Sensitivity of Disease Management Decision Aids to Temperature Input Errors Associated with Sampling Interval and Out-of-Canopy Sensor Placement

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Abstract

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Many plant disease epidemic models, and the disease management decision aids developed from them, are created based on temperature or other weather conditions measured in or above the crop canopy at intervals of 15 or 30 min. Disease management decision aids, however, commonly are implemented based on hourly weather measurements made from sensors sited at a standard placement of 1.5 m above the ground or are estimated from off-site weather measurements. We investigated temperature measurement errors introduced when sampling interval was increased from 15 to 60 min, and when actual in-canopy conditions were represented by temperature measurements collected by standard-placement sensors (1.5 m above the ground, outside the canopy) in each of three crops (grass seed, grape, and hops) and assessed the impact of these errors on outcomes of decision aids for grass stem rust as well as grape and hops powdery mildews. Decreasing time resolution from 15 to 60 min resulted in statistically significant underestimates of daily maximum temperatures and overestimates of daily minimum temperatures that averaged 0.2 to 0.4°C. Sensor location (in-canopy versus standard-placement) also had a statistically significant effect on measured temperature, and this effect was significantly less in grape or hops than in the grass seed crop. Effects of these temperature errors on performance of disease management decision aids were affected by magnitude of the errors as well as the type of decision aid. The grape and hops powdery mildew decision aids used rule-based indices, and the relatively small (±0.8°C) differences in temperature observed between in-canopy and standard placement sensors in these crops resulted in differences in rule outcomes when actual in-canopy temperatures were near a threshold for declaring that a rule had been met. However, there were only minor differences in the management decision (i.e., fungicide application interval). The decision aid for grass stem rust was a simulation model, for which temperature recording errors associated with location of the weather station resulted in incremental (not threshold) effects on the model of pathogen growth and plant infection probability. Simple algorithms were devised to correct the recorded temperatures or the computed infection probability to produce outcomes similar to those resulting from in-canopy temperature measurements. This study illustrates an example of evaluating (and, if necessary, correcting) temperature measurement errors from weather station sensors not located within the crop canopy, and provides an estimate of uncertainty in temperature measurements associated with location and sampling interval of weather station sensors.

Decision aids based on disease epidemic models are being developed increasingly for improving disease management programs (4,5,7,30–32). Models and decision aids vary in complexity, ranging from simple, single-day indices of infection favorability or cumulative favorability indices to complex, season-long simulations (3,10,12,33,35). Most are designed to account for effects of fungicide use on disease development, either quantitatively or based on simple rules. Some also include crop loss components in the decision calculation (13). All of these decision aids depend on disease models that use weather data as inputs, and many were developed using weather data collected at 15- or 30-min intervals from sensors placed in the crop canopy. Therefore, the optimum input data for running the disease models are accurate measurements taken in-canopy at a time resolution (interval) of 15 or 30 min. When the decision aids are implemented, however, such weather data may not be available because of the cost and time required to install, maintain, and manage weather-monitoring equipment and data acquisition. Instead, disease models may be run with available weather data, often from nonagricultural or other off-site locations (8). The need for accurate, site-specific weather data in the absence of on-site field measurements has motivated development of various systems to estimate surface weather at relatively high spatial resolution over large geographical areas (1,18,33). These systems typically produce estimates of weather variables at a standard meteorological placement (usually 1.5 m above the ground, over low vegetation such as mowed grass) and a time resolution of 1 h. Accuracy of site-specific weather estimates is particularly challenging in geographical regions such as the western United States that have topographic variation which can greatly complicate spatial interpolation of weather data (2). Importantly, in many regions of the western United States, there are intensively managed perennial or high-value crops for which disease management decision aids are in great demand (34).

An important consideration in implementing weather estimation protocols for supporting crop disease management decision aids is the inaccuracy introduced by errors in weather measurements relative to other sources of error. Sources of weather estimation error in on-site measurements include sensor placement (in-canopy versus standard placement) and time resolution (e.g., 15 versus 60 min). In cases where the standard-placement weather data are estimated from off-site measurements, there are additional errors associated with these estimation procedures. We propose that the impact of the weather data errors on a disease management decision aid are affected by sensitivity of the aid to the type, magnitude and frequency of errors in weather monitoring that occur.

To investigate how weather input data errors affect disease model performance, we chose three examples of decision aids to

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represent a range of complexities: decision aids for grass (*Lolium perenne*) stem rust, grape (*Vitis vinifera*) powdery mildew, and hop (*Humulus lupulus*) powdery mildew (12,20,29). Producers of these crops in the western United States are currently using these decision aids, and these crops are economically important to the western United States. Grass seed, a crop valued at $500 million annually in the western United States, can be affected severely by stem rust (caused by *Puccinia graminis* subsp. *graminicola*), which can cause >90% yield loss in some years if left untreated (26). A stem rust simulation model that uses temperature and leaf wetness measurements to estimate disease progress and the effects of fungicide applications is currently used as a decision aid (29) by grass seed managers in Oregon. The model was developed from field and greenhouse experiments that quantified components of the disease cycle (22–27). Powdery mildews of grape and hop, caused by *Erysiphe necator* and *Podosphaera macularis,* respectively, can cause total crop loss due to yield and quality effects (16,20). The management of these powdery mildews in the western United States requires regular fungicide applications (up to 14 applications per season in some instances) to ensure marketable crops (9,19,20). Grape powdery mildew management in many vineyards in the western United States is aided by the use of the Gubler/Thomas infection risk model operated using site-specific weather data (12,16) or interpolated weather data (34). This model consists of a series of rules that indicate the risk of infection on a 0-to-100 scale, based on the effect of temperature on the latent period of the disease. The risk index is then used to adjust fungicide application intervals. The hop powdery mildew index, HOPS, is a modification of the Gubler/Thomas model and consists of five hierarchical rules for recommending fungicide application intervals based on consideration of temperature and amount of rain (20). The index was developed from controlled experiments examining temperature effects on infection severity, host susceptibility, and latent period, and was subsequently modified from field observations of disease development in the Pacific Northwestern region of the United States (20). The accuracy of these disease models and indices is not addressed in this article. Instead, this study focuses on sensitivity of the models to errors in weather inputs. The study addresses errors in disease management decision aids generated by weather data errors introduced when the sampling interval of weather measurements is increased from 15 to 60 min, and in-canopy conditions are represented by weather conditions measured at standard meteorological placement (1.5 m above the ground).

Materials and Methods

Weather data were collected with automated weather stations for 2 or 3 years for each crop. At each site, two datasets of temperature observations were made: one dataset from sensors at a standard meteorological placement (1.5 m above the ground, over a grass ground cover), and another from sensors placed in the crop canopy, as described in the following sections. Measurements were taken every 15 min. Temperature data from the nine grass seed site–years were collected from early March to mid-July each year, with an average of 127 days of data per site–year (Table 1). The seasonal periods of the nine site–years during which temperature data were obtained for the grape and hop powdery mildew analyses were from mid-March to late August each year, with an average of 158 days of data per site–year (Table 1).

Temperature measurement in grass seed crops. The grass seed crop evaluated in this study was nonirrigated, perennial ryegrass that had been planted the previous autumn, and which developed to maturity during the season in which weather observations were taken (1 March to 10 July). Plants were approximately 3 cm apart in rows spaced 36 cm apart. The plants were approximately 6 cm tall at the beginning of March each year, grew rapidly in March and April so that the rows closed by late March, and reached 40 cm tall by the end of April. By 1 June each year, the plant canopy reached maximum height (80 cm), and plants typically lodged by mid-June. The height of the lodged canopy was approximately 20 cm.

