Development and Validation of an Empirical Model to Estimate the Duration of Dew Periods

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ABSTRACT

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An empirical model to estimate the occurrence and duration of dew periods was developed using hourly data for relative humidity (RH), air temperature, and wind speed from June to September 1990 for Ames, Iowa. After using a nonparametric classification procedure called CART to eliminate periods in which dew occurrence was unlikely, stepwise linear discriminant (SLD) analysis was performed with categories of measured dew (0 = no dew, 1 = dew) as the dependent variable. The resulting CART/SLD model and an alternative model that assumed dew was present when RH > 90% were validated by using hourly data from 13 weather stations in Iowa, Kansas, Nebraska, and Illinois during April through October 1992. For 17,487 potential dew hours, both models predicted the mean duration of dew periods within 1 hr, but mean square error was considerably larger for the RH > 90% model than the CART/SLD model. The CART/SLD model estimated presence or absence of dew correctly for 83.5% of the potential dew hours compared to 78.6% for the RH > 90% model. Similarly, the CART/SLD model predicted the duration of dew periods within ±2 hr on 76.0% of 1,502 nights compared to 67.2% of nights for the RH > 90% model. For both models, size distribution of errors in estimating dew duration was approximately normal for three weather stations, skewed toward overestimation for eight stations, and skewed toward underestimation for two stations. After further modification, the CART/SLD model could provide dew-period estimates over broad geographical areas for disease-warning systems that are driven by wetness duration and temperature.

Additional keywords: disease prediction, integrated pest management, weather models

The duration of wetness periods is a key input for disease-warning systems, because many fungal and bacterial pathogens are active on plant surfaces only when free water is present (3). Although the advent of electronic wetness sensors (5,8,12) and automated, programmable dataloggers has made real-time measurement of wetness-period duration far more convenient than in the past (14), U.S. growers have been hesitant to implement disease-warning systems driven by wetness data. Part of their apparent reluctance may result from the cost and unfamiliarity of wetness-measuring equipment and the labor required to monitor it (3).

An alternative to measuring wetness duration is to estimate it with models that use measurements of other meteorological variables. Relative humidity (RH) thresholds, especially RH > 90%, are used as indicators of dew (25) and/or rain, but their accuracy is often unsatisfactory (6,15,18,24,25). Multiple regression based on RH, wind speed, and minimum air temperature was used to estimate dew-period duration at an Oregon weather station, but prediction accuracy was poor when the model was tested at a nearby site (4). In Ontario, a regional wetness-estimation model based on air temperature and dew point depression, and calibrated with wetness measurements at several base stations, provided wetness estimates for the TOM-CAST disease-warning model on tomatoes, which resulted in disease control equivalent to that achieved with measured wetness duration (9). Several physical models use energy balance approaches to predict duration of wetness caused by dew, rain, or both (12). These models use data either from standard weather stations (18) or measured in or above crop canopies (17). The appropriateness of particular wetness-estimation models is dictated by operational factors such as the purpose of the work, the climate, the nature of the crop canopy, and the type and availability of meteorological inputs (12).

Automated weather stations in the United States and Canada proliferated rapidly during the 1980s, and over 800 permanent stations are now in use (16). Many states in the midwestern United States have a high density of weather stations collecting hourly data that is in the public domain. These stations routinely measure rainfall (mm) and RH, but not wetness duration. If measurements from these stations could be used to estimate dew duration with acceptable accuracy, these estimates, together with rainfall data, could form the basis of a regional wetness-duration reporting system. Such a system would be advantageous because it would enable growers to use many weather-based disease-warning systems without individually having to bear the costs and other burdens of weather monitoring.

The purposes of this study were 1) to develop and validate an empirical model to estimate dew duration from public domain weather station data gathered in four midwestern states, and 2) to compare model performance with another model based on periods of RH > 90%. A preliminary report has been published (10).

