MODELLING AND DECISION SUPPORT SYSTEM FOR PRECISION CUCUMBER PROTECTION IN GREENHOUSES

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ABSTRACT

The plant disease early warning is an essential way for protecting eco-environment and improving the level of vegetable quantity and quality safety in solar greenhouses. To realize the early warning, the cucumber disease model and decision support system were developed for precision cucumber protection in greenhouses as follow four parts. Firstly, we combined the leaf wetness sensors and estimation model based on canopy relative humidity (RH threshold model) in to the leaf wetness duration (LWD) monitoring method. The errors were around 1~2 h; compared with the LWD that was over 3 h, the monitoring effects of the method were acceptable. Secondly, we developed the primary infection situation early warning models of important diseases, such as cucumber downy mildew in solar greenhouses. The model was evaluated by over a 4-year (2006-2009) dataset in the field. The results showed that it could warn the primary infection and disease occurrence date with a probability of 95% and more than 2 days before disease appearance. Thirdly, considering the characteristics of multi-warning sources of cucumber downy mildew in solar greenhouses, the warning source traceability model for cucumber downy mildew in solar greenhouses was constructed for system ease-realization using chain-styled theory of disaster. At last, the decision support system of cucumber disease early warning in solar greenhouses was developed by Visual Studio 2005 and SQL Server 2000, which added more functions of ongoing decision making for revising cultural practices than traditional record-keeping systems. The method and system shows promise for increasing adoption for IPM in China, and can provide decision support for early warning of cucumber diseases in solar greenhouses.

Keywords: solar greenhouses; cucumber; *Pseudoperonospora cubensis*; early warning model; decision support system

INTRODUCTION

Pests as well as abiotic stress conditions commonly are heterogeneous

in time and space in a solar greenhouse(Oerke et al., 2010). The daily temperature and humidity difference in a solar greenhouse is much higher than the field. Also the mid-temperature and high humidity environment in unheated greenhouses is suitable for infection and epidemic of many diseases and pests. For example, Cucumber downy mildew, caused by *Pseudoperonospora cubensis* (Berk.&Curt.) Rostov. (Shetty et al., 2002; Yang et al., 2007), is a major limitation to the production of solar greenhouse cucumbers. For the disease has the essential characteristics of high infection and epidemic rate(Hong et al., 1989), the disease could not be controlled at economical threshold level while the cucumber is infected by the pathogen. Means for early warning primary infection are not currently available to most growers. The control of cucumber downy mildew depends on repeated fungicide sprays every 7 to 14 days or frequent application of fungicides when the symptoms appear. So the precision crop protection is needed, which describes a real-time and site-specific management system using computerized information technologies for optimal use of water, pesticides and energy to pest management in heterogeneous field situations. Precision crop protection relies upon (I) intensive sensing of environmental conditions in the crop, (II) extensive data handling and processing, (III) use of decision support systems (DSS), and (IV) control of farm machinery (actuators) in the field (Oerke et al., 2010). So an early warning model and a related decision support system are needed to best respond to consumer concerns about food quality safety, environmental protection and production cost reduction.

Infection of cucumbers by *P. cubensis* has been studied internationally for many years. A wide range of models have been developed more recently to forecast primary infection, which belong to two kinds: empirical models (Li, 2006; Yang et al., 2007) and fundamental models (Hong, 1987; Hong et al., 1989; Hong et al., 1990) . Empirical models need more scientific and sound interpretation and fundamental models are difficult to apply because of their complex parameters. There is useful potential in integrating these two kinds of models. For reaching this goal, the dominant factor is leaf wetness duration (LWD). Taken cucumber downy mildew as example, the minimal LWD for infection was 2h. Comparing with the field crops and fruit trees (Gleason et al., 2008; Kim et al., 2006; Magarey et al., 2006a; Magarey et al., 2006b; Orlandinia et al., 2008; Portraz et al., 1994; Schmitz and Grant, 2009; Sentelhas et al., 2008), the LWD monitoring and estimation methods for greenhouse crops are rarely reported. For monitoring by sensors, since the interactions between microclimate and crops influence LWD, leaf wetness sensors should be calibrated in solar greenhouse conditions; furthermore, because the cucumber leaf length, width and area are larger than common leaf wetness sensors, so the wet/dry threshold and deployment method should be investigated(Li et al., 2010b). For estimation by models, most studies concentrated on the dew (Zhang et al., 2002; Zheng et al., 1990), but the guttation water is often neglected. A comparison of the measurements of guttation water with the total amount of water on leaves in the middle of the

rice canopy showed that the guttation water amount was at least half of it(Luo and Goudriaan, 1999); in the solar greenhouses, the guttation of the cucumber leaf margin is also common. Therefore, guttation, as a contributor to leaf wetness, is of similar importance to dew formation. So there is a gap in the integration method for leaf wetness duration of cucumber in greenhouse.