Temperature was measured with Campbell Scientific Inc. (Logan, UT) weather stations equipped with model 107-L thermistor temperature probes (sensors) mounted in model 41301 vaned solar shields. Weather stations were located in the grass seed crop. For the standard-height temperature measurements, sensors were placed 1.5 m above the ground. For the in-canopy temperature measurements, sensors attached to the same weather station as the standard-placement sensors were placed so that the top of the sensor shield was at the top of the canopy, which ranged from 20 to 70 cm above the ground. The height of the sensors was adjusted to maintain this relative position as plants grew and then lodged. Leaf wetness and rainfall observations for the stem rust model were measured at canopy height and 1.5 m, respectively. Leaf wetness measurements were made with LWS237 sensors (Campbell Scientific) coated with latex paint, as described previously (23).

Temperature measurement in hop and grape crops. The hop yard used in this study was an experimental yard near Corvallis,

Table 1. Sources of weather data for comparing temperature sensor placements and time intervals of temperature measurements on performance of various disease management decision aids for grass stem rust, powdery mildew of hop, and powdery mildew of grape[a]

Crop	Site name[b]	Year	Start day	End day	Number of days[c]
Grape	Grape SkB	2007	131	244	110
Grape	Grape TpH	2007	86	243	148
Grape	Grape ArSm	2008	74	245	170
Grape	Grape Bpp	2008	61	245	184
Grape	Grape Croft	2008	71	245	173
Grape	Grape Tph	2008	73	245	171
Grape	Grape Wren	2008	71	245	173
Hop	HOP_105	2007	60	222	176
Hop	HOP_105	2008	61	197	129
Grass seed	Hys_grass	2006	61	195	128
Grass seed	Hys_grass	2007	60	195	132
Grass seed	Jcty_grass	2007	60	189	126
Grass seed	Silv_grass	2007	60	195	133
Grass seed	Hys_grass	2008	61	200	133
Grass seed	Jcty_grass	2008	61	192	125
Grass seed	Silv_grass	2008	61	190	121
Grass seed	StLs_grass	2008	67	191	118
Grass seed	Hys_grass	2009	61	193	126

[a] A description of the decisions aids can be found in literature citations for grass stem rust (29), powdery mildew of hop (20), and powdery mildew of grape (12).
[b] All sites used in this study were located in western Oregon, United States.
[c] Number of days between start and end dates of each weather data set that had usable data. See text for details on weather station equipment used in each crop.

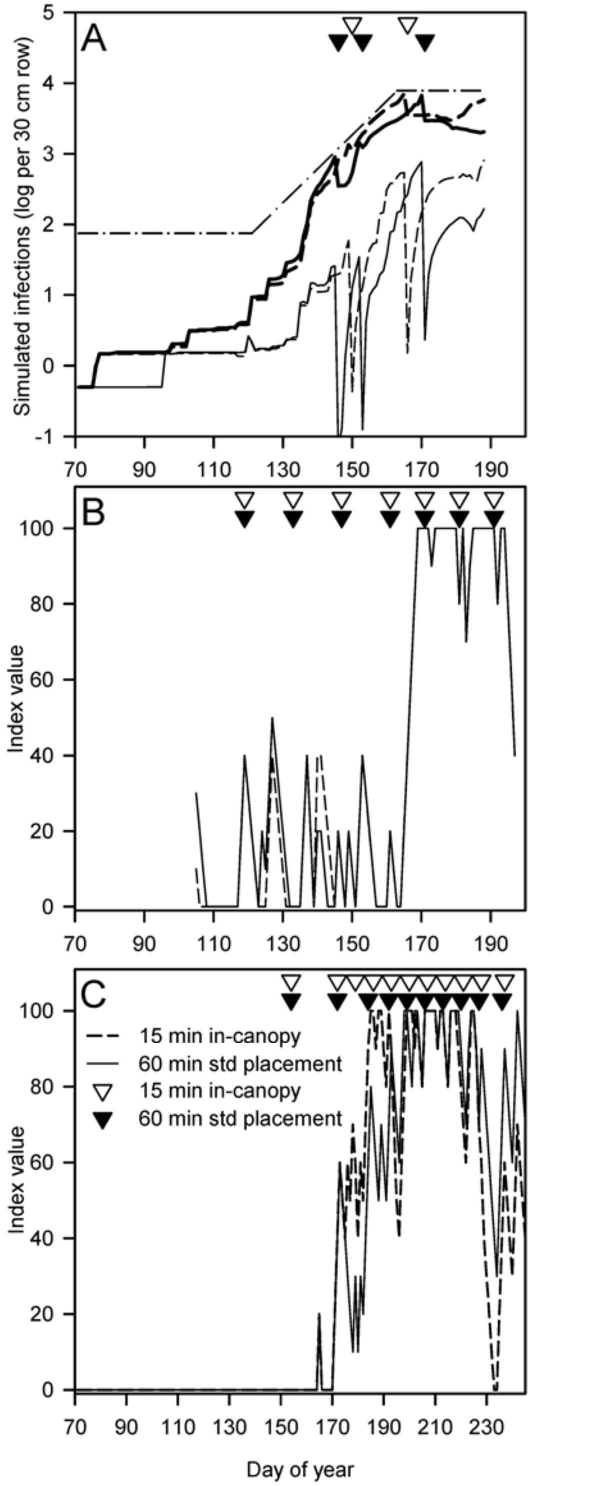

Fig. 1. Examples of results (outputs) for disease management decision aids evaluated in this article. Disease management decision aids were calculated with temperature measurements collected at 60-min intervals from standard-placement weather sensors (solid lines) or 15-min intervals from in-canopy placement sensors (dashed lines). Open (15-min in-canopy data) and closed (60-min standard-placement data) triangles indicate fungicide application dates calculated by the decision aid. **A,** Grass stem rust simulation model, which uses daily weather data to simulate development of a stem rust epidemic, including the effects of fungicide applications on disease development (29). Visible symptoms of infection (bold heavy lines) and total disease (visible plus latent infections; light lines) were simulated, and fungicide application dates (decisions) are indicated when total disease reached a threshold value (dot-dashed line). **B,** HOPS powdery mildew index (20), and **C,** Grape powdery mildew disease index (12). The cumulative index for powdery mildew, calculated from weather data, ranged from 0 to 100; the index value prescribes the date for the first fungicide application and the time intervals between subsequent fungicide applications.

OR. The hop plants surrounding the weather station (described below) were at least 6 years old and spaced on a 2.3-by-2.3-m grid pattern under a 5.5-m-tall trellis. Weather conditions in hop yards were monitored and recorded every 15 min with a Campbell Scientific CR10X weather station. In-canopy temperature measurements were made with a model HMP45C temperature and relative humidity (RH) sensor in a vaned solar shield mounted to a hop pole. Due to the rapid growth rate of hops (up to 15 to 25 cm/day; 19), the temperature sensor was placed 1.5 m above bare soil between hop plants that were cultivated for weed control. The sensor remained above the canopy from shoot emergence (mid- to late March) until mid-May, and then within the canopy for the remainder of the season. This was the position of the sensor used to develop the HOPS model (20) and is typical of how meteorological conditions are recorded within hop yards. Rainfall was measured with a model TE525 tipping bucket rain gauge mounted 5 m above the ground at the top of the hop trellis. The standard-placement temperature measurements were recorded by a similarly equipped CR10X weather station placed over mowed grass and sited outside the hop rows, approximately 200 m from the in-canopy weather station.

