INTEGRATION OF EPIDEMIOLOGICAL INFORMATION INTO A DECISION SUPPORT SYSTEM FOR LATE BLIGHT

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INTEGRATION OF EPIDEMIOLOGICAL INFORMATION INTO A DECISION SUPPORT SYSTEM FOR LATE BLIGHT

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A web-based decision support system (DSS) for potato and tomato late blight management has been developed which links several models into a system that enables prediction of disease dynamics based on weather conditions, crop information, and management tactics. Growers identify the location of their production unit of interest (latitude and longitude of field), and the system automatically obtains observed weather data from the nearest available weather station, and location-specific forecast weather data. The BlightPro DSS uses these weather data along with crop and management information to drive disease forecasting systems and a validated mechanistic model of the disease to generate location-specific management recommendations for fungicide application.

To evaluate the utility of the BlightPro DSS across a range of environments, a combination of computer simulation and field experiments was conducted. Three fungicide schedules were evaluated i) calendar-based (weekly) applications, ii) applications according to the DSS, or iii) no fungicide. Simulation experiments utilized 14 years of weather data from 59 locations in potato producing states. In situations with unfavorable weather for late blight, the DSS recommended fewer fungicide applications with no loss of disease suppression, and in situations of very favorable weather for late blight, the DSS recommended more fungicide applications but with improved disease suppression. Field evaluation was conducted in 2010, 2011,

2012, and 2013. All experiments involved at least two cultivars with different levels of resistance. DSS-guided and weekly scheduled fungicide treatments were successful at protecting against late blight in all field experiments. As expected, DSS-guided schedules were influenced by prevailing weather (observed and forecast) and host resistance and resulted in schedules that maintained or improved disease suppression and average fungicide use efficiency, relative to calendar-based applications.

A preliminary dispersal-risk model for late blight was developed using data obtained experimentally and from the published literature. The model relates availability of sporangia of *Phytophthora infestans* produced from lesions in a crop canopy to relative numbers of sporangia in the air above the crop (dispersal-risk). The model uses field-based estimates of disease severity coupled with functions that describe the effect of meteorological elements on production of sporangia, release of sporangia from sporangiophores, and escape of sporangia from a potato canopy. For each potential risk period the estimated disease severity at the source is coupled with predictors for sporangia availability, release of sporangia, and escape of sporangia. These predictors are then integrated in the form of a linear model to predict the relative number of sporangia h^{-1} that will escape the potato canopy and become available for dispersal. With field-based estimates of disease severity at a known source of late blight, variation in numbers of sporangia above the crop canopy was well described ($P < 0.0001$) by the dispersal-risk model ($R^2 = 0.91$; RMSE = 2.86 sporangia h^{-1}). The model is intended for use within the context of the BlightPro DSS. Knowledge of upcoming “high risk” periods for dispersal could be used to enhance the efficiency of disease management practices.

BIOGRAPHICAL SKETCH

Ian M. Small grew up on a small farm near Harare, Zimbabwe. While he attended high school at St John's College his love for science and nature were fostered by a wonderful biology teacher, Mrs. Loveridge, who helped lay the foundations for his career in science. Pursuing his interests in science and agriculture, he moved to South Africa to study agricultural science at Stellenbosch University, South Africa. It was during his Bachelor of Science in Agriculture degree program that he became interested in plant pathology. An excellent professor and scientist, Dr. Adele McLeod, played a pivotal role in inspiring him to continue his studies within the field of plant pathology. This led him to pursue a Master of Science degree in Agriculture with a focus on plant pathology. Through a scholarship from the South African National Science Foundation, he was fortunate to be able to join the lab of Dr. Altus Viljoen. He learned a tremendous amount working with Dr. Viljoen, but most importantly he was exposed to the impact that plant diseases can have on society. His MSc. degree, completed under the guidance of Dr. Viljoen, related to the study of resistance in maize to an important disease, Fusarium ear rot, which can result in contamination of the grain with mycotoxins. It was during this time in South Africa that he met Dr. Bill Fry. Following his MSc. degree he joined Dr. Fry's laboratory as a visiting scientist. In the spring of 2012 he enrolled as a doctoral student within the Section of Plant Pathology & Plant-Microbe Biology at Cornell University to study plant disease epidemiology and management under the guidance of Dr. Fry.

This dissertation is dedicated to my parents for their endless love, support, and encouragement.

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CHAPTER 1.

DEVELOPMENT AND IMPLEMENTATION OF THE BLIGHTPRO DECISION SUPPORT SYSTEM FOR POTATO AND TOMATO LATE BLIGHT MANAGEMENT*

ABSTRACT

A web-based decision support system (DSS) for potato and tomato late blight management has been developed which links several models into a system that enables prediction of disease dynamics based on weather conditions, crop information, and management tactics. Growers identify the location of their production unit of interest (latitude and longitude of field) and the system automatically obtains observed weather data from the nearest available weather station, and location-specific forecast weather data from the National Weather Service – National Digital Forecast Database. The DSS uses these weather data along with crop and management information to drive disease forecasting systems and a validated mechanistic model of the disease to generate location-specific management recommendations for fungicide application. An integrated alert system allows users to receive notification of upcoming critical thresholds via e-mail or text message. This system provides producers, consultants, researchers, and educators with a tool to obtain management recommendations, evaluate disease management scenarios, explore comparative epidemiology, or function as a teaching aid. In field and computer simulation experiments, DSS-guided schedules were influenced by prevailing weather and host resistance and resulted in

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schedules that improved the efficiency of fungicide use and also reduced variance in disease suppression when compared to a weekly spray schedule. In situations with unfavourable weather, the DSS recommended fewer fungicide applications with no loss of disease suppression. In situations of very favourable weather, the DSS recommended more fungicide applications but with improved disease suppression. The DSS provides an interactive system that helps users maximize the efficiency of their crop protection strategy by enabling well-informed decisions.

Additional keywords: plant disease management, decision support system, late blight, plant disease epidemiology, crop management, forecasting, potato, tomato

1. INTRODUCTION

Late blight, the plant disease caused by *Phytophthora infestans* (Mont.) de Bary, is a major constraint to potato and tomato production worldwide. A conservative estimate of the total global cost of the disease to potato production is 6.7 billion USD per year in yield losses and costs of late blight control measures (Haverkort et al., 2008). Unexpected late blight epidemics have resulted in major economic losses to growers for whom potatoes or tomatoes are the major income source (Fry et al., 2013; Fry and Goodwin, 1997). Although the disease is more problematic in rain fed agriculture such as in the northeastern USA, sporadically it can also be serious in drier production areas such as the Pacific Northwest (largest potato production area in the USA) (Johnson et al., 2000). For example the cost of managing a potato late blight epidemic in the Pacific Northwest in 1995 was estimated at 30 million USD (Johnson et al., 2000). The disease can be equally devastating to tomato producers. The most recent example occurred in 2009 when infected tomato transplants were distributed via national large retail stores who obtained transplants from a national supplier (Fry et al., 2013). The ensuing pandemic in the mid-Atlantic and Northeast regions of the U.S. devastated tomato crops for many organic farms and in many, many home gardens (Fry et al., 2013).

Management of late blight typically involves cultural procedures designed to reduce the introduction, survival, or infection rate of *P. infestans*, and the use of fungicides. When developing a late blight management strategy, there are several factors that must be considered including the influence of prevailing weather on the pathogen lifecycle and fungicide residue on the crop, late blight resistance of the cultivar being grown, and pathogen characteristics, such as resistance to highly effective fungicides. The complexity of the interactions between these factors makes rational disease management decision-making difficult, leading to implementation of either inadequate or excessive management measures. The application of disease management measures when they are not necessary is at the very least inefficient, as unnecessary applications entail costs to growers, consumers, and the environment (Fry, 1982). Effective management is achieved by integrating a variety of control measures that may differ in efficacy, duration of effectiveness, and cost (Shtienberg, 2000). This complexity creates an opportunity for a decision support system (DSS) to be used to provide science-based information to assist with this decision making.

Decision Support Systems integrate and organize available information on the pathogen, the influence of observed and forecast weather on the disease, cultivar resistance, as well as fungicide characteristics and efficacy, required to make decisions concerning the management of late blight. Computer-based DSSs can integrate these factors to deliver either general or site-specific information to the users via extension personnel, telephone, fax, e-mail, SMS, PC and websites on the Internet (Cooke et al., 2011). Forecasters such as BLITECAST (Krause et al., 1975), FAST (Madden et al., 1978), and the apple scab predictive system (Jones et al., 1980), are examples of early tools that were designed to assist farmers with decisions relating to management of potato late blight, early blight, and apple scab, respectively (Shtienberg, 2013). Since the 1990s, DSSs have been developed in many countries to assist with the management of plant diseases such as potato late blight, apple scab, cereal leaf diseases, strawberry diseases, and grape downy mildew (Pavan et al., 2011; Shtienberg, 2013). In Europe, several DSSs for late blight have been developed using various disease forecasting systems and models (Cooke et al., 2011). A list of these DSSs can be found on the Euroblight website (a potato late blight network for Europe) (http://www.euroblight.net/EuroBlight.asp). In certain European countries, such as The Netherlands, it has been reported that up to 36% of potato growers use the recommendations of commercially available DSSs to assist with their management of late blight (Cooke et al., 2011).

Under experimental settings, use of DSSs has been shown to improve disease suppression, reduce risk of crop damage, and under many circumstances reduce the quantities of active ingredients used, relative to typical spraying practices (Shtienberg, 2000). The objectives for this study were to develop and implement a web-based DSS for late blight capable of utilizing location-specific weather data to drive disease forecasters and a mechanistic model of the late blight disease, in order to provide real-time (in-season) support for late blight management in the USA.

2. SYSTEM DEVELOPMENT

The BlightPro DSS for potato and tomato late blight management (http://blight.eas.cornell.edu/blight/) was developed to integrate pathogen information (mefenoxam sensitivity and host preference), the effects of weather, host resistance and fungicide on disease progress in order to improve in-season disease management. A secondary design objective was to develop a version of the system that could be used with archived weather data to explore disease management scenarios, for comparative epidemiology, or function as a teaching aid.

2.1 Weather data

Each user defines the location of his/her management unit of interest (field) via an interactive geographic information system in the form of a Google Maps API. This provides an easy method to obtain the necessary latitude and longitude information required for the DSS (Figure 1.1).

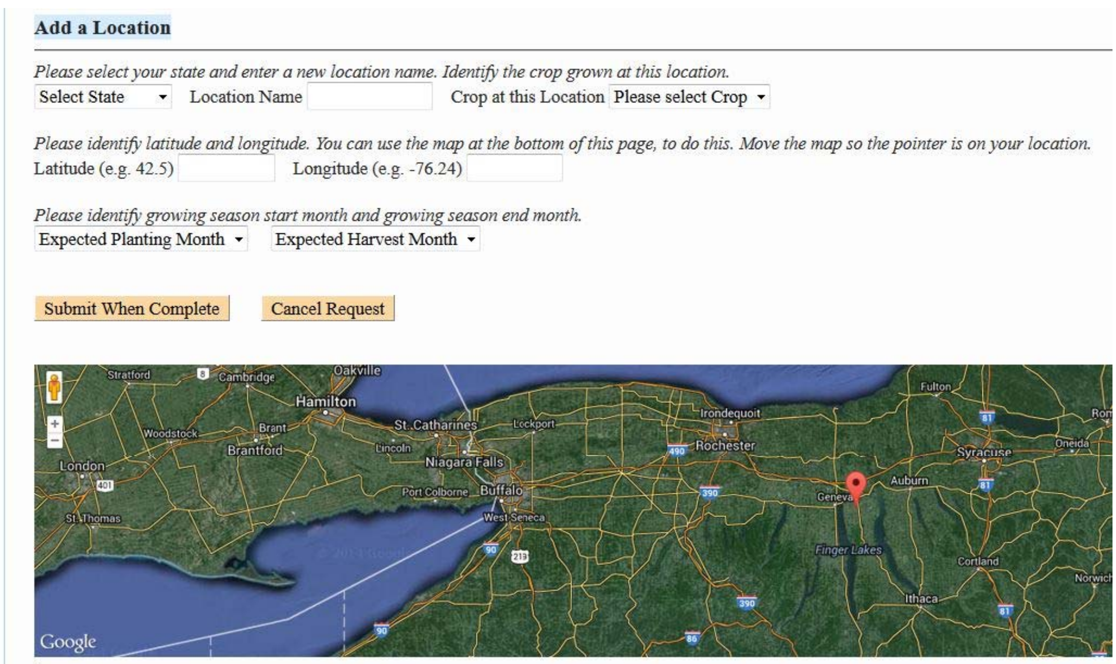

Figure 1.1. Interface for definition of new locations. A google API interface allows users to identify their location with the aid of a map. The latitude and longitude of the location is obtained automatically.

The system then automatically identifies the nearest five weather stations to the grower's location, with the closest station serving as the default source for observed weather data, and utilizes the grower location to obtain the weather forecast. The weather station may be a privately owned station (connected to a meteorological network) on the grower's farm, or a publicly accessible station e.g. an airport station. If the user intends to use a private station, the station must be capable of uploading data to a meteorological network such as NEWA (Network for Environment and

Weather Applications) in the Northeastern USA http://www.newa.cornell.edu/, or FAWN (Florida Automated Weather Network) in Florida http://fawn.ifas.ufl.edu/. Data from these networks can be accessed by the Northeast Regional Climate Center (NRCC) http://www.nrcc.cornell.edu/.

The NRCC works cooperatively with the National Climatic Data Center, the National Weather Service, state climate offices, and interested scientists in the Northeast to acquire and disseminate accurate, up-to-date climate data and information. Regional Climate Centers (RCCs) are a federal-state cooperative effort (DeGaetano et al., 2010). The National Oceanic and Atmospheric Administration (NOAA) – National Climatic Data Center (NCDC) manages the RCC Program. The six centers that comprise the RCC Program are engaged in the production and delivery of climate data, information, and knowledge for decision makers and other users at the local, state, regional, and national levels. Weather data are accessed via the Applied Climate Information System (ACIS) developed by the NOAA – RCCs (DeGaetano et al., 2015). A number of weather variables including temperature, relative humidity, precipitation, wind speed and direction are monitored and archived in real time.

The observed data are combined with high-resolution forecast data (2.5 square km grid) for the location of interest, obtained from the National Weather Service – National Digital Forecast Database (NWS-NDFD) using access routines provided by the NRCC. The NWS-NDFD short-term weather forecasts are provided in a grid format and include sensible weather elements (e.g., temperature, relative humidity, sky cover). The NDFD contains a seamless mosaic of digital forecasts from NWS field offices working in collaboration with the National Centers for Environmental Prediction (NCEP). The weather data and forecasts are updated 8 times per day. The frequency of updates depends on the rate at which new forecasts are generated by the

NWS and processed by the NRCC. As weather forecasts are updated, the outputs of the DSS will change to reflect the most recent weather data.

2.2. Cultivar resistance database

A database providing information on late blight resistance in potato and tomato cultivars was generated for the DSS using a combination of published literature and field experiments. Information on potato cultivar resistance to late blight was obtained from published plant disease management reports and field experiments (Forbes et al., 2005; Fry, 1998; Fry and Apple, 1986; Inglis et al., 1996; Jenkins and Jones, 2003; Parker et al., 1992; Stevenson et al., 2007). Field experiments to investigate potato cultivar resistance to late blight were conducted at the Homer C. Thompson Vegetable Research Farm in Freeville NY in 2011, 2012 and 2013 (Small et al., 2013). The system was initially developed for late blight of potato but extension of the system is underway to enable its use for late blight of tomato. Information on tomato cultivar resistance to late blight was obtained from published plant disease management reports (McGrath et al., 2013) and field trials (Hansen et al., 2014). A list of cultivars evaluated is available on the DSS. Currently (May 2015), there are more than 60 potato cultivars and more than 50 tomato cultivars that have been classified for their resistance to late blight. These numbers will increase as experimental data is obtained.

2.3. Disease forecasting tools

The DSS provides a platform to run late blight forecasting systems. Two systems are currently implemented: Blitecast, which is a forecast system developed to predict the initial occurrence of late blight in northern temperate climates, as well as the subsequent spread of late blight (Krause et al., 1975); and Simcast, which is a forecasting system that integrates the effect of host resistance with the effects of prevailing weather on late blight progress and the effect of prevailing weather on fungicide weathering (Fry et al., 1983). Simcast does not predict the initial occurrence of late blight (the need for a first fungicide application), but may be used to schedule subsequent applications. A user might schedule his/her initial fungicide application based on the accumulation of 18 Blitecast severity values, or a particular growth stage, and then use Simcast to schedule subsequent applications. Critical thresholds for Simcast were originally validated in field experiments using chlorothalonil as a fungicide. In order to accommodate for the variety of fungicides used by producers, thresholds were established for several of the most commonly used fungicide active ingredients e.g. copper hydroxide, cyazofamid, cymoxanil, mancozeb, mandipropamide, mefenoxam, propamocarb hydrochloride, and others. Thresholds for fungicide active ingredients (and combinations of active ingredients) were established based on field experiments, published fungicide efficacy data, and expert opinion.

2.4. Late blight disease simulator

A mechanistic model of the late blight disease on potato (Andrade-Piedra et al., 2005) is available on the system and can be used in real-time with the observed and forecast weather to predict disease dynamics and fungicide weathering and loss. The model was validated for late blight on potato and fungicide weathering on a potato canopy. Validation of the model for its ability to predict late blight of tomato and fungicide residue on tomato canopy is yet to be accomplished. The simulator may be used to evaluate disease management scenarios, or to quantify the effects of host resistance and/or fungicide. The fungicide sub-model is based on chlorothalonil, a widely used protectant fungicide (Bruhn and Fry, 1982a; Bruhn and Fry, 1982b).

2.5. System output

The DSS generates several reports, including reports on prevailing weather, disease forecast information, and late blight simulator outputs. The weather data report includes graphs illustrating 7 days of observed and 7 days of forecast weather (hourly relative humidity, hourly temperature, six-hourly precipitation). The disease forecast reports include information from: 1) Blitecast – observed and forecast daily severity values; and 2) Simcast – observed and forecast daily blight units and fungicide units. Blitecast severity values indicate the favorability of the prevailing weather for late blight progress and represent specific relationships between duration of relative humidity periods ≥ 90 % and average temperature during those periods, and their impact on late blight (Krause et al., 1975). Similarly, Simcast blight units represent the favourability of the prevailing weather for late blight progress and are also calculated based on the relationships between duration of relative humidity periods ≥ 90 % and average temperature during those periods. However, in Simcast, the calculation of blight units is influenced by the cultivar resistance to late blight with different thresholds for cultivars of different resistances. Simcast fungicide units represent the impact of prevailing weather (including precipitation) on fungicide weathering. Critical thresholds for both blight units and fungicide units are determined according to cultivar resistance (Fry et al., 1983). The reports generated by the late blight simulator are based on observed and forecast weather data and include information on: 1) simulated disease progress data; and 2) simulated fungicide residue on crop.

2.5.1. Weather data

A weather report provides users with the ability to inspect recent observed weather and forecast weather. The report contains graphs of hourly temperature and relative humidity and six-hourly precipitation, for 7 days of recent observed and 7 days of forecast weather data (Figure 1.2).

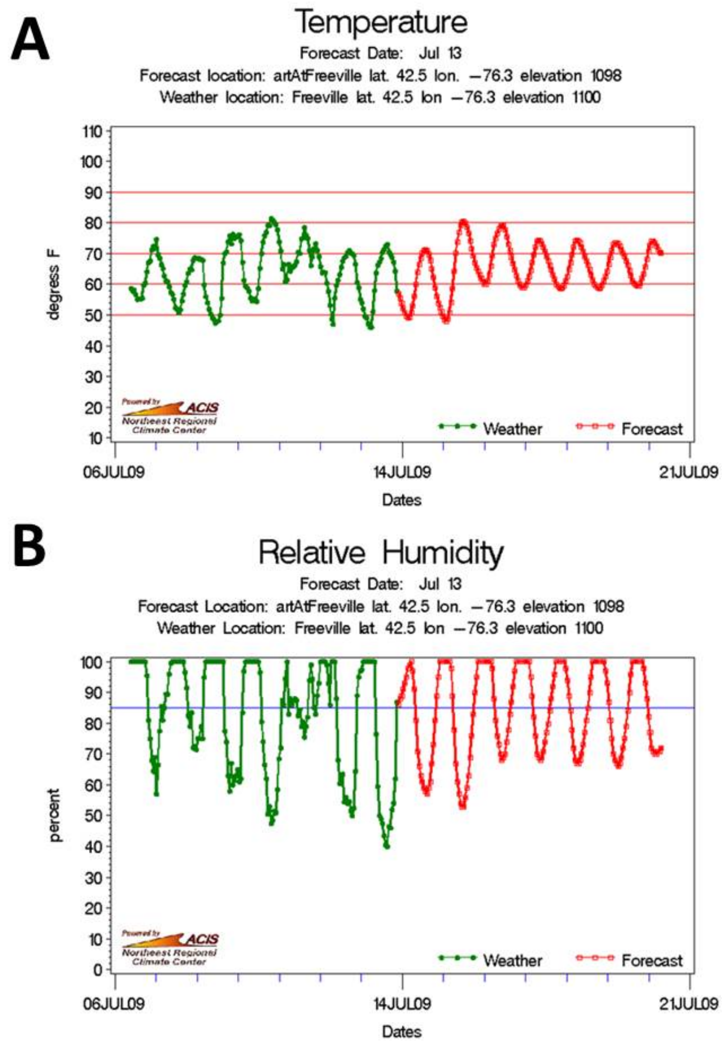

Figure 1.2. Examples of weather reports. A. Hourly temperature data for a defined location. B. Hourly relative humidity data for a defined location. Seven days of observed (green series) and 7 days of forecast (red series) weather data are represented on each report.

Decision-makers might find this information useful to verify that weather data are accurate for their location and to understand the association between prevailing weather and favorability of the weather for late blight. In addition to the detailed weather data, the system conducts an automatic check for missing weather data and a summary table indicating the number of hours of missing data for any of the relevant weather variables is presented. Since the reliability of the outputs from the disease forecasts and disease model are dependent on accurate and complete input weather data, the system has a missing-weather backup feature. If more than 6 hours of missing temperature or relative humidity data occur, the system substitutes missing data with archived forecast information for that specific location. The archived weather data consists of the first 24 hr of forecast weather, which are saved daily. For missing precipitation data, the system substitutes missing data with high resolution precipitation data generated by the NRCC. Alternatively, the user has the option to select one of the other four nearest stations as a source for the observed data.

2.5.2. Disease forecast reports

The system generates a detailed report for each disease forecasting system, Blitecast and Simcast. The detailed Blitecast report provides daily information about wet period duration and average temperature during each wet period (Figure 1.3). This information is used to calculate a daily severity value, the cumulative severity value since last fungicide application, as well as the seasonal cumulative severity value (based on the Blitecast system). The detailed Simcast report provides daily information on wet period duration and average temperature during each wet period, as well as daily precipitation/irrigation (Figure 1.4). This information is used to calculate daily blight units and daily fungicide units. Blight units indicate the favorability of the prevailing/forecast weather for late blight and fungicide units represent the influence of prevailing/forecast weather, or irrigation, on fungicide weathering. For blight units and fungicide units the daily value is presented along with the cumulative value since last fungicide application and seasonal cumulative value. A colour coding system distinguishes information based on forecast weather data from observed weather data (Figure 1.4). Critical thresholds for fungicide application are automatically indicated on the reports.

