Validation of a Commercial System for Remote Estimation of Wetness Duration

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ABSTRACT

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To assess the accuracy of remote, real-time mathematical simulations of wetness duration and air temperature, hourly measurements of wetness duration and air temperature at 18 sites in the United States and Canada from May to September 1995 were compared with simulations for these sites provided by SkyBit, Inc. SkyBit simulations of mean, maximum, and minimum daily air temperatures varied from on-site measurements by less than 0.7°C but underestimated the duration of wet periods by an average of 3.4 h/day. At five of six stations tested, SkyBit underestimates of wetness duration were significantly ($P < 0.01$) larger on days when no rain was measured than on rainy days, indicating that simulations of dew-period duration were much less accurate than simulations of rain-period duration. The vast majority of hours SkyBit misclassified as dry occurred either when entire wet periods were missed (59.3%) or when the onset of a wet period was detected late (28.4%). The results suggest that revision of SkyBit wetness-simulation models should focus on reducing error rates during dew events. In simulations using two disease-warning models, TOM-CAST and Melcast, with mean values of measured and SkyBit-simulated wetness duration, SkyBit-simulated values resulted in fewer and later fungicide spray advisories than did measured values. The magnitude of these impacts varied with the magnitude of the simulation errors and with differences in the models' decision rules.

Disease-warning systems are management tools that help growers assess the risk of crop damage from disease and thereby time the deployment of control tactics as efficiently as possible. The duration of periods of crop wetness, and air temperature during these wet periods, are key inputs for disease-warning systems because many fungal and bacterial pathogens are active only when free water is present and temperatures are conducive to their activity. Relatively few growers use disease-warning systems, however, despite convincing evidence that they can reduce pesticide use substantially compared with traditional, calendar-based spray schedules with no added risk of yield loss (1,2,4). The expense and inconvenience of measuring weather inputs, especially wetness duration, is a critical barrier to wider implementation of disease-warning systems (1,4,7).

To circumvent the need to measure wetness duration, attempts have been made to estimate it with empirical and/or quantitative models based on values of other weather parameters such as rainfall, relative humidity, wind speed, air temperature, and radiation (5,7,11). However, all of these models have significant practical limitations for growers, often due to unavailability of the inputs in the vicinity of individual farms.

The advent of commercial services that deliver site-specific, real-time estimates of wetness duration should make disease-warning systems much easier to use. SkyBit, Inc. (Boalsburg, PA), through its "E-Weather" service, is the first commercial firm to offer site-specific, simulated observations and forecasts (14). These simulations, which utilize measurements at weather stations throughout the United States and Canada, mesoscale meteorological models, and Geographic Information Systems programs, are delivered to end users by electronic mail or fax. By freeing growers from the burden of obtaining their own weather inputs, such services have the potential to accelerate implementation of disease-warning systems (1). The accuracy of these wetness

simulations requires thorough validation in field studies before they can be recommended for grower use. While electronic simulations of temperature and relative humidity have been evaluated as inputs to the Penn State Apple Orchard Consultant expert system (16) and a grape black rot expert system (18) at a single site, evaluations of simulated wetness duration as an input for disease-warning systems over multiple sites and geographic regions have not been published. The purposes of the present study were (i) to validate SkyBit estimates of wetness duration and air temperature against on-site measurements over a broad range of eastern North America; (ii) to assess the impact of wetness-estimation errors on timing of fungicide spray advisories by TOM-CAST and Melcast, disease-warning systems for tomatoes and melons, respectively; and (iii) to demonstrate an approach for validating wetness-estimation techniques as inputs to disease-warning systems.