Vineyards consisted of 10- to 25-year-old grape vines trained in a vertical shoot position with vines spaced 1.5 to 2.0 m by 2.1 to 2.7 m and with the fruiting wire 60 to 75 cm above the ground. Ground cover was retained or cultivated on alternate rows. Leaf removal in the fruiting zone (11) was conducted around Biologische Bundesanstalt, Bundessortenamt and Chemical industry (BBCH; 15) stage 75 (pea-sized berries) in all vineyards. Weather data from vineyards were collected using two different types of weather equipment that had been calibrated and compared with a Campbell Scientific CR10X weather station (as configured for hops), by operating the equipment side by side outdoors for a period of two summer months. Measurement differences between weather stations were within the equipment manufacturers' stated measurement error for each sensor. In 2007, data from two vineyards in the Willamette Valley of Oregon were collected using HOBO weather stations (Onset Computer Co., Bourne, MA). Standard-placement measurements were collected using HOBO U30 weather stations placed over mowed grass 10 m outside the trellised area, with shielded temperature/RH (S-TMB-M002) and leaf wetness (S-LWA-M003) sensors placed 1.5 m above the ground in vaned solar shields. Rain and wind sensors were placed 2.0 m above the ground. In-canopy data were collected with HOBO Micro stations with shielded temperature/RH and leaf wetness sensors placed 15 cm above the fruiting wire, within the fruiting zone for the entire growing season. In 2008, standard-placement and in-canopy weather data were collected from five vineyards in the Willamette Valley using iMETOS Ag weather stations (Pessl Instruments, Inc., Styria, Austria) with temperature/RH and leaf wetness sensors. The standard-placement sensors were placed 1.5 m above mowed grass, 3.0 m beyond the end of a vineyard row, and the in-canopy sensors were placed 15 to 20 m from the end of the row and 15 cm above the fruiting wire, so that the sensors were within the fruiting zone for the entire growing season. All data were recorded at 15-min intervals.

Analysis of temperature observations. The data for each site–year included three types: 15-min interval in-canopy temperature measurements, 60-min interval in-canopy temperature measurements, and 60-min interval standard-placement temperature measurements. Missing values were omitted from analyses (viz., if the temperature reading for any data type was missing for a given 15-min interval, all data types for that interval were deleted from the data set). To create the 60-min data sets, the hourly readings were sampled from the 15-min data sets, so that the 60-min data were point samples on the hour (e.g., values at 2:00 a.m., 3:00 a.m., and so on) rather than averages over each 60-min interval. This study was based on the assumption that temperature measured at an in-canopy height and at a 15-min interval provides the most accurate measurement of temperature in the crop. Therefore, statistical analyses in this study were used to compare the other temperature data types (60-min interval or out-of-canopy sensor location) to the in-canopy 15-min temperature measurements. Daily maximum, minimum, and average temperatures were calculated for each data type for each site–year combination, and linear regression and Pearson correlation analyses were conducted using the REG and CORR procedures in SAS 9.1 (SAS Institute, Cary, NC) to determine the degree of similarity between values derived from the 15-min canopy data and the respective values from the other sampling intervals and sensor-location data. Also, the computed differences between the 15-min in-canopy measurements and measurements from the other data types were averaged across the season for each site–year to produce an estimate of bias. Means for the arithmetic difference (positive or negative) and for the absolute value of the difference were calculated. In addition to these daily temperature values, the hourly values for in-canopy and standard-placement weather stations were compared by linear regression and correlation analysis for each site–year data set.

The effect of temperature measurement errors on decision aid performance was assessed by comparing outputs from among the different input data types for each site–year. The decision aids (stem rust simulation model and powdery mildew indices) were operated by first calculating daily outputs, such as infection probability, from the input weather data. These daily outputs were calculated for each data type for each data set, and were used in calculating results of the appropriate disease decision aid. We analyzed the effect of weather data type on daily output calculations as well as on the season-long output (e.g., number of sprays recommended and simulated area under the disease progress curve) of the decision aid. Although these decision aids are currently used by growers, their descriptions or validation of the decision aids have not yet been published in detail. The objective of this article was restricted to evaluating effects of temperature measurement errors on decision aid outputs, not validation of the decision aids.

Analysis of temperature data variation on grass stem rust simulation. The stem rust simulation model operates on a daily time step to estimate the number of active rust infection sites (latent and erumpent) in a unit area of a grass seed crop (Fig. 1A; 29). There are submodels for inoculum level, infection probability, rust latent period, plant growth stage, and fungicide effects. Temperature is a key variable affecting infection probability, rust latent period, and plant growth. Infection probability, calculated based on air temperature during leaf wetness periods overnight (during darkness) and during the first 2 h after sunrise, is expressed as the daily infection factor with an exponential value from 0 to 3 (23). Rust latent period and plant growth are calculated from heat units (degree-hours) accumulated each day (22). Fungicide effects, expressed as percent inhibition (0 to 100%), are multiplied by infection probabilities and inoculum production (25,27). The model includes a disease management action threshold (Fig. 1A) which increases monotonically during the season and is used to prescribe fungicide applications whenever the simulated disease exceeds the threshold.

For the analyses of the stem rust model daily output values, the heat units and infection probability were calculated daily for each data type of each dataset. The season-long, cumulative heat unit value total calculated from the 15-min in-canopy temperature data was compared with the total heat unit value calculated for the other temperature data types for each site–year. Similarly, the season-long averages of the daily infection probabilities computed with the different data types were compared. The simulation model was run using these inputs from each data type. The same initialization value, 10 pustules/m^2 of field area on 1 April, was used for all simulation runs. This is a reasonable initial value for a moderately severe epidemic of stem rust (W. F. Pfender, *unpublished observations*). Simulation results were first compared by calculating area under the disease progress curve (AUDPC) values for the plant development period critical to yield (26), and by recording the day on which the simulated disease level first crossed the action threshold. We also calculated healthy area duration (36) by subtracting diseased area from the simulated total plant area, integrated over time. Next, impact of the different data types on management decisions was assessed. The simulation was run with the 60-min in-canopy and standard-placement data types to specify the dates for fungicide application; then, these dates were used as fungicide input dates in the simulation run with the 15-min canopy data. With this approach, as detailed by Pfender et al. (28), we derived an estimate of the effect of applying management decisions that were derived from the 60-min interval or out-of-canopy temperature data on "actual" disease development simulated using the 15-min in-canopy data.

Effects of temperature data variation on powdery mildew indices. For grape powdery mildew, a modified Gubler/Thomas index was used that consists of the ascospore infection rule of Gadoury and Pearson (6) and the conidial stage of the Gubler/Thomas model (12) calculated daily at 6:00 a.m. using the previous 24 h of weather data. Ascospore infection was indicated when bud burst (BBCH stage 07; 15) had occurred and there was >2.5 mm of rain and an average temperature of 10°C in the previous 24-h period. A fungicide application was indicated the first time this rule was invoked. The conidial infection risk index (Fig. 1C) began to accumulate once there were three consecutive days with periods of six continuous hours between 21 and 30°C. After this condition had been met, the index accumulated 20 points for each day on which there were at least six continuous hours with temperatures between 21 and 30°C, and the index lost 10 points for each day these conditions did not occur. This rule is referred to as the "conduciveness rule". The index also lost 10 points on any day when the maximum temperature was >35°C. This rule was referred to as the "heat rule". The index had lower and upper bounds of 0 and 100, respectively. Index values of 0 to 30, 40 to 50, and 60 to 100 indicated low, medium, and high infection risks that prescribed maximum, intermediate, and minimum intervals, respectively, for fungicide spray applications according to a given fungicide label (12). HOPS (Fig. 1B) consists of a set of five hierarchical if/then statements (rules) calculated daily at 6:00 a.m. from 15-min interval temperature data and rain data collected during the previous 24-h period (20,28). The rules were evaluated in order and, if any rule was true the results of the subsequent rules did not apply. The rules were:

(i) If there were ≥6 continuous hours at >30°C, then subtract 20 points, else;

(ii) If there were >2.5 mm of rainfall, then subtract 10 points, else;

(iii) If there were ≥6 continuous hours at >30°C on the previous day, then there was no change in the index, else;

(iv) If there were ≥6 continuous hours of temperatures from 16 to 27°C, then add 20 points, else;

(v) If none of the above rules apply, then subtract 10 points.

