Use of an Empirical Model to Estimate Leaf Wetness Duration for Operation of a Disease Warning System Under a Shade in a Ginseng Field

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Abstract

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Ginseng foliar diseases are typically controlled by spray application using periodic schedules. Few disease warning systems have been used for effective control of ginseng foliar diseases because ginseng is grown under shade nettings, which makes it difficult to obtain weather data for operation of the disease warning system. Using weather data measured outside the shade as inputs to an empirical leaf wetness duration (LWD) model, LWD was estimated to examine if operation of a disease warning system would be feasible for control of ginseng foliar diseases. An empirical model based on a fuzzy logic system (fuzzy model) was used to estimate LWD at two commercial ginseng fields located in Gochang-gun and Jeongeup-si, Korea, in 2011 and 2012. Accuracy of LWD estimates was assessed in terms of mean error (ME) and mean absolute error (MAE). The fuzzy model tended to overestimate LWD during dew eligible days whereas it tended to underestimate LWD during rainfall eligible days. Still,

daily disease risk ratings of the TOM-CAST disease warning system, which are derived from estimates of wetness duration and temperature, had a tendency to coincide with that derived from measurements of weather variables. As a result, spray advisory dates for the TOM-CAST disease warning system were predicted within ± 3 days for about 78% of time windows during which the action threshold for spray application was reached. This result suggested that estimates of LWD using an empirical model would be helpful in control of a foliar disease in a ginseng field. It was also found that a spray application time model using meteorological observations may prove successful without the requirement of leaf wetness sensors within the field. Development of empirical correction schemes to the fuzzy model and a physical model for LWD estimation in a ginseng field could improve accuracy of LWD estimates and, as a result, spray advisory date prediction, which merits further studies.

Ginseng (*Panax ginseng* C.A. Meyer) is an herbaceous perennial plant whose roots have medicinal properties (26). Ginseng is adapted to cool and temperate climate. High levels of shade are required for growth of ginseng (24). For example, wild ginseng is found in the understory of deciduous forests whereas cultivated ginseng is grown under an artificial shade.

Ginseng production is often limited by foliar diseases under cool and humid weather conditions (25). Leaf blight caused by *Alternaria panax* is a common ginseng disease in Asia as well as North America (21). In British Columbia, Canada, gray mold (*Botrytis cinerea*) is one of the prevalent ginseng diseases (25). In Korea, anthracnose (*Colletotrichum gloeosporoides*) is another common foliar disease (17).

Leaf wetness duration (LWD) is an important factor that determines the risk of foliar diseases. There is no standard for installation and maintenance of LWD sensors, which makes it difficult to obtain reliable measurements of LWD (22). It would require considerable effort to measure LWD in a field. For example, reliability of leaf wetness measurements would depend on timely calibration, sensor distribution in a field, sensor position within canopy, and sensor coating

(1,27,29). Measurements of LWD are also dependent on the facing of sensors (20).

Considerable efforts have been made to develop LWD models as an alternative to LWD sensors (9). One of the simplest approaches to estimate LWD is a relative humidity (RH) model, which assumes occurrence of leaf wetness whenever RH is greater than a specific threshold, e.g., 90% (28,32). Gleason et al. (11) and Kim et al. (16) developed a nonparametric empirical model using a classification and regression tree (CART) for estimation of LWD. Sophisticated approaches including artificial neural networks and fuzzy logic systems have been applied for development of LWD models (15). Physics models based on energy balance principle have also been used to estimate LWD (27). These models have been used to estimate LWD in an open field.

Both shade and dense spacing in a ginseng field would facilitate extended LWD and, as a result, development of foliar diseases (12). Structures and shades affect wind speed and solar radiation, which would also alter temperature and humidity under the shade. However, little effort has been made to estimate LWD in a ginseng field although ginseng production has been affected by different foliar diseases. It would be worthwhile to examine if an LWD model developed for an open field would have reasonable accuracy to operate a disease forecasting system for spray application management for ginseng. Although microclimate conditions under the shade would differ from those in an open field, conditions favorable for wetness occurrence under the shade could be indicated by weather conditions outside the shade. For example, Batzer et al. (1) showed that wetness measurements near an apple tree could represent the wettest part within

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a tree canopy in spite of differences in microclimate conditions around the tree. In addition, weather measurements from a weather station outside the shade could be obtained more easily than weather data under the shade.