6/10/2010 Blitecast Report
Weather Location: Freeville 5/30/2010 to 6/10/2010
Forecast Location: freevilleFarm 6/10/2010 to 6/16/2010
Replacement for missing weather: not applicable

	Wet Period				Severity Values		
Fungicide Date	start	end	hrs.	Ave. Temp. (F)	daily	accum since last fung. appl.	season accum.
	6/15 4am	6/15 7am	3	54	0	19	19
6/14							
	6/13 7pm	6/14 9am	14	64	2	19	19
6/13							
	6/12 9pm	6/13 1pm	16	69	3	17	17
6/12							
	6/11 10pm	6/12 10am	12	61	1	14	14
6/11							
	6/10 8pm	6/11 9am	13	52	0	13	13
6/10							
	6/10 10am	6/10 11am	1	62	0	13	13
6/9							
	6/9 11am	6/10 9am	22	57	4	13	13
	6/8 9pm	6/9 8am	11	48	0	9	9
6/8							
	6/7 11pm	6/8 9am	10	52	0	9	9

Figure 1.3. Detailed Blitecast report. Daily severity values are calculated based on wet period duration and average temperature during each wet period. Information based on observed weather data has a white background and information based on forecast weather data has an orange background. When the cumulative daily severity value has exceeded a critical threshold, this is indicated by red font colour.

7/15/2010 Simcast Report for susceptible cultivar
Weather Location: Freeville 6/13/2010 to 7/15/2010
Forecast Location: freevilleFarm 7/15/2010 to 7/21/2010
Replacement for missing weather: not applicable

		Wet Period				Blight Units				Fungicide Units		
Date	Fungicide (epa number)	start	end	hours	Ave. Temp. (F)	daily	since last fung. appl.	season accum.	Rainfall (& irrigation) (inch)	daily	since last fung. appl.	season accum.
7/21										-1	**-19**	-19
		7/20 23	7/21 9	11	64.4	6	**55**	196				
7/20										-1	**-18**	-18
		7/19 22	7/20 9	12	66.2	6	**49**	190				
7/19										-1	**-17**	-17
		7/19 1	7/19 9	9	66.2	5	**43**	184				
7/18									0.01	-1	**-16**	-16
		7/18 0	7/18 8	9	66.2	5	**38**	179				
7/17									0.26	-4	**-15**	-15
		7/16 20	7/17 8	13	68.0	7	**33**	174				
7/16									0.08	-3	-11	-11
		7/15 23	7/16 9	11	69.8	6	26	167				
7/15									0.00	-1	-8	-8
		7/14 20	7/15 9	14	66.2	7	20	161				
7/14									0.00	-1	-7	-7
		7/13 20	7/14 11	16	71.6	7	13	154				

Figure 1.4. Detailed Simcast report for a defined location. The Simcast report provides daily information on wet period duration and average temperature during each wet period, as well as daily precipitation/irrigation. This information is used to calculate daily blight units and daily fungicide units. The report is divided into three sections based on background colour: white background is observed weather data used for calculations; orange background is forecast temperature, relative humidity, and precipitation; and yellow background is forecast temperature and relative humidity. Longer term precipitation forecast (beyond three days) is excluded due to high variability.

In addition to the detailed reports, a simple summary graphic is presented which clearly indicates whether or not a critical threshold is expected to occur within the upcoming 7 days, based on forecast weather (Figure 1.5).

Simcast Summary

Date	7/15	7/16	7/17	7/18	7/19	7/20	7/21
Blight Units	20	26	33	38	43	49	55
Fungicide Units	-8	-11	-15	-16	-17	-18	-19

Key	
	Below Threshold
>=30	Blight Unit Threshold Exceeded
<=-15	Fungicide Unit Threshold Exceeded

Figure 1.5. Seven-day forecast summary. A summary graphic is generated which presents key forecast information for the upcoming 7 days. Daily information is represented as columns with rows showing the accumulated blight/fungicide units. Background colour of each cell indicates whether a critical threshold has been exceeded. A key shows the applicable critical thresholds accompanied by their respective background colour.

2.5.3. Simulator reports

Three outputs are generated by the simulator: 1) a graph indicating simulated disease progress based on observed and forecast weather, cultivar resistance, and fungicide use (Figure 1.6); 2) a graph indicating simulated average fungicide residue on the potato canopy, based on observed and forecast weather and fungicide application information (Figure 1.7); and 3) a table containing a detailed numerical listing of several model outputs calculated for each day, such as disease severity and fungicide residue (Figure 1.8).

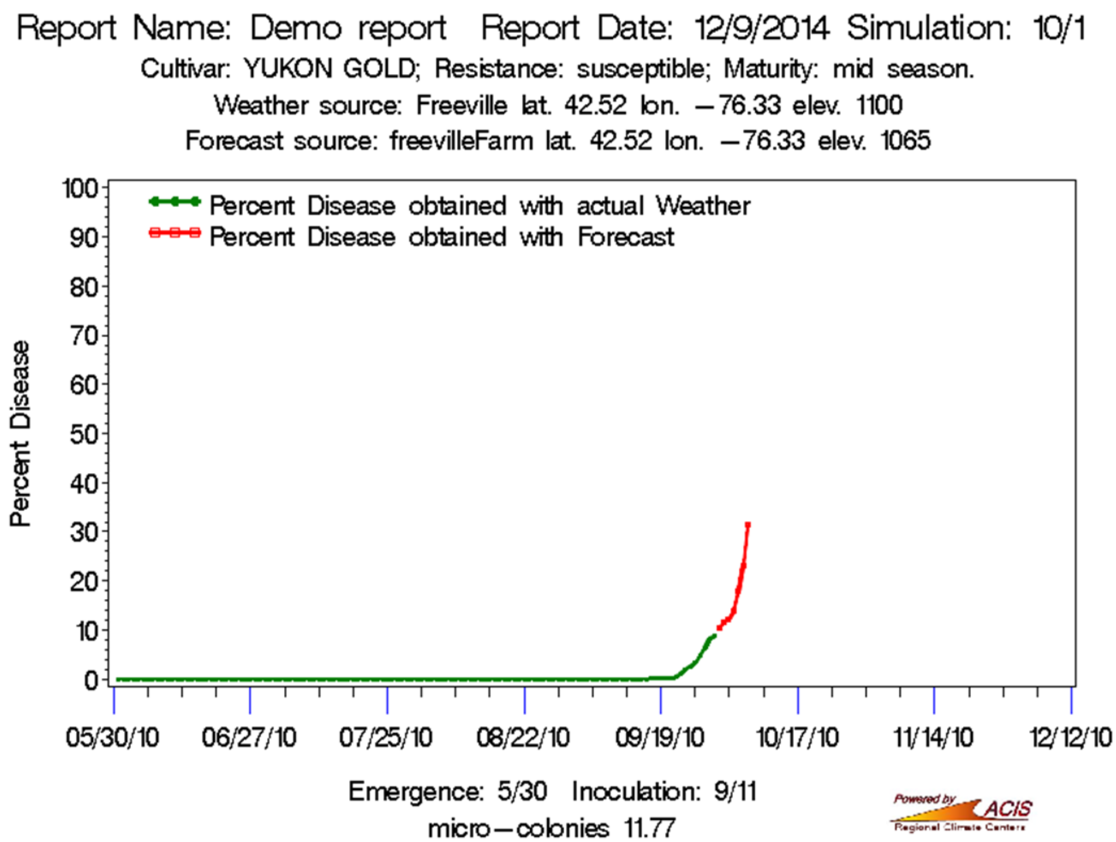

Figure 1.6. Graph showing simulated disease progress on potato. A validated mechanistic model can be used to simulate daily disease severity based on observed (green series) and forecast (red series) weather data, presence and severity of observed disease, cultivar resistance, and fungicide use.

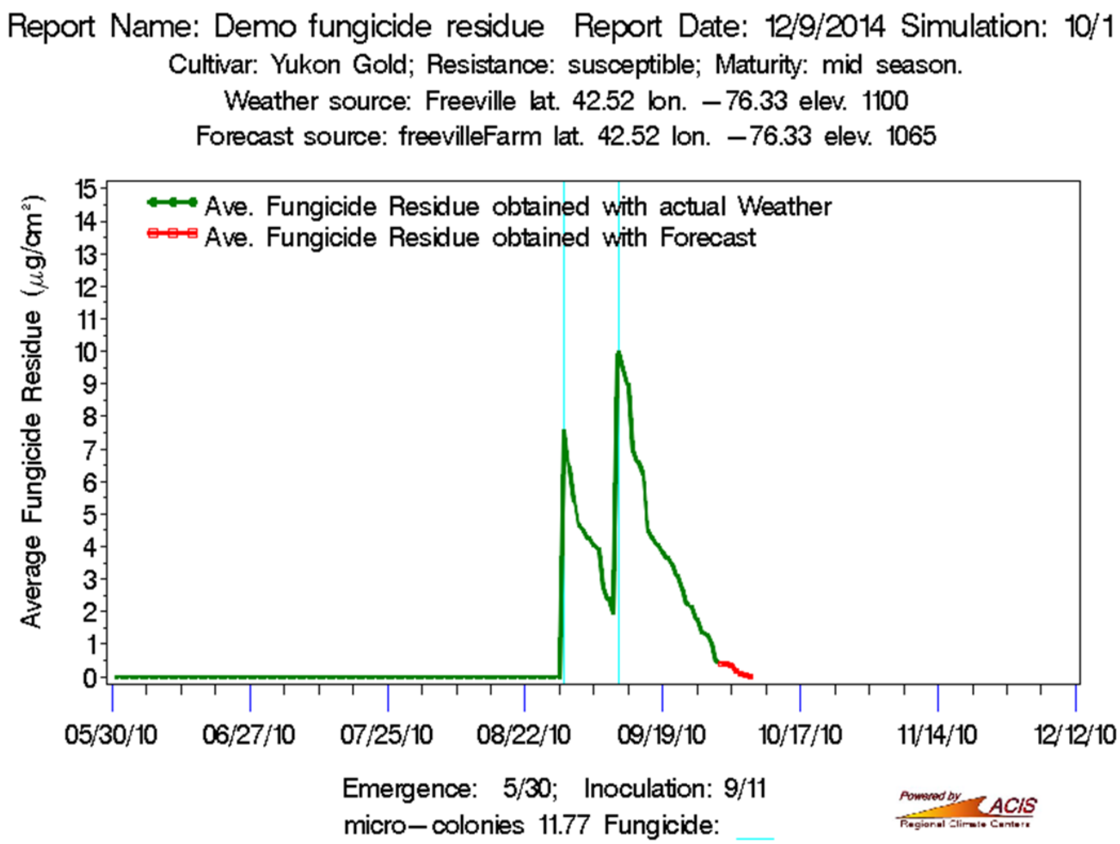

Figure 1.7. Simulated fungicide residue on potato. The predicted average fungicide residue on the plant canopy can be simulated using a validated mechanistic model for the protectant fungicide chlorothalonil on potato. Fungicide residue predictions are based on observed (green series) and forecast (red series) weather data, as well as information about fungicide applications made.

Report Name: Demo fungicide residue   Report Date 12/9/2014
Cultivar: Yukon Gold; Resistance: susceptible; Maturity: mid season.
weather: Freeville lat. 42.52 lon. -76.33 elev. 1100
forecast: freevilleFarm lat. 42.52 lon. -76.33 elev. 1065

Date	Day of Season	Num. Sporangia	Cumulative Disease Severity	Germinated Zoospores	Germinated Sporangia	New Infections	Percent Disease	Fungicide Residue
10/07/10	130	0.00	10.46	181390.38	1312.67	584.38	2.35	0.02
10/06/10	129	1671554.06	8.50	86542.56	0.00	721.58	1.56	0.05
10/05/10	128	730447.43	7.15	0.00	0.00	0.00	1.15	0.10
10/04/10	127	0.00	6.13	0.00	0.00	0.00	0.89	0.19
10/03/10	126	0.00	5.29	0.00	0.00	0.00	0.79	0.38
10/02/10	125	0.00	4.51	17919.06	0.00	78.40	0.76	0.40
10/01/10	124	233023.03	3.78	14852.65	0.00	98.75	0.70	0.42
09/30/10	123	892091.72	3.12	2320.48	6253.76	566.71	0.62	0.45
09/29/10	122	1144541.83	2.51	0.00	0.00	0.00	0.60	1.04
09/28/10	121	0.00	1.97	62769.89	704.16	197.00	0.48	1.30
09/27/10	120	602146.91	1.54	16381.90	1014.44	140.49	0.38	1.37
09/26/10	119	282489.27	1.21	0.00	0.00	0.00	0.29	1.73

Figure 1.8. Example listing of model (LB 2004) outputs. A numerical listing of several model outputs is provided in a report. Information about pathogen lifecycle stages, disease severity, and fungicide residue is provided for each day of the season. The report is divided into three sections based on background colour. The white background is observed weather data used for calculations. The beige background is forecast temperature, relative humidity, and precipitation The yellow background is forecast temperature and relative humidity.

2.6. Alert system

Optional automated alerts about upcoming critical thresholds for intervention are available to users via sms (short messaging system) text message or e-mail. An initial alert is sent out when a critical threshold is exceeded within the first 72 hr of forecast. Messages for all locations with upcoming critical thresholds are compiled into text and/or e-mail form and sent once a day to avoid multiple messages. SMS technology has been successfully used in other disease alert systems such as the Strawberry Advisory System (Pavan et al., 2011). The alert systems have been tested since 2012 to evaluate their value to the user and received positive feedback from extension personnel and producers.

2.7. Teaching tool

A training/teaching version of the system was developed that provides access to archived weather data (observed and forecast) from multiple locations and has a function that allows the user to navigate through the season by changing the 'current' date to any date in the season, enabling the user to explore the system outputs under different scenarios, or to use it to teach epidemiological principles. This provides producers, consultants, researchers and educators with a tool to evaluate disease management scenarios, explore comparative epidemiology, develop forecasting models, or function as a teaching aid.

2.8. Information technology

The system was developed using a multilayered programming approach. The layers consist of a web-based interface for the user, with programs and databases in the background. The overall system runs on a server hosted by the NRCC at Cornell University that has Quixote and CORBA installed. Password protected account information is stored in databases consisting of SQL Light tables. Disease forecasting tools, written in Python, and a mechanistic model of the disease, written in SAS, utilize input information stored in the database to generate outputs. Outputs are presented via a web interface, in HTML format, and are also generated in portable document format (pdf) using a program written in SAS. The web interface was generated using JQuery and Javascript. A tab-based interface was developed to separate sections of the DSS, such as inputs, simulator, alert setup, and irrigation input. This tab-based approach is intended to simplify the addition of other forecasts and models and to enable personalization of access to specific tabs for certain groups (basic user/consultant/extension educator/researcher). Access to certain tabs can be user-specific, as set by the administrator. An example of a reason to provide user-specific access might be based on geographic location (state), allowing the system to provide the most appropriate disease forecasting tools and models for that region.

Python programs are used to obtain observed and forecast weather data. These programs are automatically processed by Unix scripts, called “cronjobs” and executed several times a day. Complete weather records of observed and forecast weather are generated for each location (field) defined on DSS. These records are utilized by the DSS disease forecasting tools and the disease simulation model.

Disease forecasts are executed on a daily basis, or upon user request, to provide users with rapid access to results and to identify any upcoming critical thresholds that might trigger recommendations for management intervention. If a critical threshold is forecast (up to 72 hr into the future) then an automated alert will be sent to the user (if alerts have been requested).

2.9. Evaluation of the system recommendations

A preliminary version of the system has been available to extension educators and producers in NY since the 2010 cropping season. The system was evaluated by researchers in field experiments conducted each year from 2010 -2014 (Small et al., 2013) and in computer simulation experiments, as well as by extension personnel, crop consultants and commercial farms (potato and tomato). Field experiments have been conducted for both potato and tomato. In multiple field experiments, the average number of fungicide applications per season recommended for a susceptible cultivar was equivalent to a calendar-based (7-day) schedule (range: -36% to +12%, relative to a 7-day schedule). For moderately susceptible cultivars, an average reduction of 25% (range: -28% to -10%) fungicide application was achieved, relative to a 7-day schedule. For moderately resistant cultivars, an average reduction of 40% (range: -

50% to -37%) fungicide application was achieved, relative to a 7-day schedule (Small et al., 2013). These experiments demonstrated that fungicide usage can be reduced by up to 50% through the use of the DSS when conditions are not favourable for late blight, while maintaining successful disease suppression. Under favourable conditions for the disease, the DSS recommended up to 12% increase in fungicide applications, relative to a 7-day schedule (Small et al., 2013).

In order to test the system under diverse environmental conditions, field experiments were simulated using historic observed weather (2000 – 2013) from 59 potato/tomato growing locations. The computer model of the late blight disease was used to run 6912 simulations for the equivalent of 768 field experiments. Management recommendations given by the DSS were compared with calendar-based approaches to fungicide scheduling in these simulated field experiments. The average number of fungicide applications per season recommended by the DSS for susceptible cultivars was 24 % higher than a calendar-based (seven-day) schedule (range: -91 % to +91 %). For moderately susceptible cultivars, an average reduction of 15 % (range: -91 % to +36 %) fungicide application was achieved, relative to a 7-day schedule. For moderately resistant cultivars, an average reduction of 35 % (range: -91 % to 0 %) fungicide application was achieved, relative to a 7-day schedule. Simulation experiments demonstrated the potential of the system to reduce fungicide usage by up to 91% (when conditions are not favourable for late blight), while maintaining successful disease suppression. Under favourable conditions for the disease, the DSS has the potential to recommend up to 91% increase in fungicide applications on susceptible cultivars, relative to a 7-day schedule.

3. DISCUSSION

The late blight DSS provides an interactive system that helps users maximize the efficiency of their crop protection strategy by enabling well-informed decisions. In situations with unfavourable weather, the DSS recommended fewer fungicide applications with no loss of disease suppression and, in situations of very favourable weather, the DSS recommended more fungicide applications but with improved disease suppression. The benefit of using this system will be consistent disease control while enabling reduction of fungicide use under conditions that are not favourable for late blight. In addition, the system provides scientifically-based recommendations for reduced fungicide use on partially resistant cultivars. The outputs of the system are meant to aid decisions by the grower or the consultant. The system is not intended to replace grower or consultant decisions.

A large national initiative to combat late blight, USAblight (http://usablight.org/), was established in the USA to reduce losses to potato and tomato late blight by monitoring pathogen populations, developing additional resistant cultivars, and enhancing education and extension. The BlightPro DSS is a key component of this late blight community initiative. Development of an internet-based late blight DSS within the late blight research community in the USA is intended to facilitate implementation of this late blight DSS across the USA and enable future development of the late blight DSS applications by allowing exchange of components and information between partner research groups and institutions. Overall, the current system can be viewed as consisting of core components of an internet-based late blight DSS. As improved, or regionally-specific, forecasting tools become available these can be integrated into this system. A similar collaborative approach, Web-blight, was established in Nordic countries, Baltic countries, and Poland in 1998 (Cooke et al., 2011).

In response to requests for user accounts, the system has been expanded to enable its use in 19 US states. In New York alone, thirteen farms and two consultants working with one vegetable extension specialist, Carol MacNeil, as well as several farmers working independently, successfully used the BlightPro DSS in 2012 and 2013 to more effectively and efficiently control late blight, and time fungicide sprays, on over 4,000 acres of potatoes and tomatoes.

A key aspect of the development of the DSS is that it was constructed in consultation with end users, primarily extension personnel and producers. This ensured that the information provided by the system was relevant to users and that the language and formats used for the interface and outputs were intuitive and appropriate. Development of the system has been ongoing with feedback from users and new developments driving modifications to the system.

The accuracy of the outputs of this system is limited by the availability of accurate and representative weather data. Ideally, weather stations used for a particular location will be located in the crop canopy or close to the production unit of interest, with minimal infield variability. The microclimate within a canopy is likely to play an important part in the variability in performance as would other factors such as damp hollows in fields, tree shading, and differential rates of foliage growth. These all influence the in-field variability of the microclimate. In addition, the forecast information should match the meteorological conditions actually observed in order for accurate advanced decision making.

4. FUTURE RESEARCH AND DEVELOPMENT

Future research plans include the addition of existing forecasting tools for other important diseases of potatoes and tomatoes, such as early blight. This will provide a tool that will assist decision-makers with the task of understanding the complex interactions between prevailing weather, cultivar resistance to the diseases, fungicide effects and will help integrate this information into management recommendations that are appropriate for both early blight and late blight.

The current system provides recommendations for variable interval fungicide application. In certain production systems there is limited flexibility around application intervals, such as prescheduled aerial applications. To accommodate for systems with limited flexibility around application intervals, research is underway to provide recommendations for variable fungicide dose and/or type of fungicide.

The current version of the simulator is limited to a sub-model of the protectant fungicide chlorothalonil. Plans are underway to include a validated sub-model for the systemic fungicide mefenoxam (metalaxyl-m).

Information regarding the presence/absence and quantity of late blight inoculum is not an integral part of the current system. A planned expansion of the current system involves a new tool to identify the risk of infection for a known source of late blight. The USAblight pathogen monitoring database will be connected with the DSS to provide information regarding pathogen occurrence to drive a new tool that will provide infection risk alerts to users.

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CHAPTER 2.

EVALUATION OF THE BLIGHTPRO DECISION SUPPORT SYSTEM FOR MANAGEMENT OF POTATO LATE BLIGHT USING COMPUTER SIMULATION AND FIELD VALIDATION*

ABSTRACT

The objective of this study was to evaluate the utility of the BlightPro decision support system (DSS) for late blight management using computer simulation and field tests. Three fungicide schedules were evaluated i) calendar-based (weekly) applications, ii) applications according to the DSS, or iii) no fungicide. Simulation experiments utilized 14 years of weather data from 59 locations in potato producing states. In situations with unfavourable weather for late blight, the DSS recommended fewer fungicide applications with no loss of disease suppression and in situations of very favourable weather for late blight, the DSS recommended more fungicide applications but with improved disease suppression. Field evaluation was conducted in 2010, 2011, 2012, and 2013. All experiments involved at least two cultivars with different levels of resistance. DSS-guided and weekly scheduled fungicide treatments were successful at protecting against late blight in all field experiments. As expected, DSS-guided schedules were influenced by prevailing weather (observed and forecast) and host resistance and resulted in schedules that maintained or improved disease suppression and average fungicide use efficiency, relative to calendar-based applications. The DSS provides an interactive system that helps users maximize the efficiency of their crop protection strategy by enabling well-informed decisions.

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1. INTRODUCTION

The late blight disease of potatoes and tomatoes, caused by *Phytophthora infestans* (Mont.) de Bary, is a major concern for producers of these crops. Unexpected epidemics can result in significant crop losses and lead to economic failure to growers for whom potatoes or tomatoes are the major income source (Fry et al., 2013; Fry and Goodwin, 1997). Additionally, the costs of management can be very large. A conservative global estimate of these costs/losses is at least $6 billion annually (Haverkort et al., 2008). Although the disease is more problematic in rain fed agriculture such as in the northeastern USA, sporadically it can also be serious in drier production areas such as the Columbia Basin of central Washington and northcentral Oregon regions of the Pacific Northwest (largest production area in the USA) (Fry and Goodwin, 1997). For example the cost of managing a late blight epidemic in the Pacific Northwest in 1995 was estimated at $30 million (Johnson et al., 1997). On tomatoes, the disease can be and has been equally devastating. The most recent example occurred in 2009 when infected tomato transplants were distributed via national large retail stores who obtained transplants from a national supplier (Fry et al., 2013). The pandemic that followed in the mid-Atlantic and Northeast regions eliminated tomato plants in many organic farms and in many, many home gardens (Fry et al., 2013).

Management of late blight can be quite complex involving several factors. These factors include the influence of prevailing weather on the pathogen lifecycle, late blight resistance of the cultivar being grown, fungicide residue on the crop, and pathogen characteristics, such as resistance to fungicides. Management tactics involve the use of fungicides and cultural procedures. Cultural procedures are practices designed to reduce the introduction, survival, or infection rate of *P. infestans*. The complexity of the interactions among these factors makes rational disease management decision-making difficult. This complexity creates an opportunity for a decision support system (DSS) to be used to provide science-based information to assist with this decision making.

A DSS can be defined as an interactive computer-based system that helps decision makers utilize data and models to solve unstructured problems under complex and uncertain conditions (Gorry and Morton, 1971). Decision support systems for late blight integrate and organize available information on the pathogen. They also include the influence of observed and forecast weather on the disease, the effects of cultivar resistance on disease and the effects of fungicide characteristics and efficacy on the disease. All of these factors are required to make decisions concerning the management of late blight (Cooke et al., 2011).