An objective study of the performance of the disease early warning models combined with probability estimations of occurrence will lead to a better understanding of the potential usefulness of these models (Yuen and Hughes, 2002). Bayes's theorem can be a useful tool to examine how a disease early warning model (either positive or negative) affects the probability of occurrence. Bayes's theorem is basically a classifier for pattern recognition and also has been used to help modeling and prediction, parameter estimation, and optimization and control(Huang et al., 2010). Also likelihood ratios can be calculated from the sensitivity and specificity of the early warning, and provide convenient summaries of the model performance as a simpler form of Bayes's theorem. With these methods, the disease early warning system will furnish an operational model for forecasting occurrence date and probability, which is analogous to methods used for predicting the probability of precipitation (Kumar et al., 1999; Maini et al., 2004) and of earthquake (Papoulia et al., 2001; Tsapanos et al., 2001), etc. Although there were some reports about probability forecasting and warning on field crops and vegetables(Mila and Carriquiry, 2004; Vincelli and Lorbeer, 1988), little work has been done on early warning systems that involve estimates of the probability of vegetable disease occurrence in solar greenhouses.

The goal of the research reported in this paper is to obtain simple, real-time and correct results from a probability-based early warning model for the purpose of precision crop protection. In pursuit of this goal, this paper describes a solution to the problem of LWD input that uses an estimation model. The study then investigated a Bayesian analysis method for an early warning model for primary infection of cucumber downy mildew in solar greenhouses (EWMPICDW). The model was developed and implemented as a decision support system and evaluated in solar greenhouses in Beijing, China.

MATERIALS AND METHODS

Cucumber cultivation

This study was conducted in 4 cultivation seasons, 8 solar greenhouses from 2006 to 2009. The disease-resistant cucumber (*Cucumis sativus* L.) "Jingyanmini No.2" (Zhang et al., 2006a) was used in all experiments. The first experiment in the autumn-winter season was carried out at Beijing Xiaotangshan Precision Agriculture Experimental Base (Xiaotangshan), in Changping district, Beijing, PR China (40.18°N, 116.47 °E) from October 2006 to January 2007. Three greenhouses were used in the experiment. Each greenhouse was 30 m × 7 m and was constructed of metal arches covered with polyethylene films. The row of three greenhouses was oriented in a

north-south direction. The greenhouses were not heated, and they had side vents that were opened for 5–8 hours daily when the weather permitted. The cucumber seedlings were planted on October 1st and were transplanted on October 13, 2006, and the harvest season ended on January 23, 2007. Five hundred four plants were arranged in a double-row pattern with small spaces of 40 cm and large spaces of 110 cm between rows, and there was 40 cm between plants in the rows. The substrate used was a 2:1 mixture of peat and vermiculite with 500 g chicken manure and 10 g N15-P10-K15 compound fertiliser per plant. The cucumbers were maintained according to the recommendations of the Beijing Vegetable Research Center (BVRC), China, and no fungicides were applied to treat *P. cubensis* until the time of first disease onset. The second experiment in the autumn-winter season was conducted at Beijing Academy of Agriculture and Forestry Sciences (BAAFS), in Haidian district, Beijing, PR China (39.95°N, 116.29°E) from September 2008 to January 2009. The greenhouse (5 m× 4 m) was one of six rooms in a large greenhouse (north-south orientation). The greenhouse was constructed of metal arches covered with polycarbonate sheeting. A brick wall formed the eastern end of the greenhouse, and the western end was a glass window. The greenhouse used a "damp curtain-ventilator" for both vertical ventilation and cooling. The cucumber seedlings were planted on September 28th and transplanted on October 12, 2006, and the harvest season ended on January 19, 2009. Sixty-nine plants were arranged in the double-row pattern with small spaces of 40 cm and large spaces of 100 cm between rows, and there was 40 cm between plants in the rows. The substrate and cultivation practices were similar to those used in the first experiment.

The first experiment in the spring-summer season was performed at Xiaotangshan from January 2007 to August 2007. The cucumber seedlings were planted on January 7th and transplanted on February 5th. The harvest season ended on August 21, 2007. The second experiment in the spring-summer season was performed at BAAFS from January to December 2009. The cucumber seedlings were planted on January 7th and transplanted on February 5th. The harvest season ended on December 28, 2009. The greenhouses and substrate used in the spring-summer season were the same to those used in the autumn-winter season.

Microclimatic information collection

Xiaotangshan: From the transplanting date, the air temperature and relative humidity in the greenhouse were recorded every 30 min by sensors coupled to a datalogger (Portable equipment for measuring temperature, relative humidity (RH) and dew point temperature, National Engineering Research Center for Information Technology in Agriculture, Beijing, China). There were 5 sensors in each greenhouse and the total number was 15. The sensors were located in the centre of each group of crops in the greenhouse and shielded from direct solar radiation by suitable shelters. At first, the sensors were 10 cm higher than the plants and moved upwards regularly as the

plants grew. When the plants reached 1.5 m, the sensors were fixed within the central part of the canopies. The outside weather parameters, temperature, relative humidity and solar radiation were also recorded by an outside weather datalogger every day for 30 min interval. The data was transferred from the datalogger (RS485 connection) to an environmental control computer (RS232 connection) via a local area network (LAN) and stored in a Microsoft Access 2000 database.