Ginseng growers can benefit from a disease warning system that could minimize fungicide spray application without sacrificing crop yield (10). The objectives of this study were to assess accuracy of LWD estimates obtained using an existing LWD model with weather data measured outside the shade as inputs to the model and to examine feasibility of those estimates for operation of a disease warning system in a ginseng field. The use of an existing LWD model in the ginseng field would make it easy to examine and to deploy currently available disease warning systems for ginseng foliar diseases. Furthermore, disease risk could be predicted using site specific weather forecasts obtained from numerical weather models including weather forecasts when reliable estimation of LWD would be attainable using weather data outside the shade (14).

Materials and Method

Experiment sites. Measurements and estimates of LWD were compared at two commercial ginseng fields. These fields are located in Gochang-gun (35°25'07" N, 126°39'45" E) and Jeongeup-si (35°34'23", 126°46'28" E), Jeollabuk-do, Korea. These two fields were denoted as the *G* and *J* sites, respectively. Experiments were conducted during growing seasons in 2011 and 2012. In 2011, measurements were made from 4 May to 9 August at both sites. In 2012, measurements were made for the periods from 4 May to 4 September and from 17 May to 6 September at *G* and *J* sites, respectively.

At the beginning of the experiment, 5- and 4-year-old ginseng plants were cultivated at *G* and *J* sites, respectively. The areas of *G* and *J* sites were 1.2 and 2.0 ha, respectively. Standard cultivation practices for Korean ginseng were applied. For example, ginseng was planted on 0.9-m-wide raised soil beds that were 35 cm high and covered with 5 to 10 cm of straw mulch at both sites. Planting density was 44 plants m⁻² and 38 plants m⁻² at *G* and *J* sites, respectively. A woven black polypropylene shade net was placed 1.8 m above the beds to reduce solar radiation. Weeds were hand-pulled.

Different shade nettings were used by site and season. Double shading, an artificial shading method generally used in conventional ginseng cultivation of Korea, was applied at both *G* and *J* sites. At the *G* site, the double shading net consisting of a 3-layer polyethylene (P.E.) net and a 2-layer P.E. net were installed throughout the growing season in 2011. In 2012, a 3-layer P.E. net was installed until 19 May and, thereafter, a 2-layer P.E. net was additionally installed at the same site. At the *J* site, a 3-layer P.E. net was installed from the beginning of the season to 19 May and, thereafter, a 2-layer P.E. net was additionally installed in 2011. In 2012, double shading nets were installed throughout the experimental period at the same site.

Fig. 1. Schematic view of sensors installed in a ginseng field. Cylinder, square, triangle, and circle represent air temperature and humidity sensor, leaf wetness sensor, tipping bucket, and anemometer, respectively. The dashed line indicates the height of ginseng canopy under the shade.

Weather measurements. Air temperature, relative humidity (RH), wind speed, precipitation, and LWD were measured at study sites (Fig. 1). Air temperature and RH was measured by a single sensor (Model HMP45, Vaisalar, Finland) outside the shade. The same sensor was also installed under the shade for measurement of microclimate conditions altered by the shade. Wind speed was measured using the anemometer (Model 03001, Campbell Scientific, Logan, UT) installed outside the shade. Measurements were averaged for 60 min in 2011 and for 30 min in 2012, respectively.

The occurrence of wetness was detected using unpainted flat panel sensors (Model 237, Campbell Scientific). Unpainted sensors may have biases because these sensors are often insensitive to small water droplets (29). To minimize such biases, multiple unpainted sensors were installed (7,22). At each study site, two unpainted sensors were installed under the shade to measure LWD. When at least one of the wetness sensors detected wetness for >30 min in an hour, the hour was identified as an hour with wetness occurrence, i.e., a “wet” hour. Otherwise, remaining hours were classified as “dry” hours.

An empirical model to estimate leaf wetness duration. A model based on a fuzzy logic system was used to estimate LWD in the ginseng fields. It was reported that the fuzzy logic model had more spatial portability than other empirical models, including the RH and CART models (12). No physical model was considered in this study because no input data required for physical models, e.g., cloud or net radiation, were measured.