MATERIALS AND METHODS

On-site measurements. Hourly measurements of wetness and air temperature were made from May to September 1995 at 18 sites in the United States and Canada (Fig. 1). Sensors were located at unobstructed sites on managed turfgrass, on bare ground, or near the top of the canopy in melon or tomato fields. Wetness was measured as changes in electrical resistance, either of flat, printed-circuit sensors (Campbell Scientific, Logan, UT; Omnidata International, Inc., Logan, UT; Rainwise, Inc., Bar Harbor, ME; Sensor Instruments, Inc., Concord, NH) or, in Ontario only, of acrylic cylinders on which electrode wires were wound in shallow grooves cut as parallel spirals (15). Sensor surfaces were either painted with latex paint (3) (MA, IA, OH, Ontario) and oven-dried before deployment or left unpainted (NJ, IN); in Indiana, sensor faces were covered with 1-mm-mesh, nylon window screen. Wetness sensors were deployed at heights of 15 to 45 cm above the ground, except at Snyder Farm, NJ, where sensor height increased from 30 to 100 cm, corresponding to changes in height of the top of

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the tomato canopy over the course of the growing season. Flat wetness sensors were faced north at an angle of 45° to horizontal, except in Indiana and Ohio, where sensors were deployed horizontally. Wetness sensors were calibrated before use to identify resistance thresholds associated with the transition between wet and dry environmental conditions. Electronic temperature sensors were thermistors deployed at heights of 20 to 135 cm and shaded from direct sunlight. Sensor readings were recorded by dataloggers at intervals of 1 to 6 min and summarized hourly. Rainfall was measured hourly or daily at six sites.

SkyBit data generation. SkyBit processes data from the U.S. National Weather Service (NWS) and Environment Canada using computer programs based on a weather model called MASS (Mesoscale Atmospheric Simulation System), which was developed for research in remote sensing applications by Kaplan et al. (8). The MASS model simulates finer scale, near-surface weather data than NWS models and provides detailed representation of mesoscale phenomena such as surface energy and water budgets; turbulent processes in the planetary boundary layer; deep moisture convection; atmospheric condensation, evaporation, and precipitation; and long- and short-wave radiation under clear and cloudy sky conditions. SkyBit combines the MASS model with high resolution and topological interpolation techniques developed by Kelley et al. (9). The SkyBit products we chose to test were hourly observations of mean air temperature and wetness (0 = dry, 1 = wet) for each location during the previous 24 h. SkyBit simulations were delivered daily to fee-paying end users by electronic mail or fax.

Analysis of weather data. For the purpose of this analysis, on-site measurements of wetness duration and air temperature

were assumed to approximate reality, and deviations of SkyBit simulations from these values were assumed to be errors. This was a reasonable assumption because all wetness sensors were calibrated during wetness events before deployment. Daily data sets were arbitrarily begun and ended at 12:00 noon. Differences between measured and SkyBit-simulated values of wetness duration and temperature were summarized for 24-h periods and averaged over the entire season. Differences between wetness-duration measurements and simulations were compared on days with and without rainfall to assess the accuracy of SkyBit simulations for rain and dew events. Analysis of variance was used to compare differences for days with and without rainfall. Differences between wetness measurements

and simulations also were subdivided according to whether they occurred at the start, middle, or end of measured wet periods, between these periods, or during periods in which no wetness was measured.

TOM-CAST and Melcast simulations.

We simulated the impact of SkyBit wetness-estimation errors on fungicide spray advisories issued by two disease-warning systems: TOM-CAST, devised by R. E. Pitblado for early blight (pathogen: *Alternaria solani*), Septoria leaf spot (*Septoria lycopersici*), and anthracnose fruit rot of tomatoes (*Colletotrichum coccodes*) (4); and Melcast, for Alternaria leaf blight of muskmelon (*Alternaria cucumerina*) (10). Both TOM-CAST and Melcast advise application of a protectant fungicide spray when the sum of daily disease-risk ratings,

Table 1. Distribution parameters for differences (h) between measured and SkyBit-simulated wetness duration