MATERIALS AND METHODS

Weather data. Weather stations were located on mowed turfgrass on unobstructed sites. CR-10 or CR-21X dataloggers (Campbell Scientific, Logan, UT) were programmed to record data from electronic sensors at 1-min intervals and to output hourly averages of air temperature (T_{air}) and RH at 1.5- or 2.0-m height, wind speed at 3.0- or 10.0-m height, and hourly rainfall totals. Wetness duration was recorded by flat-plate electronic impedance grids (Model 237, Campbell Scientific). To imitate the emissivity of leaves, all wetness sensors were spray painted before use with one layer of black paint followed by two layers of off-white latex paint, and heat-treated to fully dry the paint. The composition of the paints is proprietary (Robert Olson, 123 McIntosh Dr., Savannah, GA 31406, *personal communication*).

Wetness sensors were calibrated in the laboratory before field use by orienting sensors at a 45° angle to the bench top and misting with water from a spray bottle. Kiloohm (kohm) output was recorded by a datalogger at 5-min intervals until the sensor face seemed to be dry. The kohm value associated with the

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time of dryoff was used as a threshold for sensor response. For all sensors, a threshold value of 900 kohm coincided with dryoff within 15 min; therefore, 900 kohm was used as the threshold value for all sensors. In the field, wetness sensors were oriented 45° from horizontal and faced north at a height of 30 cm. Dataloggers were programmed to record the proportion of each hour with sensor readings <900 kohm as wet periods.

Model development. Hourly weather data gathered at the Iowa State University Agronomy Farm near Ames from 11 June to 7 Sept 1990 were used in model development. The data set was edited first by visual inspection to eliminate hours with out-of-range or clearly erroneous values. Hours between 8 a.m. and 7 p.m. were deleted because dew was assumed to be unlikely during this period. In addition, dates on which measurable rainfall occurred were deleted.

Dew point depression ($D = T_{air} - T_{dew\ point}$), wind speed (W) (meters per second), and RH served as predictor (independent) variables. The dependent variable was classified as a 0 (dry) or 1 (wet) indicator of wetness. Hours were classified as wet if the sensor registered wetness for the entire hour or if the proportion of time the sensor was wet was greater than the proportion from the previous hour.

Next, a nonparametric classification procedure called CART (2) was used to identify thresholds of W, D, T_{air}, and RH beyond which dew formation was found to be unlikely. CART created a binary classification tree, consisting of nodes (referred to here as categories) and branches, to distinguish between wet (1) and dry (0) hours. All hours appeared at the initial category. Then CART examined each of the variables and selected one for dividing the hours into two branches. At the end of each branch is a new category. Categories that were split were called decision categories, and ones that were not split were called terminal categories. After the classification tree was created, each hour was classified as wet or dry by proceeding down the tree, beginning at the initial category, until a terminal category was reached. At each decision category, CART considered W, D, RH, and T_{air} one at a time. For each variable, CART found the boundary value that maximized the "purity" of the two resulting categories as measured by the Gini diversity index. A category was completely pure if it contained only wet hours or only dry hours, and least pure if it contained 50% each. After identifying the best boundary value for each individual variable, CART compared the results and selected the variable that best promoted the purity of the subcategories. CART continued to split categories until the terminal categories were entirely pure or contained fewer than five hours. The basic strategy in using CART was to initially fit a very large tree with more categories and branches than could be justified by the data (to reduce the chance of missing an important split) and then pruning off unimportant categories and branches. Cross-validation procedures were used to determine the appropriate amount of pruning (2).

After CART, stepwise linear discriminant (SLD) analyses (13) using the SAS computer package (SAS Institute, Cary, NC, 1989) were used to develop classification rules for hours that did not exceed any threshold created by CART.