Successful late blight management requires operational decision-making throughout the crop growing season. It is possible to make decisions in the absence of information, although they may be poor decisions. In order to make the best possible decision it is necessary to be able to both understand and have access to all relevant information (Knight, 1997). Due to the significant diversity among growers, communicating relevant information to them and educating them is a challenge. Growers may be conventional or organic; they may have large or small farms; they may be independent or part of community supported agriculture; or they may be individual home gardeners. While most growers have access to a plethora of education and extension resources (internet, email, smart phones, etc.), the information is often scattered or incomplete. A DSS can focus relevant information and tools, curated by experts, to provide a diverse audience with key information to support rational decision-making. For example, the association of pathogen phenotypes with particular genotypes and the availability of rapid genotypic analyses enables in-season disease management to be adjusted based on the results of rapid genotypic analyses. This information could be immediately conveyed to growers via a DSS. If such a system had been in place during the 2009 late blight pandemic, important information regarding the sensitivity of the lineages to a highly effective fungicide, mefenoxam, could have been quickly and directly disseminated to growers (Danies et al., 2013).

Precision agriculture, or 'smart farming', aims to optimize the yield per unit of farm land by using the most modern means in a continuously sustainable way, to achieve best in terms of quality, quantity and financial return (http://www.beechamresearch.com/download.aspx?id=40). Technologies such as decision support systems are a key component of the smart farming approach. Disease forecasting tools developed in the 20th century were the precursors to plant disease management DSSs (Shtienberg, 2013). Forecasters such as BLITECAST (Krause et al., 1975) and Simcast (Fry et al., 1983), FAST (Madden et al., 1978), and the apple scab predictive system (Jones et al., 1980), are examples of tools that were designed to assist farmers with decisions relating to management of potato late blight, early blight, and apple scab, respectively (Shtienberg, 2013).

Late blight is a disease that has received much attention in terms of disease forecasting (Hardwick, 2006). In the USA, several forecasting systems have been developed (Hyre, 1954; Krause et al., 1975; Wallin, 1962). A common characteristic of the potato late blight forecasts is that they identify a time in the season before which fungicide sprays are needed (Hyre, 1954; Wallin, 1962). For example with Blitecast, this interval is identified via 18 Severity Values (Krause et al., 1975). Following the development of Blitecast, a more comprehensive late blight forecast – Simcast (Fry et al., 1983), which integrates the effects of host resistance and fungicide as well as weather, was developed. Since the 1990s, DSSs have been developed in many countries to assist with the management of plant diseases such as potato late blight, apple scab, cereal leaf diseases, and grape downy mildew (Shtienberg, 2013). In

Europe, several DSSs for late blight have been developed using various disease forecasting systems and models. A list of these DSSs can be found on the Euroblight website (a potato late blight network for Europe) (http://www.euroblight.net/EuroBlight.asp). In North America, the BlightPro DSS was developed to integrate the effects of weather, host resistance and fungicide on disease progress in order to improve in-season late blight management. The BlightPro DSS has been available through several sources including via www.USAblight.org. The BlightPro DSS (http://blight.eas.cornell.edu/blight/) is an internet-based platform and is made up of several components. Growers identify the location of their production unit (latitude and longitude of field) and the system automatically obtains observed weather data from the nearest available weather station, and location-specific (2.5 square km grid) forecast weather data from the National Weather Service – National Digital Forecast Database. These weather data along with crop and management information are used to drive disease forecasting tools, Blitecast and Simcast (Fry et al., 1983; Krause et al., 1975), as well as a mechanistic late blight disease simulator LATEBLIGHT 2004 (LB2004) (Andrade-Piedra et al., 2005b). To inform their decision-making process, decision-makers can: utilize the cultivar late blight resistance database on the system, use the forecast information from Blitecast and/or Simcast, run in-season simulations with LATEBLIGHT 2004, and obtain up-to-date information about the sensitivity of pathogen lineages to mefenoxam. In addition, the system includes an integrated alert system, which enables the user to receive notifications about upcoming critical thresholds for intervention (fungicide application) via e-mail and/or text message. For a comprehensive description of the development and implementation of BlightPro see Small, Joseph, and Fry (2015). The objective of this study was to evaluate the utility of the BlightPro DSS using computer simulation experiments and field experiments. Utility was defined as the ability of the decision support system to enable the suppression of late blight while increasing the efficiency of fungicide use.

2. MATERIALS AND METHODS

Evaluation by computer simulation. Simulation analyses were carried out following the approach used by Shteinberg et al. (Shtienberg et al., 1989; Shtienberg and Fry, 1990). The LATEBLIGHT 2004 disease model integrated with fungicide sub-models (Andrade-Piedra et al., 2005b) was used to evaluate fungicide scheduling methods. The LATEBLIGHT 2004 model describes pathogen development as a function of weather, fungicide, and host resistance; fungicide dynamics are described as a function of weather and time since the last application. This disease model was developed and validated in small field plots (Andrade-Piedra et al., 2005a).

Simulation experiments used 14 yr of meteorological data (2000-2013), recorded from locations in Maine, Massachusetts, New York, North Carolina, North Dakota, and Wisconsin. Weather data were obtained from the Northeast Regional Climate Center. Only locations and years for which there was less than 2% missing weather data between the date of emergence and vine kill were used. This criterion resulted in 768 environments with suitable weather data. The following common parameters were used for each season: the length of the season (from the date of planting to vine kill) was 110 days; median emergence occurred on the 18th day after planting; and the initial level of late blight was 0.001% disease severity (one lesion per 10 plants). The protectant fungicide chlorothalonil was applied at a rate of 1.34 kg a.i./ha. Simulations were conducted using susceptible, moderately susceptible, and moderately resistant cultivars for each disease scenario.

Two scenarios for initial appearance of disease were investigated for each location in each season. First, the initial appearance of late blight was set to occur six days after the accumulation of 18 Blitecast severity values, because this was found to be the observed mean time of late blight appearance in field experiments where inoculated potato tubers were planted (Doster et al., 1989; Shtienberg and Fry, 1990). Second, the initial appearance of late blight was a random date between 18 Blitecast severity values and the end of the season – this scenario was included to represent the variability in initial late blight occurrence due to differences in inoculum source. We have limited our study to environments with temperate climates in which the cold winter eliminates susceptible host plants between growing seasons, requiring the disease to be initiated each growing season. The use of 18 Blitecast severity values to predict initiation of disease is appropriate in such climates. In environments where there is susceptible host tissue available year-round it is possible that the disease might be initiated at any time after emergence. This simulation study does not address the scenario where there is susceptible host tissue available year-round.

The efficacy of three spray-scheduling methods in suppressing late blight were evaluated:

i) Calendar-based strategy. Weekly sprays were initiated 35 days after planting and continued until the end of the season.

ii) DSS strategy. The DSS was used to obtain location-specific spray recommendations based on forecast programs, Blitecast and Simcast, which are integrated within the DSS. Sprays were initiated when 18 Blitecast severity values had accumulated since median emergence. Subsequent applications were timed according to the effect of weather on the pathogen (accumulation of blight units) and on fungicide weathering (accumulation of fungicide units), as obtained from Simcast reports within the DSS (Fry et al., 1983). Although DSS users could potentially also utilize information from the LATEBLIGHT 2004 model when deciding whether or not to spray, the model was not used to schedule sprays for the simulation analyses. This was avoided because the same model was utilized to conduct the simulation analyses.

iii) Unsprayed. No fungicides were applied throughout the season.

Schedules for fungicide applications were determined separately for each spray-scheduling method and were then simulated with the pathogen model. In total, 2,478 different simulations (59 locations × 14 yr × three susceptibility groups) were conducted for each of the following spray-scheduling methods: i) conventional, ii) DSS strategy, and iii) unsprayed.

After elimination of environments with missing weather, spray-scheduling by the DSS was compared with calendar-based approaches to fungicide scheduling in 6912 simulations (equivalent to 768 field experiments). Comparisons were made for i) the number of fungicide applications scheduled, ii) area under disease progress curve, iii) disease suppression relative to the unsprayed control, and iv) efficiency of fungicide use. Fungicide use efficiency (*E*) was defined as the percent disease control per application and was calculated following the approach used by Shteinberg and Fry (Shtienberg and Fry, 1990). Equation 1 is corrected from that described in 1990 as per personal correspondence with the author:

$$Fungicide\ use\ efficiency\ (E) = \{[(Au - Am)/Au]/\ N\}\ 100 \qquad (1)$$

in which *Am* = simulated area under disease progress curve (AUDPC) for a spray scheduling method, *Au* = simulated AUDPC for untreated crop, and *N* = number of applications scheduled by a method.

Field validation. The BlightPro decision support system was evaluated in field trials over four years, on susceptible 'Yukon gold' (2011, 2012, 2013), moderately susceptible 'Katahdin' (2010), and moderately resistant 'Kennebec' (2010-2013) potato cultivars at the Homer C. Thompson Vegetable Research Farm, Freeville, NY. All experiments involved at least two cultivars with different levels of resistance. Potatoes were planted on 6 July 2010, 30 June 2011, 9 July 2012, and 8 July 2013. Field experiments were planted at a later date than would be typical for the area, to ensure healthy foliage late in the season. This was done to allow inoculation at a later date in the season to avoid generating a source of inoculum for growers in the area. The experimental design was a randomized complete block design with four blocks. Plots were six rows (0.86 m spacing between rows) and 3.68 m long with 0.23 m (2010, 2011) or 0.30 m (2012, 2013) seed piece spacing. The resultant plot size was 3.68 m by 4.3 m. The soil type was a Howard gravelly loam. Fertilization was 1290 kg ha^{-1} of 13-13-13 (N-P-K) banded in-the-row at planting. Fungicide treatment programs were compared to an untreated control for each potato cultivar (Table 2.1). Two fungicides were utilized in the experiments, chlorothalonil 720 g L^{-1} (Bravo WS) at a rate of 1.75 l ha^{-1} (2010, `11, `12, `13), and mefenoxam 39.5g L^{-1} in combination with chlorothalonil 400 g L^{-1} (Ridomil Gold Bravo) at a rate of 2.92 l ha^{-1} (2012). Fungicide treatments were applied based on either a calendar or DSS-based schedule. Fungicide treatments were applied with an Air Tec side boom sprayer. The Air Tec sprayer is an air assist sprayer which improves coverage by decreasing droplet size, while also increasing penetration into dense plant canopies. The sprayer output was 187 l ha^{-1} at 40 psi, using a diaphragm pump. Sprayer speed was 4.83 km h^{-1}. The boom was 6.70 m long with nozzles spaced 0.41 m apart. Hollow cone nozzles (TX-VS12), with low pressure check valves to eliminate drip, were used.

Table 2.1. Field evaluation of fungicide scheduling strategies on potato cultivars with different levels of resistance to late blight.

Year and Cultivar	Late blight resistance [w]	Schedule [x]	Fungicide	No. sprays	AUDPC [y]	Fungicide use efficiency (E) [z]
2010						
Katahdin	MS	DSS	C	6	0.02 a	16.7
		Calendar-based	C	8	0.02 a	12.5
		Unsprayed	none	0	194.5 c	
Kennebec	MR	DSS	C	5	0.02 a	20.0
		Calendar-based	C	8	0.26 a	12.3
		Unsprayed	none	0	36.1 b	
2011						
Yukon Gold	S	DSS	C	9	0.68 a	11.1
		Calendar-based	C	8	0.10 a	12.5
		Unsprayed	none	0	821.4 c	
Kennebec	MR	DSS	C	5	0.63 a	20.0
		Calendar-based	C	8	0.14 a	12.5
		Unsprayed	none	0	504.9 b	

[w] Late blight resistance of the cultivar: susceptible (S); moderately susceptible (MS); moderately resistant (MR)
[x] Schedule: method used to schedule fungicide applications. DSS – Simcast schedule for C (chlorothalonil) or M + C (mefenoxam + chlorothalonil); Calendar - 7 day interval for C, or 14 day interval for M + C. Based on label recommendations, chlorothalonil was applied 7 days after each M + C application for the calendar schedule, or when Simcast fungicide unit threshold was reached for DSS schedule.
[y] Area under disease progress curve (AUDPC) - All values are the mean of four replicates. Means followed by the same letter within each experiment (year) are not significantly different, Tukey Kramer honestly significant difference ($P < 0.05$).
[z] Fungicide use efficiency (E) refers to the average percent disease control achieved per fungicide application.

Table 2.1. (Continued)

Year and Cultivar	Late blight resistance [w]	Schedule [x]	Fungicide	No. sprays	AUDPC [y]	Fungicide use efficiency (E) [z]
2012						
Yukon Gold	S	DSS	C	6	0.00 a	16.7
		Calendar-based	C	6	0.00 a	16.7
		DSS	M + C	2	0.00 a	20.0
			C	3		
		Calendar	M + C	3	0.00 a	16.7
			C	3		
		Unsprayed	none	0	174.3 b	
Kennebec	MR	DSS	C	3	0.01 a	33.3
		Calendar-based	C	6	0.00 a	16.7
		DSS	M + C	2	0.00 a	25.0
			C	2		
		Calendar-based	M + C	3	0.01 a	16.7
			C	3		
		Unsprayed	none	0	170.3 b	
2013						
Yukon Gold	S	DSS	C	5	0.00 a	20.0
		Calendar-based	C	5	0.00 a	20.0
		Unsprayed	none	0	573.8 b	

In all field experiments, weather conditions were conducive for late blight, with 18 Blitecast severity values being accumulated on the following dates 4 August 2010, 7 August 2011, 30 July 2012, and 14 June 2013. Sprays for the DSS schedule were initiated using chlorothalonil when the Blitecast severity values had accumulated to 18 and plants had reached at least 15-20 cm in height. Due to the late planting date, 18 severity values were reached before plants were 15-20 cm in height for all experimental years, so sprays were delayed until plants were approximately 15-20 cm. Sprays for the conventional treatment were initiated using chlorothalonil when plants were approximately 15-20 cm in height. In the 2012 field experiment, treatments including systemic fungicide (mefenoxam + chlorothalonil) were incorporated. The change from contact (chlorothalonil) to systemic fungicide sprays in the 2012 experiment was initiated for both the DSS treatment and the conventional treatment when late blight lesions were first observed in the nearby untreated experimental plots (inoculum source).

The DSS evaluation field experiments relied on natural infections from infected plants in experimental plots (artificially inoculated) at 0.5-0.8 km distance in each year. Genotypes of *P. infestans* identified in DSS evaluation experiments were determined by microsatellite analysis using an established protocol (Lees et al., 2006). Disease ratings were determined by visually assessing each plot for the percentage of diseased foliage caused by late blight using a method described by Fry (1977). Disease severity was rated every 3 – 10 days with more frequent assessments occurring during rapid epidemic development.

Statistical analyses. *Simulation analyses.* Spray-scheduling methods were compared based on the number of fungicide applications scheduled, AUDPC, disease suppression, and efficiency of fungicide use. Fungicide treatment, scheduled either by the DSS or calendar-based, significantly suppressed disease relative to the unsprayed treatment (see results section). For this reason the focus of the statistical analysis was to investigate differences between DSS and calendar-based fungicide schedules for their disease suppression.

To compare the efficacy of DSS-recommended treatment schedules with calendar-based treatment schedules, the disease suppression due to the treatment was calculated. Disease suppression (T) was defined as follows: the reduction in AUDPC due to the treatment ($AUDPC_{Unsprayed}$ - $AUDPC_{Treatment}$), converted to a proportion of the unsprayed control at that location and for the appropriate year. This proportion (T) is the reduction in disease due to the treatment (disease suppression) Eq (2).

$$Disease\ suppression\ (T) = \frac{AUDPC_{Unsprayed} - AUDPC_{Treatment}}{AUDPC_{Unsprayed}} \qquad \text{(Eq. 2)}$$

A general linear model was used (JMP® Pro, Version 11.2.0. SAS Institute Inc., Cary, NC), where the response was logit-transformed disease suppression (T). The transformation was conducted to satisfy statistical assumptions for the statistical model. Environments (year x at location y) where simulated disease severity (AUDPC) for the unsprayed treatment < 100 were excluded, which retained 673 environments. We set this minimum threshold for disease in the untreated plots to ensure that the two fungicide treatment schedules were compared for their disease suppression in environments in which there was at least some disease. Fungicide treatment schedules, cultivar late blight resistance, location year, and the interaction between fungicide treatment schedule and cultivar resistance were considered fixed effects. Least squares means (LS means) were compared using a Tukey Honestly Significant Difference post-hoc test ($P = 0.05$). Results were presented as percentage disease suppression by back transforming LS means to proportions and then multiplying by 100 to obtain a percentage. We used the result for a weekly schedule on susceptible cultivars as a baseline for adequate disease suppression. This is because we know that a weekly schedule on more resistant cultivars obviously increases disease suppression, but is also likely to use excessive fungicide.

To investigate the fungicide use efficiency of different treatments, a nonparametric test was conducted on the means for each combination of treatment and cultivar resistance (e.g. DSS schedule on susceptible cultivar). A nonparametric test was conducted because assumptions of normality were not satisfied. The response was fungicide use efficiency (E). A nonparametric comparison for each pair of treatment means was conducted using the Wilcoxon each pair test (Hsu, 1996).

Field experiments. Spray-scheduling methods (treatments) were compared based on the number of fungicide applications scheduled, mean area under disease progress curve (AUDPC), and fungicide use efficiency (E) for each treatment. A general linear mixed model was used (JMP® Pro, Version 11.2.0. SAS Institute Inc., Cary, NC), where the response was arcsine square root transformed AUDPC. Fungicide treatment schedule, cultivar late blight resistance, and the interaction between fungicide treatment schedule and cultivar resistance were considered fixed effects. The effect of block in each experiment was treated as a random effect. Each experiment (year) was analyzed separately. The restricted maximum likelihood method (REML) was used for the mixed model. Least squares means were compared using a Tukey Honestly Significant Difference post-hoc test ($P = 0.05$).

3. RESULTS

Comparison of spray-scheduling methods via computer simulation. *Number of fungicide applications scheduled*. In some cases, the DSS recommended more fungicide applications, and in other cases the DSS recommended fewer applications than the calendar-based schedule (Figure 2.1/Table 2.2). For susceptible cultivars the DSS recommended 24 % more fungicide applications (median of 14 sprays) than the weekly schedule (11 sprays). The range was -91 % to +91 %. For moderately susceptible cultivars the DSS recommended 15 % fewer applications (median of 10 sprays) relative to a seven-day schedule (11 sprays). The range was -91 % to +36 %. For moderately resistant cultivars the DSS recommended a reduction in fungicide application of 36 % (median of 7 sprays), relative to a seven-day schedule (11 sprays). The range was -91 % to 0 %. In addition to the effect of cultivar resistance on numbers of recommended sprays, the favorability of prevailing weather for late blight influenced the number of recommended applications (Figure 2.2). Higher numbers of applications were recommended when conditions were favorable for disease development. In the DSS-treated experiments, the median spray intervals were 6 days between sprays for susceptible cultivars, 9 days for moderately susceptible cultivars, and 12 days for moderately resistant cultivars (Figure 2.1).

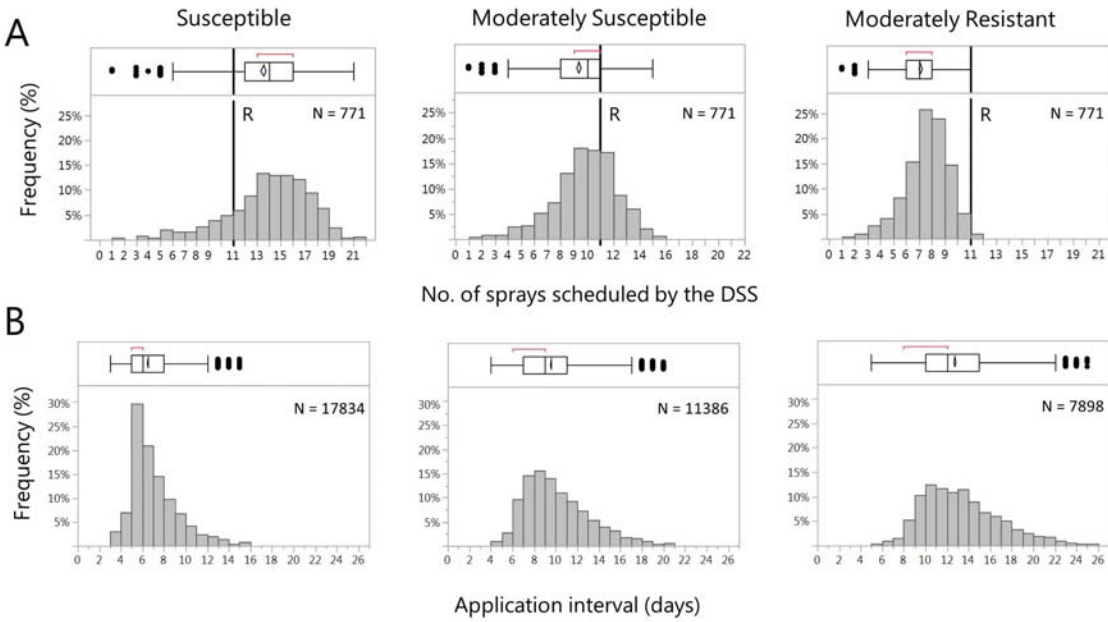

Figure 2.1. Frequency distributions. A. the number of fungicide applications scheduled using the DSS per growing season for 59 locations over 14 years (2000 – 2013). Distributions are shown separately for each cultivar resistance category. The x-axis represents the number of fungicide applications made using BlightPro from crop emergence to harvest (108 days) in a particular year at a specific location. The reference line (R) represents the number of sprays scheduled according to a calendar-based schedule (11 sprays). **B**. fungicide application intervals for DSS schedules. Distributions are shown separately for each cultivar resistance category. Each distribution represents intervals between applications for fungicide schedules generated for 59 locations over 14 years (2000 – 2013). Fungicide schedules were limited to the period from crop emergence to harvest (108 days) in a particular year at a specific location. Median fungicide application interval (days) for i) susceptible cultivars = 6 days, ii) moderately susceptible cultivars = 9 days, and moderately resistant cultivars = 12 days. N represents the number of fungicide application intervals analyzed. The outlier box plots are graphical summaries of the distribution of data. The vertical line within the box represents the median sample value. The ends of the box represent the 25th and 75th quantiles. The whiskers that extend from the ends of the box are computed as 3rd quartile + 1.5*(interquartile range), and 1st quartile - 1.5*(interquartile range). Points beyond the whiskers are possible outliers. The horizontal bracket (﹁) defines the shortest half of the data (the densest region).

Table 2.2. Simulation results under scenario where late blight was simulated to occur six days after 18 Blitecast severity values had accumulated.