BAAFS: From the transplanting date, the same sensors in Xiaotangshan were used in the greenhouse. They were arranged above the No.1, 2, 3, 5, 6 row and located in the south, middle and north part. The monitoring method was similar to Xiaotangshan.

Disease investigation

The inoculums were the natural pathogen of these greenhouses. Each investigation was conducted by the same person in the morning before the leaves were dry. After the seedlings were transplanted, an extensive survey was carried out each day until greenish infected tissues appeared. The date of the first occurrence was recorded. In Xiaotangshan, five groups of 15 plants in an "X"-pattern around the location of sensors were selected for disease observation in each greenhouse. These groups were named South-west, North-west, Middle, South-east and North-east. In Xiaotangshan, the total number of points for observation was 15. In BAAFS, fifteen groups of 4 plants in a parallel-line pattern around the sensor locations were selected for use as points for observation to provide 15 total as in Xiaotangshan. In all, the investigation included 15×4=60 points for observation over the 4 cultivation seasons. These points were numbered from 1 to 60. In this paper, we summarised our investigations from the earliest predicted infection date to the latest observed disease occurrence date for the 60 points. The resulting sample included 735 cases.

MODEL DESCRIPTIONS

Conceptual model

It is obvious that the early warning models will be suitable in practice only when input parameters are readily available and appropriately limited in number (Li, et al, 2010a). EWMPICDW was developed based on early warning theory and plant disease epidemiology, which included clarification of the meaning of warning, monitoring the warning indicators, forecasting the warning situation, tracing the warning sources and controlling the warning situation.

Clarifying the meaning of warning

The goal of this component is to confirm the object of the warning. The object addressed in the paper is the cucumber downy mildew. The indicators of measured disease include disease occurrence probability, disease incidence, disease index, etc. Because the cucumber downy mildew spreads rapidly under

favourable weather conditions, growers are primarily concerned about the possibility that infection will occur, rather than about knowing how much infection will actually take place (Arauz et al., 2010). Accordingly, the probability of disease occurrence was selected as the object of the warning for the purposes of this paper. EWMPICDW should provide early warnings before the symptom appears. These warnings would include disease occurrence (yes or no) and its probability. These warnings would be beneficial because they could serve to reduce the frequency of fungicide sprays and likewise to improve the quality of the agricultural products.

Monitoring the warning indicators

Among the warning indicators including temperature, humidity, etc, the LWD receives the most attention. Because the Leaf Wetness Duration (LWD) is difficult to monitor and is a key input to disease warning systems for crops in solar greenhouses, the RH threshold model were developed to form a practical estimation solution for LWD. In our experiment, the LWD was mainly due to guttation.

In continuous cloudy weather, the cucumber leaf wetness duration is longer, and the relative humidity in solar greenhouses is higher. The LWD estimation model based on canopy relative humidity (RH threshold model) is one of the easiest models to implement and to use (Sentelhas et al., 2008), but it should be calibrated and validated under real greenhouse conditions. Note that

$$RH \geq TR \quad （0 \leq TR \leq 100\%） \qquad\qquad (1)$$

where RH is relative humidity (%), and TR is the relative humidity threshold at leaf wetness (%).

The RH data were obtained at 5 min intervals from an automatic weather station (Vantage Pro & Plus, Davis Instruments Corp, California, USA) located in the middle section of the greenhouse. The trial-and-error method (Xiong, 2009), average value method (Gillespie et al., 1993) and the method based on frequency of leaf wetness (Zheng et al., 1990) were used to calibrate the RH threshold. The RH thresholds obtained using these 3 methods were 90%, 89% and 93%, respectively. To illustrate our approach using the trial-and-error method, we developed a calibration program using Visual C# 2005 and Microsoft Access 2003.

The trial-and-error approach (MAE=2.03) and average value approach (MAE =2.14) were superior to the method based on frequency of leaf wetness. The errors were around 2 h. Because the LWD values were over 3 h, the monitoring effects of the RH threshold (RH=89% or 90%) model were considered acceptable (Li et al., 2010c).

Forecasting the warning situation

Based on the mechanisms of cucumber downy mildew infestation, the infection condition and incubation period early warning submodels were seen to represent key stages for primary infection and were given more attention

(Fig. 1). The interval between inoculation and the appearance of disease symptoms is known as the incubation period. Disease symptoms appear following the incubation period.
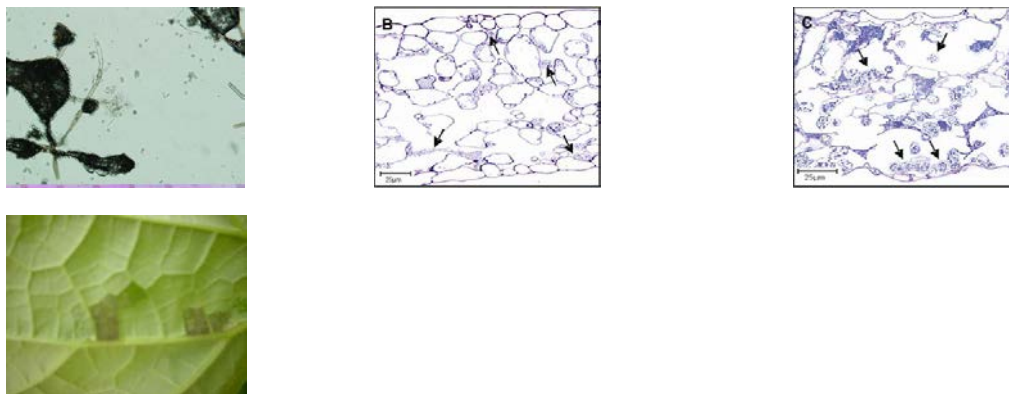
a. Pathogen　　　　　b. Infection　　　　　c. Incubation　　　　d. Appearance