Table 1. Data collection period for weather stations during 1992

State	Station	Start	End
Iowa	Ames	May 15	October 14
	Castana	June 8	August 30
	Chariton	June 7	October 19
	Crawfordsville	June 23	October 19
	Sutherland	June 8	October 19
Illinois	Bondville	June 9	October 1
	Monmouth	June 12	October 1
	Orr	June 13	October 1
Nebraska	Sidney	May 20	November 1
	Havelock	April 14	November 1
	Holdrege	June 11	November 1
Kansas	Wichita	July 31	November 1
	Tribune	July 31	November 1

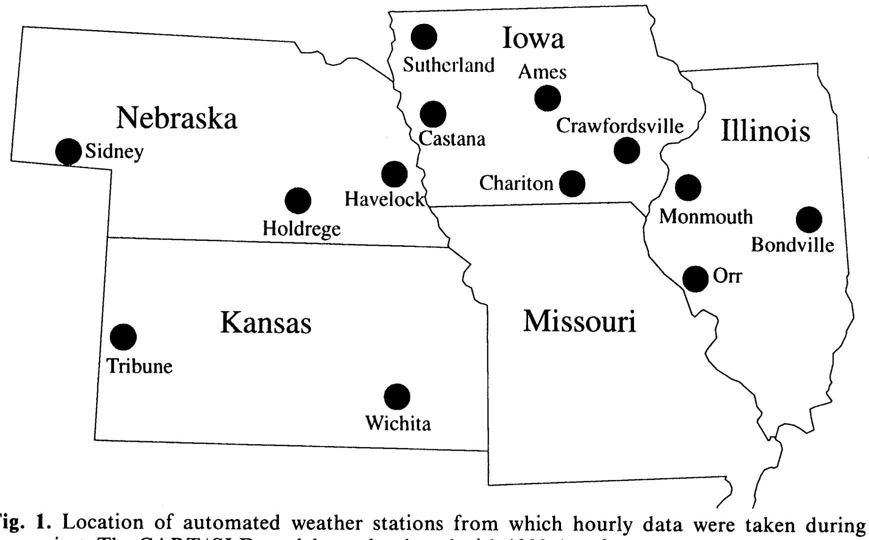

Fig. 1. Location of automated weather stations from which hourly data were taken during the project. The CART/SLD model was developed with 1990 data from the Ames, Iowa station; and both the CART/SLD and the RH > 90% models were validated with 1992 data from all 13 stations.

Model validation. The CART/SLD model was validated with hourly data from 13 weather stations in Iowa, Kansas, Nebraska, and Illinois, recorded between 17 April and 31 October 1992 (Fig. 1 and Table 1). Data sets were edited as described above, and dew-period timing and duration as estimated by the CART/SLD model were compared with measurements by wetness sensors. An alternative model, RH > 90%, which assumed dew was present at RH > 90% (22,23,25), was also tested and compared with the CART/SLD model. Estimates of dew-period duration for each location were evaluated by calculating the difference between measured and estimated hours of dew per night, the mean square error (the mean of the squared nightly differences), and the percentage of dew periods whose estimated duration was within ±2 hr of measured duration. The size distribution of wetness-duration errors (measured–estimated hours) for each station was compared by graphing the errors. Accuracy of the timing of model-estimated dew was evaluated for each location by calculating the percentage of hours in which estimated dew coincided with measured dew.

RESULTS

Validation data sets. After preliminary editing of data from the 13 stations for 1992, a cumulative total of 17,487 hr, representing 1,502 nights, remained eligible for validating the model.

CART analysis. The CART procedure assigned the hourly data to one of four categories: 1) D ≥ 3.7 C; 2) D < 3.7 C, W ≥ 2.5 m/sec, and RH < 87.8%;

3) D < 3.7 C and W < 2.5 m/sec; and 4) D < 3.7 C, W ≥ 2.46 m/sec, and RH ≥ 87.8% (Fig. 2). A high proportion of hours in categories 1 and 2 (Fig. 2) were classified as nondew hours, but categories 3 and 4 could not be discriminated clearly into either dew or nondew categories by this method. Hence, SLD analyses were applied to categories 3 and 4 to develop equations to classify these hours. For hours in category 3, dew was assumed to be present if $[(1.6064\sqrt{T_{air}}) + (0.0036\, T_{air}^2) + (0.1531\, RH) - (0.4599\, W \times D) - (0.0035\, T_{air} \times RH)] > 14.4674$ (1).