The fuzzy model takes into account energy balance on a sensor surface deriving components of an energy balance equation, e.g., net radiation and vapor pressure deficit, from air temperature, relative humidity, and wind speed (Appendix). Net radiation is the balance between incoming and outgoing energy on a surface. If net radiation becomes low, e.g., with greater outgoing energy than incoming energy, wetness is likely to occur. Vapor pressure deficit, which is the difference between actual and maximum amount of water vapor in the air at a given temperature, also affects the occurrence of wetness on a surface. Under lower vapor pressure deficit conditions, evaporation of water droplets on a surface would be limited, which creates favorable conditions for wetness occurrence. Wind also plays an important role in drying off water droplets on a surface.

Air temperature, RH, and wind speed measured outside the shade were used as inputs to the fuzzy model in order to derive its input variables, i.e., net radiation, vapor pressure deficit, and wind speed at a sensor surface. Net radiation was estimated as the difference between an atmospheric emissivity under a clear sky condition and emission of long wave radiation from the surface (15). The values of atmospheric emissivity and outgoing long wave radiation from the surface were calculated from air temperature and dew point temperature, respectively. Actual and saturated water vapor pressures in the air were calculated using air temperature and RH to obtain vapor pressure deficit. Because the shade would decrease wind speed, a simple log wind profile was used to adjust wind speed to the height of wetness sensors under the assumption of neutral stability condition for each hour as follows (16):

$$\frac{u_s}{u_a} = \frac{\ln(z_s - d) - \ln(z_0)}{\ln(z_a - d) - \ln(z_0)} \quad (1)$$

where u_s and u_a are the mean wind speed (m s⁻¹) at the height of wetness sensor z_s (0.3 m) and anemometer z_a (2 m), respectively. d and z_0 indicate the zero plan displacement and roughness length, respectively.

Analysis of observed weather data in a ginseng field. To examine microclimate conditions altered by the shade, measurements of air temperature and RH under and outside the shade were compared. Differences of these measurements were analyzed for night times during which occurrence of wetness would be affected by air temperature and humidity under the shade through energy exchange between the atmosphere and a ginseng canopy. The night-time period was defined as hours between 18:00 and 8:00 the next day (15).

Measurements of LWD were analyzed by dew and rainfall eligible days because the occurrence of wetness during days with rainfall would differ from the days without rainfall, e.g., dew eligible days.

Data from 12:00 to 11:59 the next day were compiled to a daily set to cover entire periods for dew occurrence. Daily data sets were classified into two groups, i.e., with and without measured rainfall ($>0.25 \text{ mm d}^{-1}$) to represent rainfall and dew eligible days, respectively. It was assumed that wetness occurrence detected from either wetness sensors represented true wetness occurrence in the ginseng field. Accuracy of the LWD model was compared by dew and rainfall eligible days. Estimation error of the LWD model was assessed in terms of mean error (ME) and mean absolute error (MAE). The ME, which represents the tendency of over- or underestimation error, was computed by averaging differences between measurements and estimates for each 24-h period. The values of MAE, which indicate overall accuracy, were determined by averaging the absolute differences between measurements and estimates of daily LWD for the same period over a season. The hourly rate of misclassification was also calculated for each site year.

The use of leaf wetness duration estimates as inputs to a disease warning system. Measurements and estimates of LWD were used as inputs to the TOM-CAST disease warning system, which has been used for a ginseng foliar disease (12). In TOM-CAST, a disease severity value (DSV), which represents the degree of biological and epidemiological conditions associated with disease development, is accumulated over a period. Application of a fungicide spray is recommended when cumulative values of daily DSVs become equal to or greater than a predetermined action threshold. Wetness duration and average air temperature during the wetness period are used to determine DSV (12).

Correspondence analysis was performed to compare the disease risk ratings of TOM-CAST, DSV_M , and DSV_E , which were derived from measurements and estimates of wetness duration and temperature, respectively. Because DSV ranges from 0 to 4, multiway cross-tabulation is preferable to compare the values obtained from measurements and estimates of weather variables. Correspondence analysis, which is suggested by Benzecri (2), has been used to analyze and interpret the categories of a multiway contingency table using a correspondence plot (4). The technique has been applied to marketing research and product positioning (4,13) and micro array analysis (6).