Fig.1 The primary infection mechanism of cucumber downy mildew. Fig1.a was photographed by a microscope, Fig1.b and c were chosen from a paper (Lindenthal et al., 2005), and Fig1.d was photographed by a camera.

Data from a literature on experimental infection of susceptible cucumber leaves by *P. cubensis* under controlled conditions (Cohen, 1977) were used for modelling infection. These data indicate that the minimal temperature for infection is 20℃ with 2 h of wetness (Cohen, 1977). The infection condition therefore depends on a favourable combination of LWD and mean temperature in LWD. The minimal threshold is 2 h×20 ℃=40 h·℃. This threshold agrees with many mechanistic experimental results (Hong, 1987; Shi et al., 2005). For the recovery period subsequent to transplanting cucumber seedlings, the model would run beginning on a date 1 week after transplanting. Note also that

LWD *TLWD≥40 h·℃　　　(LWD≥2 h, 5℃≤TLWD≤30℃)　　　　（2）

where LWD is leaf wetness duration (h), and TLWD is mean temperature (℃) in leaf wetness duration.

The time of first appearance of downy mildew symptoms depends more on temperature than on leaf wetness duration (Yang et al., 2007). Published data from inoculation experiments at different temperatures suggest the following values for the elapsed time between infection and symptom appearance: 2 d at 22–25°C, 3–4 d at 26–30°C, 7 d at 15–16°C and 10 d at 12–15°C (Fu and Yao, 1983). The temperature contribution rate (y) for symptom appearance was therefore measured by the reciprocal of the duration (days) of the inoculation period in the controlled experiments. The relationship of hourly mean temperature (t) and temperature contribution rate (y) was fitted using the SAS (Statistical Analysis System V.8.0.2, SAS Institute Inc., Cary, NC, USA) NLIN program with the Gauss-Newton method and expressed as:

$$y = \frac{0.0165}{1+10389.2 \cdot \exp(-0.5743 \cdot t)} \quad (p= 0.0033) \qquad （3）$$

where y is contribution rate, and t is hourly mean temperature (℃).When y

attains a value of 1, the incubation period is over and symptoms may appear.

Tracing the warning sources

Successful tracing of a disease warning to its source provides the basis of controlling disease for solar greenhouse vegetables. Using disaster chain-style theory and plant epidemiological theory (Xiao, 2006)), the problem of tracing a disease warning to its source was systematically analysed in association with disaster mitigation modes that involved cutting the disaster chain from the origin. The model took into account the multiple sources of disease early warning under solar greenhouse conditions and their effects on the modes and paths of interpretation of disease early warning. For example, because *P. cubensis* is a widely existing pathogen in cucumber production fields, and because greenhouses allow cultivation of cucurbits throughout the year, the primary inoculum sources exist in most greenhouses (Yang, et al, 2007) as the warning source. In the winter and spring, overcast, rainy, snowy and foggy weather conditions also represent potential sources of warnings of cucumber downy mildew infection. To integrate this experience and knowledge, the warning source traceability algorithm for cucumber downy mildew in solar greenhouses was constructed and tested for ease of system realisation. Detailed information about this project appears in our publication (Li, et al., 2010d).

Controlling the warning situation

Based on good agricultural practices (GAP), the control of the warning situation was established using the method of mitigation disaster by cutting the disaster chain upstream from the focus of the problem. For example, the overcast, rainy, snowy and foggy weather often represents the warning source for the occurrence of cucumber downy mildew. Farmers can enhance ventilation so as to decrease the LWD and can thereby control the conditions that would otherwise lead to infection. If the user chooses to apply chemicals, then the agents used should be suitable and justified (according to label recommendations or official registration body publication) for *P. cubensis* based on CHINAGAP (Yang, et al, 2007).

Data analysis

Analyses of sampling variance and standard deviation were done using SAS8.02 (SAS Institute Inc., North Carolina, USA). The figures were drawn using Microsoft Excel 2003. The main methods included:

Error analysis method. The estimated values and observed values were compared using random point figures. The errors were evaluated by *RMSE*, willmott agreement index(*W),* mean absolute error (*MAE) and* mean bias error (*MBE)* (Sentelhas et al., 2008).