For hours in category 4, dew was assumed to be present if $[(0.7921\sqrt{T_{air}}) + (0.0046\, RH^2) - (2.3889\, W) - (0.0390\, T_{air} \times W) + (1.0613\, W \times D)] > 37.0000$ (2).

Although RH is derived from T_{air} and D, both RH and T_{air} are used in the computations because the dew point depression has a nonlinear relationship with relative humidity across the range of ambient temperatures expected during dew formation. Using RH in addition to D enabled us to simplify the complexity of equations 1 and 2.

Accuracy and precision. Overall, both models predicted the duration of dew periods within 1 hr (Table 2). Mean accuracy (measured hours-estimated hours) of dew-duration estimates varied considerably among stations, however. Both models underestimated the duration of measured dew periods at nine weather stations and overestimated it at three stations. At Ames, the RH > 90% model overestimated, and the CART/SLD model underestimated wetness duration. For most stations, mean square error was considerably higher for the RH > 90% model than for the CART/SLD model. Again, the magnitude of the differences between models varied considerably among stations.

The proportion of hours in which occurrence or absence of dew was estimated correctly averaged about 5% higher (83.5% vs. 78.6%) for the CART/SLD model than for the RH > 90% model (Table 3). The CART/SLD model gave a higher percentage of correct estimates than the RH > 90% model for each station. Also, the percent nights in which dew duration was estimated within 2 hr was greater for the CART/SLD model (76.0%) than for the RH > 90% model (67.2%).

For both models, size distribution of errors in estimating dew-period duration per night varied considerably among weather stations (Fig. 3). The error distribution was approximately normal for Ames, Sutherland, and Monmouth; skewed toward overestimation (estimated hours exceeded measured hours) for Castana, Chariton, Crawfordsville, Tribune, Bondville, Orr, Havelock, and Sidney; and skewed toward underestimation for Wichita and Holdrege.

DISCUSSION

The CART/SLD model estimated the duration of dew periods more accurately and precisely than the model based on RH > 90%. In particular, dew-duration estimates derived by CART/SLD were substantially less variable than estimates from the RH > 90% model (Table 2). This is not surprising, because the CART/SLD model incorporates W as well as RH. In the southeastern United States, an extensive comparison of RH data from mechanical hygrothermographs with data from electronic flat-plate wetness sensors (6) concluded that neither 85, 90, 95, nor 100% RH could be used reliably to estimate hours of leaf wetness resulting from dew or rain, and that other factors affecting wetness in addition to RH, such as W, cloud cover, and soil moisture, must be considered in order to achieve acceptable accuracy (6,18). Based on our results, the CART/SLD model would be more reliable than the RH > 90% model in the midwestern United States as an input to weather-based disease warning systems. An empirical model of dew occurrence incorporating the same independent variables was tested in Oregon (4), but this is the