Correspondence plot allows inference about the similarity and differences between rows and columns of the table resulted from the cross-tabulation. For example, Gabriel (8) suggested that correspondence plot and goodness of fit test would lead to the same result. In correspondence analysis, a point profile in multidimensional space is obtained from rows of data using the value of χ^2 statistics as a distance measure. Another point profile that represents columns of data also displayed them together with the row-points in the correspondence plot. Association between a row datum and a column datum is assessed in terms of distance between these points that represent these data. Suppose there is one point that represents DSV of 0 derived from measurements of wetness duration and temperature, and another point that represents DSV of 0 obtained from estimates of those two variables. Then, the proximity of those two points in the correspondence plot indicates strong association between the given values of DSV. It was assumed that DSVs derived from LWD measurements were true risk ratings. The proximity of points that represent individual DSVs derived from measurements and estimates of weather variables were analyzed using visual inspection. The correspondence plot was obtained using JMP (version 9.0; SAS Institute Inc., Cary, NC).

Spray advisory dates derived from measurements and estimates of wetness duration and temperature, i.e., SD_M and SD_E , respectively, were compared for each site-year. At first, DSVs obtained from measurements of weather variables were accumulated until the given action threshold, which was assumed to be 10 as suggested by Hill and Hausbeck (12), was reached to determine a value of SD_M . The length of time window during which the action threshold was reached, i.e., WL_M , was also determined. Then, the values of DSV derived from estimates of the weather variables were accumulated to determine SD_E and WL_E . The differences between SD_M and SD_E were calculated for each time window. The next time window started on the day after SD_M . At the end of the timeframe, there was a time window

for which weather data were not to determine SD_M . Such time windows were removed from the analysis.

Results

Measurements of microclimate under the shade in a ginseng field.

Malfunction of temperature and RH sensors installed under the shade occurred at the *G* site in 2012. Analysis for comparing microclimate conditions between under and outside shade was performed except for weather data measured at the *G* site in 2012. Overall, it was slightly warmer, 0.16°C , under the shade than outside for hours from 18:00 to 8:00. Distribution of difference in temperature between under and outside the shade was similar for 2011 and 2012 seasons at the *J* site. In general, the warming effect of air by the shade was greater at the *G* site compared with the *J* site (Fig. 2A). More humid conditions were also observed under the shade than outside during night times. On average, RH was 2.7% greater under the shade than outside. RH was higher under the shade than outside the shade less frequently at the *G* site compared with the *J* site (Fig. 2B).

Measurement and estimation of leaf wetness duration under the shade. Overall wetness duration during which occurrence of wetness was detected by at least one of wetness sensors was slightly longer at the *G* site (7.7 h d^{-1}) than at the *J* site (6.9 h d^{-1}) (Table 1). During dew eligible days in which no rainfall $>0.25 \text{ mm}$ was measured, daily average wetness duration was similar between the sites. Wetness duration was longer at the *G* site (13.0 h d^{-1}) than

Fig. 2. Empirical cumulative distribution of differences in air temperature (A) and relative humidity (B) between under and outside the shade in ginseng fields located at Gochang (G) and Jeongup (J) sites over 2011 and 2012 seasons.

at the *J* site (10.5 h d^{-1}) during rainfall eligible days. The proportion of rainfall eligible days was lower (52.7%) at the *G* site than at the *J* site (56.8%). Wetness duration during dew and rainfall eligible days slightly differ by season. At the *G* site, for example, the difference of LWD measurements between 2011 and 2012 seasons was 1.2 h d^{-1} and 1.6 h d^{-1} for dew and rainfall eligible days, respectively.

Estimation errors of LWD by the fuzzy model differed by site and season (Table 2). Overall, the fuzzy model underestimated LWD at the *G* site whereas it overestimated LWD at the *J* site. The ME in LWD estimation by the fuzzy model ranged from -2.3 to 2.4 h d^{-1} for four site-years.

