPD = vapor pressure deficit and pRn = potential net radiation calculated from eq. 2
c. Each weight corresponding fuzzy statements was applied to calculated fuzzy value for the statements

3. Results and Discussion

The fuzzy LWD model used the same weather variable as the CART/SLD/Wind model, yet the estimation error was consistently lower over space and time. Those patterns suggested that application of fuzzy logic system may makes it possible to develop a physically oriented model that retains temporal and spatial extendibility, yet is empirically constructed. The CART/SLD/Wind model estimated LWD within average error of about 1 h, which was similar to the Fuzzy LWD model (Table 2). The magnitude of MAE of the CART/SLD/Wind model was higher (3.9 h/day) than the Fuzzy LWD model (3.4 h/day), but was similar to the result using weather data inputs that had been remotely estimated (Kim et al., 2002). The pattern of LWD across sites was similar to the previous study, too.

On the other hand, the Fuzzy LWD model had relatively consistent and low MAE across sites in LWD estimation compared with the CART/SLD/Wind model, which indicated that the fuzzy LWD model may have better spatial extendibility than the CART/SLD/Wind model (Table 2). Especially, the number of sites at which the fuzzy LWD model had less error in LWD estimation than the CART/SLD/Wind model was more during nights than 24-h periods (data not shown). Since the energy balance on a surface governs occurrence of wetness or condensation of water vapor on the surface, a physically oriented model is likely to estimate LWD caused by dew more accurately than other models. Therefore, it seemed that improved portability of the fuzzy LWD model resulted from energy balance principles included in decision rules of the fuzzy logic system.

Table 2. Mean error (ME) and mean absolute error (MAE) for estimation of wetness duration (h/day) in 1998 and 1999.

Sites	N[a]	MWD[b] (h/day)	ME (h/day) (SEM)[c]		MAE[d]	
			CART[e]	Fuzzy[e]	CART	Fuzzy
Ames, IA	303	8.7	0.3 (0.22)	-0.2 (0.22)	3.7	3.5
Lewis, IA	307	7.6	1.2 (0.25)	1.4 (0.24)	4.3	3.8
Nashua, IA	301	8.0	3.3 (0.23)	2.7 (0.23)	4.4	3.8
Sutherland, IA	306	8.0	1.4 (0.24)	1.8 (0.25)	4.2	3.9
Crawfordsville, IA	303	8.1	1.9 (0.18)	0.9 (0.17)	3.5	2.7
Belleville, IL	196	7.6	2.9 (0.24)	2.2 (0.20)	4.7	3.4
Bondville, IL	204	10.0	-1.6 (0.27)	-1.4 (0.24)	3.8	3.3
Dixon Springs, IL	225	9.2	0.4 (0.22)	-1.3 (0.22)	3.0	2.8
Monmouth, IL	231	7.5	-0.8 (0.27)	-0.8 (0.24)	4.0	3.4
St. Charles, IL	218	8.6	-0.6 (0.22)	0.0 (0.21)	3.5	2.7
Red Cloud, NE	317	7.8	1.9 (0.25)	1.6 (0.23)	4.6	3.8
Gordon, NE	322	8.5	-2.1 (0.20)	-1.3 (0.22)	3.9	3.7
O'Neill, NE	270	6.9	2.4 (0.30)	2.7 (0.29)	5.1	4.7
Sidney, NE	322	6.5	-1.0 (0.20)	0.2 (0.19)	3.0	2.7
West Point, NE	167	10.5	-1.0 (0.23)	-1.1 (0.25)	2.9	3.1
All 15 sites	3,992	8.1	0.6 (0.07)	0.6 (0.06)	3.9	3.4

a. Number of 24-h periods include in the analysis.
b. MWD = Wetness duration measured during study periods.
c. ME = mean error (Σ(estimated – measured)/h) and SEM = standard error of the mean difference.
d. MAE = mean absolute error (Σ|estimated – measured|/h).
e. CART = classification and regression tree/step wise linear discriminant analysis and Fuzzy = fuzzy wetness model. Wind speed used in both model was corrected to the level of wetness sensor, which is 0.3 m.