Index values accumulated over time, with minimum and maximum values of 0 and 100, respectively, and values of 0 to 30, 40 to 60, and 70 to 100 indicating conditions of low, moderate, or high infection risks, respectively. Analogous to the Gubler/Thomas index, rule i was considered a heat rule and rule iv a conduciveness rule for the HOPS index.

To compare index outputs obtained with each temperature data type, the difference and absolute value of the difference between the daily index values were calculated using 15-min in-canopy data versus 60-min or out-of-canopy temperature measurements each day. These values were averaged across the entire season for each site–year (Table 1) to produce an estimate of bias or absolute bias, as described above. On days with missing data, the index remained the same as the previous day.

The disease management consequences (i.e., choice of fungicide application dates) of calculating the powdery mildew indices with the different temperature data sets also was determined (post hoc) after making several assumptions. For the grape index, fungicide applications were assumed to begin when either the ascospore or the conidial rule was true, and continued until véraison (approximately 1 September). Subsequent sprays were assumed to consist of sulfur applied every 18, 14, and 7 days for index values of 0 to 30, 40 to 50, and 60 to 100, respectively. For the hop powdery mildew system, fungicide applications were assumed to begin as early as 15 April, depending on the index value, and ceased on 10 August in 2007 or 16 July in 2008 (due to the extent of the 2008 data set). Fungicide application intervals of 14, 10, and 7 days were assumed for index values of 0 to 30, 40 to 60, and 70 to 100, respectively.

To determine the degree of error resulting from differences in temperature observations, model outputs of each rule were compared by considering results calculated with 15-min in-canopy temperature data as the "true" temperature and the other data sources as "test" data. The sensitivity and specificity of model rules were computed. Sensitivity was calculated as the number of days when a positive rule was calculated, expressed as a proportion of the total number of days when the rule was truly positive (i.e., as determined from the 15-min in-canopy temperature data). Specificity was calculated as the number of days when a rule did not occur, expressed as a proportion of the total number of days when the rule was truly negative. Sensitivity and specificity can be considered special cases of positive and negative prediction accuracy. Unlike overall accuracy (both positive and negative predictions), sensitivity and specificity are properties of a predictor (in this case, prediction of 15-min in-canopy temperature measurements with temperature measurements made at a different sampling interval or sensor placement), and independent of the proportion of days that were positive or negative for a given rule in a data set (17).

Results

Correlation and bias of temperature estimates. There was a statistically significant positive correlation between 15-min in-canopy temperature data and temperature measured at a 60-min interval, whether from in-canopy or standard placement of the weather sensors (Table 2). Pearson correlation coefficients were >0.95 for all comparisons. The coefficient was greatest for the sampling interval comparison ($r \geq 0.995$ for in-canopy weather stations measuring temperature at 15- versus 60-min intervals), and was progressively lower for comparison of weather sensor location ($r \geq 0.963$ for in-canopy versus standard placement) and the combination of weather sensor location and sampling interval ($r \geq 0.954$ for 15-min in-canopy versus 60-min standard-placement temperature measurements). Correlation coefficients were greatest for comparisons of daily average temperature ($r \geq 0.991$) and were least ($r \geq 0.954$) for daily maximum and minimum temperatures. The correlation coefficient for temperature measured in the grass seed crop was not significantly different from that of the grape and hop crops for daily average and daily minimum temperatures but was significantly less ($P < 0.01$) than in the grape and hop crops for daily maximum temperature (Table 2).The temperature bias due to sampling interval or weather station sensor location was calculated based on mean differences in temperature measurements (Table 2). The biases were statistically significant (most at $P = 0.01$ and some at $P = 0.05$) for all comparisons of daily maximum temperature, as well as for daily minimum temperature (Table 2). Biases for daily average temperatures were not significant ($P = 0.05$), except for the comparison of in-canopy 15-min versus standard-placement 60-min temperatures in the grass fields (Table 2). Measurements made at 15-min intervals were equal or more extreme for daily maximum and minimum temperatures than those based on 60-min intervals. The errors in daily average temperature measurements can be smaller than the errors for maximum temperature or minimum temperature, due to offsetting errors (i.e., opposite sign) in the high and low temperatures.

For daily maximum and minimum temperatures measured in grass seed fields, mean errors in temperature measurements attributable to weather station sensor location (in-canopy versus standard placement) were significantly ($P = 0.01$) larger than those due to differences in sampling interval and significantly smaller than those attributable to the combination of out-of-canopy location and increased sampling interval. Mean errors in daily average temperature were not significantly different ($P = 0.05$) among the different weather data types from grass seed fields. For the grape and hop fields, results were similar to those from grass fields except that mean errors attributable to 15- versus 60-min sampling intervals, though numerically smaller than those due to sensor location, were not significantly different ($P = 0.05$) from them. The errors were significantly greater for the grass seed crop sites than for the grape and hop sites, except in two of the daily average temperature comparisons. Differences in the level of bias in temperature measured between the crop environments were greatest ($P < 0.001$) for the daily maximum temperature measurements. The

Table 2. Temperature measurement uncertainty due to differences in weather station sensor placement and time interval between measurements: Pearson correlation coefficients and deviations between temperature measurement at an in-canopy placement and a standard placement

	Weather data source comparison[a]								
	15-min vs. 60-min interval at an in-canopy placement			In-canopy placement vs. standard placement at 60-min intervals			In-canopy placement at 15-min intervals vs. standard placement at 60-min intervals		
		Difference (°C)			Difference (°C)			Difference (°C)	
Temperature, crop[b]	*r*	Mean	Absolute	*r*	Mean	Absolute	*r*	Mean	Absolute
Daily maximum									
Grape and hop	0.998	0.25	0.25	0.990	0.48	0.73	0.989	0.73	0.89
Grass seed	0.995	0.40	0.40	0.963	1.81	1.85	0.954	2.21	2.23
t test	**	***	***	***	***	***	***	***	***
Daily minimum									
Grape and hop	0.995	–0.23	0.23	0.974	–0.35	0.48	0.973	–0.58	0.64
Grass seed	0.985	–0.32	0.32	0.970	–0.85	0.86	0.958	–1.16	1.17
t test	ns	**	**	ns	*	*	ns	**	**
Daily average									
Grape and hop	1.000	**0.00**	0.06	0.995	**0.08**	0.29	0.995	**0.08**	0.29
Grass seed	0.999	**0.22**	0.39	0.992	**0.23**	0.40	0.991	0.24	0.42
t test	ns	**	***	ns	ns	*	ns	ns	*
Hourly									
Grape and hop	–	–	–	0.988	**0.08**	0.52	–	–	–
Grass seed	–	–	–	0.964	**0.08**	0.93	–	–	–
t test	…	…	…	ns	ns	***	…	…	…

[a] Table entries are means of the correlation coefficients (r) and differences across site–years for each of the crop types (grass seed, or grape and hops). Differences (mean difference [Mean] and mean absolute difference [Absolute]) are calculated as first source in column header – second source in column header (e.g., 15-min in-canopy measurement – 60-min in-canopy measurement). Differences printed in bold are not significantly different ($P = 0.05$) from 0; all others are significantly different from 0 at $P = 0.05$ (underlined) or $P = 0.01$.