Late blight resistance	Scheduling method		Average AUDPC and *no. of fungicide applications per season* (years 2000 - 2013) [x]														
			2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
S [w]	Conventional [y]	Mean AUDPC	2177	2169	1628	2939	2222	1944	1904	1507	1709	2153	2349	2353	1008	2767	2063
		Median AUDPC	2290	2075	1412	3108	1792	2028	1127	946	166	1958	1711	2284	102	2812	1729
		IQ range	3343	2221	2511	4637	2243	2838	2367	2600	3689	3669	4174	2517	1575	2342	3326
		Std. deviation	1786	1590	1526	2204	1810	1521	2242	1757	2105	1987	2140	1540	1464	1608	1872
		Sprays	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*
S	DSS [z]	Mean AUDPC	89	418	481	535	129	456	267	278	299	220	380	417	187	317	320
		Median AUDPC	10	212	124	80	8	163	86	38	5	29	40	68	7	121	49
		IQ range	49	529	677	815	87	471	487	216	103	300	708	622	71	539	379
		Std. deviation	209	543	715	814	277	688	350	522	768	366	579	649	423	473	568
		Sprays	*15*	*14*	*14*	*15*	*16*	*13*	*13*	*12*	*14*	*15*	*14*	*14*	*11*	*15*	*14*
S	Unsprayed	Mean AUDPC	5502	5084	4693	5236	5199	4544	4032	4445	3443	5264	4338	4608	3551	5241	4662
		Median AUDPC	5750	5782	5216	5912	5745	4973	4516	4575	4176	5441	5275	4861	4038	5250	5253
		IQ range	1112	1931	1605	1167	1339	1978	3493	1645	5641	1050	3030	1511	3844	1040	1968
		Std. deviation	1426	1360	1805	1940	1557	1757	2248	1498	2649	1091	2190	1467	2105	1005	1867
		Sprays	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
MS	Conventional	Mean AUDPC	1348	1296	888	2532	1387	1110	1353	913	1537	1388	1555	1430	623	1658	1360
		Median AUDPC	1179	940	462	2537	687	901	402	180	545	962	539	1060	22	1655	760
		IQ range	2449	1592	1364	3987	1476	1646	2571	1725	3098	2549	2783	1856	995	2114	2242
		Std. deviation	1282	1324	1079	2115	1632	1026	1870	1259	1838	1560	1684	1301	1027	1271	1532
		Sprays	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*

[w] Late blight resistance of cultivar: susceptible (S); moderately susceptible (MS); moderately resistant (MR)
[x] AUDPC and no. of fungicide applications represent the average for 59 weather stations from six states (Maine, Massachusetts, New York, North Carolina, North Dakota, and Wisconsin). Only weather stations with < 2 % missing data were included.
[y] Calendar-based sprays were initated 35 days after emergence and continued on a weekly schedule until the end of the season
[z] DSS treatment -Fungicide sprays were initiated when 18 Blitecast severity values had accumulated since median emergence and subsequent applications were timed according to Simcast

Table 2.2. (Continued)

Late blight resistance	Scheduling method		Average AUDPC and *no. of fungicide applications per season* (years 2000 - 2013) [x]														
			2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
MS	DSS	Mean AUDPC	577	1252	1140	1225	609	1222	962	798	784	803	1064	963	548	1002	927
		Median AUDPC	292	1207	971	720	303	1025	736	371	111	562	765	819	199	735	569
		IQ range	950	1936	1479	2057	981	1793	1567	1451	1552	1280	1949	1094	747	1066	1439
		Std. deviation	727	1001	1037	1168	671	1057	1036	898	1196	881	1052	942	838	831	984
		Sprays	*10*	*9*	*10*	*11*	*11*	*9*	*9*	*8*	*10*	*10*	*10*	*10*	*8*	*10*	*10*
MS	Unsprayed	Mean AUDPC	5142	4622	4287	5332	4916	4244	3755	4026	3640	4936	3892	4078	3283	4802	4359
		Median AUDPC	5557	5278	4682	5613	5416	4634	4145	4018	4439	5122	4810	4239	3825	4895	4898
		IQ range	1064	2103	2091	1049	1640	2148	3369	2046	4881	1132	3595	1873	3959	950	2092
		Std. deviation	1430	1403	1696	1460	1445	1575	2157	1465	2507	1186	2168	1511	2043	1009	1779
		Sprays	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
MR	Conventional	Mean AUDPC	35	26	18	399	105	21	132	20	157	95	80	83	9	74	89
		Median AUDPC	8	4	2	61	6	4	1	1	12	4	4	6	1	10	4
		IQ range	37	19	7	548	27	19	27	11	77	51	45	33	7	38	29
		Std. deviation	57	53	50	630	304	44	330	53	401	226	191	251	22	185	275
		Sprays	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*
MR	DSS	Mean AUDPC	94	138	176	233	117	177	125	98	204	186	151	171	33	105	144
		Median AUDPC	18	42	26	52	14	38	15	17	13	42	21	48	5	31	23
		IQ range	104	166	107	443	62	197	133	50	215	284	118	213	20	69	146
		Std. deviation	161	205	357	321	267	317	232	218	392	286	302	274	78	193	273
		Sprays	*8*	*7*	*7*	*8*	*8*	*7*	*7*	*6*	*7*	*7*	*8*	*7*	*6*	*8*	*7*
MR	Unsprayed	Mean AUDPC	3375	2249	2139	3541	2976	2136	1717	1918	2490	3099	2027	2156	1388	2720	2428
		Median AUDPC	3680	2537	2141	3921	3766	2130	1325	1922	3105	3454	2156	2346	836	2935	2683
		IQ range	1960	2303	2287	1676	3220	2523	2312	2767	3993	2485	3422	2962	2828	1849	2934
		Std. deviation	1437	1305	1447	1426	1699	1492	1609	1362	1897	1545	1663	1509	1448	1224	1620
		Sprays	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*

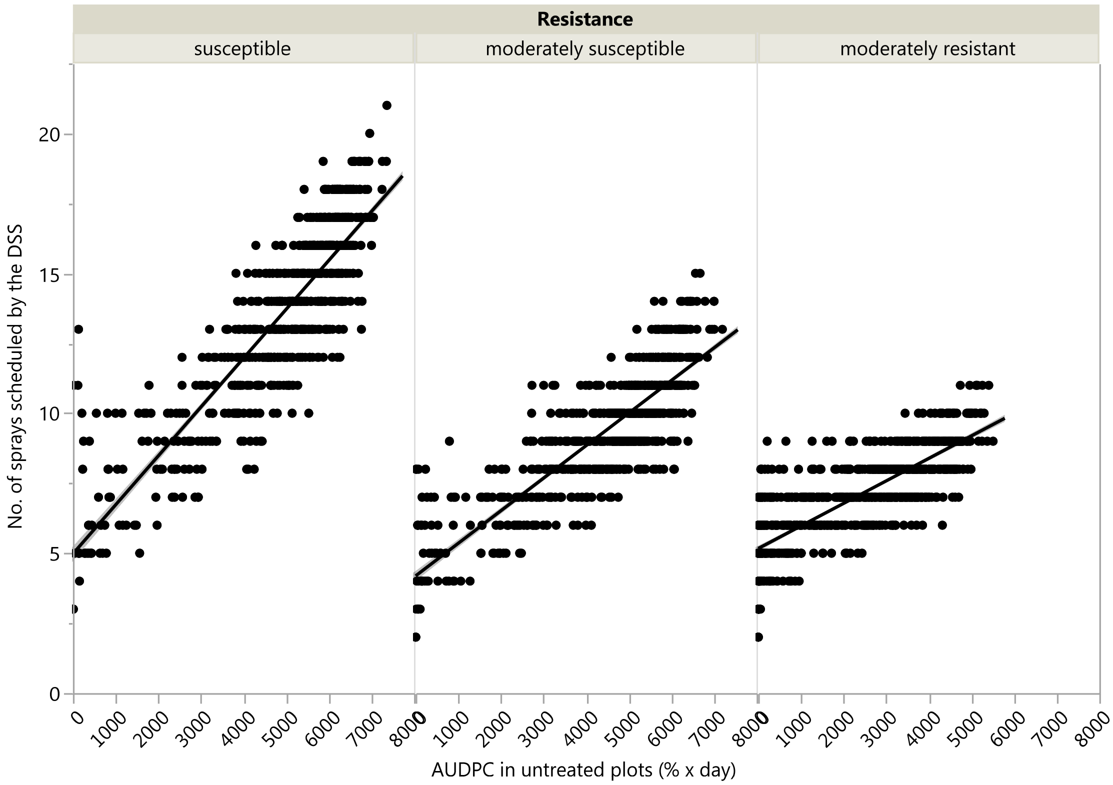

Figure 2.2. Illustration of the responsiveness/sensitivity of the DSS to the suitability of weather conditions for *Phytophthora infestans*. The suitability of weather conditions to *P. infestans* was estimated by the intensity of simulated epidemics in untreated plots and the sensitivity of the DSS by the number of scheduled sprays. In simulations the epidemic was initiated six days after 18 severity values had accumulated. Each point represents the final AUDPC in untreated plots for one year at a particular location. The line in each panel represents the best fit line to the data and is simply presented to highlight the relationship between no. of sprays scheduled by the DSS and the AUDPC in untreated plots.

Experiments when disease was initiated after the accumulation of 18 severity values (Scenario 1). *AUPDC.* The wide range of weather conditions in the 768 individual simulation experiments had a large effect on the simulated severity of late blight. Due to the non-normal distribution of the raw AUDPC data, medians and interquartile ranges are presented as descriptive statistics (Figure 2.3).

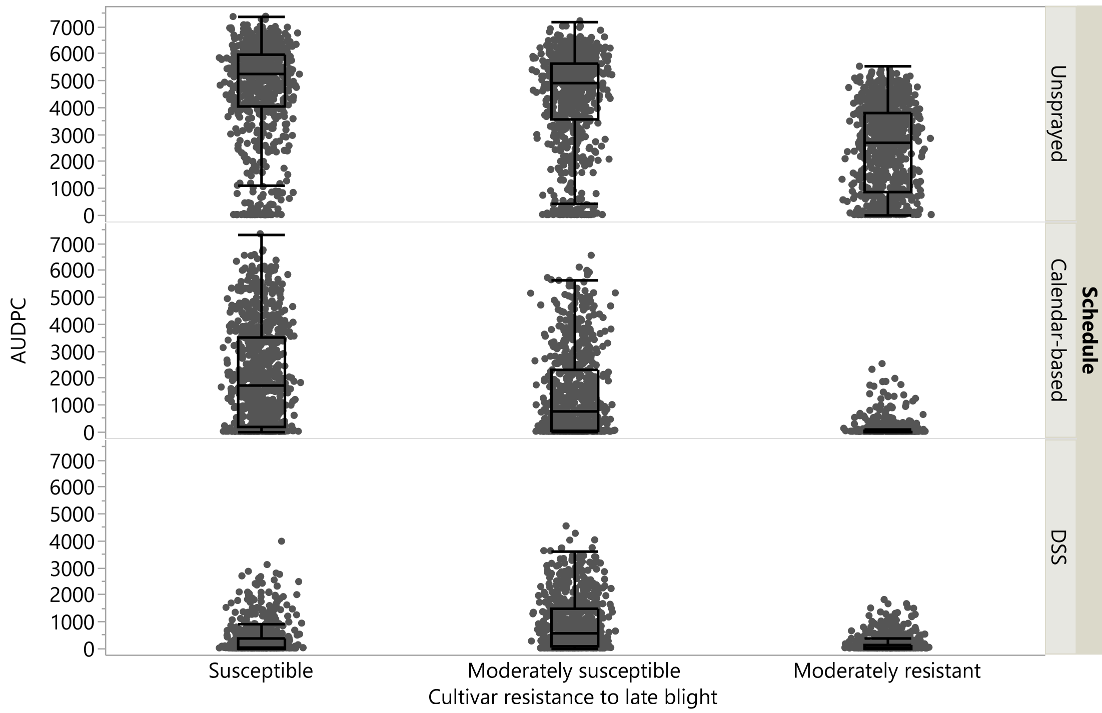

Figure 2.3. Summary of simulated disease severity (area under disease progress curve - AUDPC) for 59 locations over 14 years (2000 – 2013) (Scenario 1). Three fungicide scheduling methods were evaluated for their ability to suppress late blight (calendar-based schedule, Decision Support System-informed schedule, and unsprayed). Each scheduling method was evaluated for three categories of cultivar resistance to late blight. Late blight was simulated to occur six days after 18 Blitecast severity values had accumulated. Each point represents the final AUDPC for a schedule in one year at a particular location. The box plots overlaying the points are a graphical summary of the distribution of data. The vertical line within the box represents the median sample value. The ends of the box represent the 25th and 75th quantiles. The whiskers that extend from the ends of the box are computed as 3rd quartile + 1.5*(interquartile range), and 1st quartile - 1.5*(interquartile range).

The yearly median AUDPC for the unsprayed control ranged from 4038 in the year 2012, to 5912 in the year 2003 (Table 2.2). The median AUDPC for the unsprayed strategy was 5253 (interquartile range (IQR) = 1968) for susceptible, 4898 (IQR = 2092) for moderately susceptible, and 2683 (IQR = 2934) for moderately resistant cultivars. As expected, fungicide applications reduced these numbers dramatically. The median AUDPCs for the DSS strategy were 49 (IQR = 379) for the susceptible, 569 (IQR = 1439) for the moderately susceptible, and 22.5 (IQR = 146) for the moderately resistant cultivars, respectively (Table 2.2). This can be compared with the average AUDPC values for the calendar-based strategy of 1729 (IQR = 3326) for the susceptible, 760 (IQR = 2242) for the moderately susceptible, and 4.2 (IQR = 29) moderately resistant cultivars, respectively (Table 2.2).

Fungicide treatment, either DSS or calendar-based, dramatically reduced disease relative to the unsprayed treatment. This was supported by the fact that the 95 % confidence interval around the mean of the unsprayed treatment, for each resistance category, did not overlap with the 95 % confidence interval around the mean of either of the fungicide schedules. For this reason the statistical analysis was focused on the difference between fungicide schedules.

Disease suppression. The disease suppression for the DSS treatment, for each category of resistance, was compared to a baseline of disease suppression achieved with weekly sprays on a susceptible cultivar. The DSS-recommended spray schedules suppressed late blight to lower levels on susceptible cultivars (99.7 % disease suppression) than did the weekly schedule on susceptible cultivars (98.6 % disease suppression) ($P < 0.0001$). The DSS-recommended schedule for moderately susceptible cultivars (97.7 % disease suppression) differed significantly from the calendar-based schedule for susceptible cultivars (98.6 % disease suppression) ($P < 0.0001$). No significant difference in disease suppression was observed between the DSS strategy for the moderately resistant cultivars (99.1 % disease suppression) and the calendar-based schedule for susceptible cultivars (98.6% disease suppression) ($P = 0.12$).

Fungicide use efficiency. For all cultivar resistance categories, sprays scheduled according to the DSS strategy had a significantly higher average fungicide use efficiency (E) ($P < 0.0001$) than the calendar-based strategy (Figure 2.4). For susceptible cultivars, average disease control per application was 5.7 % for the calendar-based schedule and 7.7 % for the DSS-recommended schedule (35 % difference in fungicide use efficiency). For moderately susceptible cultivars, average disease control per application was 6.8 % for the calendar-based schedule and 9.7 % for the DSS-recommended schedule (43 % difference in fungicide use efficiency). For moderately resistant cultivars, average disease control per application was 8.8 % for the calendar-based schedule and 14.2 % for the DSS-recommended schedule (61 % difference in fungicide use efficiency).

Experiments with disease initiation at a random date after accumulation of 18 severity values (Scenario 2). Obviously, the fungicide application scheduling was independent of the initiation of the disease in the simulation experiments, so the fungicide schedules for the random initiation scenario were the same as the schedules for the ‘six days after 18 severity values’ scenario.

AUDPC. When the appearance of disease in simulations was set to occur at a random date after the accumulation of 18 severity values (SV), instead of being fixed at six days after accumulation of 18 SV, the AUDPC was reduced for all treatments (>60% reduction in average AUDPC) (Figure 2.5). The median AUDPC values for the unsprayed strategy were 1065 (IQR = 3428) for susceptible, 689 (IQR = 2998) for moderately susceptible, and 17 (IQR = 1169) for moderately resistant cultivars (Table 2.3). The median AUDPC values for the DSS strategy were 0.5 (IQR = 17) for susceptible, 1.8 (IQR = 115) for moderately susceptible, and 0.3 (IQR = 6) for moderately resistant cultivars (Table 2.3). The median AUDPC values for the calendar-based strategy were 0.9 (IQR = 120) for susceptible, 0.4 (IQR = 20) for moderately susceptible, and 0.1 (IQR = 0.4) for moderately resistant cultivars (Table 2.3).

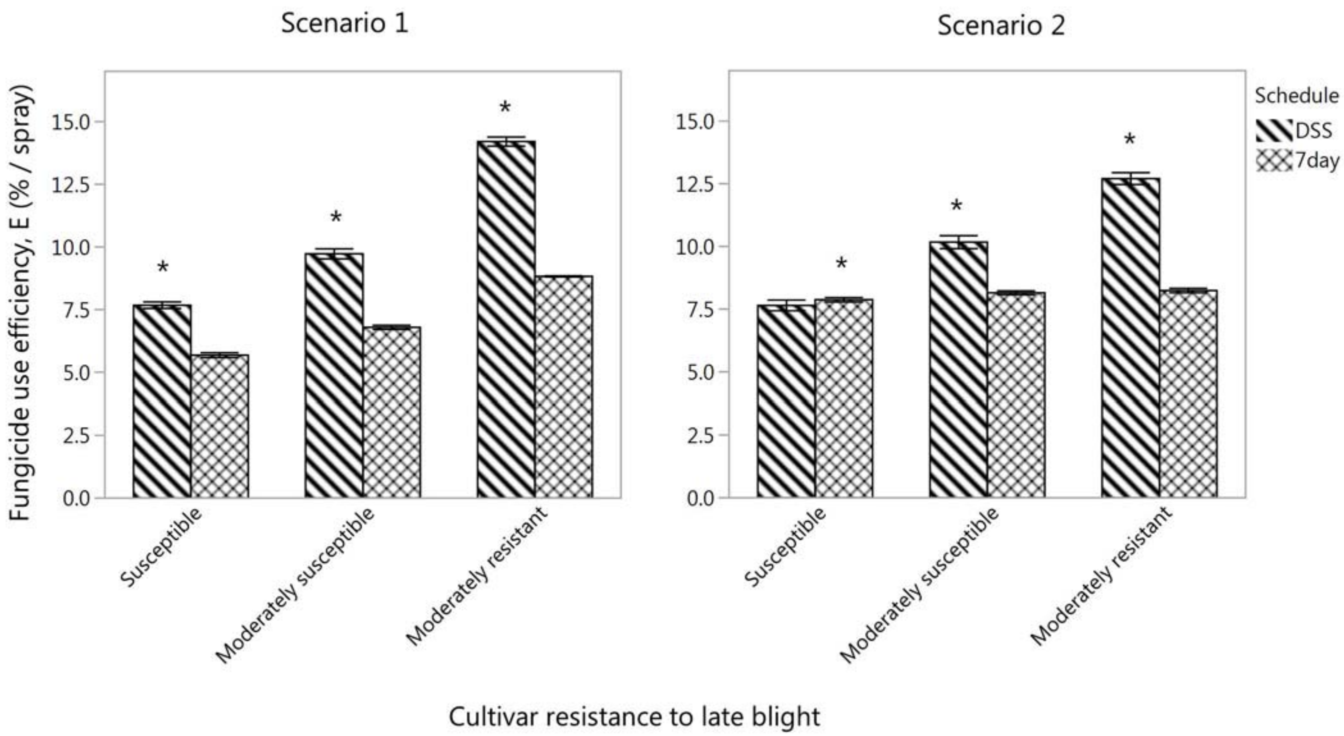

Figure 2.4. Fungicide use efficiency (reduction in area under disease progress curve per spray) of Decision Support System strategy and calendar-based (7 day) strategy, under two disease initiation scenarios. Scenario 1. late blight was simulated to occur six days after 18 Blitecast severity values had accumulated. Scenario 2. late blight was simulated to occur at a random date between six days after 18 Blitecast severity values had accumulated and the end of the season. Fungicide use efficiency was calculated for both strategies on three categories of cultivar resistance to late blight. Each error bar is constructed using 1 standard error from the mean. Asterisk indicates statistically significant difference in efficiency between DSS and calendar-based strategy ($P \leq 0.05$), within resistance category. Statistics are based on nonparametric comparison for each pair of treatment means conducted using a Wilcoxon each pair test (Hsu, 1996).

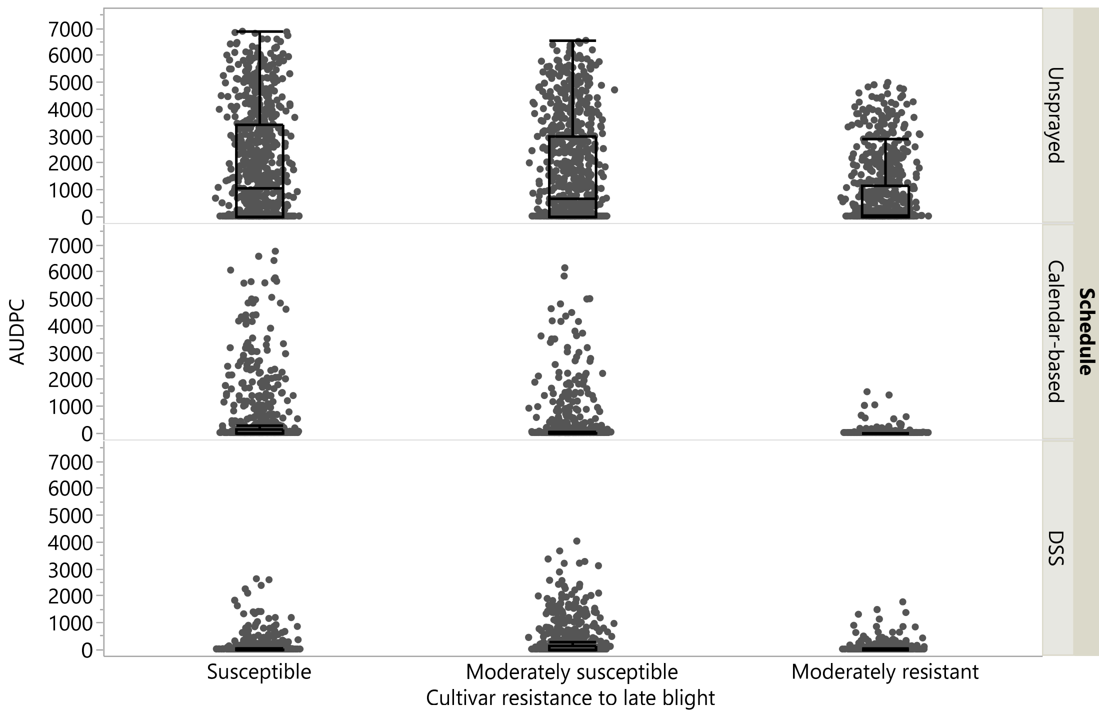

Figure 2.5. Summary of simulated disease severity (area under disease progress curve - AUDPC) for 59 locations over 14 years (2000 – 2013) (Scenario 2). Three fungicide scheduling methods were evaluated for their ability to suppress late blight (calendar-based schedule, Decision Support System-informed schedule, and unsprayed). Each scheduling method was evaluated for three categories of cultivar resistance to late blight. Late blight was simulated to occur at a random date between six days after 18 Blitecast severity values had accumulated and the end of the season. Each point represents the final AUDPC for a schedule in one year at a particular location. The box plots overlaying the points are a graphical summary of the distribution of data. The vertical line within the box represents the median sample value. The ends of the box represent the 25th and 75th quantiles. The whiskers that extend from the ends of the box are computed as 3rd quartile + 1.5*(interquartile range), and 1st quartile - 1.5*(interquartile range).

Table 2.3. Simulation results under scenario where late blight was simulated to occur at a random date between six days after 18 Blitecast severity values had accumulated and the end of the season.