Location	<i>n</i> ^a	Mean ($\bar{X}$) ^b	SE ($\bar{X}$) ^c
Acton, MA	104	4.9	0.6
Ames, IA	99	3.2	0.6
Decker, IN	76	6.7	0.7
Donaldson, NJ	108	1.5	0.5
Harrow, Ont.	73	3.0	0.6
Leamington, Ont.	94	5.9	0.5
Mondamin, IA	69	2.7	0.3
Muscatine, IA	68	3.3	0.6
Napoleon, OH	118	3.4	0.5
O'Hara, NJ	107	1.8	0.5
Oaktown, IN	75	6.5	0.7
O'Neill, IN	90	3.8	0.6
Ridgetown, Ont.	86	5.1	0.5
Scibilia, NJ	106	-0.8	0.5
Snyder Farm, NJ	129	0.9	0.4
S. Deerfield, MA	100	2.1	0.6
Stratford, IA	98	5.9	0.6
SWPAC, IN	80	5.4	0.6
All locations	1,680	3.4	

^a Number of 24-h periods included in the analysis. Calendar dates of data sets varied by location; start dates ranged from 16 May to 16 June and end dates varied from 16 August to 30 September.

^b Arithmetic mean difference (measured-simulated).

^c Standard error of mean.

Fig. 1. Location of the field sites.

termed “disease severity values” (DSV) for TOM-CAST and “environmental favorability indices” (EFI) for Melcast, reaches a threshold value.

To avoid variability in model response caused by inconsistent data record lengths at individual sites, we chose to simulate a 100-day growing season without reference

to calendar date. The simulations used a threshold of 35 DSV for the first TOM-CAST fungicide spray advisory of the season and 15 DSV for the second and subsequent sprays (4). The EFI threshold for Melcast was 20 throughout the simulation period (10). A computer program varied daily wetness-duration values randomly

about three means so that the standard deviation of the simulated values was 5.7 h, equivalent to that of measured wetness duration for all stations and dates (data not shown). The mean values of the three daily wetness duration distributions that were input to TOM-CAST and Melcast were based on: (i) mean duration of measured wetness for all stations and dates (10.0 h/day); (ii) mean measured wetness duration less the mean difference between measurements and SkyBit-simulated wetness duration for all stations and dates ($10.0 - 3.4 = 6.6$ h/day); or (iii) mean measured wetness duration less the largest mean difference between measurements and SkyBit-simulated wetness duration at any site ($10.0 - 6.7 = 3.3$ h/day). Simulated mean air temperatures during wet periods were generated as random values from a distribution with a mean of 19.0°C and standard deviation of 6.0, which approximated the observed distribution of temperature measurements for all sites. On a given day, however, the simulation program assigned the same air temperature for each of the three simulated values of wetness duration.

Table 2. Mean differences ($\bar{x}$) between measured and SkyBit-simulated values of daily wetness duration (h) for rain days and nonrain days

	Rain days		Nonrain days		Rain vs. nonrain	
	n^a	$\bar{X}_1$ (SE) ^b	n	$\bar{X}_2$ (SE)	F	$P > F$ Ho: $\bar{X}_1 = \bar{X}_2$
Harrow, Ont.	21	-0.4 (0.6) ^c	51	4.4 (0.7)	18.44	0.0001
Leamington, Ont.	34	3.2 (1.0)	60	7.5 (0.5)	16.75	0.0001
Ridgetown, Ont.	35	3.3 (0.8)	51	6.3 (0.6)	8.60	0.0043
Muscatine, IA	17	-0.7 (1.3) ^c	51	4.5 (0.6)	18.59	0.0001
Ames, IA	36	2.1 (1.1) ^c	60	3.9 (0.7)	2.14	0.1471
Napoleon, OH	24	0.2 (1.2) ^c	94	4.2 (0.5)	13.01	0.0005
Mean ^d		1.7		5.0		

^a Number of 24-h periods included in the analysis.

^b Arithmetic mean difference (measured-simulated) and standard error of the mean.

^c $\bar{X}$ is not significantly different from zero ($P > t > 0.05$, $H_0: \bar{X} = 0$).

^d Unweighted mean.