[b] Difference between the grass seed value and the grape-and-hop value, analyzed by a t test, is noted as not significant (ns) or significant at *, **, or *** = 0.05, 0.01, or 0.005, respectively.

small errors (not significant at $P = 0.05$) in hourly temperature measurements indicated that there was essentially no asynchrony in temperature differences between in-canopy and standard-placement observations.

The largest errors in temperature measurements occurred at the 15-min intervals with an out-of-canopy weather sensor location, particularly for daily maximum and minimum temperatures (Table 2). The bias was larger for the grass seed crop sites (up to 2.2°C) than for the grape and hop sites. The bias observed for grass seed crop sites reflected the greater temperature fluctuation (i.e., higher daily maximum temperature and lower daily minimum temperature) near the surface of the grass canopy than 1.5 m above the canopy.

Effects of temperature measurement errors on the grass stem rust simulation model. Daily heat unit accumulation was not affected ($P = 0.05$) by the sampling interval of temperature measurements (Fig. 2A), because the daily average temperature measurement was not affected by differences in sampling interval (Table 2). Weather sensor location had a modest but significant ($P = 0.05$) effect on measured heat unit accumulation. The lower maximum temperature measured by weather stations at standard-placement versus in-canopy height was not completely offset by the higher minimum temperature at the standard placement, with the result that heat units computed from standard-placement weather station measurements were, on average, lower than heat units calculated from in-canopy weather station measurements (Fig. 2A). This bias was fairly consistent, as indicated by the small variability in data (Fig. 2A), and could be corrected with a simple scalar multiplication (by 1.016) of daily heat units (Fig. 2A, "adjusted std 60"). This multiplier was obtained as the slope of the linear regression of in-canopy heat units versus standard-placement heat units.

Similar to this result for daily heat unit accumulation, calculation of the stem rust daily infection factor was not significantly ($P = 0.05$) affected by the sampling interval of temperature measurements (Fig. 2B). Sensor location, however, had a significant effect on calculations of the daily infection factor because the infection factor depends on temperature measured at night and during the first 2 h after sunrise, with warmer temperatures more conducive to infection than cold temperatures (23). On most days, the minimum temperature occurred approximately at sunrise, which is typical for diurnal temperature fluctuations. The higher minimum temperature recorded by standard-placement weather stations than weather stations located in-canopy (Table 2) translated to an overestimation of infection favorability by the standard-placement temperature measurement, and resulted in more predicted high-infection days and fewer low-infection days compared with the calculations made with in-canopy weather station temperature measurements (Fig. 2B).The biased infection value computed from standard-placement temperature measurements was corrected by developing a nonlinear function (described below) of temperature with lower and upper bounds of 0 and 3 log-units, respectively. The bounds corresponded to nonconducive and maximally conducive conditions (23). Temperature measurement bias associated with weather station location had little or no significant effect on calculated infection value when canopy conditions were either decidedly conducive or prohibitive for infection (23) but did have a significant effect for intermediate conditions. Pearson correlation coefficients were calculated for each site–year for the correlation between infection factor computed from actual (in-canopy) versus biased (standard-placement) temperature measurements. A second-order polynomial with intercept 0 was the simplest polynomial that adequately fit the data (Fig. 3). In addition, the importance of seasonal conditions on the infection factor bias was assessed by calculating coefficients of determination separately for each month (*analysis not shown*). Regression equations among site–years ranged from $y = 0.957x + 0.005x^2$ (least curved regression line) to $y = 0.279x + 0.229x^2$ (most curved), where y = infection value computed from in-canopy temperature data and x = infection value computed from standard-placement temperature data. Although the bias was pro-

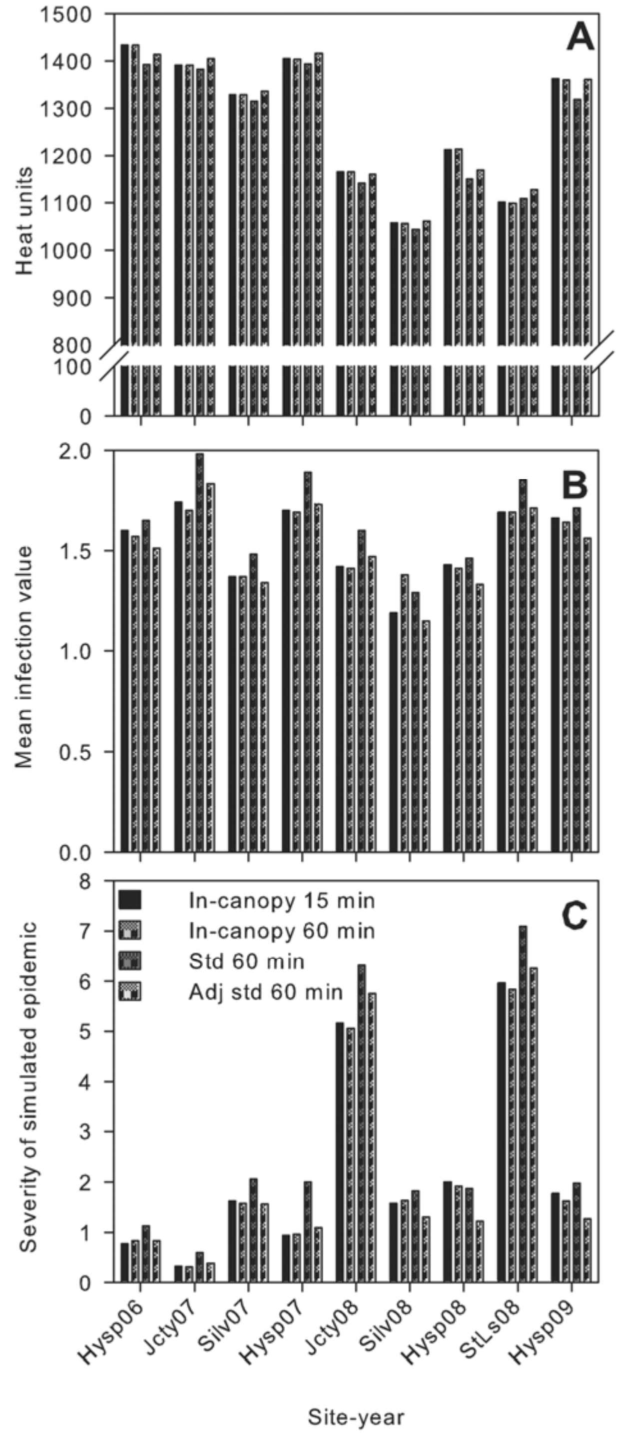

Fig. 2. Season-long components of the stem rust simulation model (29) for nine site–years of grass seed fields in Oregon, computed from four types of temperature input data: air temperature measured at the top of the grass canopy at 15- or 60-min intervals (denoted "In-canopy 15 min" and "In-canopy 60 min", respectively); measured at a standard placement, 1.5 m above the ground, in 60-min intervals ("Std 60 min"); or measured at the standard placement in 60-min intervals, then adjusted by a regression equation in order to approximate calculations from canopy-height temperature data ("Adj std 60 min"), as described in the text. **A,** Cumulative heat units. **B,** Average daily infection favorability value (range: 0 to 3.0). **C,** Simulated stem rust epidemic severity (area under disease progress curve), expressed as the square-root transformation of the percentage of healthy crop area duration (36). The labels on the x-axis are identifiers for various locations in western Oregon (Hysp = Hyslop, Jcty = Junction City, Silv = Silverton, StLs = St. Louis) followed by a year indicator (e.g., 06 = 2006). In a mixed-model analysis of variance, there was a significant ($P = 0.05$) main effect due to the std 60-min data for all computed components: heat units were significantly greater, whereas infection value and epidemic severity were smaller for the std 60-min treatment than for the other data types. There was no significant difference among the other three temperature data types.