Late blight resistance	Scheduling method		Average AUDPC and *no. of fungicide applications per season* (years 2000 - 2013) [x]														
			2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	All
S [w]	Conventional [y]	Mean AUDPC	461	353	339	594	441	595	311	315	579	283	759	497	157	703	458
		Median AUDPC	0.37	1.68	3.80	2.13	0.69	4.32	0.64	1.01	0.71	0.68	0.23	1.57	0.07	4.06	0.89
		IQ range	114	77	143	312	110	82	19	232	69	32	625	323	2	610	120
		Std. deviation	1278	921	821	1380	1090	1356	865	694	1297	854	1567	995	655	1441	1128
		Sprays	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*
S	DSS [z]	Mean AUDPC	48	104	116	133	51	153	27	91	73	26	127	65	17	74	80
		Median AUDPC	0.36	1.84	6.43	0.63	0.22	1.72	0.33	0.55	0.32	0.30	0.19	0.34	0.08	2.98	0.49
		IQ range	4	87	73	17	7	54	9	28	12	2	13	39	1	24	17
		Std. deviation	178	218	347	472	160	435	71	268	354	108	372	171	57	183	276
		Sprays	*15*	*13*	*13*	*15*	*15*	*13*	*13*	*12*	*13*	*14*	*14*	*14*	*11*	*15*	*14*
S	Unsprayed	Mean AUDPC	2133	1730	2169	1982	2003	1934	1360	1911	1826	1864	1881	1691	951	2505	1859
		Median AUDPC	1599	1298	2031	883	1009	1448	664	1068	773	1702	64	979	78	2705	1065
		IQ range	3823	3119	3346	4257	3454	3690	2289	4134	3257	3330	4395	3146	1607	4381	3428
		Std. deviation	2177	1747	1890	2216	2227	2089	1727	2049	2078	1917	2339	1892	1500	2142	2028
		Sprays	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*

[w] Late blight resistance of cultivar: susceptible (S); moderately susceptible (MS); moderately resistant (MR)
[x] AUDPC and no. of fungicide applications represent the average for 59 weather stations from six states (Maine, Massachusetts, New York, North Carolina, North Dakota, and Wisconsin). Only weather stations with < 2 % missing data were included.
[y] Calendar-based sprays were initated 35 days after emergence and continued on a weekly schedule until the end of the season
[z] DSS treatment -Fungicide sprays were initiated when 18 Blitecast severity values had accumulated since median emergence and subsequent applications were timed according to Simcast

Table 2.3. (Continued)

Late blight resistance	**Scheduling method**		**Average AUDPC and *no. of fungicide applications per season* (years 2000 - 2013)** [x]														
			2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
MS	Conventional	Mean AUDPC	267	174	163	363	359	336	172	131	356	143	450	271	71	433	265
		Median AUDPC	0.17	0.69	0.97	0.81	0.42	1.01	0.37	0.32	0.29	0.23	0.14	0.63	0.06	1.46	0.40
		IQ range	29	13	31	63	28	21	5	46	13	9	151	73	1	138	20
		Std. deviation	912	569	495	975	1139	908	594	354	885	473	1127	641	377	1052	801
		Sprays	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*
MS	DSS	Mean AUDPC	163	304	363	286	220	410	193	298	175	101	344	241	75	251	246
		Median AUDPC	1.45	5.41	23.67	1.67	1.19	11.30	0.69	4.97	1.14	1.77	0.13	1.50	0.15	15.91	1.77
		IQ range	77	490	553	120	133	208	43	125	27	30	370	227	4	225	115
		Std. deviation	452	523	692	681	523	858	436	659	552	281	702	449	234	545	570
		Sprays	*10*	*9*	*9*	*10*	*10*	*9*	*9*	*8*	*9*	*10*	*10*	*10*	*7*	*10*	*9*
MS	Unsprayed	Mean AUDPC	1908	1447	1836	1782	1917	1674	1161	1644	1581	1638	1659	1430	791	2226	1627
		Median AUDPC	1122	993	1403	436	805	657	424	552	466	1376	23	738	26	2094	689
		IQ range	3537	2725	3163	3987	3767	3049	1900	3714	3009	2816	3445	2708	993	4080	2998
		Std. deviation	2094	1584	1797	2092	2178	1958	1590	1869	1981	1804	2148	1706	1373	2011	1901
		Sprays	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
MR	Conventional	Mean AUDPC	16	2	4	36	37	17	4	1	12	4	30	5	3	31	14
		Median AUDPC	0.06	0.09	0.09	0.08	0.08	0.11	0.06	0.07	0.07	0.06	0.04	0.08	0.03	0.15	0.07
		IQ range	0.46	0.27	0.42	0.66	0.44	0.46	0.19	0.52	0.22	0.24	0.44	0.73	0.11	0.95	0.40
		Std. deviation	90	13	28	210	164	86	21	2	50	16	184	24	17	145	102
		Sprays	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*	*11*
MR	DSS	Mean AUDPC	19	16	61	47	55	85	12	24	37	13	57	36	4	32	36
		Median AUDPC	0.44	0.84	1.19	0.27	0.32	0.52	0.15	0.12	0.23	0.33	0.10	0.30	0.10	1.01	0.34
		IQ range	6.49	7.40	15.65	6.87	5.37	13.17	3.77	3.76	1.90	4.81	14.78	11.02	1.44	8.45	6.25
		Std. deviation	59	37	225	130	190	304	29	64	130	48	210	92	9	130	146
		Sprays	*8*	*7*	*7*	*8*	*8*	*7*	*7*	*6*	*7*	*8*	*7*	*7*	*6*	*8*	*7*

Table 2.3. (Continued)

Late blight resistance	Scheduling method		Average AUDPC and *no. of fungicide applications per season* (years 2000 - 2013) [x]														
			2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**All**
MR	Unsprayed	Mean AUDPC	1083	479	788	899	1097	743	465	628	827	806	796	563	308	1064	756
		Median AUDPC	28.8	38.0	66.5	7.9	40.2	13.9	12.6	11.9	9.7	66.8	1.0	17.4	0.8	227.5	16.7
		IQ range	2135	824	1593	1606	2325	1424	194	1008	1128	1347	1185	629	59	2049	1169
		Std. deviation	1489	817	1113	1305	1566	1210	977	981	1401	1283	1318	1005	824	1424	1231
		Sprays	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*

Disease suppression. Again, fungicide applications effectively reduced disease severity for all resistance categories. The DSS-recommended spray schedules suppressed late blight to lower levels on susceptible cultivars (99.8 % disease suppression) than did the weekly schedule (98.8 % disease suppression) ($P < 0.0001$). The DSS-recommended schedule for moderately susceptible cultivars (98.4 % disease suppression) however, resulted in higher disease levels than did the calendar-based schedule for susceptible cultivars (98.8 % disease suppression) ($P < 0.0001$). For moderately resistant cultivars, the DSS-recommended spray schedules suppressed late blight to lower levels (99.6 % disease suppression) than did the weekly schedule on susceptible cultivars (98.8 % disease suppression) ($P < 0.0001$).

Fungicide use efficiency. Under the random inoculation date scenario, fungicide use efficiency for the DSS-recommended schedule was higher for the moderately susceptible and moderately resistant cultivars, but not susceptible cultivars, relative to the calendar-based schedule (Figure 2.4). For susceptible cultivars, average disease control per application was 7.8 % for the calendar-based schedule and 7.3 % for the DSS-recommended schedule (7 % difference in fungicide use efficiency). For moderately susceptible cultivars, average disease control per application was 8.3 % for the calendar-based schedule and 9.7 % for the DSS-recommended schedule (17 % difference in fungicide use efficiency). For moderately resistant cultivars, average disease control per application was 9.0 % for the calendar-based schedule and 12.8 % for the DSS-recommended schedule (42 % difference in fungicide use efficiency).

Field validation. Late blight was first observed in the unsprayed plots on 15 September 2010, 12 September 2011, 2 September 2012, and 1 September 2013. In all of these experiments, favorable weather conditions for late blight resulted in rapid development of the disease in the untreated plots. In all experiments, both fungicide treatments (DSS strategy or calendar-based schedule) significantly ($P < 0.05$) suppressed late blight (Table 2.1). No significant difference in disease suppression was observed between the DSS strategy and the calendar-based schedule for all three categories of cultivar resistance ($P < 0.05$).

In experiments where chlorothalonil alone was used on a susceptible cultivar (Yukon Gold), the DSS strategy scheduled the same number (2012 and 2013 experiments) or slightly more applications (one additional spray in 2011 experiment) than did the calendar-based approach (Table 2.1). For the moderately susceptible cultivar (Katahdin), the DSS strategy scheduled fewer applications (six sprays) when compared to the calendar-based approach (eight sprays) (Table 2.1). For the moderately resistant cultivar (Kennebec), the DSS strategy scheduled fewer applications (five, five, and three sprays in 2010, 2011, 2012, respectively) when compared to the calendar-based approach (eight, eight, and six sprays in 2010, 2011, and 2012, respectively) (Table 2.1).

In the 2012 experiment a fungicide mixture (mefenoxam + cholorothalonil) alternated with chlorothalonil was used. Severity of late blight was significantly reduced in plots treated with fungicide ($P < 0.05$) relative to the unsprayed plots (Table 2.1). No significant difference in disease suppression was observed between the DSS strategies and the calendar-based strategies on either category of cultivar resistance ($P < 0.05$) (Table 2.1). However, in this experiment disease progress on cultivar Yukon Gold was limited by plant senescence which accounted for the lack of significant difference in disease severity between untreated plots of Yukon Gold (S) and untreated Kennebec (MR). For Yukon Gold, the DSS scheduled three chlorothalonil and two mefenoxam + chlorothalonil applications (Table 2.1). For Kennebec, the DSS strategy scheduled two sprays of chlorothalonil and two sprays of mefenoxam + chlorothalonil applications (two sprays). For the calendar-based schedule, both Yukon Gold and Kennebec received three sprays of chlorothalonil and three sprays of mefenoxam + chlorothalonil.

4. DISCUSSION

The purpose of this study was to evaluate the utility of the BlightPro decision support system for in-season late blight management. To evaluate the recommendations of the DSS under an extended set of environmental conditions, simulation analysis was conducted using weather data from locations in six potato producing states over 14 years producing 768 environments. As expected, host resistance and weather influenced the number of fungicide applications recommended by the DSS.

In situations with favourable weather for late blight and when a susceptible cultivar is selected, the DSS recommended more fungicide applications than a weekly schedule, but with improved disease suppression. On average, the DSS recommended fewer fungicide applications on moderately susceptible cultivars than did the calendar schedule. For moderately susceptible cultivars, the average resultant disease suppression for the DSS schedule was 97.7 %, compared with the disease suppression achieved by weekly applications on susceptible cultivars (baseline) which was slightly higher (98.6%). Although this difference is not large (1.4% disease compared to 2.3% disease) it is important because we have set a goal of achieving disease suppression at least as effective as a calendar-based approach on susceptible cultivars. The effect of moderate resistance translated to significant reduction in average number of fungicide applications recommended by the DSS (35% reduction), with disease suppression equivalent to the baseline weekly schedule on susceptible cultivars. The results of this evaluation are consistent with previous studies that investigated the ability of the forecasting systems, Blitecast and Simcast, to manage late blight of potato (Fry et al., 1983; Shtienberg and Fry, 1990; Spadafora et al., 1984).

The efficacy of individual sprays in late blight disease suppression varies depending on the timing of the application relative to the date of inoculation/infection (Shtienberg et al., 1989). However, fungicide use efficiency (E) may be used for overall comparison of fungicide-scheduling methods since it expresses an average figure for each spray's efficiency at suppressing disease (Shtienberg and Fry, 1990). The return (in percent disease control terms) of sprays scheduled according to the DSS-recommended strategy was higher than that for the calendar-based method, for all categories of late blight resistance. In addition, fungicide use efficiency increased when fungicide use was combined with higher levels of late blight resistance of the cultivar.

Two scenarios for initial appearance of disease in each season were investigated in simulation analyses. First, the initial appearance of late blight was set to occur six days after the accumulation of 18 Blitecast severity values. Second, the initial appearance of late blight was a random date between accumulation of 18 Blitecast severity values and the end of the season (random inoculation date scenario) – this scenario was included to represent the variability in initial late blight occurrence due to differences in inoculum source. We were interested to determine whether the DSS recommendations maintained their additional benefit over the calendar-based strategy under conditions where the disease might not appear from primary inoculum in the immediate area.

Under the scenario where late blight was initiated six days after 18 severity values had accumulated, the DSS demonstrated significant improvement in fungicide use efficiency relative to the calendar-based schedule for all resistance categories. As would be expected, fungicide use efficiency declined under the random inoculation date scenario, since initiation of fungicide schedules occurred independently of the appearance of the disease and, therefore, sprays prior to disease appearance did not always contribute to disease control. The DSS schedule was less efficient than the calendar-based schedule for the susceptible category, but was more efficient for moderately susceptible and moderately resistant categories. This suggests the importance of identifying the appropriate time to begin spraying. If sprays are initiated earlier than necessary, this can reduce fungicide use efficiency. Mechanisms to further refine the identification of high risk inoculation events could improve fungicide use efficiency.

It should be noted that although the fungicide use efficiency for susceptible cultivars was reduced under the variable inoculation date scenario, disease suppression with the DSS schedule was significantly improved relative to the calendar-based approach. Due to the threat of potato tuber blight, potato producers in the Northeast region of the US strive to prevent even low levels of disease in order to reduce the possibility of tuber blight infections. Therefore, even relatively small reductions in foliar disease severity would likely be preferred by growers. In the current study, tuber blight was not evaluated in field experiments or simulation analyses.

In field experiments, both DSS and calendar-based fungicide scheduling methods suppressed late blight effectively with no significant differences in final disease levels. The scheduling methods differed in the number of sprays recommended. The DSS schedule was influenced by prevailing weather and cultivar resistance and resulted in fewer fungicide sprays on cultivars with moderate susceptibility/resistance to late blight, or when weather conditions were less favourable for late blight. In seasons with weather favourable for late blight, the DSS recommended the same number or more sprays on susceptible cultivars, relative to the calendar-based scheduling method.These results were in agreement with results from the simulation analyses.

This decision support system is the first to integrate real-time location-specific observed and forecast weather (National Digital Forecast) to drive these forecasting systems, as well as the LATEBLIGHT simulator (LB2004 version with fungicide sub-models), to enable informed in-season decision making. A previous study by Raposo et al (1993) determined that there was a benefit to incorporating forecast weather information into the disease forecasting systems. However, the improvement in disease management (reduction in AUDPC) realized depended on the accuracy of the weather forecast and ranged from 5% reduction in disease severity for weather forecasts available in 1993, up to 10% reduction if perfect knowledge of future weather 1 and 2 days in advance was available (Raposo et al., 1993). Additionally, weather forecasts provided an increased benefit in environments that were less favourable for late blight development (Raposo et al., 1993). It should be noted that observed and forecast weather information were utilized to provide DSS-recommended schedules for field experiments, but DSS-recommended schedules for simulation analyses were created using only historic records of observed weather. In the simulation experiments, actual weather forecasts were not available. Historic records of observed weather data could not be used to generate forecasts, because the historic observed weather data is equivalent to perfect knowledge of future weather and therefore does not include the inherent variability due to in accurate weather forecasts.

The model we used simulates the effects of environment and cultivar resistance on the development of *P. infestans*, and includes a sub-model for the initial deposition of the fungicide chlorothalonil and its subsequent weathering, redistribution, loss, and efficiency. The models used for simulation of the disease have been developed and improved over the past four decades (Andrade-Piedra et al., 2005b; Bruhn and Fry, 1981; Doster et al., 1990). The models predict disease development in small plots of potatoes and all tests of predictions have been done in small plots. Evaluation of the model predictions have been compared to observed epidemics in small plots over 100 times, under diverse environmental conditions (Andrade-Piedra et al., 2005a; Andrade-Piedra et al., 2005c; Shtienberg and Fry, 1990). The models are useful tools to compare the effects of treatments applied in small plots (Shtienberg and Fry, 1990). Thus, the model should be a good predictor of results from small field plots, and is appropriately used when a large number of field experiments is prohibitively expensive and time consuming (Raposo et al., 1993). It should be noted that limitations of small-plot field experiments will apply equally to the conclusions from simulation analyses.

In simulation analyses, disease suppression for DSS schedules with moderately susceptible cultivars did not meet our criterion of disease suppression at least equivalent to the average for a weekly schedule on a susceptible cultivar. The DSS forecasting systems have since been adjusted to improve disease suppression for the moderately susceptible category by modifying the critical thresholds (Blight Units and Fungicide Units) for this resistance category based on simulation results. Optimization of DSS forecasting systems is underway to maximize fungicide use efficiency for all categories of cultivar resistance while maintaining disease suppression.

The current system provides recommendations for variable interval fungicide application. In certain production systems there can be limited flexibility around application intervals; to accommodate these situations, we are currently investigating mechanisms to include variable dose rather than variable time of fungicide application.

The Simcast forecasting system was initially developed for late blight of potato but extension of the system is underway to enable its use for late blight of tomato.

Preliminary field testing of the system for tomato late blight management has demonstrated that the DSS recommendations can be used successfully.

Future research will include the addition of existing forecasting tools for other important foliar disease of potato and tomato, such as early blight.

Many decision support systems have been developed for plant diseases, and experimental testing has demonstrated their ability to improve disease suppression and lower risk of crop damage, yet some of these systems have been used widely and others have not (Shtienberg, 2013). In the case of intensive crops and disease systems, such as late blight of potato and tomato, farm managers attempt to minimize the risk of performing a false-negative action (not spraying when spraying was necessary) (Shtienberg, 2013). As stated by Shtienberg, "The farmer's main concern is not only to minimize the average cost of the control strategy, but also to avoid extremely large variation" (Shtienberg, 2013). The results from this study have demonstrated that the use of disease forecast driven recommendations can deliver improved disease management and reduce variability in disease suppression, relative to a seven-day calendar-based management strategy. A secondary benefit is that fungicide use can be reduced when conditions are not favorable for late blight, and/or when partially resistant varieties are grown. Furthermore, the risk calculations of managers of intensive crops are likely to change as a result of changing regulatory pressures and public perceptions of pesticide use, which will accelerate the adoption and use of DSSs in these crops (Shtienberg, 2013).

Technologies such as decision support systems are key components of the precision agriculture/smart farming approach. The outputs of this DSS are meant to aid decisions by the grower or the consultant. Rather than replace farmer expertise and gut feeling, decision support systems such as the BlightPro DSS can help users maximize the efficiency of their crop protection strategy by enabling well-informed decisions. The system is not intended to replace grower or consultant decisions.

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CHAPTER 3.

A SEMI-QUANTITATIVE MODEL FOR PREDICTING THE DISPERSAL OF *PHYTOPHTHORA INFESTANS* SPORANGIA FROM A CROP CANOPY*

ABSTRACT

A preliminary dispersal-risk model for potato late blight has been developed using data obtained experimentally and from the published literature. The model relates availability of sporangia of *Phytophthora infestans* produced from lesions in a crop canopy to relative numbers of sporangia in the air above the crop (dispersal-risk).The model uses field-based estimates of disease severity coupled with functions that describe the effect of meteorological elements on production of sporangia, release of sporangia from sporangiophores, and escape of sporangia from a potato canopy. The model requires average hourly temperature, relative humidity, and wind speed. Historic (observed) weather data as well as forecast weather data can be used as inputs. For each potential risk period the estimated disease severity at the source is coupled with predictors for sporangia availability, release of sporangia, and escape of sporangia. These predictors are then integrated in the form of a linear model to predict the relative number of sporangia h^{-1} that will escape the potato canopy and become available for dispersal. With field-based estimates of disease severity at a known source of late blight, variation in numbers of sporangia above the crop canopy was well described ($P < 0.0001$) by the dispersal-risk model ($R^2 = 0.91$; RMSE = 2.86 sporangia h^{-1}). The model is intended for use within the context of the BlightPro decision support system for late blight. Knowledge of upcoming "high risk" periods for dispersal could be used to enhance the efficiency of disease management practices.

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1. INTRODUCTION

Late blight of potato and tomato is devastating because of the very rapid asexual reproduction of *P. infestans* which leads to dramatic population explosions of this pathogen. The devastating nature of late blight epidemics is primarily due to the capability of the pathogen to be aerially dispersed and its very rapid development after establishment in a field. Under favorable conditions, disease cycles can be completed within 4-5 days on a susceptible host and without fungicide applications can result in complete crop loss within just a couple of weeks. Fear of these crop losses causes producers to rely heavily on fungicide applications to manage late blight (Fry 2008).

Several models and algorithms to predict the occurrence of potato late blight have been developed (Hyre 1954; Krause et al. 1975; Wallin 1962). A common characteristic of the early potato late blight forecasts is that they identify a time in the season before which fungicide sprays are needed (Hyre 1954; Wallin 1962). For example with Blitecast (Krause and Massie 1975), the most popular potato late blight forecast in the USA, this interval is identified via 18 Severity Values (Krause and Massie 1975). (Severity values are units that quantify “development time” of the pathogen. Once the initial threshold is reached, subsequent fungicide applications are recommended after the accumulation of 5-7 Severity Values.) This is logical in the potato agroecosystem in northern temperate zones because the pathogen typically overwinters in infected tubers, but these general assumptions (infected tubers as the main source of the pathogen) do not fit potato and tomato production systems in southern temperate or semi-tropical climates where susceptible host tissue is available year-round.

After fungicide applications have been initiated there are other systems that can be used to obtain recommendations for when subsequent fungicide applications should take place. Some years ago a more comprehensive late blight forecast –

Simcast (Fry et al. 1983), which integrates the effects of host resistance and fungicide as well as weather, was developed. More recently, this forecasting system has been made available in "real time" on a web-based Decision Support System (BlightPro DSS) (Small et al. 2015a). Growers identify the location of their production unit of interest (latitude and longitude of field) and the system automatically obtains observed weather data from the nearest available weather station, and location-specific forecast weather data from the National Weather Service – National Digital Forecast Database, for up to 7 days in the future. The DSS uses these weather data along with crop and management information to drive disease forecasting systems and a validated mechanistic model of the disease to generate location-specific management recommendations for fungicide application.

A limitation of most forecasts for late blight, including the ones available within the DSS described above, is that they do not take spatial aspects of the disease cycle into account (beyond the individual plant/field level). Most late blight forecasts assume that viable inoculum is present at a location of interest, or that it arrives daily, which is not necessarily the case. Because late blight occurrences are now being reported on a "real-time" basis in the United States (http://usablight.org/), it is possible to know if late blight is in an area, and if it is, one can use knowledge of the source and weather to identify a risk of dispersal to another nearby site.

Long range movement of *P. infestans* occurs with infected plants (typically infected seed tubers or infected transplants). After the pathogen is established, environmental conditions play a major role in the development of a late blight epidemic. In order for an epidemic to progress the pathogen must be able to reproduce and disperse to other healthy and susceptible host plants. Short-range dispersal of *P. infestans* primarily occurs via airborne sporangia, with the majority of airborne sporangia likely to be deposited within several meters of the inoculum source

(Waggoner 1952). Aerial dispersal over longer distances can take place, possibly over distances of several kilometers (Aylor et al. 2011; Skelsey et al. 2009), but survival of sporangia is a limiting factor for long-distance dispersal because sporangia are very sensitive to solar radiation (Mizubuti et al. 2000). Therefore, short range transport and subsequent infection from local sources of the pathogen is very important.

Infection risk from a local source via aerially dispersed sporangia of *P. infestans* is determined by several factors (Aylor 1986; Skelsey et al. 2009): (1) the number of sporangia available for dispersal; (2) the fraction of the available sporangia that are released from sporangiophores and escape the canopy; (3) the dilution of sporangia by the wind and their removal from the air by deposition processes; (4) the survival of sporangia during flight; and (5) the efficiency of deposition of sporangia on susceptible tissue and subsequent infection. Thus, a general framework for aerial dispersal of *P. infestans* sporangia exists. However, there are constraints on using precise infection risk models based on each of these processes. Some steps are remarkably complicated, and others require information not easily acquired. Thus for current practical application, simplifications are necessary.

The objective of this work was to construct a model of dispersal risk that could be used in near real-time in a Decision Support System such as "BlightPro". This dispersal risk tool had to be based on information readily available such as weather data at specific locations, and reports of late blight occurrence in the vicinity of the crop of interest. The model is based on weather data at the site of interest, relations between disease intensity and sporangium availability, and functions describing the release and escape of sporangia from a crop canopy. The model is fit to precise data from an experiment in which disease intensity, numbers of available sporangia, weather data at the site, and escape of sporangia were measured (Aylor et al. 2001).

2. MATERIALS AND METHODS

To quantify sporangia production as a function of disease intensity and weather, field experiments were conducted in Freeville, NY during the summer of 1999. Detailed methods for determining the relationship between disease severity and the quantity of sporangia available for release, and for measuring the rate of release and escape of sporangia from the canopy have been reported previously (Aylor et al. 2001). The summary data for this experiment have been reported (Aylor et al. 2001) but model construction requires the detailed individual data, which have not been reported previously.

2.1 Environmental data

Environmental data were collected as described by Aylor et al. (2001). Meteorological elements were monitored continuously near the center of the test site (Figure 3.1). Wind speed (u) and direction, air temperature (TH), relative humidity (RH), and solar irradiance were recorded (Figure 3.2 – Temp, RH, Wind speed, Solar irradiance). Wind speed was measured using cup anemometers located at heights of 0.7, 1.55, and 3.25 m above the ground in 1999. Temperature and relative humidity were measured with a probe that was shielded from the sun and located at a height of 2.2 m. Solar insolation was sensed by a pyranometer at a height of 2.4 m. These instruments were sampled at 10-sec intervals and averaged for 1 h.