Bayesian analysis method. If a method correctly estimated presence in an interval of time, it was scored in box *X*. If a method failed to estimate presence when it did occur, it was scored in box *Y*. If a method estimated presence when it did not occur, it was scored in box *S*. Finally, if a method

correctly estimated absence, it was scored in box Z. The model estimation results were also analyzed considering each sample using a contingency table (Table 1). Then the sensitivity (S_{en}), specificity (S_{pe}), accuracy (A_{cc}, i.e. Youden Index), false negative rate (F_{nr}) and false positive rate (F_{pr}) were computed using the data in Table 1.

Table 1 Category and summary of calculation results of early warning model for cucumber downy mildew in greenhouse

N	Estimated--Yes	Estimated--No
Observed--Yes	Hits（X）	Misses（Y）
Observed--No	False alarms（S）	Correct negatives（Z）

In general, based on the Bayesian Theorem, let A represent disease occurrence, $P(A)$ is the prior probability of disease occurrence based on our past experience(Yuen and Hughes, 2002). According to our investigated disease data between 2006 and 2009, there were 41 points with cucumber downy mildew occurrence among the 60 points. So $P(A)=41/60=0.68$, and then the prior probability of disease nonoccurrence, $P(\bar{A})=0.32$, and $P(A)+P(\bar{A})=1$. Next, let B represent an early warning of the occurrence of disease and $\bar{B}$ an early warning of the nonoccurrence of disease. Sensitivity is the conditional probability $P(B|A)$, which represent the probability of an early warning of disease occurrence given that disease actually occurred. Similarly, $P(\bar{B}|\bar{A})=S_{pe}$, $P(\bar{B}|A)=F_{nr}$, $P(B|\bar{A})=F_{pr}$. From the point of view of practical disease early warning, we are usually less interested in sensitivity and specificity as such, and more concerned with posterior probabilities (i.e. conditional probabilities) such as $P(A|B)$, the probability of disease occurrence, given an early warning of occurrence; and $P(\bar{A}|\bar{B})$, the probability of nonoccurrence of disease, given an early warning of nonoccurrence. Furthermore, the likelihood ratio of a positive early warning ($LR(A,B)$) is a useful measure that contains information from both sensitivity and specificity to summarize the results. Likewise, we can also define the likelihood ratio of a negative early warning ($LR(A,\bar{B})$). The equations could be seen in previous paper(Zhao et al., 2011). To summarize, from the point of view of making predictions of disease occurrence, we would ideally like a predictor to have $LR(A,B)$ as large as possible, and simultaneously have

$LR(A,\overline{B})$ as small as possible.

RESULTS

Model evaluations

The early warning results were evaluated in 2-site and 4-year data. From the error analysis, the model had good performance, with the accuracy (W=0.87). The estimation error was about 4 d (MAE=4.25); however, considering that the PIEW could early warning infection condition, the warning could be provided before the symptom appearance and the incubation period was often more than 2 d, so the error would be reduced to less than 2 d. The result will meet the requirement of cucumber downy mildew early warning in greenhouses. From Fig.2 ($RMSE$=8.74), there were a few points in the vertical axis, so the model should be improved for reduced the omitting points (i.e. miss warning rate).
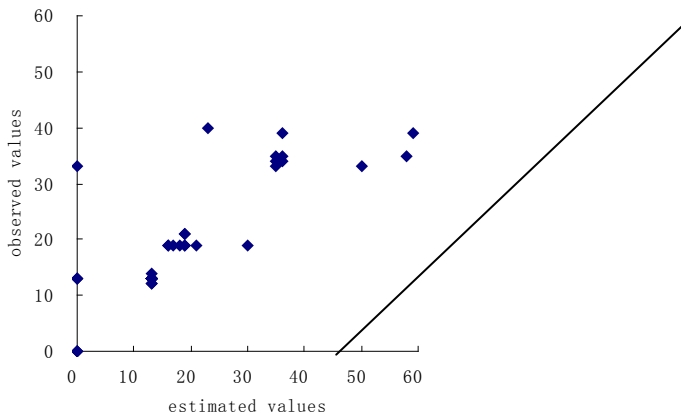

Fig.2　Comparison of occurrence date between observed values and simulated values under the early warning model for cucumber downy mildew in greenhouse (PIEWCDW)

From Table 2, the model had good performance with sensitivity being 0.68, specificity 0.92 and accuracy 0.60. Using the PIEWCDW, a positive early warning increased the chance of disease occurrence from 0.68 to 0·95, so we could warn the cucumber downy mildew occurrence with 95% probability. While a negative early warning decreased the occurrence chance from 0.68 to 0.42, but the probability of disease occurrence was still near to 0.5: disease occurrence and nonoccurrence were equally likely, despite the negative early warning. So the early warning for nonoccurrence should be improved, which is similar to Fig. 2.

In likelihood ratio of Bayesian theorem, $LR(A,B)$=8.5＞1, $LR(A,\overline{B})$=0.35 ＜1, the model had relative ideal results.