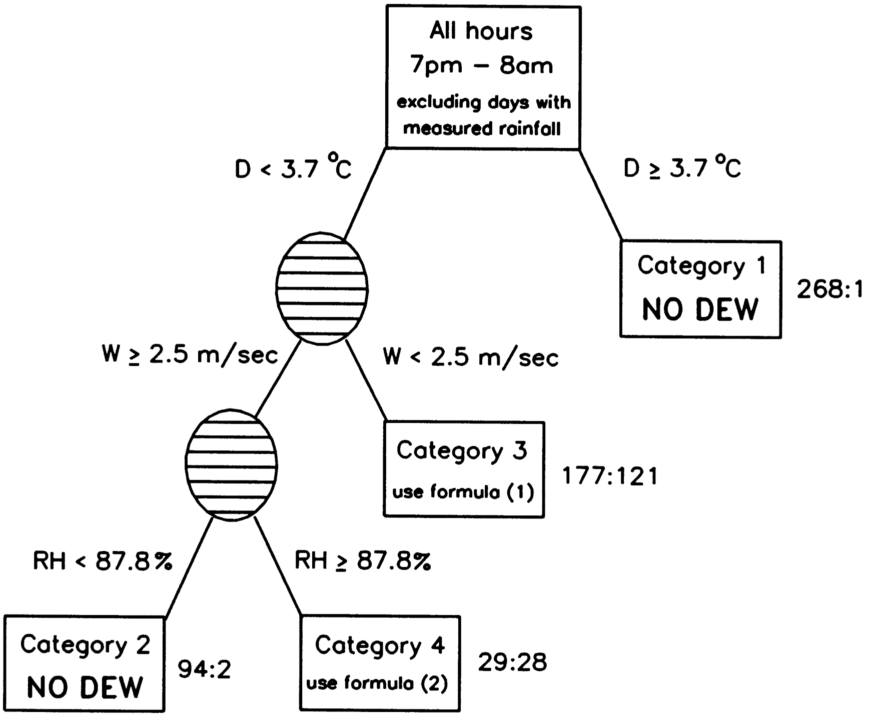

Fig. 2. Classification tree created by the CART procedure (2) for presence or absence of dew in hourly data from a weather station near Ames, Iowa in June–Sept 1990. The CART procedure classified hours of data according to whether the occurrence of dew was unlikely (categories 1 and 2) or uncertain (categories 3 and 4) based on values of dew point difference (D), wind speed (W), and relative humidity (RH). Next to each category is the ratio of hours in which no wetness was measured to hours in which wetness was measured.

Table 2. Mean, variance, and mean square error of difference between measured and model-estimated hours of dew per night

	Mean hr (measured–estimated)		Mean square error[a]	
Location	RH > 90% model	CART/SLD model	RH > 90% model	CART/SLD model
Ames	0.75	−0.27	18.9	8.7
Castana	−2.18	−1.93	18.3	11.5
Chariton	−0.88	−1.36	9.3	6.4
Crawfordsville	−1.19	−1.70	15.6	11.7
Sutherland	−0.86	−1.88	14.4	12.5
Bondville	−2.32	−1.71	12.5	6.7
Monmouth	−1.30	−0.70	10.3	6.5
Orr	−2.97	−3.05	19.7	18.2
Sidney	−1.07	−0.08	10.9	2.5
Havelock	0.09	0.06	9.6	5.6
Holdrege	0.45	0.45	2.0	1.9
Wichita	3.34	1.65	28.5	14.1
Tribune	−2.22	−1.44	13.3	7.4
Mean	−0.68	−0.77	13.5	8.2

[a] Mean square error = $\Sigma(\text{measured–estimated})^2/n$, in which n is number of nights available for dew.