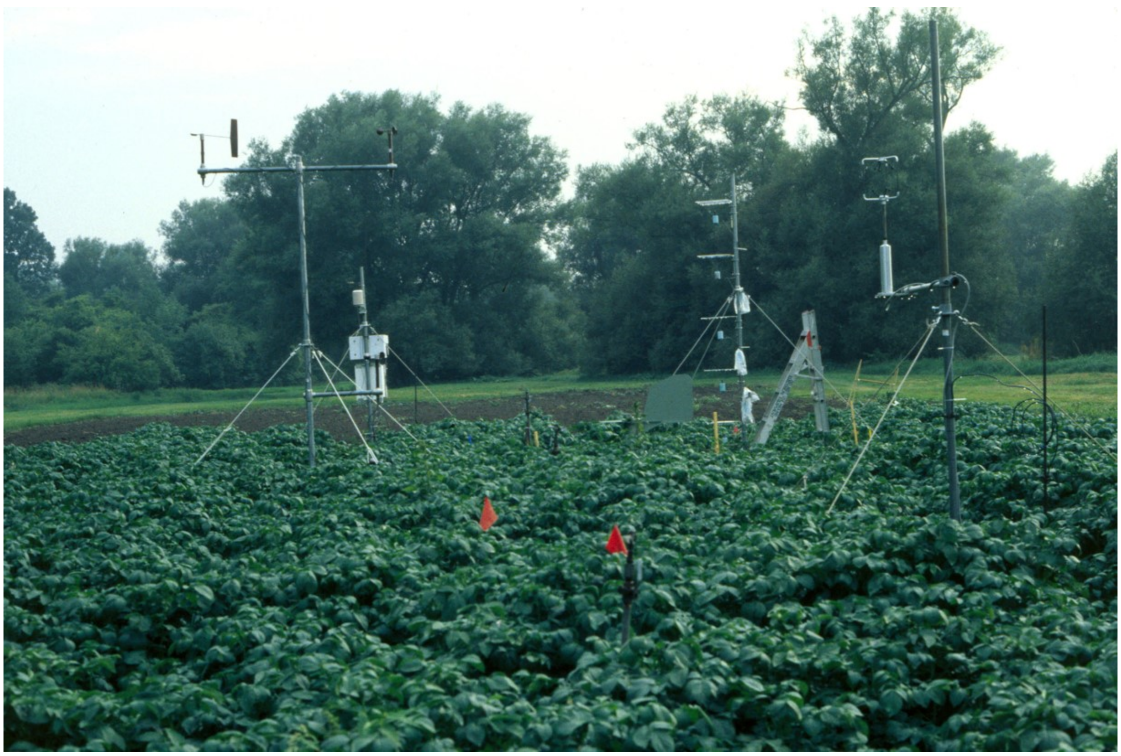

Figure 3.1. Field experiment to assess production, release and escape of sporangia from a potato crop infected with *Phytophthora infestans*. Meteorological equipment and spore samplers were positioned near the center of the experimental plot.

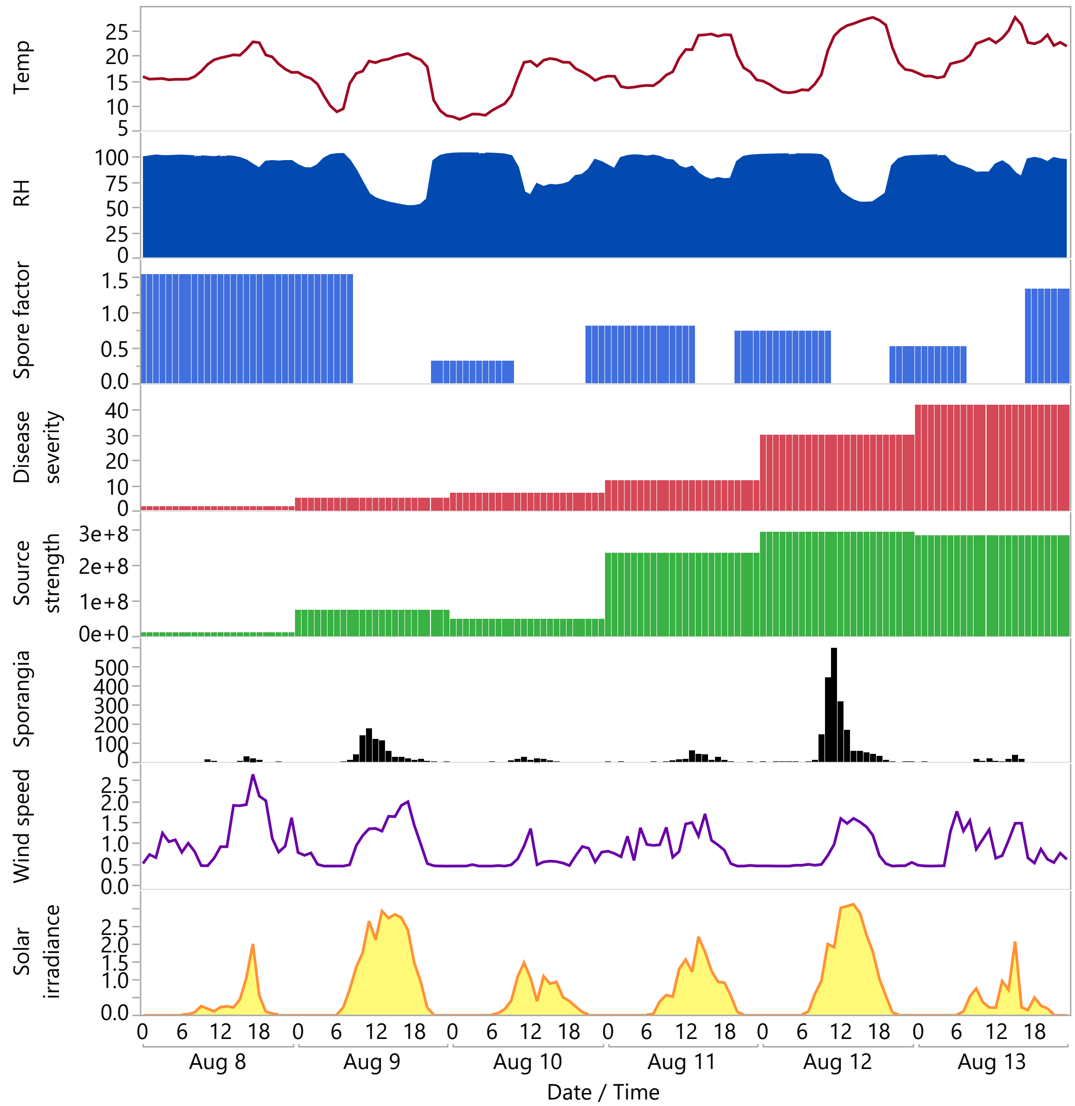

Figure 3.2. Summary illustration of factors contributing to escape of sporangia from a potato canopy. Temp - air temperature (°C); **RH** – relative humidity (%); **Spore factor** – measure of favorability for sporulation. Determined for periods with RH > 85% for more than 6 hours. Favorability calculated using temperature for each hour of the event. **Disease severity** assessed visually each day as a percentage of leaf area infected with late blight. **Source strength** – total standing spore crop of sporangia (sporangia m^{-2}) was estimated by counting number of lesions (x) in four 0.25×0.25 m^2 sampling grids and the average number of sporangia per lesion washed from three to five sampled lesions (y). Spore crop was calculated as ($x \times y$). **Sporangia** – number of sporangia caught by a Burkard sampler above an infected potato canopy. Sporangia were counted in 15 min intervals and integrated to provide a total for each hour on each day. **Wind speed** – average hourly wind speed (m s^{-1}) measured at 1.55 m above the ground. **Solar irradiance** (MJ m^{-2}) – sensed by a pyranometer at a height of 2.4 m.

2.2 Model components

Disease severity. Disease ratings were determined by visually assessing each plot for the percentage of diseased foliage caused by late blight using a method described by Fry (1977) (Figure 3.2 – Disease severity).

Sporulation. The first step required for aerial dispersal is the formation of sporangia on infected tissue - sporulation. Sporulation is influenced by relative humidity and temperature and occurs between approximately 7 – 25°C, with an optimum around 15°C (Crosier 1934; Mizubuti and Fry 1998). A sporulation event is identified as a period of at least 6 consecutive hours with RH > 85% or 90%, depending on the position of the RH sensor. For this study the critical threshold was set as 85% since the sensor was positioned above the canopy at a height of 2.2 m. If there has been at least 6 h with RH > 85%, temperature for each subsequent hour (with RH > 85%) is used in a relative sporulation rate (rSR) function (Eq. 1) to calculate the relative favorability of the temperature for sporulation.

$$\mathrm{rSR} = -4.796667 + 1.021578 \times \mathrm{TH} - 0.056437 \times \mathrm{TH}^2 + 0.000931 \times \mathrm{TH}^3$$
$$(7 \leq \mathrm{TH} \leq 25) \qquad \text{(Eq. 1)}$$

The relative sporulation rate, rSR, calculated for each hour of the event (after the minimum 6 h), is then totaled to provide an estimate of the overall favorability of the period for sporulation (TrSR). This total is then input into the following function to determine a spore factor (SporeFCT) (Figure 3.2 – Spore factor):

$$SporeFCT = (max\,(((TrSR)\,/\,(24 - HoRHSpor)), 0) \qquad \text{(Eq. 2)}$$

where HoRHSpor is the minimum period of high relative humidity (RH > 85%) required for sporulation (set as 6 h). This approach is based on a modification of the calculation of sporulation rate (SR) as used in the LB2004 model described by Andrade-Piedra et al. (2005).

Release. After sporulation, the sporangia must be released from sporangiophores. Sporangial release is initiated by a drop in relative humidity, which results in hygroscopic twisting of the sporangiophore (Leach 1975; Neufeld et al. 2013; Pinckard 1942). The fraction of released spores released every hour from sporangiophores, f_r (-), is calculated using the function (Eq. 3) described by Skelsey et al. (2009). The calculated fraction released is inversely related to the humidity level below 90%.

$$f_r = \begin{cases} 0 & RH \geq 90 \\ \dfrac{1}{RH - 91} & RH < 90 \end{cases}$$

(Eq. 3)

An additional function was included to account for the effect of rate of change in relative humidity on spore release (Eq. 4). The following additional factor was implemented:

$$delta\ RH\ factor = \begin{cases} 0 & RH_{t-2} - RH_t < 0 \\ \min\left(1, \dfrac{(RH_{t-2} - RH_t)}{30}\right) & RH_{t-2} - RH_t > 0 \end{cases}$$

(Eq. 4)

where RH_t (%) represents relative humidity at time *t* and RH_{t-2} (%) represents the relative humidity two hours prior to *t*. The combination of the function f_r (Eq. 3) and the *delta RH factor* (Eq. 4) was used to represent the favorability of environmental conditions for release.

Escape. Spores that have been released must then escape the canopy of the crop to become available for long distance dispersal. The structure of the potato canopy and its effect on wind statistics plays an important role in determining spore escape (Aylor et al. 2001). The fraction of released spores that escape the canopy, f_e, was evaluated using two approaches. For the first approach we evaluated the method (Eq. 5) used by Skelsey et al. (2009) to calculate the escape fraction (f_e):

$$f_{e\ Skelsey} = exp\left(-LAI\sqrt{\frac{v_d}{\kappa u_2}}\right)$$

(Eq. 5)

where LAI (-) is the leaf area index, κ is the von Kármán constant (0.40), v_s (m s^{-1}) is the settling velocity for *P. infestans* sporangia estimated according to Gregory (1973) as 0.0085 m s^{-1}, v_d (m s^{-1}) is three times v_s. The wind speed, u_2 (m s^{-1}), was calculated from wind speeds, u_1 (m s^{-1}), measured at h_1 (3.25 m for this study), relative to a displacement height, *d*, using a standard logarithmic wind profile with stability correction (Eq. 6) (Arya 2001);

$$u_2 = u_1 * ((LN((h_2 - d)/z_0)/(LN((h_1 - d)/z_0))))$$

(Eq. 6)

where h_2 is the characteristic height at which wind speed is calculated for equation 6 is assumed to be the canopy top (0.7 m), giving maximum escape. The displacement height, *d*, was set as 0.43 m following the approach used by Skelsey et al. (2009). *LN* is the natural log. The surface roughness length parameter, z_0, was set as 0.1 to represent agricultural land with low crops and occasional large obstacles. As noted by Skelsey et al. (2009), a standard logarithmic wind profile is not valid for wind speeds at and just above the top of the canopy; however, a standard logarithmic wind profile is a desirable model simplification. This simplification allows for calculation of escape using wind speed transformed from a measurement at another height (e.g. 10 m forecast height).

For the second approach we used a method (Eq. 7) derived from Aylor (1999) to approximate the fraction of sporangia escaping from the top half of the canopy (f_e)

$$f_{e\ Aylor} = \frac{100}{1 + 7f_x LAI \times \frac{v_s}{u_*}}$$

(Eq. 7)

where u_* represents the friction velocity (m s^{-1}), and f_x (-) is the horizontal projection of the leaf tissue area. The LAI for the crop was ≈ 5.4 m^{-2} m^{-2}. As an approximation, we took half of the leaf area to be projected horizontally and half to be projected vertically, so that the horizontally projected component of the LAI was 2.7 (Aylor et al. 2001). The product of $f_x LAI$ (set equal to 2.7) is the amount of the canopy leaf area per ground area projected in the horizontal direction (Aylor et al. 2001). The choice of canopy structure (i.e. more erect or more horizontal) has a relatively modest effect on escape (Aylor et al. 2001). Friction velocity, u_*,was calculated according to a formula derived from Arya (2001) and using parameters described by Aylor et al. (2001).

It should be noted that spore escape from sources in lower levels of the canopy would be reduced relative to sources in the upper canopy. In addition, this simplified analysis is not appropriate for conditions where inertial impaction of spores plays a prominent role in deposition and where deposition on the ground is important (Aylor 1999).

After preliminary analysis of the two approaches, we decided to use the Skelsey method since both methods yield similar results (data not shown), but the Skelsey method required fewer meteorological inputs. More accurate alternatives could be implemented depending on available meteorological data.

Algorithm implementation. In order to calculate spore factor, spore release, and spore escape, an algorithm was developed in the Python programming language. The algorithm uses hourly weather data as inputs (temperature (°C), RH (%), wind speed (m sec^{-1})) as well as an estimate of disease severity at the source (%). The algorithm is not restricted to a daily time step or specific window for spore release, which enables the identification of potential sporulation events that span multiple days. As a first step, the algorithm identifies sporulation events and determines the favorability of each event for sporulation (Eq. 2). As a next step, the suitability of the conditions for release of sporangia is calculated for each hour using equation 3 and equation 4. Finally, the fraction of released sporangia expected to escape the canopy is calculated for each hour using equation 5. Inputs required for equation 5 are calculated using equation 6.

Model components. To predict the number of sporangia escaping the canopy and becoming available for dispersal, the relationship between number of escaped sporangia measured and disease severity, spore factor, release fraction, delta RH factor, and escape fraction was first examined graphically for each day during the period from 8 August to 13 Aug. Based on the diurnal nature of spore escape (Figure 3.3), statistical analyses were conducted using hourly spore capture data for the period from 8 am to 8 pm for each day (99% of sporangia escaped during this period). One outlier was excluded from the analysis (09 00 h observation on 12 August). The data point was excluded because sporangia were sampled at a time point when RH was recorded as 100%, which makes spore release highly unlikely. Given the acknowledged ≈ 30 min time accuracy of the Burkard data, it is entirely feasible that the sporangia sampled were actually released just after 10 00 h when RH decreased. An alternative explanation is that the RH sensor did not record an accurate reading for this hour.

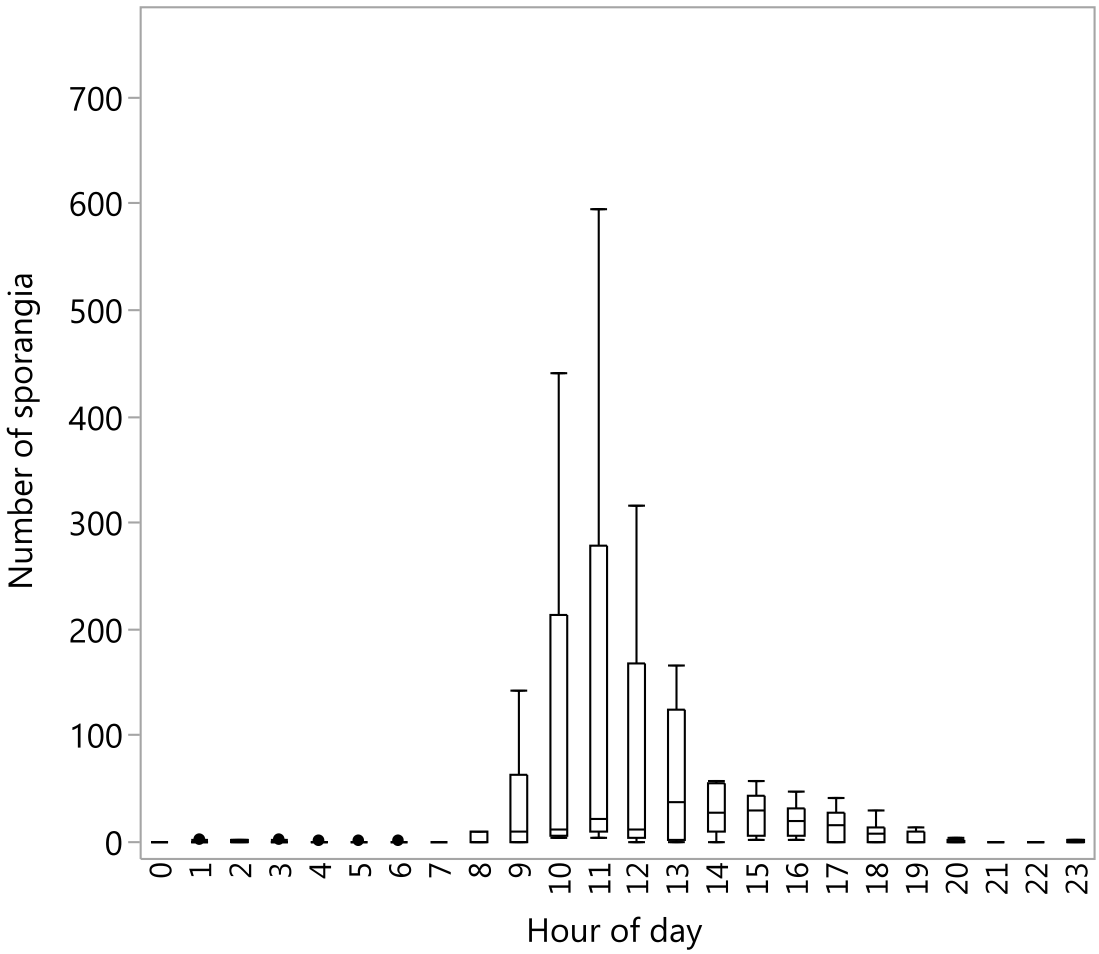

Figure 3.3. Diurnal pattern of aerial concentration of *Phytophthora infestans* sporangia above a potato canopy during a late blight epidemic at Freeville, NY. Data represents sporangia captured by a Burkard sampler, with an orifice 0.7 m above the ground, over the period from 8 August to 13 August. Sporangia were counted in 15 min intervals and integrated to provide a total for each hour on each day. The box plots are a graphical summary of the distribution of data. The horizontal line within the box represents the median sample value. The ends of the box represent the 25th and 75th quantiles. The whiskers that extend from the ends of the box are computed as 3rd quartile + 1.5*(interquartile range), and 1st quartile - 1.5*(interquartile range).

General linear models were used to describe the relationship between the number of sporangia and percent disease, spore factor, release fraction, delta RH factor, escape fraction, and all interactions up to the 5th degree. Based on a residual analysis, it was determined that a square root transformation should be applied to the response variable to ensure that the model assumptions of normality and homogeneous variance were met. For the spore prediction model, the fixed effects of percent disease, spore factor, release fraction, delta RH factor, escape fraction, and all interactions up to the 5^{th} degree were tested using F tests based on the ANOVA decomposition. All predictors were continuous and were untransformed. For all models evaluated, a lack of fit test was conducted and assumptions of normal distribution and equal variance of experimental errors for the models were tested using methods described by Ott (2010). Briefly, residual values were plotted against observed values and visually assessed for any systematic pattern. A continuous normal curve was fit to the residuals distribution and goodness of fit tested with Shapiro-Wilk W test.

The quality of spore model predictions was first assessed through a graphical comparison of predicted and observed hourly spore capture. To enable the graphical comparison, model results were back transformed by squaring the results from the prediction equation. Both summary and difference statistics were used to evaluate model performance. Coefficients of multiple determination (R^2) were calculated to estimate the variability explained by the regression equations and the root mean square error, RMSE, was calculated to compare predicted and observed values. The final model was chosen based on the inclusion of biologically meaningful predictors and their interactions. However, to assist with selection process and to determine the simplest meaningful model, Akaike information criterion with a correction for finite sample size (AICc) was considered in the selection of the final model. Additionally, to guard against overfitting cross-validation was conducted by calculating the K-fold R Square (k = 10) for the model. Based on the principle of effect heredity, all of the lower-order components of significant higher-order effects were retained. All statistical analyses were conducted using JMP® Pro, Version 12.2.0. SAS Institute Inc., Cary, NC

3. RESULTS

3.1 Disease severity and standing crop of sporangia

Disease increased from 1.5 % on 8 August to 42% on 13 August (Figure 3.4 – Disease severity). The total standing spore crop (source strength) also generally increased over time, ranging from 10.4×10^6 sporangia m^{-2} on 8 August to 2.9×10^8 sporangia m^{-2} on 12 August (Figure 3.4 – Sporangia). This wide range in standing spore crop is due to the increasing size of the source (new lesions and larger lesions) and due to the effects of different environments on sporulation by *P. infestans*.

The height within the canopy was associated with the quantity of available sporangia. Numbers of sporangia were consistently higher in the lower canopy than the upper canopy (Figure 3.4 – Sporangia). In the lower canopy the mean standing spore crop ranged from 7.5×10^6 sporangia m^{-2} on 8 August to 2.1×10^8 sporangia m^{-2} on 12 August. In the upper canopy the mean standing spore crop ranged from 2.8×10^6 sporangia m^{-2} on 8 August to 9.9×10^7 sporangia m^{-2} on 13 August. The difference in available sporangia between lower and upper canopy can be explained by the higher number of lesions present in the lower canopy, which was typically double or triple the number present in the upper canopy (data not shown).

The standing spore crop varied among days, and was not always related only to disease severity. For example, despite the higher disease severity on 13 August (42%) relative to disease severity on 11 August (12%), the numbers of available sporangia were quite similar for those two days (Figure 3.4 – Sporangia). Conversely, a slight increase in disease (5%) was accompanied by a dramatic increase in total available sporangia (1.9×10^8 sporangia m^{-2}) between 10 August and 11 August. As illustrated below, these differences were associated with different environmental conditions on the different days.