gressively larger from March to July (*data not shown*), these site–year and month effects were less than the overall variability in bias. Therefore, we used the combined data set (all months and all site–years) to derive the regression equation (Fig. 3) to be used as the adjustment algorithm for correcting the infection value derived from standard-placement temperature measurements. That equation is Adjusted Infection Value = $0.634x + 0.113x^2$, where x = infection value calculated with standard-placement weather station temperature measurements at a 60-min interval. The season-long averages of the adjusted infection value (Fig. 2B, adjusted std 60) were not significantly different ($P = 0.22$, paired t test) from the values computed from the 15-min in-canopy temperature data, whereas the uncorrected values computed from standard-placement temperature measurements were significantly larger ($P = 0.001$, paired t test) than those from the 15-min in-canopy temperature measurements.

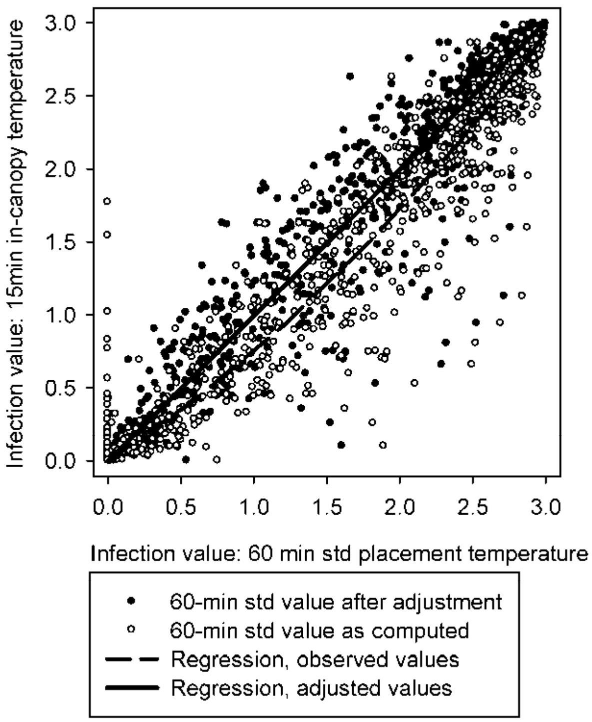

Fig. 3. Comparison of daily infection favorability values (Infection value) for stem rust, computed from different temperature data sources for nine site–years in grass seed fields. Infection values computed from in-canopy 15-min-interval temperature data, considered to be the true value, are compared with infection values computed from 60-min-interval standard-placement temperature data, or to the latter values adjusted post calculation to approximate canopy data, as described in the text.

The rust simulation model produced an output of estimated disease severity each day (Fig. 1). AUDPC from days 160 to 180, a predictor for yield loss due to stem rust (26), was greater for simulations run using standard-placement temperature data (mean = 12.3%) than for simulations run using in-canopy data (mean = 8.4%) (Fig. 2C). This bias toward larger AUDPC values (i.e., greater disease) was statistically significant ($P = 0.04$, paired t test) and resulted from the upward bias of the daily infection factor (Fig. 2B) associated with standard-placement versus in-canopy temperature measurements. This bias was offset partially by the lower values for heat unit accumulation (Fig. 2A) when the simulation was run with the nonadjusted standard-placement data. In simulations run with the adjusted standard-placement heat unit and infection values, the AUDPC (mean = 9.1%) was similar ($P = 0.26$, paired t test) to the result for simulations run with the in-canopy data (Fig. 2C). Due to variability in the degree of error from input temperature data propagated through the simulation model, some simulations were undercorrected and others were overcorrected by the adjusted inputs. Across the nine site–years, the errors in AUDPC of the standard-placement simulations were –0.5 to 14.7% (results for standard-placement weather station sensor minus in-canopy weather station sensor results), whereas the errors in AUDPC from the adjusted standard-placement simulations were –2.5 to 6.5%.The stem rust model includes predicted effects of fungicide applications on daily disease severity. Therefore, disease management scenarios (i.e., timing and number of fungicide applications) derived from simulations run with different temperature weather data inputs can be compared (28). The simulations were run for the nine site–years using in-canopy and adjusted standard-placement weather station temperature measurements (Table 3), with a common initial value for stem rust severity on 1 April. Use of the ad-

Table 3. Simulated outcomes for grass stem rust management determined by the stem rust decision aid when operated with temperature inputs from either the in-canopy (15-min interval) measurements or the standard-placement (60-min interval) measurements that had been adjusted to correct bias[a]

Site	Year	Weather input[b]	First spray date	Number of sprays	AUDPC[c]	Diseased area (%)[d]
Hys	2006	In-canopy 15-min	3 May	2	6.0	0.20
		Adj Std 60-min	30 April	2	0.2	<0.01
Jcty	2007	In-canopy 15-min	4 May	2	13.7	0.29
		Adj Std 60-min	6 May	2	11.7	0.25
Silv	2007	In-canopy 15-min	28 April	1	4.4	0.08
		Adj Std 60-min	16 May	2	17.7	0.33
Hys	2007	In-canopy 15-min	1 May	1	8.2	0.17
		Adj Std 60-min	29 April	1	11.4	0.24
Jcty	2008	In-canopy 15-min	6 May	3	7.6	0.15
		Adj Std 60-min	5 May	3	2.1	0.04
Silv	2008	In-canopy 15-min	10 April	2	14.1	0.24
		Adj Std 60-min	13 April	2	6.0	0.10
Hys	2008	In-canopy 15-min	6 May	3	9.5	0.20
		Adj Std 60-min	15 May	2	15.0	0.32
StLo	2008	In-canopy 15-min	6 May	3	8.5	0.17
		Adj Std 60-min	6 May	3	8.5	0.17
Hys	2009	In-canopy 15-min	6 May	2	8.5	0.19
		Adj Std 60-min	17 May	2	7.3	0.16
Mean	…	In-canopy 15-min	1 May	2.1	8.9	0.47
		Adj Std 60-min	5 May	2.1	8.9	0.41

[a] Outputs from a stem rust simulation model that includes effects of fungicide applications on rust epidemic severity.
[b] Weather inputs for spray decisions: Adj Std 60-min is the input from standard-placement, 60-min interval temperature measurements modified by an appropriate correction algorithm (see the main text) to estimate measurements obtained by in-canopy sensors sampling at 15-min intervals. All simulations were run with 10 pustules/m^2 of field area on 1 April for stem rust severity at the start of the season.
[c] Area under the disease progress curve (AUDPC) in units of 1,000 pustule-days/0.06 m^2 of the crop from days 160 to 180.
[d] Diseased area expressed as a percentage of the total plant area from day 160 to 180.

justed standard-placement weather station temperature measurements altered the decision for timing the first fungicide application compared with the result using in-canopy temperature data, usually by <3 days but by more than 14 days in one site–year (Silv 2007). In seven of the nine site–years, the number of sprays recommended was not changed by the use of adjusted standard-placement temperature data, and there was one site–year each with a decrease or increase of one recommended fungicide spray. We simulated the epidemic outcome that would be obtained if the adjusted standard-placement temperature measurements were used in the decision aid to make fungicide application decisions. The fungicide application dates derived from the simulation using adjusted inputs were used to run the epidemic simulation based on actual (in-canopy 15-min interval) temperature data. Averaged across site–years, the simulated AUDPC of the epidemic as managed by the recommended fungicide applications was not significantly different between the simulations run with in-canopy temperature data and those run with adjusted standard-placement temperature data (Table 3). There was variability in the magnitude and sign (positive or negative) of AUDPC differences between the two simulations for each site–year (Table 3); however, the AUDPC during the time of the season critical for yield (26) was, in all cases, <1% of the healthy area duration, as defined by Waggoner and Berger (36). Previous research (26) indicated that a stem rust disease severity of <1% during this critical period for disease does not have a significant effect on grass seed yield.