Hourly misclassification rate of wetness occurrence for the fuzzy model was similar between site-years except for the *G* site in 2011 (Fig. 3). Overall, the fuzzy model overestimated wetness occurrence during night and hours immediately after sunrise. In contrast, it tended to underestimate wetness occurrence during daytime and hours immediately after sunset. At the *G* site in 2011, the fuzzy model underestimated wetness occurrence most hours.

During dew-eligible days, the fuzzy model tended to overestimate LWD (Table 2). For example, the ME in LWD estimation by the fuzzy model ranged from -0.1 to 2.6 h d^{-1} . In particular, large overestimation errors of the fuzzy model occurred during nights. For example, except at the *G* site in 2011, the ME of the fuzzy model was $>2.0 \text{ h}$ per night (Table 3).

The fuzzy model had the tendency to underestimate LWD during rainfall eligible days (Table 2). For example, the fuzzy model failed to identify wetness occurrence for $>3.0 \text{ h d}^{-1}$ at the *G* site in 2011. During daylight hours, underestimation error by the fuzzy model was relatively large. For example, the ME of the fuzzy model ranged from -2.8 to -0.2 h per daytime (Table 3).

The use of leaf wetness duration estimates as inputs to a disease warning system. Points that represented each class of disease risk ratings derived from measurements of DSV_M tended to be close to points that indicated the same category of ratings derived from estimates of

DSV_E in the correspondence plot (Fig. 4). For example, points that represented DSV_M and DSV_E of 0 were at proximity for all of the site-year. However, points that represented DSV_E of 4 were missing or distant from the points that represented DSV_M of 4 in three out of four-site years.

Estimates of wetness duration and temperature during the period tended to result in spray advisory dates SD_E earlier than spray advisory dates SD_M derived from measurements of weather variables except for the *G* site in the 2011 season (Fig. 5). In particular, SD_E tended to be earlier than SD_M for time windows such that >10 days were taken to reach actual action threshold. For example, action

Table 1. Summary of measurements (Sen) and estimates (Fuz) of wetness duration at Gochang (*G*) and Jeongup (*J*) sites over 2011 and 2012 seasons

Site	Season	All ^a			Dew ^a			Rain ^a		
		N ^b	Sen ^c	Fuz	N	Sen	Fuz	N	Sen	Fuz
<i>G</i>	2011	98	8.6	6.2	62	5.7	5.6	36	13.5	7.4
	2012	122	7.0	7.5	84	4.5	6.5	38	12.5	9.6
	all	220	7.7	6.9	146	5.0	6.1	74	13.0	8.5
<i>J</i>	2011	98	6.6	7.9	60	4.5	7.1	38	9.9	9.3
	2012	108	7.1	9.5	75	5.3	7.7	33	11.2	13.7
	all	206	6.9	8.8	135	5.0	7.4	71	10.5	11.3

^a All, dew, and rain indicate all of days included in the data set, days with rainfall $\leq 0.25 \text{ mm}$ in a 24 h period, and days with rainfall $>0.25 \text{ mm}$, respectively.

^b N is the total number of 24-h periods in the data set.

^c Average leaf wetness duration measured by two unpainted sensors per 24-period.

Table 2. Estimation errors of LWD by the fuzzy model at Gochang (*G*) and Jeongup (*J*) sites over 2011 and 2012 seasons

Site	Season	All ^a			Dew ^a			Rain ^a		
		N ^b	ME ^c	MAE ^c	N	ME	MAE	N	ME	MAE
<i>G</i>	2011	98	-2.3	4.4	62	-0.1	3.3	36	-6.2	6.4
	2012	122	0.5	3.4	84	2.0	2.8	38	-2.8	4.7
	all	220	-0.8	3.9	146	1.1	3.0	74	-4.4	5.6
<i>J</i>	2011	98	1.3	3.5	60	2.6	3.9	38	-0.6	3.0
	2012	108	2.4	3.0	75	2.4	2.6	33	2.4	4.0
	all	206	1.9	3.3	135	2.5	3.1	71	0.8	3.5

^a All, dew, and rain indicate all of days included in the data set, days with rainfall $\leq 0.25 \text{ mm}$ in a 24 h period, and days with rainfall $>0.25 \text{ mm}$, respectively.