Table 3. Percentage of hours in which measured wetness status (wet or dry) was misidentified by SkyBit

Location	Total h with measured wetness	Wet h identified as dry (%)	Total h without measured wetness	Dry h identified as wet (%)	Total h identified correctly (%)
Acton, MA	1,259	59.8	1,236	9.1	65.3
Ames, IA	1,085	89.0	1,259	13.0	65.7
Donaldson, NJ	980	56.4	1,612	9.9	72.5
Harrow, Ont.	670	50.7	1,005	11.9	72.5
Leamington, Ont.	1,110	61.9	1,082	10.5	63.5
Mondamin, IA	766	61.1	1,524	4.5	76.6
Muscatine, IA	807	54.3	772	13.5	65.7
O'Hara, NJ	929	55.0	1,615	8.1	74.8
Ridgetown, Ont.	731	66.6	1,243	5.2	72.0
Scibilia, NJ	675	41.2	1,710	11.8	79.9
Snyder Farm, NJ	882	38.9	2,213	10.4	81.5
S. Deerfield, MA	1,118	51.2	1,259	16.3	67.3
All 12 locations	11,012	55.1	16,530	10.1	71.9

RESULTS

The number of 24-h periods included in data records for individual locations ranged from 68 to 129, for a total of 1,680 observation days. Records of hourly temperature measurements were available for 13 stations, and hourly rainfall measurements were available for six stations.

Mean differences between on-site measurements and SkyBit simulations varied widely among sites, but SkyBit underestimated wetness duration at most sites (Table 1). The average underestimate was 3.4 h/day. Large standard deviations indicated considerable variability in the accuracy of the SkyBit wetness estimates at many sites. SkyBit averages for mean, maximum, and minimum daily temperatures

Table 4. Wetness hours identified incorrectly by SkyBit and timing of errors relative to on-site measurements of wetness duration

Location	Total h wet ^a	Wet h missed ^b	Wet hours misidentified as dry (%)				Wet h added by SkyBit ^d	Dry hours misidentified as wet (%)			
			Start of wet period	Mid-period ^c	End of wet period	Entire wet period missed		Start of wet period	Between wet periods ^e	End of wet period	Entire period in error
Acton, MA	1,259	753	24.8	3.2	10.9	61.0	113	14.2	39.8	46.0	0
Ames, IA	1,085	640	33.1	7.2	7.7	52.0	164	8.5	2.4	63.4	25.6
S. Deerfield, MA	1,118	572	51.6	4.0	4.7	39.7	205	11.2	27.3	61.5	0
Donaldson, NJ	980	553	27.7	1.8	6.3	64.2	160	14.4	16.3	48.8	20.6
Harrow, Ont.	670	340	22.4	7.9	8.2	61.5	120	35.8	10.8	43.3	10
Leamington, Ont.	1,110	687	15.1	6.6	13.5	64.8	114	20.2	45.6	26.3	7.9
Mondamin, IA	766	468	29.9	2.4	3.0	64.7	69	26.1	2.9	60.9	10.1
Muscatine, IA	807	438	48.4	5.5	4.1	42.0	104	0	12.5	7.7	79.8
O'Hara, NJ	929	511	25.4	2.0	6.7	65.9	131	25.2	18.3	38.9	17.6
Ridgetown, Ont.	731	487	15.2	4.9	2.7	77.2	65	30.8	20.0	30.8	18.5
Scibilia, NJ	675	278	17.6	6.1	9.4	66.9	201	16.4	20.9	47.3	15.4
Snyder Farm, NJ	882	343	30.0	7.6	10.8	51.6	230	27.0	16.5	37.0	19.6
All 12 locations	11,012	6,070	28.4	4.9	7.3	59.3	1,676	18.4	19.6	44.3	17.7

^a Measured by electronic wetness sensors.

^b On-site sensors measured wetness, but SkyBit simulated dry conditions during the hour.

^c SkyBit interpreted a single wet period as two discontinuous periods.

^d On-site sensors did not detect wetness, but SkyBit simulated wetness was present.

^e SkyBit interpreted discontinuous wet periods as one continuous wetness event.

varied from on-site measurements by less than 0.7°C (data not shown), so temperature differences between SkyBit and on-site measurements were not analyzed further.

At five of the six stations that recorded

rainfall, SkyBit underestimates of wetness duration were significantly ($P < 0.01$) larger for days without rainfall than for days on which rainfall was measured (Table 2). The average SkyBit underesti-

mate of wetness duration was 5.0 h on nonrain days and 1.7 h on rain days, a nearly threefold difference.