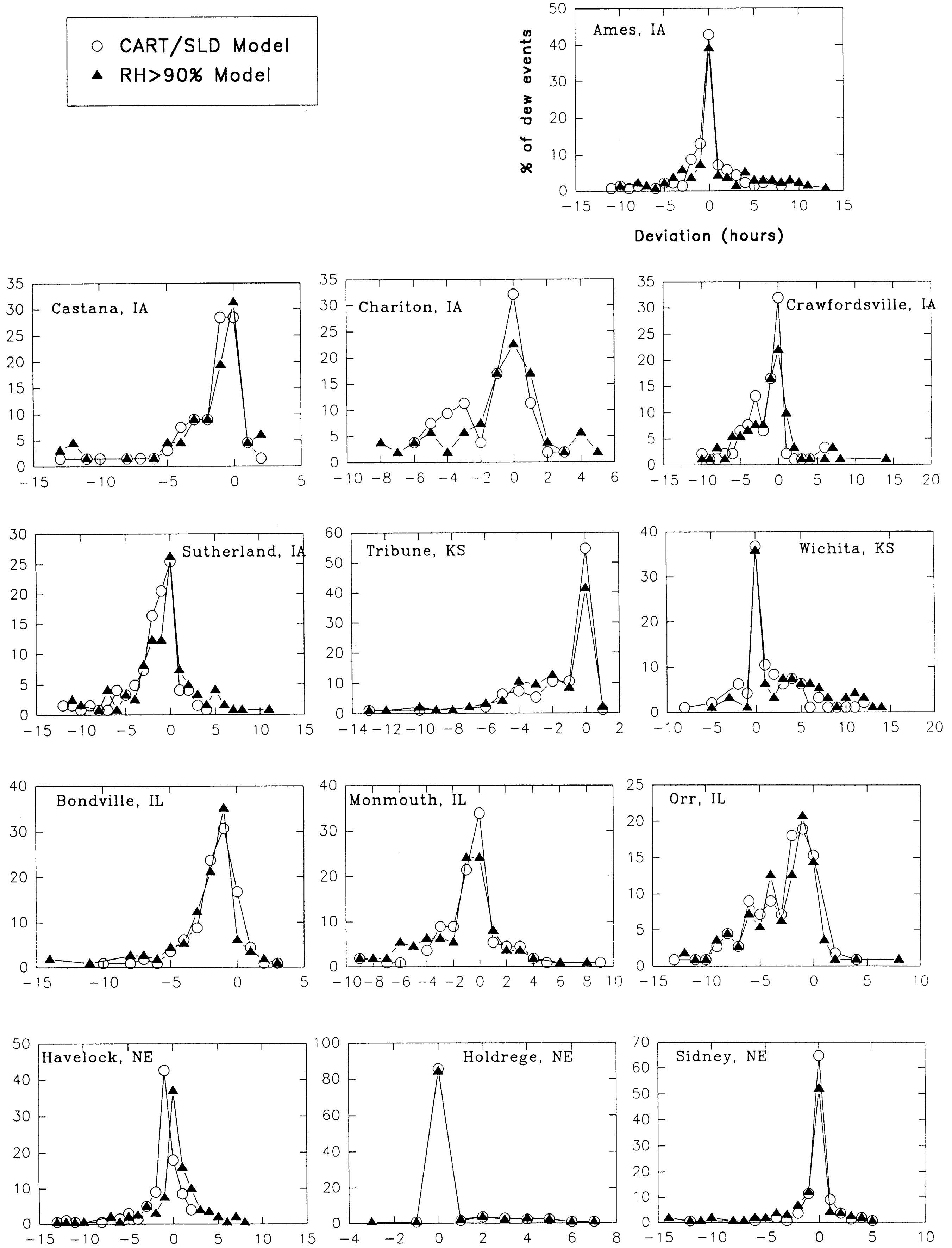

Fig. 3. Distribution of differences of measured vs. estimated dew-period duration for the CART/SLD model and the RH > 90% model at 13 weather stations during 1992.

first test of an empirical dew-estimation model in the midwestern United States.

CART improved the subsequent performance of SLD analysis by identifying abrupt but physically reasonable thresholds separating wet and dry hours along boundaries between vectors of weather variables; whereas the smooth boundaries available to SLD analysis alone cannot describe these thresholds as accurately. The formation of dew on leaves is dependent on the simultaneous influences of D, W, and T_{air}. The first CART branching (Fig. 2) was based on D. When D is small, slight leaf cooling will result in dew formation; but when D is large, it is unlikely that leaf cooling in the natural environment would be sufficient to permit the formation of dew. The second branching was based on W. When W is large, the leaf temperature does not decrease to the extent found under still air conditions. The third branching was based on RH. Under humid conditions, dew may exist even with considerable air movement. We used SLD in conjunction with CART to obtain more economical models for classifying hours that do not exceed thresholds (Fig. 2, categories 3 and 4).

The CART/SLD model needs additional refinement before it is applied to disease-warning systems. To calculate total wetness duration, the CART/SLD model must be modified to include rainfall and irrigation. A likely source of significant error in dew-period estimation is the absence of data on cloud cover. In southern Ontario, an energy balance model using standard weather station data for cloud cover in addition to air temperature, dew point temperature, and wind speed estimated dew duration within 1 hr for exposed leaves of four crop species (7,18). Another source of error is the occurrence of mist or fog, which results in wetness but does not register as rain in tipping-bucket rain gauges. Modeling of hourly temperature and/or barometric pressure during clear, cloudy, and foggy nights may reveal relationships that help identify the presence or absence of clouds and mist. The differences in dew-period estimation error patterns among weather stations (Fig. 3) may be attributable to variations in microtopography, to weather patterns such as cloudy nights, to the behavior of weather sensors, or to a combination of these factors.