Effects of temperature measurement errors on powdery mildew indices. The grape powdery mildew ascospore rule calculation was not affected by the sampling interval of temperature measurement or the weather station sensor location (Table 4). The sensitivity and specificity of the ascospore rule when calculated with these data were both 1.0. For the grape and hop powdery mildew indices, the number of days for which the conduciveness rule applied was greater for the standard-placement 60-min temperature data than for the in-canopy 15-min temperature data in seven of the nine site–years; therefore, the average effect of increased sampling interval was an increase in the number of days declared conducive for powdery mildew. Temperature sensor location had a minor effect on calculation of the conduciveness rule, and that effect was inconsistent across site–years. Sensitivity and specificity of the conduciveness rule calculation were little affected by sampling interval or sensor location for all site years except the cooler (i.e., historically fewer growing degree days than average for the Willamette Valley; *data not shown*) vineyard sites, TpH and Wren, in 2008. These sites had sensitivities of 0.87 and 0.84 and specificities of 0.98 and 0.96, respectively, which were lower than all other sites. The relatively low sensitivity indicated that weather station sensor placement and intervals between temperature measurements at these sites led to underestimation of the number of days declared conducive for powdery mildew infection compared with when the index was calculated with temperature data measured with in-canopy sensors at 15-min intervals.

The heat rule calculated the same number of days for eight of the nine site–years when the standard-placement 60-min temperature interval data were used in comparison with the in-canopy 15-min temperature data. The heat rule result was the same for five of the nine site–years for the 60-min data from standard datalogger sensor placement compared with 15-min data from the in-canopy sensor. The average number of days with inhibitory upper temperatures for powdery mildew was not affected by sensor location or

Table 4. Effects of weather inputs on powdery mildew index rule calculations[a]

			Number of days rule is calculated to apply			Rule sensitivity[b]			Rule specificity[b]		
Crop, site	Year	Weather input[c]	Asc	Cond	Heat	Asc	Cond	Heat	Asc	Cond	Heat
Grape											
SkB	2007	In-canopy 15-min	8	50	2						
		In-canopy 60-min	8	54	2	1.00	0.96	1.00	1.00	0.96	1.00
		Std 60-min	8	54	2	1.00	0.91	1.00	1.00	0.91	1.00
TpH	2007	In-canopy 15-min	8	46	1						
		In-canopy 60-min	8	48	1	1.00	0.96	1.00	1.00	0.97	1.00
		Std 60-min	8	47	1	1.00	0.94	1.00	1.00	1.00	1.00
ArSm	2008	In-canopy 15-min	10	45	5						
		In-canopy 60-min	10	46	5	1.00	0.98	1.00	1.00	0.98	1.00
		Std 60-min	10	46	5	1.00	0.98	1.00	1.00	0.98	1.00
Bpp	2008	In-canopy 15-min	10	44	3						
		In-canopy 60-min	10	46	3	1.00	1.00	1.00	1.00	0.98	1.00
		Std 60-min	10	49	2	1.00	0.95	0.67	1.00	0.91	1.00
Croft	2008	In-canopy 15-min	6	43	10						
		In-canopy 60-min	6	46	9	1.00	0.98	0.90	1.00	0.97	1.00
		Std 60-min	6	46	9	1.00	0.98	0.90	1.00	0.97	1.00
TpH	2008	In-canopy 15-min	7	45	1						
		In-canopy 60-min	7	46	1	1.00	1.00	1.00	1.00	0.99	1.00
		Std 60-min	7	41	2	1.00	0.87	1.00	1.00	0.98	0.99
Wren	2008	In-canopy 15-min	4	38	6						
		In-canopy 60-min	4	39	6	1.00	0.95	1.00	1.00	0.98	1.00
		Std 60-min	4	39	3	1.00	0.84	0.50	1.00	0.96	1.00
Hop											
205	2007	In-canopy 15-min	…	76	1	…			…		
		In-canopy 60-min	…	82	2	…	0.99	1.00	…	0.83	0.99
		Std 60-min	…	82	2	…	0.99	1.00	…	0.83	0.99
205	2008	In-canopy 15-min	…	41	7	…			…		
		In-canopy 60-min	…	40	7	…	0.95	1.00	…	0.98	1.00
		Std 60-min	…	40	7	…	0.95	1.00	…	0.98	1.00
Mean		In-canopy 15-min	7.6	47.6	4.0	…			…		
		In-canopy 60-min	7.6	49.7	4.0	1.00	0.97	0.99	1.00	0.96	1.00
		Std 60-min	7.6	49.3	3.7	1.00	0.93	0.90	1.00	0.95	1.00

[a] Asc = ascospore rule, Cond = conduciveness rules, and Heat = heat rule.

[b] Sensitivity and specificity are for rules calculated with in-canopy 60-min or standard-placement 60-min interval (Std 60-min) data, using measurements by in-canopy sensors recording temperature at 15-min intervals as the true value for comparison. See the main text for a description of the rules.

[c] Weather inputs are the weather station location (in-canopy versus standard placement; see the main text for details) and time interval of the temperature measurements (15- versus 60-min intervals).

time interval for temperature measurement, and the average sensitivity and specificity of the heat rules when calculated with 60-min, standard-placement data were 0.93 and 1.00, respectively. However, there was a reduction from six to three in days when the heat rule was activated at the Wren 2008 location using 15 min in-canopy temperature data versus 60-min standard-placement temperature data.

The powdery mildew index produces an output from which fungicide application recommendations are made based on the risk category (Fig. 1B and C). The management decisions (i.e., fungicide application number and timing) recommended by the powdery mildew index calculated with standard-placement 60-min temperature data were compared with decisions prescribed by temperatures collected from in-canopy sensors at 15-min intervals (Table 5). There was no difference between the temperature data sources for the date of the first recommended fungicide spray for grape powdery mildew. Averaged across the nine site–years, there was essentially no difference in number of recommended fungicide applications or application intervals although, for two of the individual site–years, the number of sprays recommended differed by ±1 depending on the specific temperature data sources.

Discussion

This study demonstrated the variability that can occur in disease forecasting systems or decision aids based on the effects of errors in temperature measurements associated with time interval of temperature measurement and weather sensor placement relative to the crop canopy. Overall, increasing the sampling interval of temperature readings from 15- to 60-min intervals had little impact on results of the three management decision aids evaluated in this study. The relatively small increase in temperature range (i.e., minimum and maximum daily temperatures) that was measured with the shorter (15-min) sampling interval is expected to have an impact only in situations where the actual temperature is near a threshold important for a calculation or management recommendation in a given decision aid.