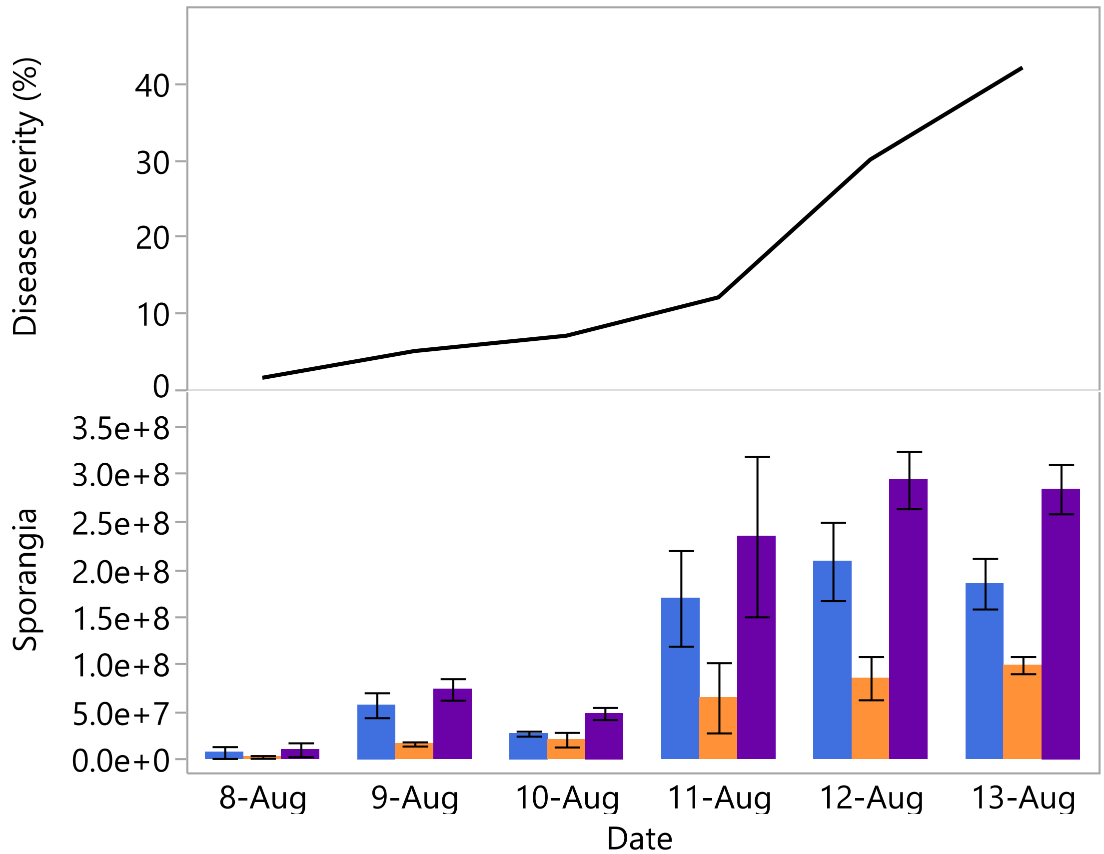

Figure 3.4. Disease severity and standing crop of *Phytophthora infestans* sporangia for the assessment period at the field site in Freeville, NY. The solid line represents the mean disease severity assessed visually as the percent of the leaf area infected on each date when sporangia were collected. Standing spore crop of sporangia was evaluated each morning, before dew dried from the plants (usually before 7:30 to 8:00 am). Standing spore crop of sporangia (sporangia m^{-2}) was estimated by counting number of lesions (x) in four 0.25×0.25 m^2 sampling grids for two strata (lower canopy (x_l): 0 to 0.4 m; upper canopy (x_u): > 0.4 m) and the average number of sporangia per lesion washed from three to five sampled lesions (y). Spore crop was calculated as ($x \times y$). Bars with blue fill are mean spore crop for lower canopy; bars with orange fill are mean spore crop for upper canopy; bars with purple fill are total spore crop for lower and upper canopy.

3.2 Meteorological variables and dynamics of sporangia production, release and escape

Hourly average air temperature, RH, wind speed, and solar irradiance followed a diurnal pattern (Figure 3.2). Air temperature increased during the day (06 00h to 18

00h) and decreased overnight (18 00 h to 06 00 h). During the study period, recorded temperatures ranged from 7.2 to 27.7°C. Often, relative humidity was inversely related to air temperature and decreased during the morning to a minimum around 12 00 h, increasing again in the late afternoon and early evening (18 00h), except during the day on 8, 11, and 13 August where RH did not decrease, or decreased slowly. Relative humidity ranged from 47.5 to 100%. Wind speed ranged from 0.45 to 2.64 m s^{-1} and global radiation ranged from 0 to 3.11 MJ m^{-2}. Wind speed fluctuated during the day and was generally calm at night. Wind speeds were consistently higher on sunny days (9 August and 12 August) in comparison to overcast days with lower solar irradiance (10 and 13 August). Sudden increases in solar irradiance were accompanied by increased wind speeds, e.g. the afternoon of 8 August, when the maximum wind speed for the study was observed.

Sporangia production. Several periods of high relative humidity were observed during the study, and using equation 2, these were used to calculate the spore factor (blue bars on the spore factor x-axis of Figure 3.2). The y-axis for the spore factor graph indicates the overall favorability of the temperature during the sporulation event (calculated using equation 2). High RH events ending on 9 August, 11 August, and 12 August were favorable for sporulation, with temperatures close to the optimal sporulation temperature of 15°C. High RH events ending on 10 August and 13 August were less favorable. For example, air temperature overnight on 9/10 August dropped to 7.2°C which is unfavorable for sporulation – which is evident from the lower total spore crop (source strength) on 10 August, relative to 9 August, despite a slight increase in disease severity from the 9 August to 10 August (Figure 3.4 – Disease severity and Sporangia).

Release of sporangia. Release of sporangia is initiated by a drop in relative humidity. On days where there was a spore crop available at the end of a sporulation period (Figure 3.2 – spore factor x-axis), substantial release of sporangia occurred when relative humidity dropped below 90%, as described by the “release” function. However, the magnitude of release was also determined by the rate of change of relative humidity. For example, when the release events on 11 and 12 August are compared, both days started with comparable spore crops (Figure 3.2 – Source strength), relative humidity dropped below 90% on both days, and similar wind speeds were recorded during the dispersal events yet there was a substantially higher number of sporangia released on 12 August. This can be explained by the rapid drop in relative humidity on the morning of 12 August in comparison to 11 August when the relative humidity did not decrease to the same extent, or as rapidly.

Escape of sporangia. Escape of sporangia followed a diurnal pattern, with 99% of sporangia being released and escaping between 08 00 h and 20 00 h (Figure 3.3). The daily observations appeared to be log-normally distributed. This distribution is likely due to the initial release of sporangia increasing as RH decreases and wind speed increases, followed by a decline as the numbers of sporangia available for release diminishes, and/or the conditions for escape become less favorable. Numbers of sporangia sampled during dispersal events ranged from 0 to 595 sporangia per hour (Figure 3.2 – Sporangia). As expected, the numbers of sporangia escaping the canopy increased with increasing available spore crop and increasing wind speed (Figure 3.2 – Wind speed). Wind speed is a major factor contributing to escape and this is accounted for in the escape function (Eq. 5). Solar irradiance is known to impact temperature, RH, and wind speed, which was evident over the course of the study. High solar irradiance was accompanied by increases in air temperature, decreases in RH, and increases in wind speed and volatility. On sunny days, 9 and 12 August, there were higher numbers of sporangia sampled during release events (Figure 3.2 – Sporangia). The highest recorded number of sporangia occurred on 12 August at 30% disease severity, maximum spore crop of 2.9×10^8 sporangia m^{-2}, optimal conditions for release of sporangia, elevated wind speeds, and sunny day. Interestingly, on 8 August the wind speed increased to the maximum observed for the study (2.64 m s^{-1}) but this increase was not accompanied by a major escape event. This could have been due to limited release of sporangia from sporangiophores because the RH did not decrease substantially on 8 August (Figure 3.2 – RH), or the fact that there was a very limited spore crop available (source strength).

Model. To predict dispersal potential (numbers of airborne sporangia), a linear model consisting of various combinations of predictors (mean disease severity (Disease), spore factor (SporeFCT), release functions – f_r (Release) and change in RH (DeltaRH), and escape function (Escape)), and their interactions was developed. The transformed response (square root of hourly number of sporangia) was well described by the linear model ($P < 0.0001$). See Table 3.1 for effects included in the final model. All parameters included in the model were either significant according to F-tests ($P \leq 0.03$), or were retained according to the principle of effects heredity (Table 3.1). The model consisted of the linear combination of all terms shown in Table 3.2. Parameter estimates are shown in Table 3.2. Plots of residual versus observed values did not reveal any systematic pattern in the residuals (data not shown). Residuals were normally distributed (Shapiro Wilks W test, $P = 0.26$). The Lack of fit test was not significant ($P = 0.13$).

Table 3.1. Model effects and F-test results.

Source [z]	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Disease	1	1	78.05297	27.4534	<.0001
SporeFCT	1	1	101.14	35.57	<.0001
Release	1	1	4.48554	1.5777	0.2149
DeltaRH	1	1	16.0139	5.6325	0.0215
Escape	1	1	39.08896	13.7487	0.0005
Disease*Release	1	1	99.78	35.10	<.0001
Disease*DeltaRH	1	1	47.76	16.80	0.0002
Disease*SporeFCT	1	1	157.12	55.26	<.0001
Release*Escape	1	1	25.82	9.08	0.004
Release*DeltaRH	1	1	14.60	5.14	0.0278
Release*SporeFCT	1	1	42.44	14.93	0.0003
Escape*DeltaRH	1	1	57.70	20.30	<.0001
Escape*SporeFCT	1	1	39.37	13.85	0.0005
DeltaRH*SporeFCT	1	1	92.80	32.64	<.0001
Disease*Release*DeltaRH	1	1	98.69	34.71	<.0001
Disease*Release*SporeFCT	1	1	46.54	16.37	0.0002
Disease*DeltaRH*SporeFCT	1	1	153.38	53.95	<.0001
Release*Escape*DeltaRH	1	1	21.39	7.52	0.0084
Release*Escape*SporeFCT	1	1	17.53	6.17	0.0164
Escape*DeltaRH*SporeFCT	1	1	17.85	6.28	0.0155

Disease - mean disease severity assessed visually as the percent of the leaf area infected on each date when sporangia were collected
SporeFCT - sporulation factor calculated based on duration of high relative humidity (> 85%) prior to dispersal event and favorability of temperature for sporulation
Release - proportion of sporangia predicted to be released from sporangiophores, f_r (calculated based on function described by Skelsey et al 2009)
DeltaRH - factor calculated to describe the effect of change of relative humidity on release of sporangia
Escape - proportion of sporangia predicted to escape the potato canopy based on wind speed and leaf area index (calculated based on function described by Skelsey et al 2009)
The sample size (n) for the model was 72 hourly observations of sporangia above a potato crop canopy. Observations were made between 08 00 h to 20 00 h on 8 - 13 August

Table 3.2. Parameter estimates and standard errors.

Term [z]	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-19.22	9.03	-2.13	0.0382
Disease	0.64	0.12	5.24	<.0001
Release	9.26	7.37	1.26	0.2149
Escape	-128.35	34.61	-3.71	0.0005
DeltaRH	-22.36	9.42	-2.37	0.0215
SporeFCT	44.59	7.48	5.96	<.0001
(Disease-16.0563)*(Release-0.60096)	-2.30	0.39	-5.92	<.0001
(Disease-16.0563)*(DeltaRH-0.17777)	0.42	0.10	4.1	0.0002
(Disease-16.0563)*(SporeFCT-0.48202)	2.34	0.32	7.43	<.0001
(Release-0.60096)*(Escape-0.11206)	315.42	104.67	3.01	0.004
(Release-0.60096)*(DeltaRH-0.17777)	62.84	27.73	2.27	0.0278
(Release-0.60096)*(SporeFCT-0.48202)	-88.50	22.91	-3.86	0.0003
(Escape-0.11206)*(DeltaRH-0.17777)	-425.31	94.41	-4.51	<.0001
(Escape-0.11206)*(SporeFCT-0.48202)	164.21	44.13	3.72	0.0005
(DeltaRH-0.17777)*(SporeFCT-0.48202)	70.54	12.35	5.71	<.0001
(Disease-16.0563)*(Release-0.60096)*(DeltaRH-0.17777)	-5.08	0.86	-5.89	<.0001
(Disease-16.0563)*(Release-0.60096)*(SporeFCT-0.48202)	-3.15	0.78	-4.05	0.0002
(Disease-16.0563)*(DeltaRH-0.17777)*(SporeFCT-0.48202)	7.56	1.03	7.35	<.0001
(Release-0.60096)*(Escape-0.11206)*(DeltaRH-0.17777)	691.98	252.30	2.74	0.0084
(Release-0.60096)*(Escape-0.11206)*(SporeFCT-0.48202)	-357.76	144.08	-2.48	0.0164
(Escape-0.11206)*(DeltaRH-0.17777)*(SporeFCT-0.48202)	253.46	101.15	2.51	0.0155

[z] Terms are centered on their mean e.g. mean Disease = 16.0563
Disease - mean disease severity assessed visually as the percent of the leaf area infected on each date when sporangia were collected
SporeFCT - sporulation factor calculated based on duration of high relative humidity (> 85%) prior to dispersal event and favorability of temperature for sporulation
Release - proportion of sporangia predicted to be released from sporangiophores, f_r (calculated based on function described by Skelsey et al 2009)
DeltaRH - factor calculated to describe the effect of change of relative humidity on release of sporangia
Escape - proportion of sporangia predicted to escape the potato canopy based on wind speed and leaf area index (calculated based on function described by Skelsey et al 2009)
The sample size (n) for the model was 72 hourly observations of sporangia above a potato crop canopy. Observations were assessed between 08 00 h to 20 00 h on 8 - 13 August
The R square for the model was 0.91 and the Root Mean Square Error was 2.86 sporangia per hour

A significant proportion of the variability in hourly sporangia numbers was explained by the regression equation ($R^2 = 0.91$). Graphical comparison of predicted and observed values of the back transformed response showed generally good agreement in the pattern and magnitude of the response between the predicted and observed values (Figure 3.5). Root mean squared error was used to compare the predicted and observed values of the transformed response and a good fit of the model was observed (RMSE = 1.69 $\sqrt{sporangia\ h^{-1}}$). Cross-validation illustrated that there was a reasonable fit of the model (K-fold $R^2 = 0.68$).

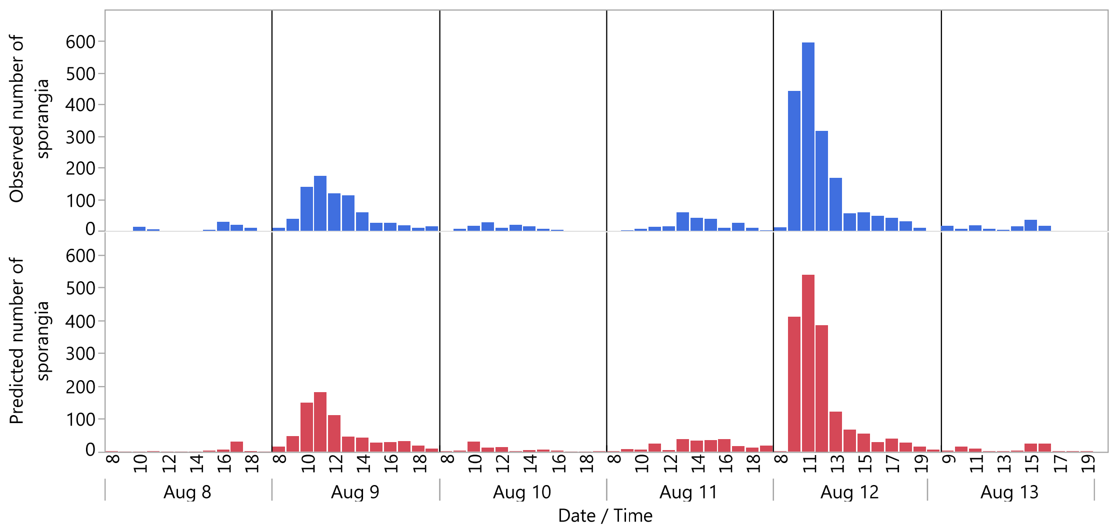

Figure 3.5. Comparison between between predicted and observed numbers of sporangia above a potato canopy infected with *Phytophthora infestans*. Predictions from the dispersal-risk model are shown in red (after back transforming). The observed number of sporangia sampled with a Burkard spore sampler are shown in blue. The hourly observations for the statistical analysis were limited to the hours from 08 00 h to 20 00 h, since 99% of sporangia were sampled during this period.

Interactions between predictors were expected given the complexity of processes involved in production, release, and escape of sporangia. Significant 3rd order interactions between predictors were observed (Table 3.1). To gain an understanding of the interactions occurring between predictors and their effects on the response, we investigated prediction profile plots at various levels of each predictor, while centralizing other predictors at their mean values.

Disease severity prediction profiles. At increasing disease severity levels we observe that there was a strong and increasingly elevating effect of sporulation factor (above the mean spore factor level) on the predicted numbers of airborne sporangia (Figure 3.6). This indicates that as disease severity level increases the level of sporulation becomes an increasingly important factor. There was also a weak but increasingly elevating effect of Release at levels of Release below the mean.

Spore factor prediction profiles. As the level of the spore factor predictor increased there was an increasingly strong effect of deltaRH factor. Levels above the mean deltaRH factor elevated the predicted numbers of airborne sporangia (Figure 3.7). At increasing sporulation factor levels we observe that there was a strong and increasingly elevating effect of disease severity (above the mean disease severity level) on the predicted numbers of airborne sporangia. In other words, there is a strong interaction between sporulation and disease severity and under favorable conditions for sporulation the level of disease severity at the source (infected tissue that can potentially sporulate) becomes increasingly important.

Release prediction profiles. At low levels of release there was a strong elevating effect of sporulation factor on the number of airborne sporangia predicted, but this elevating effect diminished as release increased (Figure 3.8). This suggests that under highly favorable conditions for sporulation low levels of release are important but this sensitivity decreases as the level of release increases. There was also a weak reductive effect of escape, which diminished as release increased.

DeltaRH factor prediction profiles. As the level of deltaRH factor increased there was an increasingly reductive effect of escape (at levels above the mean for escape) on the predicted number of airborne sporangia. This was in contrast to an increasingly elevating effect of spore factor (at levels above the mean for spore factor) (Figure 3.9). In other words, more sporangia were observed above the canopy when high rates of change of RH occurred following an event that was highly favorable for sporulation, but this was moderated by the level of escape.

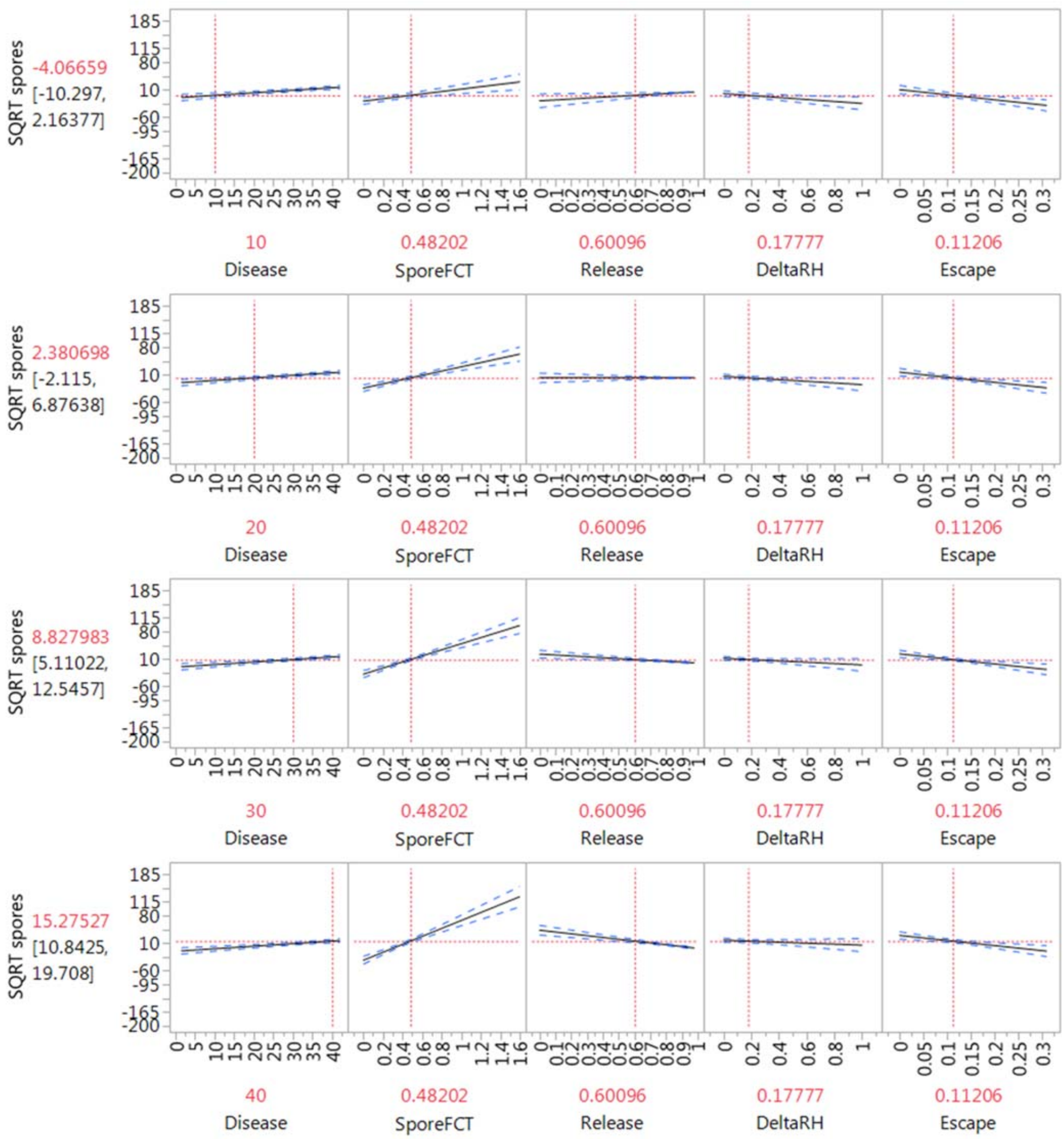

Figure 3.6. Prediction profiles for levels of disease severity. The Y-axis is the model response - predicted square root of spores. Four levels of disease severity are shown in the four panels and all other predictors are centered at their mean value. The value in red above the x-axis is the level of the predictor.

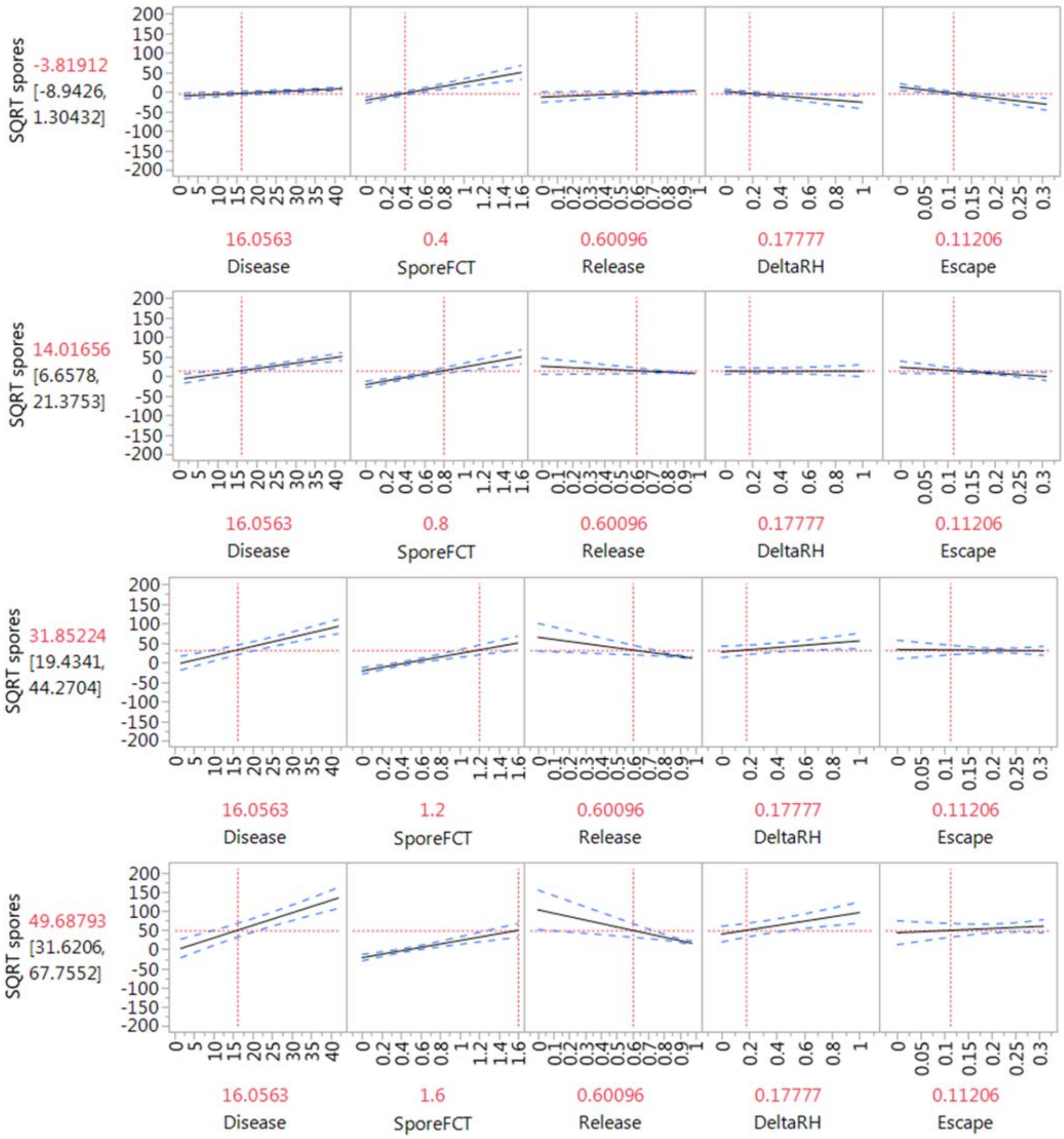

Figure 3.7. Prediction profiles for levels of the spore factor predictor (SporeFCT). The Y-axis is the model response - predicted square root of spores. Four levels of SporeFCT are shown in the four panels and all other predictors are centered at their mean value. The value in red above the x-axis label is the level of the predictor.