At the 12 stations for which hourly wetness measurement records were available, SkyBit misidentified 55.1% of measured wet hours as dry (Table 3). The mean error rate for hours measured as dry, but misidentified by SkyBit as wet, was much lower (10.1%). A majority (59.3%) of the hours that SkyBit misidentified as dry occurred during wetness events that were missed entirely by SkyBit (Table 4). An additional large component (28.4%) of wet hours was missed at the beginning of wetness periods, whereas fewer hours were missed at the end of a wetness period (7.3%) or when SkyBit simulated a dry period during a continuous period of measured wetness (4.7%).

TOM-CAST and Melcast accumulated DSV and EFI, respectively, progressively more slowly when mean daily wetness duration was reduced by 3.4 h/day (the overall mean difference between SkyBit and measured wetness duration) or 6.7 h/day (the largest mean difference observed for any station) (Fig. 2). Simulated wetness values, adjusted to reflect the overall mean underestimate and largest observed mean underestimate, resulted in fewer fungicide spray advisories and time lags of 8 to 49 days in issuing spray advisories compared with the 10 h/day standard (Table 5). When simulated mean wetness duration values averaged 6.6 h/day instead of 10 h/day, TOM-CAST spray advisories were 8, 24, and 34 days late and Melcast advisories were 8, 24, and 43 days late for the first, second, and third sprays of the season, respectively.

DISCUSSION

SkyBit simulations of daily wetness duration differed substantially from on-site measurements. In general, SkyBit underestimated the duration of wet periods. This trend prevailed over a broad geographic region despite different sensor designs, coatings, deployment angles, and microenvironments. Even at four New Jersey stations where the SkyBit underestimates were relatively small (<2 h/day), variability in the size of estimation errors was

Fig. 2. Accumulation of TOM-CAST disease severity values (DSV) (A) and Melcast environmental favorability indices (EFI) (B) over a simulated 100-day growing season. Mean daily wetness durations were 10.0 h (mean of measurements for all sites and dates), 6.6 h (adjusted for mean SkyBit underestimate of wetness duration for all stations and dates), or 3.4 h (adjusted for largest mean SkyBit underestimate of wetness duration for any site). Fungicide spray advisories are indicated in ascending order, beginning with 1, the first spray advisory of the season.

Table 5. Number of fungicide sprays recommended by TOM-CAST and Melcast disease-warning systems for mean daily wet periods of 10.0 h^a, 6.6 h^b, and 3.3 h^c, and time lags of fungicide spray advisories for the first three sprays of the season in the 6.6 h/day and 3.3 h/day wetness simulations compared with 10.0 h/day wetness duration

Disease-warning system	Fungicide sprays per season			Time lag ^d					
				First spray		Second spray		Third spray	
	10.0 h	6.6 h	3.3 h	6.6 h	3.3 h	6.6 h	3.3 h	6.6 h	3.3 h
TOM-CAST	6	4	1	8	49	24	...	34	...
Melcast	6	4	1	8	29	22	...	43	...

^a Mean of daily wetness duration measured at all sites and dates.

^b 10.0 h/day – 3.4 h/day. 3.4 h/day = mean SkyBit underestimate of wetness duration for all stations and dates.

^c 10.0 h/day – 6.7 h/day. 6.7 h/day = largest mean SkyBit underestimate of wetness duration for any station (Decker, IN).

^d Assuming a mean air temperature of 19.0°C, with a standard deviation of 6.0°C, during wetness periods, an initial-spray advisory threshold of 35 disease severity values (DSV) and a threshold of 15 DSV for subsequent spray advisories (4).

quite large. Errors in estimation of air temperature were relatively small. Truxall (17), comparing on-site measurements and SkyBit-simulated forecast data for 2 months at a single site (Rock Springs, PA), found that SkyBit forecasts were fairly accurate predictors of air temperature but underpredicted measured relative humidity.