^b N is the total number of a 24-h period in the data set.

^c ME and MAE indicate mean error and mean absolute error per 24-h period. Negative values of ME indicate underestimation error (estimates – measurements).

Fig. 3. Hourly error in LWD estimation at Gochang (*G*) and Jeongup (*J*) sites over 2011 and 2012 seasons: **A**, error rate, which is average difference between measurements and estimates of wetness occurrence in a given hour, and **B**, absolute error rate, which is averages of absolute difference between measurements and estimates.

Table 3. Mean errors (MEs^a) of LWD by the fuzzy model at Gochang (*G*) and Jeongup (*J*) sites during day and night time over 2011 and 2012 seasons.

Site	Season	All ^b			Dew ^a			Rain ^a		
		N ^c	Night ^d	Day ^d	N	Night	Day	N	Night	Day
<i>G</i>	2011	98	-1.1	-1.2	62	0.2	-0.3	36	-3.4	-2.8
	2012	122	1.3	-0.7	84	2.1	-0.1	38	-0.6	-2.1
	all	220	0.2	-0.9	146	1.3	-0.2	74	-2.0	-2.4
<i>J</i>	2011	98	1.7	-0.4	60	2.8	-0.2	38	0.1	-0.7
	2012	108	2.6	-0.1	75	2.5	0.0	33	2.7	-0.2
	all	206	2.2	-0.2	135	2.6	-0.1	71	1.3	-0.4

^a Negative values indicate underestimation error (estimates – measurements).

^b All, dew, and rain indicate all of days included in the data set, days with rainfall $\leq 0.25 \text{ mm}$ in a 24 h period, and days with rainfall $>0.25 \text{ mm}$, respectively.

^c N is the number of nights or days in the data set.

^d Night and day represent time periods from 18:00 to 8:00 in the next day and from 8:00 to 18:00 in a given day, respectively.

threshold was reached within 10 days for 87.5% of time windows when estimates of weather variables were used as inputs to TOM-CAST at the *J* site in 2011. When measurements of weather variables were used as inputs, the action threshold was reached within 10 days only for 50% of time windows at the same site-year. The median difference between SD_E and SD_M ranged from -1.5 to 1.5 days for given sites and seasons. About 78% of SD_E was obtained within ± 3 days of SD_M (Fig. 5). Only about 5% of SD_E was 3 days later than SD_M .

Discussion

To our best knowledge, this study is the first report on estimation of LWD and its application to a disease warning system in a ginseng

field. The shade over a crop canopy would affect occurrence of LWD, and as a result, disease development (31). For example, Elad et al. (5) reported that severity of pepper powdery mildew increased by up to 275% under the shade. Because various crops including blueberries, grapes, peppers, and others have been cultivated under the shade, the results from this study would be useful in estimation of LWD and assessment of the risk of foliar disease outbreaks for crops grown under the shade.

Only a small number of studies have been conducted to evaluate effectiveness of a disease warning system for ginseng disease management although disease warning systems have been developed for many other crops. For example, TOM-CAST, which is a disease

Fig. 4. Correspondence plot of disease severity values derived from measurements (W) and estimates (F) of wetness duration and temperature. The digit at the end of each label represents the value of DSV, which ranged from 0 to 4.

Fig. 5. Empirical cumulative distributions of the number of days during which action threshold was reached using spray advisory dates derived from measured (A) and estimated (B) weather data, respectively, and the difference for these spray advisory dates (C). G and J represent Gochang and Jeongup sites, respectively. The number followed by G or J indicate the given season.

warning system based on cumulative hours of LWD and temperature, has been used for control of carrot foliar blight (3). Hill and Hausbeck (12) found that a treatment program based on TOM-CAST was able to limit development of foliar disease with a smaller number of spray applications. However, they also found that fewer spray applications resulted in less seed yield. The effectiveness of such a treatment program could be improved considering the fact that a single unpainted wetness sensor was installed at their experiment site. Painted sensors are more sensitive to small droplets of water on a leaf than unpainted ones (29). Thus, it was likely that unpainted sensors would have recorded less LWD during their experiments, which would have caused underestimation of the disease risk.