Table 2　Bayesian analysis of early warning results of PIEWCDW

	Estimated--Yes	Estimated--No	Total numb	Prior probabil	Posterior probabilit

				er	ity	y
Observed-- Yes	X=84 $P(B|A)=0.68$	Y=39 $P(\bar{B}|A)=0.32$	123		$P(A)=0.68$	$P(A|B)=0.95$
Observed-- No	S=34 $P(B|\bar{A})=0.08$	Z=425 $P(\bar{B}|\bar{A})=0.92$	459		$P(\bar{A})=0.32$	$P(\bar{A}|\bar{B})=0.58$
Total number	118	464	582			

Model for DSS development

We developed the early warning system based on the model using Visual C# 2005 and Microsoft Access 2003. The user could collect information about the cucumbers, the pathogen, cultivation and environmental conditions and generate early warnings of infection and occurrence of cucumber downy mildew (Fig. 3).
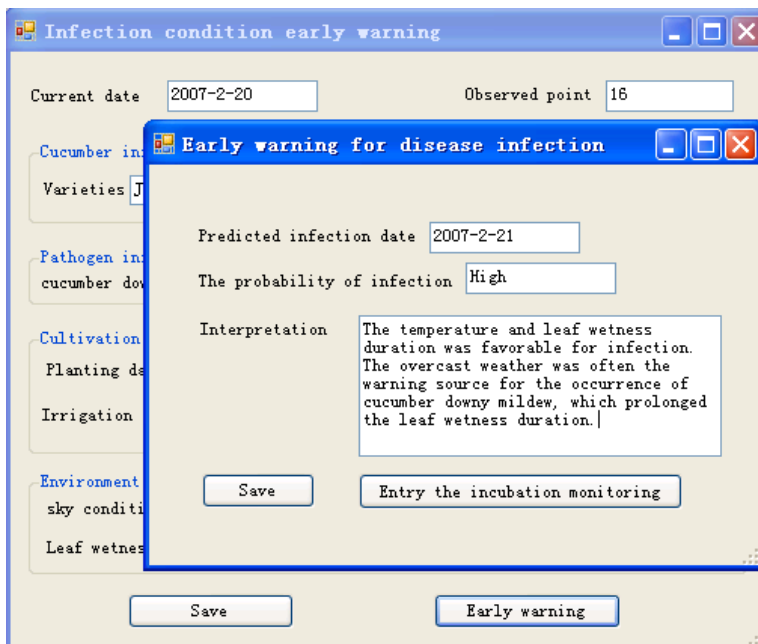
a Infection condition early warning
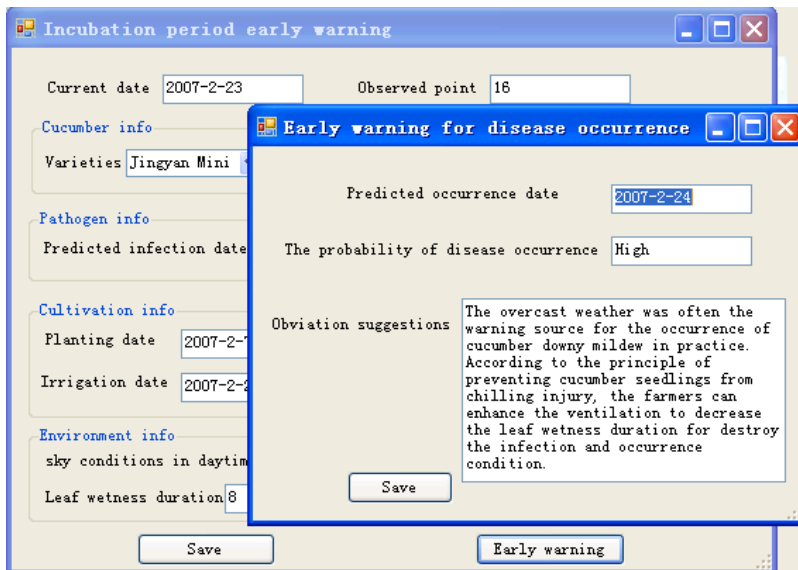
b Incubation period early warning

Fig.3   Early warning system for primary infection of cucumber downy mildew in solar greenhouses

DISCUSSIONS

Comparing with the existing model and system for early warning(Li et al., 2010a), the LWD increased the mechanics of models. The early warning models for plant diseases had two kinds(Madden and Ellis, 1988): fundamental models had higher accuracy and scientific meaning, but they were difficult to apply because of their complex parameters(Hong, 1987; Hong et al., 1989; Hong et al., 1990); empirical models were more simple, but they needed more scientific and sound interpretation (Li, 2006; Yang et al., 2007). Especially, many models selected relative humidity and temperature as main inputs (Ju, 2006; Xu, 2004), and paid no attention to the leaf wetness duration, which is essential for pathogen infection of leaf diseases in theory and real greenhouses, such as cucumber downy mildew. The model PIEWCDW integrated these two kinds of models and extracted the dominant factors. The leaf wetness duration monitoring by sensors and estimation by relative humidity-based model were investigated in order to support the early warning model for ultimate early warning system. A solution of model error analysis was also provided and the error would be reduced to less than 2 d. Based on Bayesian theorem, we could warn the cucumber downy mildew occurrence with 95% probability. The objective study of the performance of the early warning model will lead to a better understanding of disease occurrence probability than the subjective experiences. The results are similar to weather forecast and benefit for disease probability early warning.