SkyBit underestimates of wet-period duration were much larger for dew than for rain periods. Possible sources of inaccuracy include the simulated inputs to SkyBit's wetness-estimation algorithm (e.g., wind speed, relative humidity, air temperature) and the algorithm itself. The present study, however, did not quantify the relative contributions of these sources. In other work, empirical (5) or energy-balance (11) models, based on measurements of standard meteorological parameters, estimated the timing (11) or duration (5) of dew periods with considerably more accuracy than did SkyBit in the present study. The vast majority (87.7%) of hours SkyBit misclassified as dry occurred either when entire wet periods were missed or when the onset of a wet period was detected late. Therefore, revision of SkyBit wetness-simulation models could focus on reducing error rates during these periods.

In our simulations, TOM-CAST and Melcast recommended fewer and later fungicide sprays when means of measured wetness duration were reduced by mean SkyBit errors. These changes potentially could compromise disease control efficacy. Our simulations, however, did not attempt to simulate the impact, if any, of delayed fungicide sprays on disease development. Field trials at many locations over several growing seasons are needed to determine the impact of SkyBit wetness-simulation errors on crop disease control. Based on a 2-month, single-site field trial using the Penn State Apple Orchard Consultant disease-warning system for apple scab (pathogen: *Venturia inaequalis*) (18), Russo et al. (14) concluded that timing of fungicide-spray recommendations based on SkyBit-simulated weather inputs for air temperature, relative humidity, and precipitation varied little from recommendations derived from on-site measurements, but did not document impacts on disease control. In operational use, factors that were ignored in our simulation will affect the degree to which SkyBit wetness-estimation errors influence the performance of TOM-CAST or Melcast. Examples of these real-world factors include decision rules that supplement the basic disease-warning algorithm, such as those based on crop development stage (e.g., Melcast specifies applying the first fungicide spray when vines in adjacent rows converge [10]) or calendar date (e.g., TOM-CAST specifies application of a fungicide spray on 11 July if none was applied earlier [4]). For other disease-warning systems, the impact of SkyBit errors on system performance will also

depend on each system's characteristic sensitivity to particular input parameters, such as wetness duration, air temperature, relative humidity, and precipitation.

Our study is in several ways a stringent test of SkyBit. Most growers who are potential users of disease-warning systems do not measure hourly wetness or air temperature on their farms. If they use such systems, growers often depend on wetness and temperature measurements made many miles away under the assumption—typically untested—that weather conditions on their farm closely mimic those at the measurement site (4). A more realistic test of SkyBit's accuracy, therefore, would compare its errors with errors incurred in using wetness and temperature measurements taken at various distances (e.g., 10, 20, or 40 km) from a production field. Moreover, on-site measurements of environmental parameters, especially wetness duration, can vary greatly within a crop canopy. Measurements made adjacent to, or even within, a crop canopy are at best only approximations of wetness duration elsewhere in the canopy or the field. For some crops and disease-warning systems, weather data, whether measured or estimated, may need to be calibrated to account for characteristics of the crop canopy and microtopography (1,13,17). Furthermore, wetness-duration measurements are subject to errors whose magnitude can vary with sensor design (6,15), surface coating (3,6), orientation (3), and calibration method (5,12,15). All of these potential error sources were present our study.

We have demonstrated that errors in SkyBit-simulated leaf wetness can substantially alter the behavior of disease-warning systems, and that the magnitude of the impact depends on the particular system. These errors need to be reduced before simulations can be a reliable source of wetness-duration estimates for disease-warning systems. The approach used here could be applied to validate other wetness-estimation models in the future.

Documentation of the magnitude of SkyBit's wetness-estimation errors should not be interpreted as a rejection of this approach. Electronic weather services are a new and emerging technology that shows great promise for application to disease management. Our work illustrates that university and agribusiness researchers must work together with the designers of this new technology to ensure that their products meet the needs of decision makers in the field. Recently (October 1996), SkyBit introduced new versions of its E-Weather models that are designed to address shortcomings in the simulation and forecasting of environmental wetness periods (J. Russo, SkyBit, *personal communication*).

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