Our results suggested that spray advisory dates derived from estimates of LWD using the fuzzy model would be helpful for control of a foliar disease in a ginseng field. The frequency of spray advisory dates predicted within ± 3 days was greater (78%) than that in previous study (70%) in which LWD estimates obtained from weather forecasts were used as inputs to the TOM-CAST in an open field (11). Spray advisory dates derived from estimates of weather variables tended to be predicted to occur earlier than a date derived from measurements of weather variables, which would minimize disease damage from no alarm error from TOM-CAST. For example, Hill and Hausbeck (12) reported that TOM-CAST 10 DSV schedule was not enough to protect ginseng yields, which may have resulted from intermittent no-alarm for disease risk. Still, field experiments for independent validation would be merited to examine the effectiveness of TOM-CAST using estimates of wetness duration and temperature as inputs under different conditions. Caution is also needed in application of the fuzzy model at other sites because accuracy of the fuzzy model could differ by specific microclimate conditions in a given ginseng field.

It appeared that the values of DSV derived from estimates of wetness duration and temperature were reliable enough to make it possible to predict spray advisory date with reasonable accuracy. For example, correspondence analysis indicated general agreement between each category value of DSV derived from measurements and estimates of weather variables. Still, estimates of LWD obtained from the fuzzy model resulted in substantial error in predicting the highest values, i.e., 4, of DSV. Nevertheless, such values of DSV occurred infrequently (3.8% of all study dates), which could have had a relatively small impact on accurate prediction of spray advisory dates.

Estimation errors of LWD by the fuzzy model in ginseng fields were within the range of errors in previous studies although those errors were relatively greater under the shade than in open fields. For example, Kim et al. (15) reported that LWD estimates for the fuzzy model were within 1 h d^{-1} during 44.6% of dew eligible days for sites in the Midwestern United States. Under the shade in the present study, the fuzzy model estimated LWD within 1 h d^{-1} during 43.4% of dew eligible days. Still, the fuzzy model had considerably large errors during rainfall eligible days. In the present study, the number of days during which LWD was estimated within 1 h d^{-1} was considerably lower (31.0%) than that (38.3%) in the previous study (15). As a result, in part, the fuzzy model had relatively large error in estimating LWD at ginseng fields compared with other study areas in open fields. For example, Kim et al. (17) showed that the MAE by the fuzzy model ranged from 1.1 to 4.7 h d^{-1} among 43 sites under different climate conditions. According to the empirical cumulative probability density function defined using those values of MAE, the probability such that the fuzzy model would have the same value of MAE obtained in this study, e.g., $>3.4 \text{ h d}^{-1}$ at the *J* site, was about 10%.

It seemed that errors in estimating LWD under shade resulted from, in part, the fact that the effect of the shade on microclimate in a ginseng field was compounded in terms of wetness occurrence because the shade increased RH as well as air temperature during the night. As air temperature increases, air can hold more water vapor, which facilitates evaporation of free water on leaves. In contrast, dew occurs more easily under high humidity because a relatively large amount of water vapor is available for condensation with small change in temperature. Still, the difference of air temperature and RH between under and outside the shade varied by sites and seasons,

which would make it difficult to identify the empirical relationship between weather conditions outside the shade and occurrence of wetness over different locations and seasons.

It is likely that overestimation error of LWD by the fuzzy model during dew eligible days was caused by the radiation environment under the shade. In the fuzzy model, incoming long wave radiation from clear sky and outgoing long wave radiation from the leaf are calculated to determine energy balance on a leaf for estimation of wetness occurrence. However, long wave radiation from the clear sky would be less than that from the shade in a ginseng field, which caused the fuzzy model to underestimate the net radiation on the leaf. As a result, the fuzzy model would estimate occurrence of wetness more readily for the periods during which no wetness was recorded under the shade.