The method used to calibrate the wetness sensors may also have been a source of error. The use of wetness thresholds obtained during the drying of sensors on a laboratory bench can result in underestimating the duration of dew periods by an average of 1.4 hr and obscures variability among sensors in response to dew onset (19). To measure dew duration more reliably, wetness sensors should be calibrated during the onset of actual dew periods (19).

After the modifications described above, the CART/SLD model could have broad geographic applicability for implementing disease-warning systems that are driven by wetness and temperature. The fact that hourly data from most of the existing U.S. and Canadian weather networks are in the public domain and available in a real-time mode should make disease-warning systems far less expensive and more convenient to manage than privately owned weather stations. Physical models of dew duration, requiring only standard weather station data for input, have also been used successfully for regional disease-warning schemes (9).

A limitation of weather station data is that the duration of wetness within a crop canopy is influenced by microenvironmental factors such as crop architecture and the position of leaves within the canopy (12,17,18). In practice, however, weather station data recorded near rather than within crop canopies has been used successfully to implement disease-warning systems for processing tomatoes (9,11). Nevertheless, for some crops and disease-warning systems, it will be necessary to calibrate standard weather station data to account for characteristics of the crop canopy (3,20,24).

Another step needed to develop useful regional wetness estimates is to delineate local wetness patterns in areas between weather stations. In southern Ontario, when a regional model for wetness duration based on hourly values of dew point depression was used as input for the TOM-CAST disease-warning system, the estimates provided data for control of fungal diseases equivalent to those obtained by on-site wetness measurements (9). This system used daily wetness-duration measurements at regional sites to calibrate the model-derived wetness estimates for nearby locales. Such an approach could enhance the accuracy of the CART/SLD model for geographic regions of the midwestern United States. Application of Geographic Information Systems techniques has improved the prospects for a regional weather-monitoring network that could deliver reliable wetness information to disease-warning systems. Accurate, high-resolution, real-time estimates of rainfall timing and amount in eastern North America, derived from ground-based radar (1), are now commercially available (e.g., WSI Inc., Billerica, MA, and SkyBit, Inc., Boalsburg, PA). The domain of weather station data could be extended by using numerical models to interpolate data values in the areas between stations (20) and by estimating the effects of the geophysical characteristics of the local terrain on the variables (20,21). By freeing individual growers from the burden of monitoring the weather, a reliable, regional weather-monitoring network could speed the implementation of Integrated Pest Management tactics.

Table 3. Accuracy[a] of two models in predicting the timing and duration of dew at 13 weather stations in 1992

	Hours predicted correctly (%)[b]		Dew-period duration estimated within 2 hr (%)[c]	
Station	**RH > 90% model**	**CART/SLD model**	**RH > 90% model**	**CART/SLD model**
Ames	76.7	82.6	58.0	77.5
Castana	74.6	80.0	70.2	71.6
Chariton	76.7	81.8	67.9	66.0
Crawfordsville	73.8	77.3	59.3	58.2
Sutherland	75.6	79.1	63.1	70.5
Bondville	82.0	84.0	67.5	76.3
Monmouth	79.1	83.6	65.2	74.1
Orr	72.7	74.0	52.3	54.1
Sidney	84.6	92.4	79.0	92.7
Havelock	81.5	85.7	73.5	83.0
Holdrege	91.4	92.0	90.7	91.4
Wichita	71.0	80.5	46.3	66.3
Tribune	82.2	88.4	64.2	76.8
Mean	78.6	83.5	67.2	76.0

[a] The standard of accuracy is wetness measured by electronic sensors.
[b] [Hours in which presence or absence of dew estimated correctly/n] $\times$ 100, where n = total hours in edited data set.
[c] [(Nights in which dew duration estimated correctly within $\pm$ 2 hr)/n] $\times$ 100, where n = total number of nights in edited data set.

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