The importance of the location of weather station sensor placement (in-canopy versus standard placement at a 1.5-m height) differed among the three crops examined. For grape and hop, the in-canopy temperature measurements were very similar to the standard-placement weather station temperature measurements. This may be due to the nature of the canopy of these perennial crops under the prevailing cultural practices and climatic conditions of the Pacific Northwest region of the United States. The grapevines used in this study were trained in a vertical shoot position and leaves were removed from the eastern side of the fruiting zone to increase light and air penetration, which probably resulted in the canopy having minimal effect on air temperature. Under conditions where the grape canopy is pruned and managed differently, the in-canopy temperature could deviate from the standard-placement temperature more widely than under the conditions of this study. Similarly, for hop, the in-canopy temperature sensor was not located completely within the vegetative canopy but 1.5 m above the ground within the influence of the 5.5-m-tall hop canopy. Although hop plants may reach 5.5 m in height, plants were spaced on a 2.3-by-2.3-m lattice pattern, and lateral growth of branches typically did not begin until early July. Thus, the canopy is relatively open for much of the season and allows some mixing of advected air, reducing canopy effects on temperature. In the grass seed crops, in-canopy temperatures were measured closer to the soil surface (grass canopy or ground) than in the grape or hop crops. Therefore, the grass seed crop in-canopy temperature measurements displayed greater diurnal amplitude of temperature than the standard-placement observations. This differential is a well-known feature of near-ground air temperature (21). The failure of the standard-placement weather station sensor to measure accurately the true daily maximum temperature of the grass seed crop canopy did not have a marked impact on the grass stem rust model performance but made a slight difference in the measurement of accumulated heat units to predict plant and pathogen growth. In contrast, the bias of the standard-placement weather stations sensor in overestimating early-morning daily minimum temperature at the grass canopy level resulted in frequent overestimation of infection favorability on days with cool mornings. This effect of temperature measurement error on simulated disease was not uniformly expressed, however. On days when the in-canopy morning temperature was warm and

Table 5. Powdery mildew management outcomes for decision aid operated with temperature inputs from either standard-placement, 60-min interval or in-canopy, 15-min interval sensors[a]

Crop, site	Year	Weather input[b]	First spray date	Number of fungicide applications	Application interval (days)	Date index reached 60
Grape						
SkB	2007	In-canopy 15-min	12 May	14	8.1	27 May
		Std 60-min	12 May	14	8.1	27 May
TpH	2007	In-canopy 15-min	14 April	15	10.1	1 June
		Std 60-min	14 April	15	9.4	1 June
ArSm	2008	In-canopy 15-min	20 May	13	7.9	22 June
		Std 60-min	20 May	13	7.9	22 June
Bpp	2008	In-canopy 15-min	20 May	11	9.4	22 June
		Std 60-min	20 May	12	8.6	22 June
Croft	2008	In-canopy 15-min	21 May	12	8.5	22 June
		Std 60-min	21 May	12	8.5	22 June
TpH	2008	In-canopy 15-min	25 May	12	8.2	22 June
		Std 60-min	25 May	12	8.2	22 June
Wren	2008	In-canopy 15-min	3 June	10	8.9	22 June
		Std 60-min	3 June	10	8.9	22 June
Mean	…	In-canopy 15-min	16 May	12.4	8.7	15 June
		Std 60-min	16 May	12.6	8.5	15 June
Hop						
205	2007	In-canopy 15-min	27 April	11	10.6	…
		Std 60-min	27 April	11	10.6	…
205	2008	In-canopy 15-min	27 April	7	13.1	…
		Std 60-min	27 April	8	11.5	…
Mean	…	In-canopy 15-min	27 April	9.0	11.9	…
		Std 60-min	27 April	9.5	11.1	…

[a] Fungicide application decisions (number of applications and interval between applications) based on operating the powdery mildew decision aid using one of the two weather input types. An index threshold of 60 is important for the grape powdery mildew index because this threshold determines when the first fungicide application should be made and initiates accumulation of subsequent risk values.

[b] Weather inputs are the sensor location and measurement time interval. Std = standard placement.

highly favorable for infection, temperature overestimation by the standard-placement weather stations had little effect on the calculated infection value.

In a disease model which is significantly affected by weather input errors, it is useful to devise correction algorithms so that the standard-placement weather station temperature data can produce model outputs similar to those produced by in-canopy weather stations. In some cases, a simple correction of the temperature measurement can be made. The daily heat unit accumulation for the grass stem rust model was corrected fairly reliably by simply adding the calculated average daily bias to the standard-placement weather station data. However, in some site–years, this approach was not effective, probably because the difference in diurnal temperature fluctuation between ground-level sensors versus sensors located 1.5 m above the ground depended to some extent on daytime solar radiation intensity and nighttime cloud cover, which varied among site–years. The daily infection favorability value in the grass stem rust model is a more complex calculation than the heat unit summation. Infection favorability is a nonlinear function, and temperature input errors have relatively small effects when the true temperature is either highly favorable or highly unfavorable for infection but have a greater effect under intermediate conditions. For this function, errors due to temperature sensor placement were reduced more by applying a correction algorithm to the computed infection favorability value than to the temperature data used to compute the value.

Simulation-based disease models or decision aids may be less subject to threshold errors than are rule-based indices but could amplify errors due to the compounding effect of calculations that are repeated in time or are cumulative. Nonetheless, in this study, it was relatively simple to correct the bias and produce an output similar to that of in-canopy temperature data for the grass stem rust model. Simulation-based decision aids have an added benefit of allowing estimation of disease management outcomes when the decision aid is operated under a range of data sources (in-canopy, standard-placement, and standard-placement temperature data after correction; 28).

For disease management decision aids other than those used in this study, the importance of weather station sensor placement may vary depending on the extent of temperature-altering crop-canopy effects and the nature of the disease model. If measurements from standard-placement weather station sensors are similar to those from in-canopy weather stations sensors, there will be little effect on decision aid performance. For example, the potato late blight model Blitecast performed similarly when operated with weather data collected in or out of the canopy early in the season but differences in severity value accumulation were more substantial as the potato canopy developed and had a greater effect on in-canopy air temperature (14). When there is a difference between in-canopy and standard-placement weather station temperature measurements, threshold-based decision aids may be particularly sensitive to errors when true conditions are near the threshold on multiple, consecutive days. For example, the Gubler/Thomas powdery mildew model heat rule has a 35°C threshold that was missed on 2 days in this study, by 0.1 and 0.8°C, respectively, for 60-min, in-canopy temperature measurements at the Wren 2008 location. These misses resulted in an increase in the index values calculated. In this specific instance, failure to invoke the heat rule on these days did not affect the final management decisions, partly because the 2 days of overestimated infection risk were not consecutive. Because the in-canopy weather station was located 23 m south and 6 m lower in elevation from the standard-placement weather station, these differences may be related to elevation differences and not differences in sensor placement within the canopy. These differences may be common in vineyards on sloped terrain and should be considered by growers when making management decisions.

The results described in this study are for temperature measurements. Moisture conditions (e.g., RH and leaf wetness) are more difficult to measure accurately and may display larger discrepancies than temperature between in-canopy and standard-placement weather sensors. The results of this study also represent only one climate zone, the maritime west coast of the United States, which consists of cool, wet winters and warm, dry summers. Weather station sensor placement may have a different or more important effect on temperature measurements and decision aid outputs in more temperate regions or arid environments.

This study demonstrated that understanding canopy location and sampling interval effects on air temperature measurement may permit assessment of the need to correct decision aids for errors in temperature measurements associated with out-of-canopy sensors. Adjustments may be needed for a particular decision aid, based on sensitivity of that decision aid to the introduced errors, and can be devised so that out-of-canopy temperature data can be used. Assessment of the degree of uncertainty introduced by measured or estimated temperature data is beneficial for determining the contribution of this error to decision aid uncertainty (28).

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