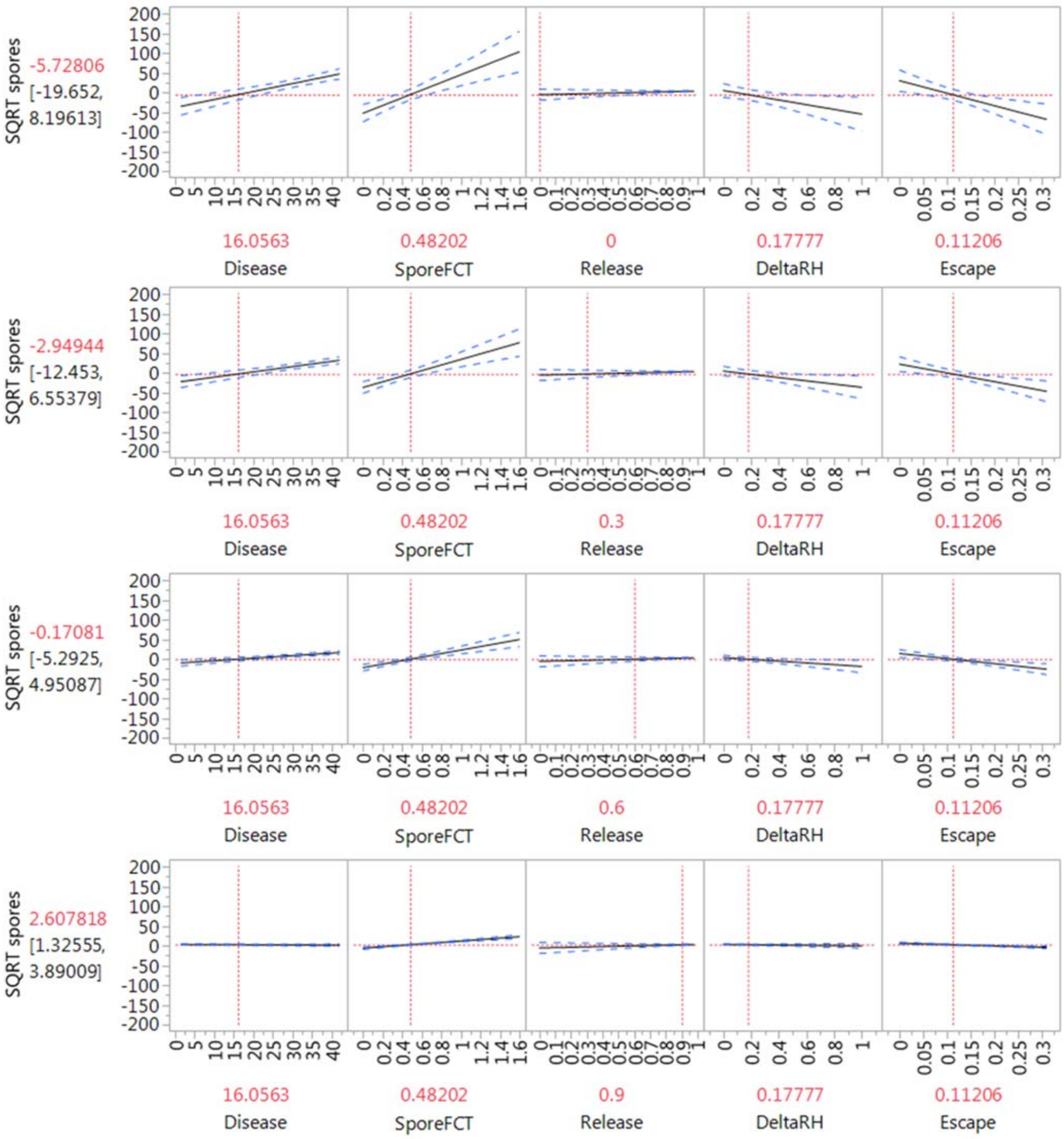

Figure 3.8. Prediction profiles for levels of the release predictor. The Y-axis is the model response - predicted square root of spores. Four levels of release are shown in the four panels and all other predictors are centered at their mean value. The value in red above the x-axis label is the level of the predictor.

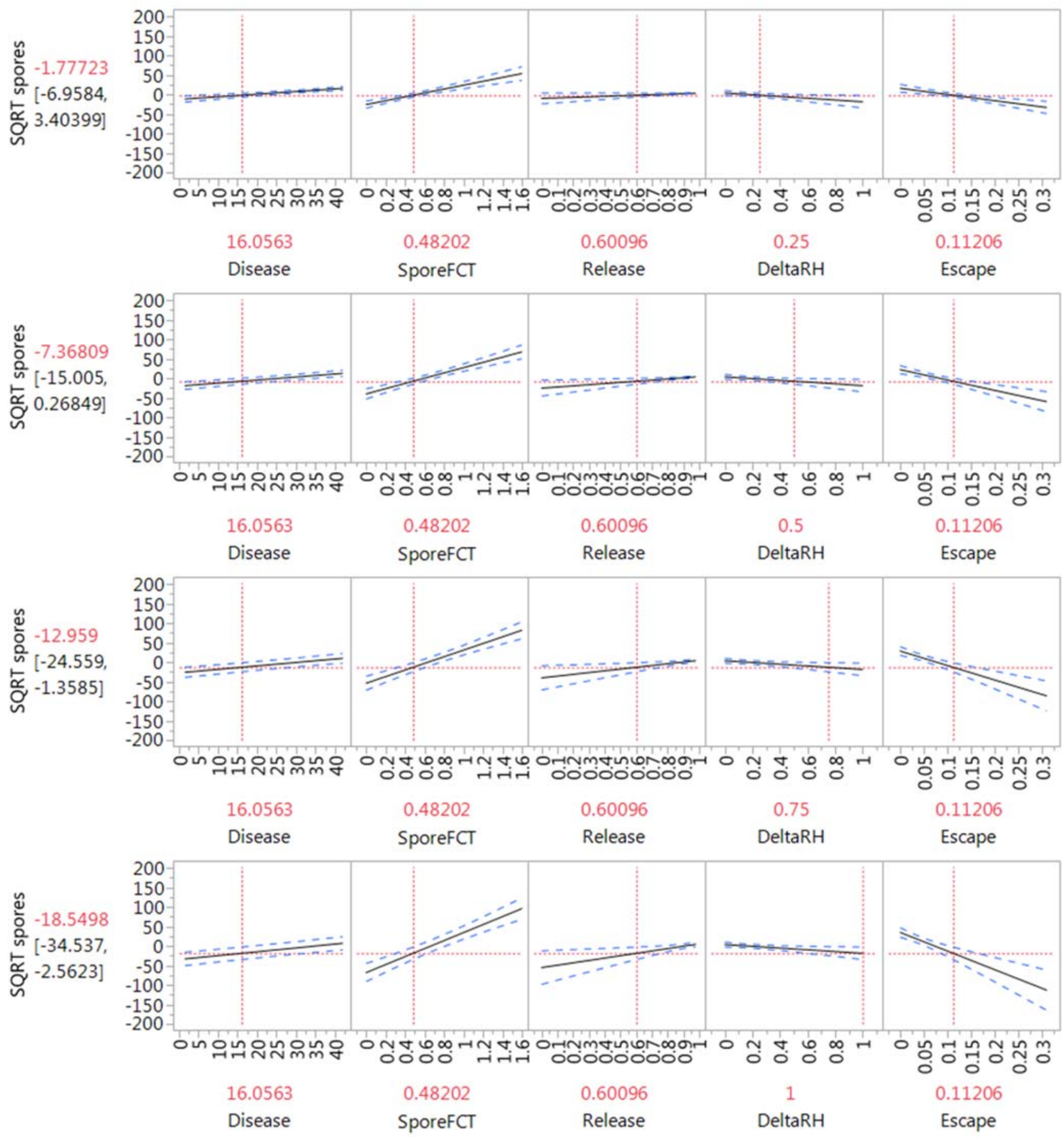

Figure 3.9. Prediction profiles for levels of the deltaRH predictor. The Y-axis is the model response - predicted square root of spores. Four levels of deltaRH are shown in the four panels and all other predictors are centered at their mean value. The value in red above the x-axis label is the level of the predictor.

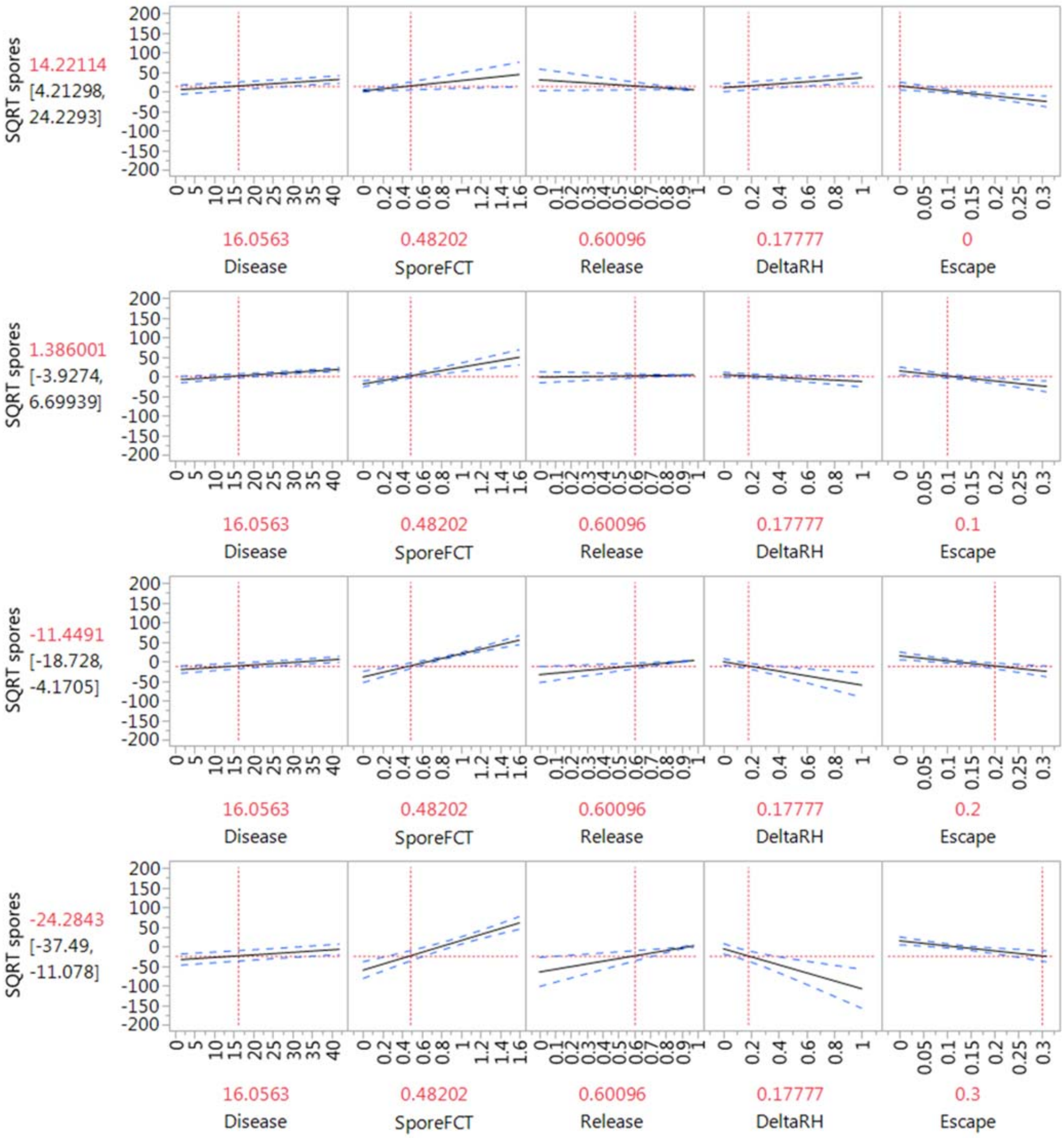

Figure 3.10. Prediction profiles for levels of the escape predictor. The Y-axis is the model response - predicted square root of spores. Four levels of escape are shown in the four panels and all other predictors are centered at their mean value. The value in red above the x-axis label is the level of the predictor.

Escape prediction profiles. Increases in the level of escape were accompanied by interactions with deltaRH factor, release, and spore factor. A strong and variable interaction occurred with deltaRH. At a low level of escape there was a strong elevating effect of deltaRH factor on the predicted number of airborne sporangia. As the level of escape increased this changed to an increasingly reductive effect of deltaRH for levels above the mean deltaRH factor. A significant but weak reductive effect of release, was observed with increasing levels of escape. Additionally, an increasingly elevating effect of spore factor occurred with increasing levels of escape (Figure 3.10).

4. DISCUSSION

Using previously published data (Andrade-Piedra et al. 2005; Aylor et al. 2001; Crosier 1934; Mizubuti and Fry 1998), and some unpublished experimental data concerning quantitative relationships between source strength and dispersal, we have constructed a model to predict dispersal-risk. With field-based estimates of disease severity at a known source of late blight, variations in aerial sporangia above the crop canopy were well described ($P < 0.0001$) by the dispersal-risk model (adjusted R^2 = 0.91; RMSE = 2.86 sporangia h^{-1}).

Knowledge of the availability of sporangia from infected sources is key to successful modelling of inoculum dispersal. Estimation of source strength is often achieved through daily measurements of the standing spore crop at the study site. Despite the importance of this information, it is almost never available on a near-real time basis. Additionally, determination of the standing spore crop is labor-intensive and time-consuming, and is thus impractical for regional forecasting programs that use field surveys to determine the geographic extent and strength of inoculum sources (Aylor et al. 2001; Neufeld et al. 2013). To avoid the need to manually estimate standing spore crop, the model utilizes common field-based assessment (or estimation) of disease severity in combination with readily available meteorological data to provide approximations of sporangia availability and ultimately predict the relative number of sporangia h^{-1} that is likely to escape the canopy into the atmosphere above an infected field and become available for dispersal.

To characterize the relationship between disease severity and availability of sporangia, we assessed the standing spore crop prior to dispersal each day for the duration of the study. The wide range of total available standing spore crop observed in this study was due to the increasing size of the source (new lesions and larger lesions) and due to the effects of different environments on sporulation by *P. infestans*. In addition, the height within the canopy was associated with the quantity of available sporangia. Numbers of sporangia were consistently higher in the lower canopy than the upper canopy. This was largely due to differences in numbers of lesions at the two canopy levels. However, the number of sporangia per lesion varies greatly, even in apparently uniformly infected plants. Differences result from variation in meteorological variation in the environment, from micrometeorological variations in the plant canopy, and from size and age of the lesions (Rotem 1988). There is usually a relatively short period of several days between the appearance of a lesion, its expansion over the whole leaf and death of the leaf. Completely blighted and dead leaves produce few, if any, sporangia (Bashi et al. 1982). As a result, sporangia production will increase up to a maximum, as disease severity increases, and then decrease thereafter as the amount of healthy leaf area decreases. In this study, the highest disease severity for which we have an assessment of available sporangia was 42%. It is likely availability of healthy tissue had not yet become a limiting factor for sporangial production. For this reason it should be noted that the model should not be used at disease severities above 42% since this will be beyond the x-space of the disease severity predictor.

A key next step in the process of dispersal is the release of sporangia from sporangiophores. Numbers of sporangia captured at canopy height (0.75 m) showed a strong diurnal pattern with majority of release recorded between 08 00 h and 20 00 h. This diurnal pattern of release is in line with those reported for other airborne oomycete pathogens (Aylor and Taylor 1983; Neufeld et al. 2013). Release of *P. infestans* sporangia and of other downy mildew pathogens has been shown to be associated with a decrease of RH and evaporation of moisture from leaf surfaces (Leach 1975; Neufeld et al. 2013; Pinckard 1942). Release of *P. infestans* sporangia near our inoculum source varied considerably across each of the sampling days. For example, there was a substantial difference in the number of sporangia captured on 11 August and 12 August despite comparable source strength, spore factor, and escape potential. A major difference between the two days was the rate of change of RH during the dispersal event, since there was a slow decline of RH during the event on 11 August in comparison to the rapid change in RH on 12 August. This motivated the development of the function to describe the effect of change in RH – deltaRH factor. The importance of the deltaRH factor was supported by its involvement in the significant three-way interaction between disease severity, sporulation factor, and deltaRH ($P < 0.0001$) as well as the three-way interaction between disease severity, release, and deltaRH ($P < 0.0001$).

Escape of sporangia from the canopy is influenced by several factors including wind speed and turbulence, height of spore release, and canopy structure (Aylor 1990). Conditions over the course of the study were moderately favorable for escape. The higher in the canopy the inoculum source is located and the stronger the wind speed, the greater the number of sporangia that can escape the canopy (Aylor et al. 2001). A wind speed of 1 to 2 m s^{-1} is sufficient to remove a sizeable proportion of the available sporangia from a potato crop canopy. These same speeds can transport sporangia for 10 to 20 km in less than 3 h (Aylor et al. 2001). However, the ability of the transported sporangia to cause infection will be dependent on their survival in transit. Solar irradiance, temperature, and relative humidity are the most important variables that influence the survival of *P. infestans* sporangia with the viability of sporangia exposed for 1 h on a sunny day being reduced by ≈ 95% (Mizubuti et al. 2000). The dispersal distance of viable *P. infestans* sporangia will depend on inoculum source strength, escape fraction, and survival of sporangia in transit.

Our calculations of escape fraction are based on the assumption of neutral atmospheric conditions. It is possible that unstable atmospheric conditions could result in escape values higher than our escape functions would calculate. We have also assumed that the source is present in the top of the canopy, yielding maximum escape. Additionally, the LAI for period of data capture was relatively consistent, so we could assume a constant LAI for our calculations. In reality, high disease levels will cause the LAI to decline. This limits the current model to use in situations with a full crop canopy and disease severity between 1.5 and 42 %, as this was the range of disease severity over the course of the study.

A major goal of this study was to use data to develop a dispersal-risk model that will eventually form the basis for a dispersal-risk algorithm that can be implemented on the BlightPro decision support system (Small et al. 2015b) to improve the efficiency of late blight management. The objective of the algorithm is to use reports of late blight in combination with weather data to predict conditions that will enable *P. infestans* to sporulate from infected tissue at a known site, to be dispersed from that site, to be transported in a viable condition to a second site, and to germinate and infect a potato or tomato crop at that second site. Currently, the model developed from this study is not connected to a particle dispersion model. Progress is being made with respect to our understanding of aerial transport of *P. infestans* between fields (Aylor et al. 2011). In future, the dispersal-risk tool could be integrated with a Lagrangian stochastic model (Aylor et al. 2001; Aylor et al. 2011) and other atmospheric transport models, such as HYSPLIT (Draxler and Hess 1998) or FLEXPART (Stohl et al. 1998), to predict pathways of sporangia transport and deposition across a range of spatial scales. Weather data along the projected pathways of sporangia transport can be used to predict the viability of the sporangia and suitability of conditions for infection based on RH, temperature, and exposure to solar radiation which would enable predictions of risk of disease outbreak. These future developments could follow the framework described by Aylor (1986), or Skelsey et al. (2009).

Skelsey et al. developed a spatial component for a decision support system as a proof of concept (Skelsey et al. 2009) and we have used some components of this model. Although we have used some components, there were three limitations/assumptions that motivated us to develop a new algorithm: 1) a constant source strength is assumed which is a desirable simplification if no source information is available, but this information can be updated if known sources are identified; 2) the release function was not empirically validated for *P. infestans* and required the addition of the delta RH factor in the present study to adequately represent observed release patterns; and 3) dispersal events were limited to between 06 00 h to 14 00 h. The diurnal pattern identified in the present study identifies 08 00 h to 20 00 h as being the period when 99% of sporangia were sampled above the potato canopy (Figure 3.3). Supporting the importance of sporangia sampled after 14 00 h, Bashi et al. (1982) found spores released later in the afternoon can be an important source of viable spores.

Current forecast systems on the BlightPro DSS assume that late blight is present in the production area. The ability to predict the potential arrival of pathogen inoculum could improve the efficiency of late blight management. Integration of knowledge from USAblight on confirmed occurrence information into the dispersal-risk tool will enable site-specific risk prediction for the user's location. We expect the new forecast to provide highly specific (and therefore much improved) information concerning potential dispersal of inoculum. In places where there is susceptible foliage year round (Florida), the pathogen may be available year round, and a “dispersal alert” based on the algorithm described in the present study could be very helpful to schedule fungicide applications. In other locations, there can be large differences in planting dates and the “dispersal alert” would be very helpful for later planted crops.

We propose that the dispersal-risk algorithm that we have developed be used to assist with timing of fungicide applications (in a similar manner to Skelsey et al. (2009)), but that it also be used to inform choice of fungicide active ingredient. There are diverse active ingredients used against late blight (with varying degrees of efficacy) (Mayton et al. 2001), including some fungicides with the ability to be transported within the plant and with activity against established infections (Milgroom and Fry 1988). We foresee the output from the algorithm being used to modify recommendations from existing late blight forecasts, such as Simcast, to provide information that would inform users of diverse dispersal events that might require diverse fungicides.

For practical purposes, more data will be required to validate the results reported in this study, particularly where the relationship between disease severity and aerial concentration of sporangia or sporangia escape is intended for use within a predictive framework on the BlightPro DSS. Although the dispersal-risk model that we developed described the variations in aerial sporangia above the crop canopy very well for the data set on which it was constructed, it is likely that the model is overfit because of the limited combinations of disease severity and environmental conditions included in the dataset. We used cross-validation (k-fold) to verify that the model was not extremely overfitted and the K-fold R^2 (0.67) indicated a reasonable model fit. In order to validate the current model it will be necessary to train and test it against a broader range of combinations of disease severity levels and environmental conditions. Data such as those generated by Aylor et al (Aylor et al. 2011) would be particularly useful in this regard.

In the context of the BlightPro decision support system, the dispersal-risk model is intended as a tool to provide information that will inform decisions relating to application of fungicide. Ultimately, the accurate prediction of exact numbers of sporangia arriving is not essential as long as the resulting spray decision is appropriate. For this reason the model is being evaluated for its utility as a classification tool (identifying high-risk dispersal events).

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