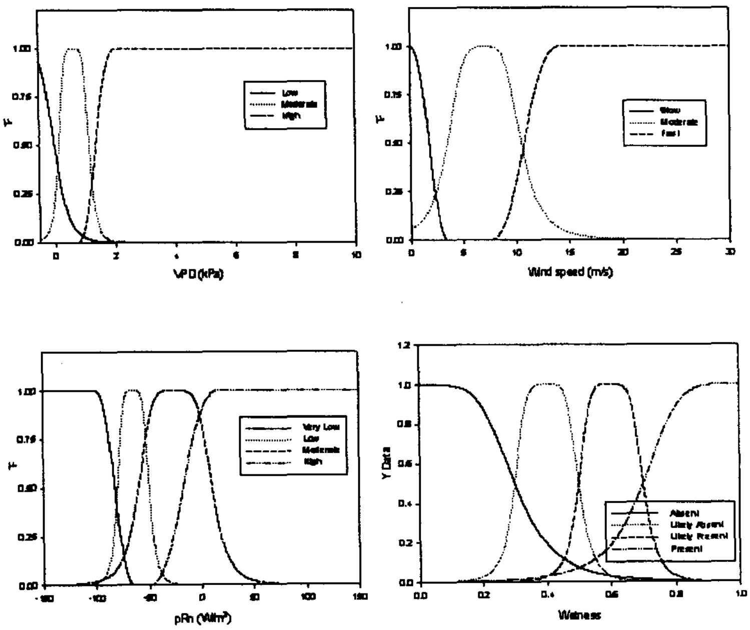

Figure 1. Membership functions of variables included in fuzzy logic system to estimate leaf wetness duration.

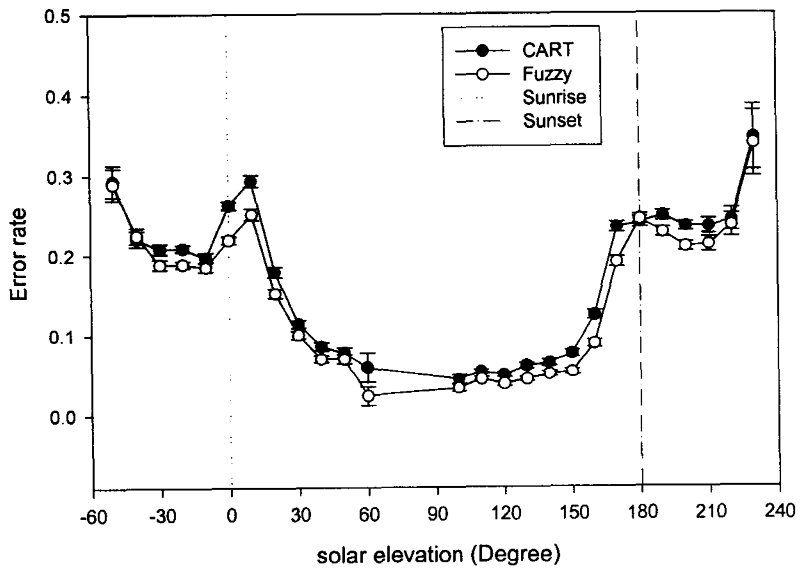

Figure 2. Error pattern in LWD estimation with respect to progress of time in a day in terms of solar elevation. Relative solar elevation with time β_{rs} of a day, which ranged from −90° to 270°, was calculated to identify time periods during sunrise and sunset using the calculated solar elevation β. Before noon, the value of β_{rs} was same as that of β. For hours later than 12:00, β_{rs} = 180° - β. Therefore, the time periods during which $90° < \beta_{rs} < 0°$, $0° \leq \beta_{rs} \leq 180°$, and $180° < \beta_{rs} < 270°$ were considered to be midnight to sunrise, daytime, and sunset to midnight, respectively.

4. References

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