Like all models, the PIEWCDW sometimes provided incorrect early warning. The frequency of incorrect early warning will influence the rate of adoption of a method by potential users, and its continued use. The probable reasons were the accuracy of leaf wetness duration monitoring method and estimation model. In contrast to air temperature, LWD is a difficult variable to

monitor or to estimate because it is driven by both atmospheric conditions and their interactions with the structure and composition of the crop canopies (Sentelhas et al., 2005). Leaf wetness sensors may not simulate the real situation, and only relative humidity-based estimation model would have some errors. For LWD is an initial factor for model, so if there is error for LWD input, such as not detecting the LWD appearance, then the early warning model would omit the warning. Maybe the combination and reduction of the LWD monitoring and estimation method should be investigated furthermore(Li et al., 2010b).

The second reason was the limitation of prior probability of cucumber downy mildew. In reality, we have often little information on prior occurrence of diseases. Although we estimated the prior probability of cucumber downy mildew using 4-year and 2-site data set, the use of historical data in order to estimate the prior probabilities involved assumptions about similar weather, cultivars, cultural practices, and pathogen population for other sites(Yuen and Hughes, 2002). These assumptions may or may not be true. It is essential for model extension that obtaining more disease occurrence data from different years and sites for validation in future.

Still, our results suggest that the LWD monitoring method and estimation model can provide LWD values accurately enough to implement disease early warning systems that use LWD as an input. Knowing the performance of PIEWCDW by probability will enable the targeting of areas where there is a chance that it might be used. With further testing, these methods may help to encourage growers in solar greenhouses to apply disease early warning systems for reducing the frequency of fungicide sprays and then improving the agricultural product quality.

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REFERENCES

Arauz, L.F., Neufeld, K.N., Lloyd, A.L., Ojiambo, P.S., 2010. Quantitative models for germination and infection of Pseudoperonospora cubensis in response to temperature and duration of leaf wetness. Phytopathology 100, 959-967.

Gillespie, T.J., Srivastava, B., Pitblado, R.E., 1993. Using operational weather

data to schedule fungicide sprays on tomatoes in southern Ontario, Canada. Journal of Applied Meteorology 32, 567-573.

Gleason, M.L., Duttweiler, K.B., Batzer, J.C., Elwynn Taylor, S., Sentelhas, P.C., Monteiro, J.E.B.A., Gillespie, T.J., 2008. Obtaining weather data for input to crop disease-warning systems: leaf wetness duration as a case study. Scientia Agricola 65, 76-87.

Hong, C.X., 1987. A simulation model for the cucubmer downy mildew (*Pseudoperonospora cubensis*) under plastic shelter. Beijing Agricultural University, Beijing.

Hong, C.X., Xiao, Y.Y., Zeng, S.M., 1989. Modelling of the cucumber downy mildew under plastic shelter conditions. Acta Phytophylacica Sinica 16, 217-220 (in Chinese with English abstract).

Hong, C.X., Xiao, Y.Y., Zeng, S.M., Huang, Z.S., Yang, Y.R., 1990. Quantitative analysis of the epidemic process of cucumber downy mildew. Acta Phytophylacica Sinica 17, 263-268 (in Chinese with English abstract).

Huang, Y.B., Lan, Y.B., Thomson, S.J., Fang, A., Hoffmann, W.C., Lacey, R.E., 2010. Development of soft computing and applications in agricultural and biological engineering. Computers and Electronics in Agriculture 71, 107-127.

Ju, R.H., 2006. Ecosystem monitoring and the decision system for diseases and insect pest management of cucumber in SES greenhouse. China Agricultural University, Beijing.

Kim, K.S., Gleason, M.L., Taylor, S.E., 2006. Forecasting Site-Specific Leaf Wetness Duration for Input to Disease-Warning Systems. Plant Disease 90, 650-656.

Kumar, A., Maini, P., Singh, S.V., 1999. An Operational Model for Forecasting Probability of Precipitation and Yes/No Forecast. Weather and Forecasting 14, 38-48.

Li, H.M., 2006. The survey criterion for diseases and insect pests forecast in vegetables. Shanghai Scientific & Technical Publishers, Shanghai.

Li, M., Qian, J.P., Yang, X.T., Sun, C.H., Ji, Z.T., 2010a. A PDA-based record-keeping and decision support system for traceability in cucumber production. Computers and Electronics in Agriculture 70, 69–77.

Li, M., Zhao, C.J., Li, D.L., Wang, C., Yang, X.T., 2010b. Calibration method of leaf wetness sensor for cucumber in solar greenhouse. Transactions of the CSAE 26, 224-230 (in Chinese with English abstract).

Li, M., Zhao, C.J., Qiao, S., Qian, J.P., Yang, X.T., 2010c. The leaf wetness duration estimation model based on canopy relative humidity for cucumber in greenhouse. Transactions of the CSAE (submitted).

Lindenthal, M., Steiner, U., Oerke, E.-C., 2005. Effect of Downy Mildew Development on Transpiration of Cucumber Leaves Visualized by Digital Infrared Thermography. Phytopathology 95, 233-240.