In development of the fuzzy model, it was assumed that occurrence of wetness would be dependent on only long wave radiation in an open field. On days with rainfall, such an assumption for the radiation environment under the shade is not valid, which resulted in a relatively large error in LWD estimation by the fuzzy model. No explicit process for evaporation of free water on leaves has been implemented for the fuzzy model (15). Instead, drying off process within the fuzzy model is dependent on the parameters determined empirically to distinguish occurrence and evaporation of free water in an open field. During daytime, evaporation of rain droplets occurs readily after rainfall as soon as solar radiation reaches the leaf surface in the open field. Under the shade, however, the amount of solar radiation is considerably lower compared with that in the open field. Therefore, evaporation of rain drops occurs less readily, which causes prolonged wetness duration under the shade during days with rainfall. For example, LWD was about 8.0 h d^{-1} longer at the *G* site during rainfall eligible days than dew eligible days. In addition, the shade would cause slow wind speed, which would limit evaporation of water on leaves further.

Correction schemes to the fuzzy model would be useful to reduce estimation error of LWD, which would make it more feasible to assess the risk of foliar ginseng diseases based on the fuzzy model (18). For example, the MAE of the fuzzy model decreased by 38% at the *J* site in the 2011 season when the correction factor for unpainted sensors was applied (Appendix). Still, spatial portability of the correction factor should be examined before such a correction scheme is used in practice. This merits an additional study to evaluate and develop a simple correction scheme for the fuzzy model using different approaches, e.g., a simplex training algorithm (23) and consideration of RH (30). For example, MAE of the RH model, which determines occurrence of wetness with $>90\%$ of RH, was 18% lower than that of the fuzzy model at the *J* site in 2011 during dew eligible days although MAE of the former was 4%, 32%, and 46% greater than that of the latter at the other site years. In particular, a correction scheme during days with rainfall would be needed because the MAE of the fuzzy model was considerably larger during these days. In addition, a shading plate has been used to prevent rain drops from depositing into a ginseng canopy (17,19). Under such a shade, a correction factor to the fuzzy model for rainfall eligible days could reduce errors of LWD estimation.

An energy balance model could take into account complex microclimate conditions under the shade to estimate LWD accurately. For example, energy exchange between the atmosphere and the shade as well as leaves of ginseng can be calculated using an energy balance model, which allows reliable estimation of LWD. Energy balance models usually require cloud cover or net radiation data to determine latent heat flux in an open field. However, under the shade, accurate measurements of net radiation data may not be necessary. A shade cloth has time-invariant physical properties, which would make it feasible to estimate its temperature. For example, the radiant energy under the shade increases whenever the temperature of the shading material itself exceeds air temperature. Accurate estimates of shade temperature would allow reliable estimation of LWD within a ginseng canopy under the shade. Furthermore, the energy balance model could have greater spatial portability. This merits further studies to develop a physical model and to compare the model with empirical approaches for LWD estimation.

Appendix

The fuzzy model estimates the occurrence of wetness using a set of rules that describe energy balance principle in natural language (15). For example, a rule expressed in an if-statement is used to describe energy balance on a surface, e.g., 'if net radiation is low, then wetness is likely to occur.' Each rule is evaluated calculating a degree of membership based on membership functions and fuzzy operators. A membership function, which is defined as shapes, e.g., a bell-shaped curve, is defined for a natural language terms, e.g., 'low' for each input variable of a fuzzy logic system. For example, the membership function that defines 'low' for net radiation is used to convert net radiation data at a given time into a value m between 0 and 1, i.e., degree of membership. Fuzzy operators are used to combine degrees of membership to evaluate phrases in a rule statement, e.g., 'if-then' or 'and.' Once a set L , which represents the outcome of evaluation, is obtained from each rule, all of L are combined into a single set O through an aggregation process. Later, the set O is converted back to a final value between 0 and 1, which represent absence or presence of wetness. Absence of wetness is predicted when the final value is <0.5 ; otherwise, occurrence of wetness is predicted. In addition, a correction factor has been used to adjust outputs of the fuzzy model to a specific condition on occurrence of wetness. For example, Kim et al. (17) showed that a correction factor can be used to reduce error of LWD estimation compared with unpainted sensors. In the present study, the MAE of the corrected fuzzy model was smaller (2.4 h d^{-1}) than that of the fuzzy model (3.9 h d^{-1}) at the J site in 2011 during dew eligible days. At the G site in 2011, however, the corrected model had larger MAE (4.3 h d^{-1}) than the fuzzy model did during the same periods (3.3 h d^{-1}).

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