Luo, W., Goudriaan, J., 1999. Effects of altering water temperature on leaf wetness in paddy rice crops. Agricultural and Forest Meteorology 97, 33-42.

Madden, L.V., Ellis, M.A., 1988. How to develop plant disease forecaster. Pages 191-208. Springer, Berlin.

Magarey, R.D., Russo, J.M., Seem, R.C., 2006a. Simulation of surface wetness with a water budget and energy balance approach. Agricultural and Forest Meteorology 139, 373-381.

Magarey, R.D., Seem, R.C., Russo, J.M., 2006b. Grape canopy surface wetness: Simulation versus visualization and measurement. Agricultural and Forest Meteorology 139, 361-372.

Maini, P., Kumar, A., Singh, S.V., Rathore, L.S., 2004. Operational model for forecasting location specific quantitative precipitation and probability of precipitation over India. Journal of Hydrology 288, 170-188.

Mila, A.L., Carriquiry, A.L., 2004. Bayesian Analysis in Plant Pathology. Phytopathology 94, 1027-1030.

Oerke, E.-C., Gerhards, R., Menz, G., Sikora, R.A., 2010. Precision Crop Protection -the Challenge and Use of Heterogeneity. Springer.

Orlandinia, S., Massettib, L., Dalla Marta, A., 2008. An agrometeorological approach for the simulation of *Plasmopara viticola*. Computers and Electronics in Agriculture 64, 149-161.

Papoulia, J., Stavrakakis, G., Papanikolaou, D., 2001. Bayesian estimation of strong earthquakes in the Inner Messiniakos fault zone, southern Greece, based on seismological and geological data. Journal of Seismology 5, 233-242.

Portraz, K.J., Gleason, M.L., Hockmuth, M.L., Parker, S.K., Pearston, G.A., 1994. Testing the accuracy and precision of wetness sensors in a tomato field and turfgrass. Journal of the Iowa Academy of Sciences 101, 56-60.

Schmitz, H.F., Grant, R.H., 2009. Precipitation and dew in a soybean canopy: Spatial variations in leaf wetness and implications for Phakopsora pachyrhizi infection. Agricultural and Forest Meteorology 149, 1621-1627.

Sentelhas, P.C., Gillespie, T.J., Batzer, J.C., Gleason, M.L., Monteiro, J.E.B.A., Pezzopane, J.R.M., Pedro Junior, M.J., 2005. Spatial variability of leaf wetness duration in different crop canopies. International Journal of Biometeorology 49, 363–370.

Sentelhas, P.C., Marta, A.D., Orlandini, S., Santos, E.A., Gillespie, T.J., Gleason, M.L., 2008. Suitability of relative humidity as an estimator of leaf wetness duration. Agricultural and Forest Meteorology 148, 392-400.

Shetty, N.V., Wehner, T.C., Thomas, C.E., Doruchowski, R.W., Shetty, K.P.V., 2002. Evidence for downy mildew races in cucumber tested in Asia, Europe, and North America. Scientia Horticulturae 94, 231-239.

Tsapanos, T.M., Lyubushin, A.A., Pisarenko, V.F., 2001. Application of a Bayesian Approach for Estimation of Seismic Hazard Parameters in Some Regions of the Circum-Pacific Belt. Pure and Applied Geophysics 158, 859-875.

Vincelli, P.C., Lorbeer, J.W., 1988. Relationship of participation probability to infection potential of Botrytis squamosa on onion. Phytopathology 78, 1078-1082.

Xiao, S.S., 2006. Theory and application of chain-styled of disaster. Science Press (in Chinese), Beijing.

Xiong, W., 2009. The performance of CERES-Wheat model in wheat planting areas and its uncertainties. Journal of Applied Meteorological Science 20, 88-94.

Xu, N., 2004. Forecasting and management system of cucumber powdery mildew and downy mildew in plastic greenhouse tunnel. Nanjing Agricultural University, Nanjing.

Yang, X., Li, M., Zhao, C., Zhang, Z., Hou, Y., 2007. Early warning model for cucumber downy mildew in unheated greenhouses. New Zealand Journal of Agricultural Research 50, 1261-1268.

Yuen, J.E., Hughes, G., 2002. Bayesian analysis of plant disease prediction. Plant Pathology 51, 407-412.

Zhang, Y.S., Jewett, T.J., Shipp, J.L., 2002. A dynamic model to estimate in-canopy and leaf-surface microclimate of greenhouse cucumber crops. Transactions of the ASAE 45, 179-192.

Zhao, C.J., Li, M., Yang, X.T., Sun, C.H., Qian, J.P., Ji, Z.T., 2011. A data-driven model simulating primary infection probabilities of cucumber downy mildew for use in early warning systems in solar greenhouses. Computers and Electronics in Agriculture 76, 306-315.

Zheng, H.S., Chen, D.S., Liu, H.Z., 1990. A method of calculating dew duration on cucumber leaves in film plastic greenhouse. Transactions of the CSAE 6, 43-49 (in Chinese with English abstract).